

International Business Cycles: World, Region, and Country-Specific Factors

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The paper investigates the common dynamic properties of business-cycle fluctuations across countries, regions, and the world. We employ a Bayesian dynamic latent factor model to estimate common components in macroeconomic aggregates (output, consumption, and investment) in a 60-country sample covering seven regions of the world. The results indicate that a common world factor is an important source of volatility for aggregates in most countries, providing evidence for a world business cycle. We find that region-specific factors play only a minor role in explaining fluctuations in economic activity. We also document similarities and differences across regions, countries, and aggregates. (JEL F41, E32, C11, C32)

Is there a *world business cycle*? Recent studies have indeed provided evidence that there are many cross-country links in macroeconomic fluctuations.¹ For example, studies of pairwise correlations by David Backus et al. (1995) and Marianne Baxter (1995) find that business cycles in major industrialized economies are quite similar. Enrique G. Mendoza (1995) and Kose (2002) document that business cycles of developing economies have characteristics similar to

those of developed countries.² More structured time-series analyses also find comovement in subsets of countries. In particular, Allan Gregory et al. (1997) use Kalman filtering and dynamic factor analysis to identify the common fluctuations across macroeconomic aggregates in G7 countries.³ Todd E. Clark and Kwanho

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¹ Understanding the similarities of business-cycle fluctuations across countries has long been a subject of interest to macroeconomists. See Victor Zarnowitz (1992) for a survey of this research program.

² Stefan Gerlach (1988), using spectral methods, finds that movements in industrial production indices in a number of OECD countries are correlated. In a recent paper, U. Michael Bergman et al. (1998) study cross-country correlations of several macro aggregates of 13 industrialized countries and find that business-cycle fluctuations are highly synchronized across countries and across monetary regimes. Mario J. Crucini (1999) establishes a link between those studies employing stochastic dynamic macroeconomic models that try to explain common fluctuations across countries, and those empirical studies documenting features of international business cycles. Kose and Kei-Mu Yi (2001, 2003) study whether standard multicountry business-cycle models can generate the observed relationship between international trade and business-cycle comovement. Michael Kouparitsas (1997a, b) studies the transmission of international business cycles from the developed countries in the North to the developing economies in the South.

³ Alan Stockman (1988) employs an error-correction method and finds that a substantial fraction of variation in industrial production is due to global sector-specific and country-specific disturbances in major industrialized economies. Stefan C. Norrbom and Don E. Schlagenhauf (1996) also employ a dynamic factor model to examine the role of world, nation-specific, and industry-specific factors in explaining common movement across G7 countries, Belgium, and Netherlands. Their results indicate that while the world and country-specific factors explain some fraction of

Shin (2000) use a VAR factor model to study the importance of common and country-specific shocks in accounting for variation in industrial production in European countries. Robin L. Lumsdaine and Eswar S. Prasad (2003) develop a weighted aggregation procedure, and examine the correlations between the fluctuations in industrial output in 17 OECD countries and an estimated common component, and find evidence for a world business cycle and for a European business cycle.⁴

What is common to these studies of international business cycles is that they are not studies of the *world*. Data limitations and econometric intractability have heretofore limited attention to small groups of countries, or to ad hoc world aggregates, and there has not been a detailed study of whether fluctuations are associated with worldwide, regional, or country-specific shocks. We address this and related issues by employing a Bayesian dynamic latent factor model to estimate common dynamic components in macroeconomic aggregates (output, consumption, and investment) in a 60-country sample covering seven regions of the world. In particular, we simultaneously estimate (i) a dynamic factor common to all aggregates, regions, and countries (the world factor); (ii) a set of seven regional dynamic factors common across aggregates within a region; (iii) 60 country factors to capture dynamic comovement across aggregates within each country; and (iv) a component for each aggregate that captures idiosyncratic dynamics. By design, the dynamic factors capture all intertemporal cross-correlation among the observable variables.

The econometric methodology we employ permits us to examine multiple common factors. Otkrok and Whiteman (1998) developed a Bayesian single dynamic factor model to study coincident and leading economic indicators using the data of the state of Iowa. We extend their work to a multiple-factor setting and employ it in an international business-cycle context. One of the major advantages of our

industrial output, the industry-specific factor plays a minor role.

⁴ Nicos Christodoulakis et al. (1995), Michael J. Artis et al. (1997), Artis and Wenda Zhang (1997), Bergman et al. (1998), and Jean Imbs (1999) also find high correlations across output fluctuations in several European countries.

Bayesian procedures over those used in earlier studies in the dynamic factor framework is that the method works well with the large cross section of data necessary to uncover worldwide comovement. In addition to working efficiently with large cross sections of data, our method can also easily handle a large number of dynamic factors.

We are therefore able to examine regional and country-specific cycles simultaneously with the world business cycle. The importance of studying all three in one model is that studying a subset of countries can lead one to believe that observed comovement is particular to that subset of countries when it in fact is common to a much larger group of countries. For example, in light of our results, the distinct "European" business cycle apparent in studies of comovement in European countries appears to be an artifact of limited samples—we find that the comovement among European countries is due to comovement common to all countries in the world.

Understanding the sources of international economic fluctuations is important both for developing business-cycle models and making policy. For example, if most of the variation in economic activity in a set of countries with different economic policies, institutions, and economic structures is explained by a world business cycle, this lends support to the predictions of theoretical models emphasizing the common characteristics in the operations of markets rather than the differences in economic policies or institutional environments in those countries.⁵ Similarly, if a significant fraction of domestic business cycles is due to the common world factor, this implies that policies targeting external balances to stabilize sudden movements in economic activity might be ineffective.

Our results indicate that there *is* a distinct world business cycle—the world factor seems to account for a significant fraction of output growth fluctuations in many countries. The factor is quite persistent, and reflects many major worldwide economic events, including the

⁵ In a recent paper, Gregory and Head (1999) document that common movements explain a significant fraction of productivity fluctuations and a much smaller part of the investment movements. They construct a stochastic dynamic model that is consistent with these features.

steady expansionary period in the 1960's, the global recession of the mid-1970's, the recession of the early 1980's, and the downturn in the early 1990's. Likewise, the country factors, though less persistent, also exhibit some important historical episodes. For example, the U.S. country factor moves in accord with many of the NBER reference cycles, and the country factors of Latin American economies affected by the debt crisis in 1982 reflect that event.

Upon decomposing the variance of each aggregate into the fractions attributable to each type of factor, we find that the world factor accounts for a larger fraction of business-cycle variability in developed countries than in developing countries. The variance decompositions also show that the world factor accounts for a larger share of the fluctuations in output than in consumption in the majority of the countries in our sample. Further, except for the North America factor, we find little evidence for region-specific fluctuations.

There are of course countries for which the world factor is less important than country-specific events. To study the pattern of variance decompositions, we use regressions of the fraction of the variance of each country's observables (output growth, consumption growth, investment growth) attributable to a factor (world, regional, country) on a variety of explanatory variables related to country characteristics. We find that the world factor is more important in explaining fluctuations in developed, stable economies, whereas country-specific factors are more important in developing, volatile economies.

The next section briefly lays out our approach. Section II presents the world and other factors, and studies the relationship among the country-specific, regional, and worldwide fluctuations. Section III investigates the persistence properties of the world factor. Section IV studies the relative importance of the various factors across countries using variance decompositions; Section V provides the characterization of the pattern of variance decomposition results. Section VI concludes.

I. Methodology

The econometric model used here is a multi-factor extension of the single dynamic unob-

served factor model in Otrok and Whiteman (1998). Such models are the dynamic counterparts to *static* unobserved factor models that are common in psychology. A static factor model provides a description of the variance-covariance matrix of a set of random variables; the method of principal components is one implementation of this idea. A dynamic factor model provides a description of the spectral density matrix of a set of time series, and thus the factor(s) describe contemporaneous and temporal covariation among the variables.

Specifically, suppose \mathbf{x}_j is a vector of Q measurements of person j 's academic achievement (e.g., GPA, class rank, scores on the PSAT, SAT, ACT, GRE, GMAT, etc.) and Σ is the associated covariance matrix. Then \mathbf{x}_j is said to have factor structure if Σ can be written in the form

$$\Sigma = \Gamma\Gamma' + \mathbf{U}$$

where Γ is $Q \times K$, $K \ll Q$, and \mathbf{U} is diagonal with positive entries on the diagonal. This structure implies that \mathbf{x}_j can be thought of as being explained by a set of K common factors and idiosyncratic noise. That is,

$$\mathbf{x}_j = \mathbf{af} + \mathbf{u}_j$$

where \mathbf{f} is a $K \times 1$ vector of factors, \mathbf{a} is the $Q \times K$ vector of "factor loadings," and \mathbf{u}_j is the person-specific noise. Typically, one employs the identification assumptions that the factors are independent and have variance 1.0, and that the \mathbf{u}_j 's are independent and identically distributed across individuals. If there is no other information on the factors \mathbf{f} , they are "unobservable" and their characteristics must be learned indirectly via the pattern of correlation in the \mathbf{x}_j 's. It might be thought that the vector of scores would be determined in large part by a small number of factors ("intelligence," "test-taking ability," etc.), but there is no direct way of identifying what the factors are, only indirect ones via the factor loadings.

In the time-series context, suppose \mathbf{y}_t is a Q -dimensional vector of covariance stationary time series at date t (e.g., growth rates of output, consumption, and investment in 60 countries), and \mathbf{S}_{yy} is its associated spectral density matrix. Then the time series $\{\mathbf{y}_t\}$ is said to have *dy-*

namic factor structure if \mathbf{S}_{yy} can be written in the form

$$\mathbf{S}_{yy} = \mathbf{LL}' + \mathbf{V}$$

where \mathbf{L} is $Q \times K$, $K \ll Q$, and \mathbf{V} is diagonal with positive entries on the diagonal. This structure means that all of the comovement among the variables is controlled by the M -dimensional set of “dynamic factors.” In addition, in the time domain, \mathbf{y}_t can be represented as

$$\mathbf{y}_t = \mathbf{a}(L)\mathbf{f}_t + \mathbf{u}_t$$

where $\mathbf{a}(L)$ is a $Q \times K$ matrix of polynomials in the lag operator, $\{\mathbf{f}_t\}$ is a K -dimensional stochastic process of the factors, and the errors in \mathbf{u}_t may be serially but not cross-sectionally correlated. The factors are in general serially correlated, and may be observed or unobserved.

In our implementation, there are K dynamic, unobserved factors thought to characterize the temporal comovements in the cross-country panel of economic time series. Let N denote the number of countries, M the number of time series per country, and T the length of the time series. Observable variables are denoted $y_{i,t}$, for $i = 1, \dots, M \times N$, $t = 1, \dots, T$. There are three types of factors: N country-specific factors ($f_n^{country}$, one per country), R regional factors (f_r^{region} , e.g., one each for North America, Latin America, Africa, Developed Asia, Developing Asia, Europe, and Oceania), and the single world factor (f^{world}). Thus for observable i :

$$(1) \quad y_{i,t} = a_i + b_i^{world} f_t^{world} + b_i^{region} f_{r,t}^{region} + b_i^{country} f_{n,t}^{country} + \varepsilon_{i,t}$$

$$E\varepsilon_{i,t}\varepsilon_{j,t-s} = 0 \text{ for } i \neq j,$$

where r denotes the region number and n the country number. The coefficients b_i^j are the factor loadings, and reflect the degree to which variation in $y_{i,t}$ can be explained by each factor. Notice that there are $M \times N$ time series to be “explained” by the (many fewer) $N + R + 1$ factors. The “unexplained” idiosyncratic errors $\varepsilon_{i,t}$ are assumed to be normally distributed, but

may be serially correlated. They follow p_i -order autoregressions:

$$(2) \quad \begin{aligned} \varepsilon_{i,t} &= \phi_{i,1}\varepsilon_{i,t-1} + \phi_{i,2}\varepsilon_{i,t-2} + \dots \\ &\quad + \phi_{i,p_i}\varepsilon_{i,t-p_i} + u_{i,t} \\ Eu_{i,t}u_{j,t-s} &= \sigma_i^2 \text{ for } i = j \text{ and } s = 0, \\ &\quad 0 \text{ otherwise.} \end{aligned}$$

The evolution of the factors is likewise governed by an autoregression, of order q_k with normal errors:

$$(3) \quad f_{k,t} = \varepsilon_{f_k,t}$$

$$(4) \quad \begin{aligned} \varepsilon_{f_k,t} &= \phi_{f_k,1}\varepsilon_{f_k,t-1} + \phi_{f_k,2}\varepsilon_{f_k,t-2} + \dots \\ &\quad + \phi_{f_k,q_k}\varepsilon_{f_k,t-q_k} + u_{f_k,t} \\ Eu_{f_k,t}u_{f_k,t} &= \sigma_{f_k}^2; Eu_{f_k,t}u_{i,t-s} = 0 \\ &\quad \text{for all } k, i, \text{ and } s. \end{aligned}$$

Notice that all the innovations, $u_{i,t}$, $i = 0, \dots, M \times N$ and $u_{f_k,t}$, $k = 1, \dots, K$, are assumed to be zero mean, contemporaneously uncorrelated normal random variables. Thus all comovement is mediated by the factors, which in turn all have autoregressive representations (of possibly different orders).

There are two related identification problems in the model (1)–(4): neither the signs nor the scales of the factors and the factor loadings are separately identified. Signs are identified by requiring one of the factor loadings to be positive for each of the factors. In particular, we require that the factor loading for the world factor be positive for U.S. output; country factors are identified by positive factor loadings for output for each country, and the regional factors are identified by positive loadings for the output of the first country listed for each region in the Appendix A. Scales are identified following Thomas J. Sargent and Christopher A. Sims (1977) and James H. Stock and Mark W. Watson (1989, 1993) by assuming that each $\sigma_{f_k}^2$ is equal to a constant.

Because the factors are unobservable, special methods must be employed to estimate the

model. Gregory et al. (1997) follow Stock and Watson (1989, 1993) and treat a related model as an observer system; they use classical statistical techniques employing the Kalman filter for estimation of the model parameters, and the Kalman smoother to extract an estimate of the unobserved factor. Otrok and Whiteman (1998) used an alternative based on a recent development in the Bayesian literature on missing data problems, that of "data augmentation" (Martin A. Tanner and Wing H. Wong, 1987).

In our context, data augmentation builds on the following key observation: if the factors were observable, under a conjugate prior the model (1)–(4) would be a simple set of regressions with Gaussian autoregressive errors; that simple structure can in turn be used to determine the conditional (normal) distribution of the factors given the data and the parameters of the model. Then it is straightforward to generate random samples from this conditional distribution, and such samples can be employed as stand-ins for the unobserved factors. Because the full set of conditional distributions is known—parameters given data and factors, factors given data and parameters—it is possible to generate random samples from the joint posterior distribution for the unknown parameters and the unobserved factor using a Markov-Chain Monte Carlo (MCMC) procedure. In particular, taking starting values of the parameters and factors as given, we first sample from the posterior distribution of the parameters conditional on the factors; next we sample from the distribution of the world factor conditional on the parameters and the country and regional factors; then we sample each regional factor conditional on the world factor and the country factors in that region; finally, we complete one step of the Markov chain by sampling each country factor conditioning on the world factor and the appropriate regional factor.⁶ This sequential sampling of the full set of conditional

distributions is known as "Gibbs sampling" (see Siddhartha Chib and Edward Greenberg, 1996; John Geweke, 1996, 1997).⁷ Under regularity conditions satisfied here, the Markov chain so produced converges, and yields a sample from the joint posterior distribution of the parameters and the unobserved factors, conditioned on the data. Additional details can be found in Appendix B and Otrok and Whiteman (1998).⁸

A practical benefit of our procedure is that it can easily be applied to a large cross section of countries. The reason is that a large cross section merely means a large number of very simple conditional normal distributions of the form of equation (1). What makes the problem challenging is a long time series—because the covariance matrices in the conditional distributions for the factors are of dimension T ; if it is not practical to invert these directly, specialized recursive procedures must be employed. Thus while the estimation problem can be difficult in the time-series dimension, it easily decomposes into independent, simple calculations in the cross section. Classical maximum likelihood methods generally do not so decompose, and are difficult to apply to a problem of this dimension, because with over 1,600 parameters and 68 dynamic factors, the dimension of the problem poses a serious challenge to current hill-climbing techniques.⁹

⁷ Technically, our procedure is "Metropolis within Gibbs," as one of the conditional distributions—for the autoregressive parameters given everything else—cannot be sampled from directly. As in Otrok and Whiteman (1998), we follow Chib and Greenberg (1996) in employing a "Metropolis-Hastings" procedure for that block.

⁸ We add regional and country factors, which appear in equations for a subset of the observable variables, to the single factor model in Otrok and Whiteman (1998). This results in some additional modifications to the conditional distributions of the observables given the factors (as there are additional factors). The conditional distributions for each of the factors given the parameters and the other factors is derived as in Otrok and Whiteman (1998, pp. 1003–4): derivation of each factor conditional requires the completion of a square to obtain the mean and variance (f , \mathbf{H}^{-1} in their notation) of the Gaussian distribution in their expression (9). Thus the covariance matrix (\mathbf{H}^{-1}) for a factor involves squares of quasi-differencing matrices (their \mathbf{S}_i matrices) from equations in which that factor appears, and the mean involves the matrix weighted average of residuals from those equations.

⁹ A classical alternative that *does* exploit the decomposition involves using the "EM" algorithm to maximize the

⁶ The sampling order within each step is irrelevant. All that matters is that samples are taken from each of the "blocks" of unknowns (parameters, world factor, regional factors, country factors) conditional on the data and all the other blocks. We in fact experimented with changing the order, and the results obtained were identical to those presented below.

The data are from the Penn World Tables (PWT), version 5.5 (see Robert Summers and Alan Heston, 1991, and Heston et al., 1994). We use output, consumption, and investment data, and restrict attention to those countries with a data quality grade of C– or higher, and for which data are available for each of the years 1960–1990.¹⁰ Each series was log first-differenced and demeaned (as in Otrok and Whiteman, 1998).¹¹ Thus we used $M = 3$ series per country for $N = 60$ countries, with $T = 30$ time series observations for each. The countries in our data set and our $R = 7$ regional definitions are given in Appendix A. One concern with procedures that extract measures of the world business cycle is that large countries drive the world component simply because of their size. In the procedure used here we are working in growth rates, so the size of the country can have no direct impact on the results. That is, the econometric procedure that extracts common components does not distinguish between a 2-percent growth rate in the United States and a 2-percent growth rate in the Ivory Coast.¹² Put another way, the procedure is a

likelihood function. In this procedure, given an initial guess at the factors, regressions are used to maximize the likelihood (the “M” step); then the Kalman smoother is used to estimate (the “E” step) the factors given the regression estimates. This sequential process continues until the likelihood is maximized. This can take a very long time. In general applications, the accepted practice is to use EM to get “close,” and then switch to a direct hill climb; the switch is not feasible for a problem as large as ours.

¹⁰ We do not consider the periods of fixed and flexible exchange rate regimes separately, for two reasons. First, there is not conclusive evidence about whether one ought to split the sample in this way. For example, Baxter and Stockman (1989), Baxter (1991), and Shaghil Ahmed et al. (1993) find that different types of exchange rate regimes do not result in significant changes in the behavior of the main macroeconomic aggregates, though Gerlach (1988) concludes that the exchange rate regime has a significant impact on the stylized business-cycle facts. Second, we do not have enough data to examine the fixed and flexible exchange rate periods separately. There are only 12 observations for the fixed exchange period and 18 for the flexible period.

¹¹ The qualitative results in the paper do not change much when we use Hodrick-Prescott filtered versions of the logarithms of the raw data series. The one notable exception is that the importance of the world factor for explaining output volatility in the United States falls to 16 percent. All other results documented below remain unchanged.

¹² We also estimated the model using per capita growth rates, and the results were virtually identical.

decomposition of the second moment properties of the data (e.g., the spectral density matrix).

In our implementation, the length of both the idiosyncratic and factor autoregressive polynomials is 3. The prior on all the factor loading coefficients is $N(0, 1)$. For the autoregressive polynomials parameters the prior was $N(0, \Sigma)$,

$$\text{where } \Sigma = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.25 \end{bmatrix}. \text{ Because the}$$

data are growth rates, this prior embodies the notion that growth is not serially correlated; also, the certainty that lags are zero grows with the length of the lag.¹³ Experimentation with tighter and looser priors for both the factor loadings and the autoregressive parameters did not produce qualitatively important changes in the results reported below. As in Otrok and Whiteman (1998), the prior on the innovation variances in the observable equations is Inverted Gamma (6, 0.001), which is quite diffuse.

Because we are not sampling from the posterior itself (the elements of the Markov chain are converging to drawings from the posterior), it is important to monitor the convergence of the chain. We did so in a number of ways. First, we restarted the chain from a number of different initial values, and the procedure always converged to the same results. Second, we experimented with chains of different lengths ranging from lengths of 5,000 to 50,000. For chains of length 10,000 or greater the results were the same. The results we report in the paper are based on a chain of length 50,000.

II. The Dynamic Factors

Figure 1 presents the median of the posterior distribution of the world factor, along with 33- and 66-percent quantile bands; the narrowness of the bands indicates that the factor is estimated quite precisely. The fluctuations in the factor reflect the major economic events of the last 30 years: the steady expansionary period of the 1960's, the recession of the mid-1970's (associated with the first oil price shock), the

¹³ Otrok and Whiteman (1998) discuss the procedure for ensuring stationarity of the lag polynomial. The method involves drawing from a truncated normal distribution in the Metropolis-Hastings step described in footnote 7.

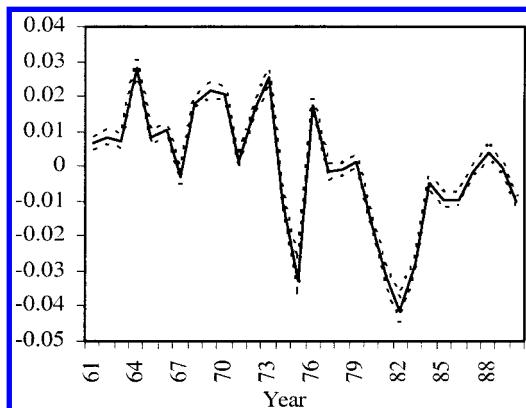


FIGURE 1. WORLD FACTOR

recession of the early 1980's (associated with the debt crisis and the tight monetary policies of major industrialized nations), and the downturn and recession of the early 1990's.

Our estimate of the world factor suggests that the downturn in the early 1980's was as severe as the recession of the mid-1970's. In contrast, Gregory et al. (1997), who restricted their attention to a sample of output, consumption, and investment series for the G7 countries, found that the world component exhibited a more severe recession in 1974 than in 1982. Thus it seems that our inclusion of developing economies as well provides a different picture of the two recessions.¹⁴ In particular, the debt crisis marking the recession of 1982 heavily affected economic activity in a number of developing countries, especially those in Latin America. Evidently, developed countries were hit harder by the oil shock of the 1970's, while the rest of the world was hit harder by the shocks of the 1980's.

¹⁴ To ensure that this result is due to the scope of the sample, and not our approach, we employed our procedures to estimate a dynamic factor model using the G7 data employed by Gregory et al. (1997), and found a result similar to theirs, that the unobserved aggregate factor displays a deeper downturn in 1974 than 1982. To further examine the depth of these two different recessionary periods, we also computed an aggregate world output measure (following Raymond Riezman and Whiteman, 1992) using the size-weighted aggregate output of the countries in our sample, and compare this measure with the estimated world factor. This world aggregate output also has the property that the mid-1970's recession is slightly less severe than that in 1982.

Because the factor is unobservable and we have merely extracted an estimate of it based on its hypothesized relationships to time series we can observe, it is much easier to determine what the factor *is not* than to agree on what it *is*. For example, the relationship between international macroeconomic activity and changes in oil prices has received considerable attention in the literature;¹⁵ is the world factor anything more than a stand-in for oil prices? Indeed, it displays its largest troughs just after large sudden increases in the price of oil.¹⁶ But to be more precise, the contemporaneous correlation between the median world factor and the change in the oil price is negligible (-0.07), and the correlation between the oil price change and the world factor one year later is only -0.26 . This correlation is driven in large part by two observations in the data set. Dropping the 1974 oil price increase (and the corresponding fall in the world factor in 1975) lowers the correlation to -0.16 . Eliminating the 1980 oil price increase and subsequent fall in the world factor drops the correlation to -0.06 . Thus while oil prices may be an important source of international shocks, understanding world business cycles will likely require going beyond oil price changes alone.

To attempt to discover whether the world factor is an amalgam of oil shocks and something else, e.g., monetary policy shocks, we studied a variety of dynamic systems with multiple world factors. Yet across multiple identifications, we found no significant evidence of a second world factor. We employed identification schemes for the second world factor ranging from a positive loading for the output of a major oil-exporting country (Venezuela), a positive loading for the output of a developed Asian country (Japan), to a positive loading for the output of a developing country (Kenya). Finally, we estimated a model with the second world factor normalized to German investment growth. In all cases, the second factor was highly correlated with the first, and displayed a variance several orders of magnitude smaller than that of the first. Further, its introduction to

¹⁵ See Backus and Crucini (2000).

¹⁶ To be more specific, major oil price increases of 1974 and 1980–1981 were followed by the global recessions of 1975 and 1982. The oil price data is from Backus and Crucini (2000).

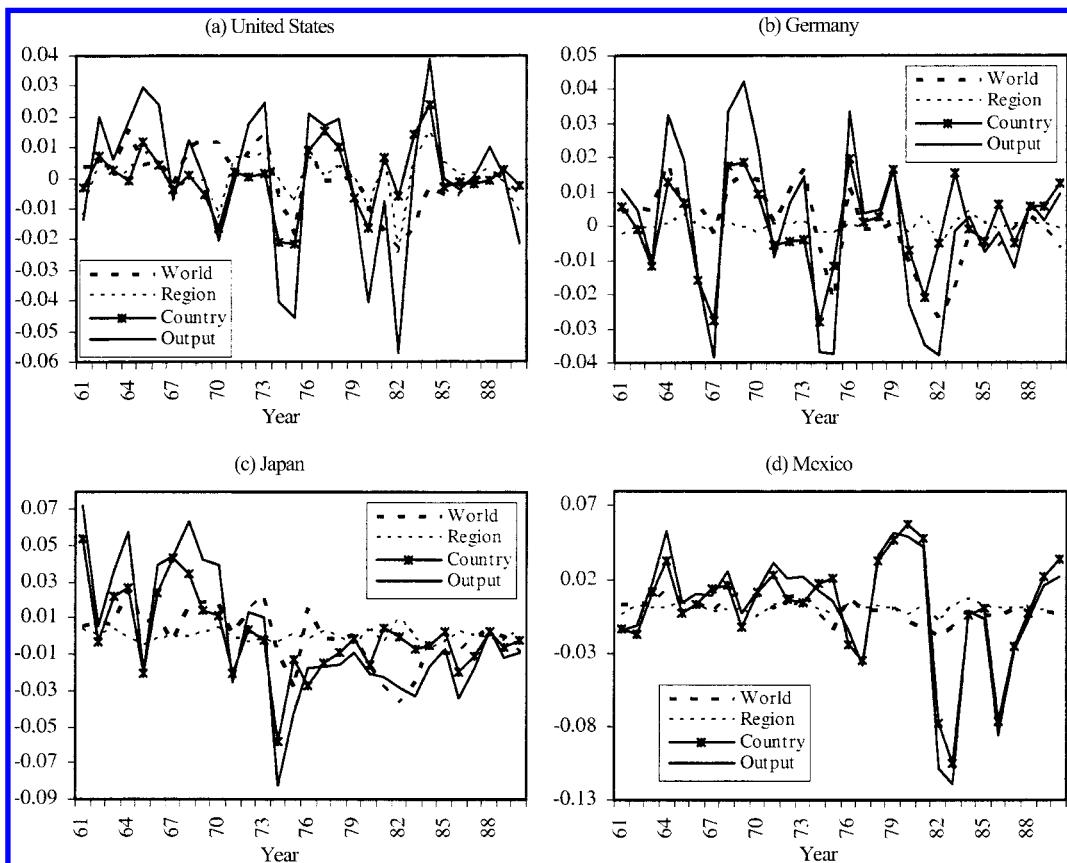


FIGURE 2. RESCALED OUTPUT AND DYNAMIC FACTORS

the analysis changed very little else, and in particular did not change estimates of the first factor in a qualitatively meaningful way. Finally, while formal Bayesian model comparison via odds ratios is problematic with models as complex as ours, we did calculate values of the Jushan Bai and Serena Ng (2002) factor model selection criteria at the posterior median of all our parameters. None of their six criteria favored increasing the number of world factors from 1 to 2.

To gain some insight into what the world factor is capturing, and how the various factors interact, we also studied relationships among the world factor, country factors, regional factors, and output in four selected countries: the United States, Germany, Japan, and Mexico. The results are presented in Figures 2(a)-2(d).

In Figure 2(a) we plot the median of the U.S.

country-specific factor along with the world factor, the North American regional factor, and the growth rate of U.S. output. To make the scales comparable, the country, region, and world factors are multiplied by their median factor loadings in the U.S. output equation. Thus the sum of the three scaled factors and the idiosyncratic component of U.S. output is equal to the U.S. output (growth) series.

Several of the peaks and troughs of the U.S. country factor coincide with NBER reference dates: the recessions of 1970, 1975, 1980, and 1982, and the booms of 1973, 1981.¹⁷ Similarly, movements in the world factor are consistent

¹⁷ The NBER reference business-cycle dates: Troughs: February 1961, November 1970, March 1975, July 1980, November 1982, March 1991. Peaks: April 1960, December 1969, November 1973, January 1980, July 1981, July 1990.

with some of the business-cycle reference dates: the troughs of 1975, 1980, 1982, and the peaks of 1969, and 1973. While the U.S. factor and the world factor exhibit some common movements (e.g., the troughs of 1975, 1980, and 1982, and the peak of 1973), there are also some notable differences between the two factors: the world factor is booming in 1970, whereas the U.S. country factor reflects the domestic contraction. An additional difference is that the world factor shows a relatively prolonged recession during the 1980's, while the U.S. country factor exhibits back-to-back booms in 1981 and 1984. The correlation between the median world factor and U.S. output growth is 0.616, indicating that the United States represents an important source of world economic fluctuations.

Figure 2(b) presents the median of the German country-specific factor along with the world factor, the European regional factor, and the growth rate of German output. Again, the country, region, and world factors are multiplied by their median factor loading coefficients. The country factor captures the German recessions of 1967, 1975, and 1982, and exhibits the peaks of 1964, 1973, and 1979.¹⁸ The pattern of fluctuations suggests that the German recession of 1982 and the boom of 1973 were worldwide events, while the recovery of the mid-1970's, the peaks of 1979 and 1983, and the troughs of 1969 and 1975 were more distinctly German phenomena. The European regional factor only loosely reflects German output, though it does reflect the German recessions of 1967, 1975, and 1982, and peaks of 1964 and 1973.

Figure 2(c) displays the medians of the Japan, world, and developed-Asia factors, together with the growth rate of Japan's output. Note that the very rapid growth of the late 1960's was distinctly Japanese—the world factor does not show strong comovement with Japanese output during this period, but the country-specific factor does. The OPEC recession hit harder and faster in Japan than the rest of the world, reflecting Japan's strong dependence on imported oil. While the estimated country-specific factor displays minor recessions in 1965, 1971, and

1980, the growth rates of output during these years are positive. The reason is that while Japanese output increased in 1965, 1971, and 1980, there were marked declines in Japanese investment just before or during these years, and the estimated country factor captures the common movements in output, consumption as well as investment. For the first half of the 1980's, as Japan went, so went the world. But the downturn of the latter half of the decade was idiosyncratically Japanese.

The country-specific factors of developing economies also exhibit some important historical episodes. For example, the country factors of several Latin American economies (such as Chile and Argentina) display the downturn associated with the debt crisis in 1982. Figure 2(d) plots the median of the Mexican factor along with the medians of the world and region factors and Mexican output growth. The pattern of comovements reveals that since the mid-1970's, fluctuations in Mexico have been very different from those in the rest of the world and even in Latin America—the country factor moves very closely with output growth during the large swings surrounding the debt crisis.

The results reported in this section suggest that to the extent that there are country-specific, regional, and worldwide sources of economic shocks, these play different roles at different points in time and around the globe. In some episodes, the country factor was more strongly reflective of domestic economic activity, while in others the domestic growth reflected the common worldwide pattern embodied in the world factor. After assessing the persistence properties of the dynamic factors in the next section, we examine the quantitative importance of the common factors in explaining variations in output, consumption, and investment growth more formally in Section IV.

III. Persistence Properties of the Dynamic Factors

Are common, worldwide fluctuations more persistent than those in individual countries or regions? To measure persistence, we calculate the first-order autocorrelation implied by the parameters of the estimated autoregressive coefficients [equations (3) and (4)] at each step of the estimation procedure so that we can calcu-

¹⁸ These peak and trough dates are taken from Artis et al. (1997).

TABLE 1—AUTOCORRELATIONS OF DYNAMIC FACTORS

World	0.482	Latin America	-0.059	Asia (Developed)	0.018	Europe	-0.095
North America	-0.042	Africa	0.014	Asia (Developing)	-0.057	Oceania	0.071

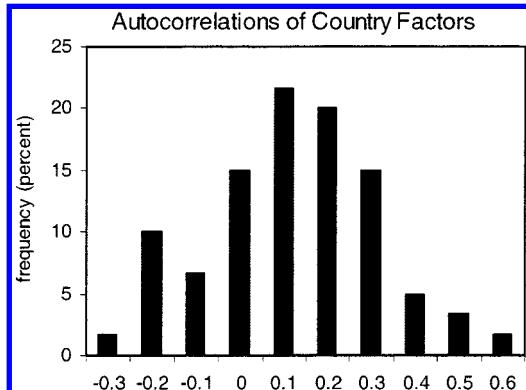


FIGURE 3. AUTOCORRELATIONS OF THE COUNTRY FACTORS

late the distribution of the estimates.¹⁹ The medians of the estimated autocorrelations for the world and region factors are presented in Table 1. The medians of the country factor autocorrelations are presented in a histogram in Figure 3. To save space we do not report the quantiles of the distribution, but the estimates are generally fairly tight.

The world factor has large and positive autocorrelation (0.48); the 33 percent and 67 percent quantiles of this distribution were 0.44 and 0.52. Compared to the autocorrelations of the regional factors and most of the country factors, the world factor is much more persistent—the largest regional factor autocorrelation is 0.07 for Oceania, while the North American, Latin American, developing Asia, and European factors are negatively autocorrelated and thus strongly mean reverting.

The autocorrelations of the country-specific factors vary substantially across countries, ranging from a low of -0.35 (Senegal) to a high of 0.52 (Spain). More than two-thirds of the coun-

try factors exhibit positive autocorrelation. However, in most cases the autocorrelation is much smaller than that of the world factor. The high serial correlation in the Spanish factor is not surprising given that Spain's output, consumption, and investment time series are more persistent than those of other countries. Indeed, the Spanish factor is the only country factor more persistent than the world factor. Countries whose country factors exhibit relatively low negative autocorrelation, such as Bangladesh, Colombia, Senegal, and Sri Lanka all have negatively autocorrelated output, consumption, and investment growth. Similarly, countries whose country factors exhibit relatively high positive autocorrelations, such as Spain, Philippines, Singapore, and Norway have positively autocorrelated growth in output, consumption, and investment series.²⁰

The results indicate most of the persistent, or low frequency, comovement across economies is captured by the world factor. The higher-frequency comovement seems to be captured by the regional and country factors.

IV. Variance Decompositions

To measure the relative contributions of the world, region, and country factors to variations in aggregate variables in each country, we

¹⁹ We also calculated autocorrelations for the factors by calculating the first autocorrelation of the factors themselves at each step of the estimation procedure. The differences between results obtained using the two approaches are minor.

²⁰ Our results regarding persistence properties of world and country factors are different than those of Gregory et al. (1997) on some dimensions. For example, their results suggest that the Japan and Germany factors are negatively autocorrelated, while the Canada, France, and Italy factors are positively autocorrelated. We find that the Canada, Germany, France, and Japan factors are positively autocorrelated, and the Italian factor is negatively autocorrelated. Considering the different scopes (recall that they use only G7 countries, while we use 60 developing and developed countries), data (they use quarterly data for 1970–1993 and we use annual data for 1960–1991), and the differences between models, some discrepancies are to be expected. One important similarity between the two sets of findings should be highlighted: in each study, the world factor is more persistent than the country factors and countries' aggregate output in most cases.

TABLE 2—VARIANCE DECOMPOSITIONS FOR THE NORTH AMERICA REGION

	O	World			Region			Country			Idiosyncratic		
		1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3
United States	O	32.2	35.1	38.1	20.4	27.3	34.5	21.5	28.2	34.4	6.9	7.9	9.0
	C	31.5	34.4	37.4	9.4	14.5	21.0	11.9	17.9	24.1	26.4	29.9	33.1
	I	15.0	17.1	19.4	23.8	31.2	39.3	30.9	40.0	48.0	7.3	9.5	12.1
Canada	O	32.7	35.8	38.9	27.0	36.1	44.2	11.4	19.8	27.8	6.2	7.1	8.2
	C	22.6	25.1	27.5	22.4	32.0	42.1	13.1	22.7	32.7	15.3	17.5	19.8
	I	11.1	13.0	15.1	22.6	32.7	45.8	22.9	36.0	47.8	12.2	15.2	18.5
Mexico	O	14.3	16.2	18.2	0.7	1.5	2.8	75.5	77.8	80.1	2.7	3.2	3.8
	C	12.5	14.2	16.0	0.5	1.2	2.4	75.0	77.4	79.5	5.1	6.0	6.9
	I	14.2	16.0	18.0	0.8	1.8	3.3	59.5	62.3	64.8	17.1	18.7	20.1
Regional Median	O	32.2	35.1	38.1	20.4	27.3	34.5	21.5	28.2	34.4	6.2	7.1	8.2
	C	22.6	25.1	27.5	9.4	14.5	21.0	13.1	22.7	32.7	15.3	17.5	19.8
	I	14.2	16.0	18.0	22.6	31.2	39.3	30.9	40.0	48.0	12.2	15.2	18.5

estimate the share of the variance of each macroeconomic aggregate due to each factor. We decompose the variance of each observable into the fraction that is due to each of the three factors and the idiosyncratic component. With orthogonal factors the variance of observable i can be written:²¹

$$(6) \quad \text{var}(y_{i,t}) = (b_i^{\text{world}})^2 \text{var}(f_t^{\text{world}}) + (b_i^{\text{region}})^2 \text{var}(f_{r,t}^{\text{region}}) + (b_i^{\text{country}})^2 \text{var}(f_{n,t}^{\text{country}}) + \text{var}(\varepsilon_{i,t}).$$

The fraction of volatility due to, say, the world factor would be:

$$\frac{(b_i^{\text{world}})^2 \text{var}(f_t^{\text{world}})}{\text{var}(y_{i,t})}.$$

These measures are calculated at each pass of the Markov chain; dispersion in their posterior

distributions reflects uncertainty regarding their magnitudes.

We present the variance shares attributable to the common factors for North America and Europe in Tables 2 and 3. As summary measures of the importance of the factors, these tables present regional medians of posterior quantiles as well as 33-percent and 67-percent quantiles of posterior shares for each country. Complete tables with the variance decompositions for each of the remaining countries are given in the Appendix (Tables A1–A5).

As Table 2 shows, the world factor explains a significant fraction of the fluctuations in all three aggregates in North American countries. The world factor edges out the regional factor as dominant, though both play an important role in North America. In these economies, the country-specific factor plays an important role in accounting for the investment dynamics: for the median country, 40 percent of the investment variation is due to the country-specific factor.

Table 3 presents variance decompositions for European countries. The world factor explains more than 33 percent of output- and 26 percent of consumption-growth variability. However, the world factor share of output-growth volatility ranges widely across these countries, from a low of less than 4 percent in Iceland to a high of 68 percent in France. Roughly half of the volatility in output growth and about 35 percent of variation in investment growth is explained by country-specific factors. Notably, the European regional factor plays a relatively minor role in accounting for the economic activity in these

²¹ Even though the factors are uncorrelated, samples taken at each pass of the Markov chain will not be, purely because of sampling error. To ensure adding up, we took a further step for these calculations, and orthogonalized the sampled factors, ordering the world factor first, the regional factor second, and the country factor third. The sample correlations between the raw factors was small (the standard error of a correlation with 30 observations is 0.18), so the order of orthogonalization has little impact on the results. All of the results remain qualitatively the same under alternative orderings, and the quantitative differences are small.

TABLE 3—VARIANCE DECOMPOSITIONS FOR EUROPE

		World			Region			Country			Idiosyncratic		
		1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3
France	O	65.4	68.2	70.8	2.4	4.0	5.9	10.9	13.8	16.8	11.1	12.6	14.4
	C	35.7	39.0	42.3	3.6	6.1	8.9	2.0	4.4	8.2	43.1	46.9	50.5
	I	46.8	51.1	55.2	1.9	3.6	5.8	15.9	22.3	28.4	16.7	20.7	25.1
Austria	O	48.3	51.3	54.1	2.0	3.7	5.7	19.7	23.6	27.3	16.8	19.9	23.5
	C	8.7	10.0	11.5	0.9	2.0	3.7	25.2	33.9	42.1	44.1	52.1	60.6
	I	47.6	51.0	54.3	0.3	0.8	1.6	5.2	9.0	14.2	32.0	36.2	40.3
Belgium	O	54.6	59.1	63.2	4.0	6.3	9.0	10.4	14.7	19.6	15.2	17.4	19.8
	C	50.4	52.7	55.1	0.6	1.3	2.3	0.6	1.5	3.1	39.9	42.6	45.0
	I	30.4	34.5	38.7	3.0	5.7	9.1	23.7	31.2	38.3	19.8	25.4	31.9
Denmark	O	20.2	22.2	24.4	0.5	1.2	2.5	63.0	65.6	68.2	8.4	9.6	10.8
	C	9.7	11.2	12.8	0.9	2.0	3.8	47.0	50.4	53.8	32.3	34.8	37.4
	I	19.0	21.2	23.5	0.7	1.6	3.3	62.4	65.7	69.0	7.6	9.5	11.5
Finland	O	12.6	14.6	16.7	1.0	2.3	4.4	63.7	67.4	71.0	11.0	13.3	15.9
	C	5.9	7.1	8.4	0.9	2.1	4.1	6.8	9.9	13.3	75.1	78.4	81.7
	I	1.5	2.3	3.3	0.9	2.3	4.5	65.7	71.0	75.9	17.8	21.9	26.4
Germany	O	52.7	55.0	57.2	0.5	1.3	2.6	33.0	35.8	38.5	5.4	6.2	7.2
	C	38.4	41.2	44.1	0.2	0.6	1.2	14.4	16.9	20.0	37.6	39.7	41.8
	I	31.8	34.2	36.6	0.7	1.8	3.7	49.8	53.8	57.5	5.8	7.5	9.6
Greece	O	34.2	37.0	40.0	0.4	1.1	2.2	46.2	49.9	53.6	8.0	10.0	12.4
	C	2.3	3.2	4.4	0.7	1.6	3.1	32.7	39.1	45.2	48.6	54.2	60.2
	I	35.9	38.1	40.5	0.4	1.0	2.0	30.4	34.6	39.1	21.6	24.8	28.3
Iceland	O	2.9	3.6	4.3	0.4	1.0	2.0	73.8	77.5	80.6	13.9	16.8	20.0
	C	5.6	6.5	7.5	0.3	0.8	1.6	63.8	68.1	72.3	19.5	23.3	27.5
	I	0.1	0.1	0.2	0.4	1.0	2.0	30.5	35.4	40.1	57.5	62.2	66.9
Ireland	O	15.3	16.7	18.2	0.3	0.7	1.6	48.2	54.2	59.8	21.8	27.0	33.0
	C	21.0	23.1	25.3	1.0	2.2	3.8	34.3	40.0	45.5	28.0	33.5	38.8
	I	23.7	25.5	27.3	0.2	0.6	1.2	5.5	9.5	13.9	58.8	63.1	67.0
Italy	O	33.9	36.6	39.3	1.5	2.8	4.4	47.1	50.4	53.6	7.8	9.0	10.3
	C	35.0	37.2	39.4	1.9	3.5	5.4	17.2	20.2	23.3	35.1	37.6	40.1
	I	15.9	18.7	21.5	1.3	2.6	4.5	60.0	64.4	68.6	9.8	12.3	15.2
Luxembourg	O	10.9	12.7	14.6	0.9	2.2	4.4	60.4	64.2	67.6	16.1	19.0	21.7
	C	42.3	44.4	46.3	0.3	0.7	1.3	0.1	0.3	0.7	51.6	53.6	55.7
	I	1.4	2.1	2.8	0.6	1.4	2.9	75.4	79.9	84.0	11.0	14.6	18.7
Netherlands	O	60.9	63.1	65.3	0.2	0.4	0.8	15.7	18.9	22.1	14.6	16.9	19.3
	C	45.7	48.9	52.2	0.6	1.3	2.5	1.0	2.6	5.3	40.4	43.7	46.9
	I	28.0	30.9	33.8	0.8	1.9	3.7	26.9	35.4	43.1	23.4	30.2	37.4
Norway	O	4.8	5.8	7.0	0.9	2.0	3.7	45.5	51.7	57.1	33.5	38.6	44.5
	C	0.2	0.4	0.8	0.5	1.2	2.6	49.6	58.6	66.4	30.1	37.5	46.5
	I	0.4	0.7	1.1	0.9	1.9	3.4	4.2	7.1	11.1	84.2	88.5	91.9
Portugal	O	20.1	22.3	24.5	0.9	1.9	3.4	56.9	61.0	64.9	10.1	13.0	16.4
	C	5.2	6.3	7.7	0.3	0.7	1.4	44.7	49.1	54.0	38.5	42.8	46.9
	I	22.6	24.7	26.8	1.5	2.9	4.6	13.1	16.6	19.9	51.7	54.6	57.7
Spain	O	31.1	33.5	35.8	2.5	4.5	7.0	52.2	55.1	58.1	4.7	5.4	6.3
	C	35.6	38.0	40.5	2.2	4.0	6.2	43.5	46.5	49.6	8.6	10.0	11.5
	I	14.6	16.6	18.7	2.6	4.9	8.0	57.7	61.7	65.7	12.8	15.0	17.3
Sweden	O	17.8	19.5	21.3	0.5	1.2	2.4	41.2	46.6	51.5	26.9	31.3	36.2
	C	24.1	26.0	28.0	0.3	0.8	1.7	14.5	19.4	24.5	47.2	52.2	57.0
	I	2.7	3.6	4.7	0.8	1.9	3.8	34.8	42.9	50.7	41.8	49.4	57.2
Switzerland	O	21.2	23.8	26.5	0.5	1.3	2.6	59.0	62.3	65.7	9.3	10.9	12.7
	C	35.7	37.8	40.0	0.9	1.9	3.4	28.1	31.3	34.5	25.1	27.6	30.2
	I	9.3	11.5	13.9	0.7	1.7	3.3	62.1	66.8	71.3	14.9	18.1	21.3
United Kingdom	O	17.1	18.9	20.7	0.8	2.0	3.9	62.5	65.7	68.8	9.7	11.4	13.4
	C	3.7	4.6	5.5	1.0	2.4	4.4	50.2	55.2	60.0	31.6	35.9	40.3
	I	15.3	17.4	19.5	0.7	1.7	3.5	46.4	51.3	55.9	23.7	27.5	31.5
Regional Median	O	31.1	33.5	35.8	0.8	1.9	3.4	47.1	51.7	57.1	11.1	13.3	16.4
	C	24.1	26.0	28.0	0.9	1.9	3.4	28.1	33.9	42.1	38.5	42.6	46.5
	I	22.6	24.7	26.8	0.8	1.9	3.7	30.5	35.4	43.1	23.4	27.5	31.9

TABLE 4—VARIANCE DECOMPOSITIONS FOR WORLD AND G7

		World			Region			Country			Idiosyncratic		
		1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3
World Median	O	13.2	14.7	16.5	0.9	2.2	4.3	60.8	65.0	68.6	10.7	12.8	14.7
	C	7.3	8.6	10.0	1.0	2.3	4.3	44.8	49.8	54.6	24.8	27.1	30.9
	I	5.8	7.3	8.6	0.8	1.9	3.9	29.1	35.0	40.0	42.5	46.7	50.1
G7 Median	O	33.9	36.6	39.3	1.9	4.0	5.9	33.0	35.8	38.5	6.9	7.9	9.5
	C	33.3	36.0	38.8	1.9	3.5	5.4	14.4	20.2	24.1	31.6	35.9	40.1
	I	15.9	18.7	21.5	1.7	3.6	5.8	37.6	42.1	48.0	12.2	15.2	18.5

countries: it accounts for more than 5 percent of output volatility in only one country (Belgium). The country-specific factor and the idiosyncratic components seem to be important in inducing variations in consumption and investment in European countries: together they explain 77 percent of consumption volatility and 63 percent of investment volatility.

Though less important than in North America and Europe, the world factor explains a noticeable fraction of aggregate volatility in countries in Latin America, Developed Asia, and Oceania (see Tables A1, A3, and A5). For example, the world factor accounts for more than 14 percent of output and 7 percent of consumption volatility in Latin American countries, and between 6 and 15 percent of the output variance in the Developed Asia and Oceania regions. As in Europe, country-specific factors capture the greatest share of output fluctuations in the regions.²²

Unlike North America and Europe, for Africa, the country factors explain the majority of volatility in output and consumption (see Table A2), accounting for more than 68 percent of output volatility and 76 percent of consumption variation. A large fraction, 88 percent, of investment variability is due to the idiosyncratic components in African countries. The world factor explains little of output variation in most Afri-

can economies; evidently, African economic fluctuations are not like those in most of the rest of the world.

Another region with little apparent comovement with the rest of the world is Asia (Developed and Developing; see Tables A3 and A4). In this region, country factors again play the dominant role in explaining the volatilities of growth in output and consumption. Country factors explain about 70 percent of output variation and half of consumption volatility. Moreover, as in African countries, most of the variation in investment is attributable to the idiosyncratic component, and the world factor plays a modest role, explaining only 5 percent of output volatility. Japan is the only outlier in Asia; for it, the world factor is much more important, and the country and idiosyncratic factors less important, than in the rest of the region. The finding that the world factor explains 38 percent of Japanese output growth volatility and 36 percent of consumption growth volatility is much closer to the results for other G7 economies than the Asian region.

Tables 2–4 and the tables in Appendix A exhibit some important regularities. The first is that there is a world business cycle. As Table 4 indicates, the world factor (the world business cycle) accounts for almost 15 percent of aggregate variation in output growth, almost 9 percent of consumption growth variation, and 7 percent of investment growth volatility. The histogram in Figure 4 further illustrates this point. This figure shows that in the majority of countries the world factor explains a significant amount of output growth volatility. Further, most countries' output and consumption growth factor loadings on the world factor are distinctly positive (the posterior distributions of the factor loadings have very little mass in symmetric

²² Because there are only two countries (six series) in our version of Oceania, identification of the two country factors and the region factor is weak at best. The static factor model for six series and three factors (the world factor can be thought of as identified in the remainder of the world) is not restrictive, meaning that identification of the dynamic region and country factors for Oceania rests on subtleties in the dynamics of the observables and factors. Thus we draw no conclusions about the country and region factors for Oceania.

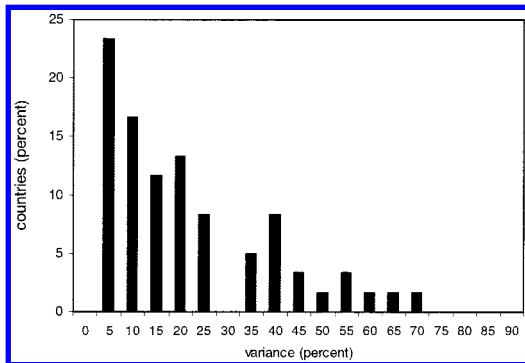


FIGURE 4. OUTPUT VARIANCE DUE TO WORLD FACTOR

intervals about zero).²³ Thus because the world factor is identified by a positive factor loading for U.S. output growth, there is a sense in which what is good for the United States is good for the world.

Second, the world factor plays a more important role in explaining economic activity in advanced industrialized countries than it does in developing economies. Table 4 compares the world median to the G7 median: while the world factor explains 37 percent of output growth volatility in the G7 economies, 15 percent of output growth variation in other countries is attributable to the world factor. This pattern extends to consumption and investment growth: the world factor captures almost 19 percent of the variation in investment growth, and approximately 36 percent of consumption growth volatility in the G7 economies.²⁴

Third, the world and regional factors together account for a larger share of fluctuations in output growth than in consumption growth in 42 out of 60 countries. While these two factors together explain more than 11 percent of consumption growth volatility, they account for around 17 percent of aggregate output growth volatility. This implies that in most countries

²³ There are too many factor loadings (540) for us to report the posterior distributions.

²⁴ Our results regarding the world factor being more important in explaining the business-cycle fluctuations in the developed economies than those in the developing ones are consistent with the findings in Kouparitsas (1997a). He finds that productivity shocks originating in the developed northern countries play a much smaller role in explaining the volatility of the developing southern countries' output than those productivity shocks originating in the South.

the country factor plays a more important role in explaining consumption movements than the world and regional factors. This result is consistent with a widely documented observation in the international business-cycle literature: cross-country correlations of output growth are larger than those of consumption growth.²⁵

Fourth, country factors and idiosyncratic components play a much larger role in accounting for investment dynamics than the world and region factors. The country factor explains 35 percent of investment growth fluctuations, and the idiosyncratic (unexplained) components account for 47 percent (see Table 4). The world and regional factors combined account for only 9 percent of investment growth volatility. The idiosyncratic behavior of investment volatility in our model is consistent with observed cross-country investment correlations: these correlations are low and generally lower than the cross-country correlations of output (see Christodoulakis et al., 1995; Christian Zimmermann, 1995).²⁶

Fifth, investment dynamics are much more idiosyncratic in developing countries than in developed ones. More than 83 percent (Developing Asia) and 88 percent (Africa) of investment volatility must be attributed to idiosyncratic components, while for developed economies the largest role for such components is in Developed Asia, where roughly 41 percent of the variation in investment is idiosyncratic.²⁷ In contrast, 15 percent of G7 and 28 percent of

²⁵ Backus et al. (1995) refer to apparent inconsistency between the theory and the data as "the quantity anomaly." (A simple model with risk sharing would suggest that consumption across countries ought to be more correlated than output.) We computed cross-country correlations of output and consumption and found that 1,087 out of 1,770 consumption growth correlations across countries are lower than the associated output growth correlations.

²⁶ Zimmermann (1995) uses the quarterly data of 19 industrialized countries. His results indicate that 70 out of 110 cross-country investment correlations are lower than those of output. Christodoulakis et al. (1995) use the annual data of 12 EU countries. They find that 48 out of 66 cross-country investment correlations are lower than those of output. We also computed cross-country correlations of output and investment for the economies in our sample: 1,098 out of 1,770 cross-country investment correlations are lower than those of output correlations.

²⁷ One explanation for the large role of the idiosyncratic factor in developing economies is measurement error. If measurement error is larger in developing economies, which

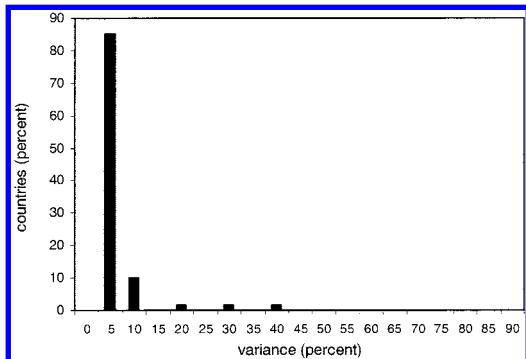


FIGURE 5. OUTPUT VARIANCE DUE TO THE REGIONAL FACTOR

European investment volatility is idiosyncratic. The investment and output dichotomies between the developing and developed economies pose questions for future research: what forces drive output and investment dynamics in developing economies to be so different from one another and the world, and why are fluctuations in developed economies so similar?

Sixth, our findings indicate that regional factors play a minor role in explaining macroeconomic variation: they explain less than 3 percent of output, consumption, and investment growth volatility in the median country (see Table 4). The regional factor seems to be playing its most important role in the North America region.²⁸ The histogram in Figure 5 illustrates how small a role the regional factors play in explaining output variability.

Finally, we find no evidence of the European cycle, for little of the volatility of the European aggregates can be attributed to the common European factor. This result stands in contrast to those of several recent studies that have argued to the contrary. Lumsdaine and Prasad (2003) estimated a European common component using industrial production data for 14 European countries; they found high positive correlations

the quality ratings in the Penn World tables indicate is true, then this error will be picked up by the idiosyncratic factor.

²⁸ This result is consistent with those of Bergman et al. (1998) who find, through cross-country correlations of output fluctuations for the 1880–1995 period, business cycles in Canada and the United States move very closely during the 1880–1995 period for all monetary regimes they examine.

between country fluctuations and the European component. They interpret this result as an evidence for a European business cycle. In a related study, Artis et al. (1997) examined cycles using industrial production data for G7 and five other European economies. They concluded that there exists a European business cycle. In a recent paper, Bergman et al. (1998) found high and significant correlations between output fluctuations of six European countries and interpreted this result as an outcome of a European common market. Our findings indicate that a significant fraction of the common variations across economies is captured by the world factor. That is, while the European aggregates do display comovement, the source is not distinctly European, but rather, worldwide. Moreover, this result is robust to redefinitions of the European region. We estimated a model with two European factors, one for a group of “core” European countries (France, Germany, Belgium, Netherlands, Italy, and Ireland), and a second factor for the remaining European countries, with the other regions defined as previously. The results are virtually unchanged. The regional factor for the core group of European countries explained 6 percent of output volatility, 3 percent of consumption volatility, and 7 percent of investment volatility.

V. The Relation Between Economic Structure and the Dynamic Factors

To aid in interpreting the 180 variance decompositions of the previous section and the Appendix, in this section we attempt to characterize the relationship between the structural characteristics of economies and the relative importance of the three types of factors. To do this, we employ a simple data summary device involving regressions. In particular, we regress the fraction of variance of an observable (output, consumption, investment) attributable to a particular factor (world, regional, country-specific) on a variety of explanatory variables that are related to country characteristics. It should be emphasized that the regressions in Tables 5A–5C are merely suggestive of a response surface; the reported *t*-statistics only suggest which regularities merit further study. Reading too much into the *t*-statistics is problematic because there appears to be some

TABLE 5A—REGRESSION OF OUTPUT VARIANCE DECOMPOSITION ON ECONOMIC STRUCTURE VARIABLES

Variable	World factor			Country factor			Regional factor		
	$R^2 = 0.425$			$R^2 = 0.427$			$R^2 = 0.136$		
	Coefficient	t-statistic	Prob	Coefficient	t-statistic	Prob	Coefficient	t-statistic	Prob
PC GDP	0.0617	0.9250	0.36	-0.0384	-0.4956	0.62	0.0682	2.2954	0.03
Gov Shr	0.0007	0.2042	0.84	0.0063	1.5338	0.13	0.0000	0.0156	0.99
Man Shr	0.0007	0.1841	0.86	0.0082	1.8884	0.07	-0.0026	-1.5409	0.13
GDP Vol	-5.9243	-3.9835	0.00	6.7740	3.9214	0.00	0.7696	1.1620	0.25

heteroskedasticity (“Developed” vs. “Developing”) in the error terms.

Table 5A summarizes our results about the link between the structural characteristics of an economy, and the role of the dynamic factors in explaining output growth volatility. Summary statistics from three regressions are reported in the table. For example, the columns under “World factor” report results of regressing the (median) fraction of variance of each country’s output growth attributable to the world factor on a set of four explanatory variables. The columns under “Country factor” report results from a similar regression using the median fraction of output volatility accounted for by the country factor, and so on. In this and the consumption and investment growth regressions to follow, the four explanatory variables are ratio of per capita GDP to U.S. per capita GDP (PCGDP), the share of government expenditure in GDP (Gov Shr), manufacturing’s share of output (Man Shr), and volatility of GDP growth (GDP Vol).²⁹

The coefficient on the volatility of GDP growth in the regressions using the world factor variance decompositions is sizeable and negative, indicating that in less volatile economies, the world factor is more important in explaining

output fluctuations. This is consistent with the finding in Section IV, that the world factor played a more important role in explaining output fluctuations in developed economies: more developed economies have less volatile aggregate output fluctuations. The level of income and the relative sizes of government and the manufacturing sectors do not help explain the cross-country pattern of world factor variance decompositions.

The country and regional factors are more important the more volatile the economy; what distinguishes them from one another involves the level of income and the size of the manufacturing sector. Consistent with the developing-developed distinction developed above, the country factor plays a more important role in poorer economies.³⁰ In contrast, though, the country factor is more important the larger is manufacturing’s share of output. The regional factor is more important in economies with the opposite characterization, those with higher per capita GDP and smaller manufacturing sectors. The relationship between richer countries and the regional factor is consistent with previous results that link the economies of more developed countries more tightly together.

Table 5B shows the connection between country characteristics and the role of the dynamic factors in explaining consumption growth volatility. The pattern of results is similar to that for output volatility: the world factor

²⁹ PCGDP: Real GDP per capita in constant dollars (expressed in international prices, base 1985) from PWT; Gov Shr: Real Government share of GDP [percent] (1985 intl. prices) from PWT; Man Shr: Manufacturing value added (percent of GDP) from World Tables 1994; output volatility is the standard deviation of output growth over the sample period. We have experimented with a variety of explanatory variables such as population, area, composition of exports, composition of imports, terms of trade volatility, openness, composition of GDP, and industrial structure. None of these variables is important in our regressions when they are considered together with volatility and per capita GDP.

³⁰ Head (1995) finds that country size is negatively correlated with the volatility of main macroeconomic aggregates. He develops a model that generates this feature of the data as the aggregate shocks affecting all countries have a relatively larger impact on smaller countries. Crucini (1997) constructs a multicountry general-equilibrium model to study business cycles in countries of different size and finds that the model is consistent with several features of the data.

TABLE 5B—REGRESSION OF CONSUMPTION VARIANCE DECOMPOSITION ON ECONOMIC STRUCTURE VARIABLES

Variable	World factor			Country factor			Regional factor		
	Coefficient	t-statistic	Prob	Coefficient	t-statistic	Prob	Coefficient	t-statistic	Prob
PC GDP	0.1301	2.1481	0.04	-0.1001	-1.2016	0.24	0.0422	1.7447	0.09
Gov Shr	0.0007	0.2227	0.83	0.0137	3.0850	0.00	0.0000	-0.0219	0.98
Man Shr	0.0004	0.1281	0.90	0.0020	0.4376	0.66	-0.0023	-1.7167	0.09
GDP Vol	-2.7301	-2.0226	0.05	6.3365	3.4132	0.00	0.6320	1.1735	0.25

TABLE 5C—REGRESSION OF INVESTMENT VARIANCE DECOMPOSITION ON ECONOMIC STRUCTURE VARIABLES

Variable	World factor			Country factor			Regional factor		
	Coefficient	t-statistic	Prob	Coefficient	t-statistic	Prob	Coefficient	t-statistic	Prob
PC GDP	0.0750	1.4123	0.16	0.2170	2.0135	0.05	0.0779	2.8790	0.01
Gov Shr	0.0025	0.8866	0.38	-0.0027	-0.4636	0.65	0.0020	1.3621	0.18
Man Shr	0.0049	1.6297	0.11	0.0139	2.3064	0.03	-0.0018	-1.1591	0.25
GDP Vol	-2.1749	-1.8382	0.07	0.8758	0.3647	0.72	-0.1705	-0.2826	0.78

is more important the less volatile the economy, the country-specific factor is more important the poorer the economy, and the regional factor is more important the richer the economy. We also find that government's share is positively related to the importance of the country factor.

Table 5C reports results on the link between the structural characteristics and the role of common factors in explaining investment growth volatility. Recalling that roughly half of investment growth volatility is idiosyncratic (Table 4), it is likely to be difficult to discern patterns in the importance of the three factors in explaining it. Indeed, the three factors are all more important in explaining investment growth volatility the richer the economy. We also find that as GDP volatility falls the world factor explains more of the variance in investment growth, a result that is consistent with the greater comovement of developed economies that we document above.

VI. Conclusion

In this paper we employ a Bayesian dynamic latent factor model to study the dynamic comovement of macroeconomic aggregates in a broad cross section of countries. We provide an

analysis of comovement across the world, across regions, and within countries. Our paper also makes a methodological contribution as it provides a framework to study multiple types of comovement simultaneously using a large cross section of data.

We find that there is a significant common world component present in the fluctuations in almost all of the countries in the sample. While a substantial fraction of economic fluctuations is explained by the world factor in developed economies, the country-specific factor and the idiosyncratic component account for more of the volatility in developing economies. Given the world factor, we find that regional business cycles, except for North America region, do not play an important role in explaining aggregate volatility. We argue regional factors found to be important in previous studies are in fact proxies for a broader, worldwide factor.

In contrast to output growth fluctuations, consumption and investment dynamics are driven more by country and idiosyncratic factors. In particular, the country dynamic factors play a more important role in explaining consumption fluctuations than the world and regional factors, a result that is consistent with imperfect consumption risk sharing among countries. We find that the country-specific and idiosyncratic com-

ponents account for the bulk of the volatility in investment.

Our results also suggest that countries for which the world factor seems to be important—countries that comove with the world business cycle—are those with less volatile GDP. Further, less developed economies are more likely to experience country-specific cycles. Evi-

dently, there is a world business cycle, and, unsurprisingly, it reflects economic activity in the developed economies. Further study of the temporal evolution of the world factor we have identified and its relationship to other macroeconomic aggregates may prove fruitful in the search for the *sources* of comovement documented in this paper.

APPENDIX A: DEFINITIONS AND DETAILED RESULTS Regional Definitions

<i>North America</i>	<i>Latin America</i>		<i>Europe</i>		<i>Africa</i>	<i>Asia (Developing)</i>	<i>Asia (Developed)</i>
USA	Costa Rica	Bolivia	France	Italy	Cameroon	Bangladesh	Hong Kong SAR
Canada	Dominican Republic	Brazil	Austria	Luxembourg	Ivory Coast	India	Japan
Mexico	El Salvador	Chile	Belgium	Netherlands	Kenya	Indonesia	Korea
<i>Oceania</i>	Guatemala	Ecuador	Denmark	Norway	Morocco	Pakistan	Malaysia
Australia	Honduras	Paraguay	Germany	Portugal	Senegal	Philippines	Singapore
New Zealand	Jamaica	Peru	Greece	Spain	S. Africa	Sri Lanka	Thailand
	Panama	Uruguay	Iceland	Sweden	Zimbabwe		
	Trinidad	Venezuela	Ireland	Switzerland			
	Argentina			United Kingdom			

TABLE A1—VARIANCE DECOMPOSITIONS FOR LATIN AMERICA

		World			Region			Country			Idiosyncratic		
		1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3
Costa Rica	O	40.7	43.4	45.9	2.2	5.3	9.8	33.5	38.5	43.1	7.8	9.6	11.9
	C	31.9	34.6	37.1	1.0	2.5	4.9	18.6	24.4	30.3	30.7	35.3	40.3
	I	5.7	6.7	7.8	4.0	8.7	15.2	30.6	37.9	45.2	35.3	42.5	49.5
Dominican Republic	O	7.3	8.5	9.8	2.9	7.1	14.0	71.7	78.4	82.7	3.6	4.5	5.5
	C	6.9	8.2	9.7	2.8	6.9	13.9	67.6	74.2	78.7	7.7	8.9	10.2
	I	5.3	6.2	7.2	2.2	5.1	9.4	43.3	47.5	51.1	37.3	39.4	41.4
El Salvador	O	20.3	22.9	25.6	1.6	3.5	6.8	60.8	64.8	68.4	5.5	6.4	7.4
	C	19.8	22.2	24.8	1.8	4.2	7.9	61.5	65.7	69.5	4.6	5.5	6.6
	I	10.4	11.5	12.8	0.5	1.3	2.6	9.3	10.9	12.5	73.6	74.9	76.2
Guatemala	O	46.2	48.8	51.5	0.5	1.1	2.3	38.7	41.7	44.6	5.7	6.7	7.8
	C	45.9	48.6	51.3	0.6	1.4	2.7	37.4	40.4	43.4	6.7	7.8	9.1
	I	9.4	10.8	12.2	0.4	0.9	1.9	32.6	36.0	39.8	47.9	51.2	54.1
Honduras	O	32.1	34.9	37.9	0.7	1.8	3.8	38.6	42.7	46.6	15.9	18.3	20.8
	C	15.3	17.2	19.0	1.2	2.8	5.4	57.2	61.8	65.6	12.8	15.7	19.0
	I	15.7	17.6	19.5	1.0	2.5	4.8	0.4	0.9	1.8	73.9	76.9	79.6
Jamaica	O	6.7	7.7	8.9	1.1	2.8	5.9	63.7	68.9	73.5	14.1	17.8	21.9
	C	0.1	0.2	0.4	1.2	3.0	6.2	67.1	72.1	77.3	17.3	21.4	25.9
	I	0.2	0.5	0.9	3.5	6.3	9.7	0.4	1.0	2.0	87.3	90.8	93.8
Panama	O	0.3	0.6	1.1	0.6	1.4	2.7	69.6	75.7	80.8	15.6	20.5	26.4
	C	0.6	1.0	1.4	0.6	1.4	2.7	40.3	46.7	53.7	42.5	49.4	55.7
	I	0.1	0.1	0.2	0.3	0.8	1.6	27.4	34.5	40.7	57.3	63.6	70.6
Trinidad	O	1.5	2.1	2.9	0.9	2.1	4.3	86.8	89.2	91.0	4.4	5.3	6.3
	C	0.3	0.6	1.0	1.0	2.5	4.8	88.3	90.9	92.8	3.9	4.8	5.8
	I	1.2	1.8	2.4	1.3	2.7	4.7	2.2	3.0	3.9	89.6	91.7	93.2
Argentina	O	12.9	14.3	15.7	0.4	0.9	1.9	76.8	78.8	80.7	3.7	4.6	5.7
	C	8.9	10.2	11.4	0.5	1.2	2.5	66.1	69.3	72.1	15.7	17.8	20.1
	I	11.9	13.2	14.5	0.4	1.0	2.0	55.0	58.0	61.0	24.4	26.8	29.2
Bolivia	O	39.1	42.4	45.7	0.4	0.9	1.9	18.4	25.0	31.5	24.3	30.0	36.1
	C	5.8	7.0	8.5	2.0	4.5	8.5	7.6	14.6	23.7	59.6	69.1	76.5
	I	6.5	8.1	10.0	0.3	0.8	1.6	6.9	13.6	22.1	67.8	75.5	81.4
Brazil	O	21.6	23.5	25.4	2.7	4.6	7.1	58.0	61.5	64.7	6.9	8.7	10.7
	C	14.9	16.7	18.4	3.6	6.0	8.8	45.6	50.1	54.2	22.5	25.6	28.8
	I	18.1	19.7	21.2	0.4	0.9	1.9	27.7	31.8	35.8	43.1	46.5	50.1
Chile	O	12.2	13.9	15.8	1.8	4.3	9.0	61.3	66.4	70.3	12.0	13.5	14.9
	C	15.0	17.1	19.2	1.8	4.5	9.0	66.6	71.6	75.6	2.8	4.0	5.4
	I	5.8	7.1	8.4	0.4	1.1	2.2	9.2	11.9	14.4	76.1	78.3	80.6
Colombia	O	29.8	32.0	34.2	0.5	1.3	2.7	44.6	48.6	52.1	13.9	16.5	19.4
	C	24.8	26.7	28.7	0.6	1.4	2.8	39.9	45.2	50.1	20.6	24.7	29.7
	I	5.3	6.5	7.8	0.5	1.2	2.4	15.1	20.3	26.0	65.1	70.5	75.2
Ecuador	O	6.4	7.5	8.7	0.4	1.0	2.0	67.7	72.2	76.4	13.7	17.6	22.1
	C	3.6	4.6	5.6	0.6	1.4	2.8	44.7	49.5	54.1	38.8	42.8	47.2
	I	0.5	0.9	1.4	1.2	2.7	5.0	34.6	39.1	43.5	50.9	55.4	59.6
Paraguay	O	2.3	3.1	4.0	0.7	1.7	3.6	84.3	86.9	88.9	5.4	6.7	8.1
	C	0.9	1.4	2.0	0.6	1.5	3.0	81.5	84.1	86.4	9.9	11.6	13.4
	I	11.9	13.6	15.4	1.1	2.6	4.9	31.6	34.7	37.5	44.0	46.9	49.9
Peru	O	1.8	2.5	3.2	0.2	0.5	1.1	88.2	90.0	91.7	4.6	5.9	7.6
	C	3.4	4.4	5.5	0.5	1.1	2.2	73.3	75.9	78.4	15.1	17.2	19.5
	I	0.3	0.5	0.9	0.4	0.9	1.9	48.8	52.4	55.6	41.7	44.9	48.2
Uruguay	O	7.6	8.8	10.0	0.5	1.1	2.2	80.0	82.3	84.4	5.2	6.4	7.9
	C	3.6	4.4	5.3	0.7	1.5	3.0	72.5	75.6	78.3	14.8	17.0	19.4
	I	3.2	4.1	5.1	1.5	3.1	5.6	42.5	46.2	49.7	41.4	44.7	48.1
Venezuela	O	15.6	17.5	19.5	0.5	1.1	2.3	45.6	51.0	56.2	23.9	29.0	34.0
	C	0.8	1.3	1.9	0.5	1.2	2.5	22.0	26.9	32.2	63.6	68.7	73.6
	I	5.3	6.4	7.6	0.5	1.3	2.6	45.9	52.1	58.3	32.6	38.8	44.8
Regional Median	O	12.6	14.1	15.7	0.6	1.5	3.2	62.5	67.7	71.9	7.4	9.2	11.3
	C	6.3	7.6	9.1	0.8	2.0	3.9	59.4	63.7	67.5	15.4	17.5	19.8
	I	5.5	6.6	7.8	0.5	1.3	2.6	29.2	34.6	38.7	49.4	53.3	56.9

TABLE A2—VARIANCE DECOMPOSITIONS FOR AFRICA

		World			Region			Country			Idiosyncratic		
		1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3
Cameroon	O	0.2	0.5	0.8	1.1	2.8	6.0	57.3	63.5	69.3	24.9	30.0	35.1
	C	0.7	1.0	1.5	1.3	3.5	7.7	58.6	65.5	72.0	19.8	25.2	30.8
	I	0.1	0.2	0.5	1.0	2.5	4.7	0.3	0.7	1.5	92.5	95.1	97.0
Ivory Coast	O	16.7	19.6	22.5	1.9	4.3	8.7	60.9	66.0	70.4	5.8	7.2	8.7
	C	12.2	14.7	17.4	1.4	3.5	7.1	64.2	69.1	73.2	8.6	10.2	11.8
	I	8.1	9.5	11.0	1.0	2.5	5.1	13.2	15.9	18.6	67.9	69.9	72.0
Kenya	O	0.1	0.1	0.2	3.8	9.5	19.3	71.6	81.3	86.9	6.5	8.0	9.5
	C	0.7	1.0	1.4	3.8	9.4	19.1	71.9	81.9	87.7	4.6	6.1	7.8
	I	8.5	9.8	11.1	0.5	1.1	2.2	0.3	0.7	1.3	85.4	87.1	88.7
Morocco	O	1.5	2.2	3.0	2.1	4.6	8.0	78.6	82.3	85.3	7.8	9.4	11.2
	C	2.7	3.5	4.4	1.3	2.7	4.9	79.5	82.5	85.2	8.0	9.8	11.6
	I	1.2	1.9	2.5	0.9	2.2	4.4	0.6	1.3	2.2	90.7	93.0	94.7
Senegal	O	1.5	2.1	2.8	1.3	3.1	6.2	74.9	79.1	82.5	11.0	13.5	16.4
	C	0.1	0.3	0.6	1.2	2.9	5.8	74.8	79.0	83.0	12.4	15.4	18.6
	I	2.3	3.4	4.7	1.2	2.6	4.8	0.3	0.6	1.3	89.1	91.7	93.9
South Africa	O	13.6	15.1	16.7	3.2	7.4	13.6	58.7	65.1	70.2	8.1	9.9	12.0
	C	7.7	9.0	10.4	2.7	6.3	12.4	51.5	58.4	64.5	19.4	22.6	26.3
	I	2.0	2.7	3.4	1.9	4.5	8.7	25.4	30.6	35.8	55.0	59.2	63.4
Zimbabwe	O	1.4	1.9	2.6	0.9	2.2	4.4	62.4	67.5	72.6	21.5	26.1	30.4
	C	0.4	0.7	1.0	1.1	2.4	4.5	70.3	76.0	81.3	13.9	18.8	24.2
	I	0.1	0.2	0.4	2.0	4.4	8.0	2.3	4.9	8.1	83.6	87.7	91.5
Regional Median	O	1.5	2.1	2.8	1.9	4.3	8.0	62.4	67.5	72.6	8.1	9.9	12.0
	C	0.7	1.0	1.5	1.3	3.5	7.1	70.3	76.0	81.3	12.4	15.4	18.6
	I	2.0	2.7	3.4	1.0	2.5	4.8	0.6	1.3	2.2	85.4	87.7	91.5

TABLE A3—VARIANCE DECOMPOSITIONS FOR ASIA (DEVELOPED)

		World			Region			Country			Idiosyncratic		
		1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3
Hong Kong SAR	O	13.5	14.9	16.4	0.6	1.5	3.3	58.1	62.9	66.9	15.1	18.4	22.0
	C	5.7	6.7	7.8	0.7	1.8	3.7	44.9	50.2	55.6	33.9	39.1	44.0
	I	6.8	7.7	8.7	0.8	2.1	4.4	40.7	46.6	51.9	35.7	40.7	45.8
Japan	O	35.8	38.2	40.4	1.9	4.1	7.4	43.7	47.7	51.4	6.5	7.8	9.5
	C	33.3	36.0	38.8	1.6	3.2	5.4	29.2	33.4	37.5	23.0	25.5	28.2
	I	27.6	29.6	31.6	1.7	3.8	7.0	37.6	42.1	46.4	19.3	22.2	25.0
Korea	O	5.2	6.1	7.1	1.8	4.2	8.7	62.6	69.0	74.2	13.2	16.9	21.4
	C	4.8	5.8	6.9	1.2	3.1	6.3	53.4	58.6	63.5	25.5	29.9	34.2
	I	1.9	2.5	3.1	0.6	1.4	2.9	5.7	9.1	12.8	81.0	84.8	88.6
Malaysia	O	5.2	6.4	7.8	0.9	2.2	4.2	83.5	86.0	88.0	3.5	4.2	5.0
	C	2.8	3.8	4.9	0.7	1.8	3.6	63.4	66.2	68.8	24.6	26.6	28.6
	I	3.1	4.1	5.3	0.9	2.1	4.1	83.3	85.9	88.1	5.6	6.7	7.9
Singapore	O	1.4	2.0	2.7	0.3	0.8	1.6	78.5	81.6	84.5	11.8	14.2	17.2
	C	0.2	0.4	0.7	0.3	0.8	1.7	77.6	80.7	83.7	14.2	16.9	19.8
	I	7.1	8.4	9.8	2.8	5.3	8.4	11.0	12.9	14.8	68.7	71.9	74.9
Regional Median	O	5.2	6.4	7.8	0.9	2.2	4.2	62.6	69.0	74.2	11.8	14.2	17.2
	C	4.8	5.8	6.9	0.7	1.8	3.7	53.4	58.6	63.5	24.6	26.6	28.6
	I	6.8	7.7	8.7	0.9	2.1	4.4	37.6	42.1	46.4	35.7	40.7	45.8

TABLE A4—VARIANCE DECOMPOSITIONS FOR ASIA (DEVELOPING)

		World			Region			Country			Idiosyncratic		
		1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3
Thailand	O	10.8	12.2	13.7	1.4	3.3	6.8	62.5	67.5	71.7	11.2	13.8	16.8
	C	10.1	11.4	12.9	1.6	3.9	7.8	44.8	51.0	56.3	25.8	30.0	34.5
	I	2.8	3.6	4.4	0.5	1.2	2.5	31.1	36.4	41.9	51.6	56.8	62.0
Bangladesh	O	1.3	1.8	2.5	11.0	18.8	27.4	41.4	50.0	58.3	20.6	26.6	32.2
	C	3.5	4.4	5.3	10.2	17.7	26.3	40.7	49.4	57.9	19.2	25.0	30.9
	I	0.1	0.1	0.3	0.4	1.1	2.2	0.4	0.9	1.9	95.1	96.7	97.9
India	O	4.4	5.2	6.0	3.8	7.5	12.3	44.4	51.7	58.9	25.9	32.0	38.4
	C	3.9	4.8	5.7	1.3	3.2	6.7	41.3	48.1	55.0	34.1	40.4	46.5
	I	0.1	0.2	0.4	0.5	1.3	2.7	4.5	7.0	10.2	85.9	89.8	92.8
Indonesia	O	4.9	6.0	7.2	0.5	1.3	2.6	67.5	73.0	77.5	13.6	17.7	22.6
	C	20.5	22.5	24.4	0.8	1.9	3.5	24.9	29.2	33.6	40.3	44.6	48.7
	I	0.1	0.1	0.3	0.4	1.1	2.2	46.6	53.2	58.8	38.3	43.9	50.2
Pakistan	O	0.6	1.0	1.5	0.7	1.6	3.3	75.3	78.5	81.5	14.7	17.4	20.0
	C	0.9	1.4	1.9	1.6	3.8	6.7	75.3	79.5	83.2	10.8	13.4	16.3
	I	1.4	1.9	2.5	0.8	1.9	3.9	9.6	11.6	13.7	80.0	83.1	85.7
Philippines	O	3.2	4.1	5.0	0.4	1.0	2.0	79.1	82.1	84.9	9.2	11.4	14.1
	C	4.2	5.1	6.0	0.6	1.3	2.7	44.2	48.8	53.1	39.1	43.0	47.3
	I	0.1	0.2	0.3	0.8	1.8	3.2	63.5	67.8	72.0	24.9	28.8	33.0
Sri Lanka	O	6.2	7.3	8.6	1.6	4.2	9.1	63.2	69.9	74.7	12.6	15.1	18.0
	C	5.9	6.8	7.9	3.0	6.7	12.6	60.4	67.8	73.4	12.5	15.3	18.5
	I	0.1	0.2	0.5	4.2	8.1	13.4	0.3	0.8	1.5	83.7	89.4	93.7
Regional Median	O	4.4	5.2	6.0	1.4	3.3	6.8	63.2	69.9	74.7	13.6	17.4	20.0
	C	4.2	5.1	6.0	1.6	3.8	6.7	44.2	49.4	56.3	25.8	30.0	34.5
	I	0.1	0.2	0.4	0.5	1.3	2.7	9.6	11.6	13.7	80.0	83.1	85.7

TABLE A5—VARIANCE DECOMPOSITIONS FOR OCEANIA

		World			Region			Country			Idiosyncratic		
		1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3	1/3	Med	2/3
Australia	O	17.4	19.3	21.5	1.7	3.8	7.3	61.4	65.0	68.3	8.7	9.9	11.1
	C	17.0	18.6	20.2	0.7	1.7	3.4	36.9	39.9	42.6	36.4	38.5	40.4
	I	11.2	12.8	14.6	2.1	4.6	8.7	68.7	72.9	76.4	5.6	7.4	9.3
New Zealand	O	9.3	10.9	12.5	1.0	2.3	4.8	68.7	72.4	75.6	10.4	12.3	14.5
	C	7.8	9.0	10.2	1.3	2.8	5.0	20.0	24.1	28.2	58.2	62.2	66.3
	I	5.9	7.5	9.2	1.1	2.6	5.4	63.5	68.7	73.3	14.7	18.1	21.6
Regional Median	O	13.4	15.1	17.0	1.3	3.1	6.1	65.0	68.7	72.0	9.5	11.1	12.8
	C	12.4	13.8	15.2	1.0	2.3	4.2	28.5	32.0	35.4	47.3	50.4	53.4
	I	8.5	10.2	11.9	1.6	3.6	7.0	66.1	70.8	74.9	10.2	12.7	15.4

APPENDIX B: THE MCMC APPROACH TO DYNAMIC FACTOR ANALYSIS

The dynamic factor analysis model in equations (1)–(4) can be thought of as consisting of a specification of a Gaussian probability density for the data $\{y_t\}$ conditional on a set of parameters φ and a set of latent variables $\{f_t\}$. Call this density function $g_y(\mathbf{Y}|\varphi, \mathbf{F})$ where \mathbf{Y} denotes the $MNT \times 1$ vector of data on the observables, and \mathbf{F} denotes the $KT \times 1$ vector of dynamic factors. In addition, there is a specification of a Gaussian probability density $g_f(\mathbf{F})$ for \mathbf{F} itself. Given a prior distribution for φ , $\pi(\varphi)$, the joint posterior distribution for the parameters and the latent variables is given by the product of the likelihood and prior, $h(\varphi, \mathbf{F}|\mathbf{Y}) = g_y(\mathbf{Y}|\varphi, \mathbf{F})g_f(\mathbf{F})\pi(\varphi)$.

As is shown in Otrok and Whiteman (1998), although the joint posterior $h(\varphi, \mathbf{F}|\mathbf{Y})$ is extremely cumbersome, under a conjugate prior for φ the two conditional densities $h(\varphi|\mathbf{F}, \mathbf{Y})$ and $h(\mathbf{F}|\varphi, \mathbf{Y})$ are quite simple. Moreover, it is possible to use this fact and Markov-Chain Monte Carlo methods (MCMC) to generate an artificial sample $\{\varphi^j, \mathbf{F}^j\}$ for $j = 1, \dots, J$ as follows:

1. Starting from a value \mathbf{F}^0 in the support of the posterior distribution for \mathbf{F} , generate a random drawing φ^1 from the conditional density $h(\varphi|\mathbf{F}^0, \mathbf{Y})$.
2. Now generate a random drawing \mathbf{F}^1 from the conditional density $h(\mathbf{F}|\varphi^1, \mathbf{Y})$.
3. This process is repeated, generating at each step drawings $\varphi^j \sim h(\varphi|\mathbf{F}^{j-1}, \mathbf{Y})$ and $\mathbf{F}^j \sim h(\mathbf{F}|\varphi^{j-1}, \mathbf{Y})$.

Under regularity conditions satisfied here (see Tanner and Wong, 1987), the sample so produced is a realization of a Markov chain whose invariant distribution is the joint posterior $h(\varphi, \mathbf{F}|\mathbf{Y})$.

What makes this process feasible is the simplicity of the two conditional distributions. For example, $h(\varphi|\mathbf{F}, \mathbf{Y})$ is easily constructed from equation (1) when \mathbf{F} is known. In particular, equation (1) is just a normal linear regression model for y_i given the factors (albeit a regression that has autocorrelated errors). Because the prior for the intercept and factor loadings is Gaussian, the conditional posterior for the pa-

rameters (σ_i , a_i , and the b_i 's) is also Gaussian. The other conditional density, $h(\mathbf{F}|\varphi, \mathbf{Y})$ is a little more complicated because it is the solution to a Gaussian signal extraction problem. Kalman filter techniques are commonly used to solve such problems, but when the time series is short, as in this application, it is straightforward to solve the problem directly. Solving the problem without using the Kalman filter is especially useful when the number of factors is large, as in the problem we study. (With a large number of factors the state equation in the Kalman filter can become computationally very burdensome.) Otrok and Whiteman (1998) do this as follows: first, they write the joint density for the data and the dynamic factors given the parameters as a product of NMK independent Gaussian densities (NM of them are associated with the observable time series, K with the dynamic factors). Second, from this joint distribution, simple normal distribution theory is used to obtain the conditional distribution for any one of the factors given the rest and the parameters. These normal distributions involve inverses of $T \times T$ covariance matrices that can be handled using conventional procedures provided T is not large. In the model analyzed here, $T = 30$ is not problematic.

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