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An Endogenously Clustered Factor Approach to International Business Cycles*

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Abstract

Factor models have become useful tools for studying international business cycles. Block factor models can be especially useful as the zero restrictions on the loadings of some factors may provide some economic interpretation of the factors. These models, however, require the econometrician to predefine the blocks, leading to potential misspecification. In Monte Carlo experiments, we show that even small misspecification can lead to substantial declines in fit. We propose an alternative model in which the blocks are chosen endogenously. The model is estimated in a Bayesian framework using a hierarchical prior, which allows us to incorporate series-level covariates that may influence and explain how the series are grouped. Using international business cycle data, we find our country clusters differ in important ways from those identified by geography alone. In particular, we find that similarities in institutions (e.g., legal systems, language diversity) may be just as important as physical proximity for analyzing business cycle comovements.

[JEL: C33; C52; E32; F44]

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1 Introduction

Previous studies have documented evidence of correlation in business cycles across countries [e.g., Engle and Kozicki (1993) and Clark and Shin (2000) among many others]. But what makes certain countries share common movements in their business cycles? In particular, do similarities in some country characteristics (e.g., industrial similarity, proximity, language, trade) lead to correlation in those countries' business cycles? Empirical models comparing business cycles across countries generally take one of two approaches to explaining this correlation: (1) Country cycles are estimated separately and then compared or (2) cycles are estimated jointly with numerous assumptions made on the correlation structure.

For the most part, these approaches are motivated by the need to reduce complexity and potential parameter proliferation. The former approach leaves the country combinations unrestricted (i.e., any two countries' cycles can be correlated), whereas the latter explicitly imposes or excludes the correlation. Depending on the econometric techniques used to compute the cycle, one approach may be more suitable than the other. For example, the first approach might define a country's cycle based on a Markov-switching model or a trend-cycle decomposition, methods typically reserved for smaller systems of equations.[1] The second approach might define a common cycle via a factor model, where the factor loadings reflect the degree of correlation among country cycles [e.g., Bai (2003); Bai and Ng (2002); Forni, Hallin, Lippi, and Reichlin (2000, 2005); and Stock and Watson (2002a,b)].

In a series of recent papers, Kose, Otrok, and Whiteman (2003, 2008; henceforth KOW) propose a factor model with a block structure for the factor loadings.[2] This block structure provides a straightforward interpretation that may be lacking in standard factor models. Countries within a block have cycles that are correlated through a regional factor, whereas countries in different blocks are correlated only through a global factor. The standard factor model can emulate a block factor model if the loadings on the regional factors are close to zero. Even in that case, however, the standard factor model allows for some cross-country

[1] Exceptions are Hamilton and Owyang (2012) and Kaufmann (2010), who use approaches similar to ours in this paper in a Markov-switching environment.

[2] See also Boivin and Ng (2006); Onatski (2007); and Hallin and Liška (2011).

correlation for countries outside its block, whereas a block factor model remove cross-block correlation altogether. The significant advantage of the block factor model is that it allows a larger number of less-pervasive (regional) factors, only a few of which affect any particular country. Thus, correlations across a small number of countries may be identified in block factor models but missed in standard factor models, in which the correlation is swamped by the large cross section. The disadvantage of the block factor structure is that the blocks (or clusters) are generally predetermined, meaning significant *ex ante* assumptions must be made about which countries' cycles are correlated.

In this paper, we adopt the block factor approach but relax the assumption that the blocks are known ex ante. The model is similar to KOW with an additional membership indicator determining to which block a country belongs. We assume block membership is a multinomial choice—i.e., a country cannot belong to more than one block. This multinomial approach to the block structure lends itself to estimation with Bayesian methods. In the simplest execution of the multinomial approach, we can assume either a uniform or Dirichlet prior on the membership indicator, giving the model the appearance of a clustering algorithm. For the uniform prior, cluster membership depends solely on the business cycle characteristics of the country's data compared with the other members of the cluster. For the Dirichlet prior, increasing the size of the cluster increases the ex ante probability a country is sorted to it.

On the other hand, the prior probabilities can be determined by country characteristics. To that end, we adopt a multinomial logistic prior on cluster membership [see also Frühwirth-Schnatter and Kaufmann (2008); Hamilton and Owyang (2012)] that allows us to (1) incorporate country-specific characteristics (e.g., location, industrialization, trade patterns) and (2) test competing hypotheses about which influences determine the countries that comove. Once the ex post country groupings are determined, potential commonalities within groups could be useful in determining important features that any successful model of the international business cycle should possess. For example, if we find that common language is a better determinant of cross-correlation than physical distance, models of trade may consider common language rather than geography as the determinant of iceberg costs.

By being agnostic about block membership, we allow the data to cluster based on both their business cycle features and on country-specific characteristics. For example, countries could form groups based on their proximity, coordinated policies, and/or structural innovations. In this sense, we are not a priori guided by any one particular theoretical model.

In Monte Carlo experiments with simulated data, we draw an obvious conclusion: Empirical results, their economic interpretation, and the degree of confidence we place in them depend greatly on the specification of the block structure. When the clusters are known (and correct), the standard KOW block factor model performs well. However, we find that small ex ante misspecifications of the block structure can lead to dramatic deviations from the true model and substantial reductions in fit.

Our empirical application extends KOW's study of cross-country correlations. Using annual gross domestic product (GDP) growth rates for 60 countries, we find that although some regional/geographic correlation does exist, there is also evidence against the prevailing belief that geographic proximity is the major determinant of cross-country comovements. We find evidence of only three clusters. The first consists of many of the industrialized nations: Japan and most of Europe, excluding the U.K. and Denmark. A second cluster is composed of the U.K. and its former British Commonwealth countries: Australia, Canada, India, New Zealand, and the U.S., among others. A third cluster consists of South American countries, Mexico, and a few other countries. We find that—as opposed to physical distance—linguistic diversity and legal institutions are among the country-level determinants of this "regional" clustering. We also find that allowing the data to determine the clustering leads to substantially higher contribution of the cluster (or regional) factor to the overall volatility of output. Moreover, we find that endogenously determining the clusters improves the quasi-out-of-sample properties of the model.

The balance of the paper is organized as follows: Section 2 presents the endogenous clustered factor model. Section 3 outlines the Bayesian techniques we use to estimate the model. In this section, we focus on estimation of the model with a uniform prior on cluster membership. Section 4 presents some Monte Carlo evidence showing how well our algorithm identifies the clusters and the consequences of exogenously misidentifying them. Section 5 presents results from the model with international business cycle data. Section 6 summarizes and concludes.

2 Empirical Model

Suppose that we have a panel of N series, $y_n = [y_{n1}, ..., y_{nT}]$, each of length T. Correlation in the panel can be sorted into common movements that affect all series and those that affect only a few series. We refer to the former as global factors and to the latter as cluster factors (or regional factors). Suppose there is a single global factor and there are M clusters for which a series y_n belongs to a single cluster i; then, y_{nt} can be expressed as a function of the global factor F_{Gt}; a single cluster factor F_{it}; an intercept β_{n0}; and an error term, ε_{nt}:

$$y_{nt} = \beta_{n0} + \beta_{nG} F_{Gt} + \beta_{ni} F_{it} + \varepsilon_{nt}, \tag{1}$$

$i = 1, \ldots, M$, $t = 1, \ldots, T$, and $n = 1, \ldots, N$, where $M \ll N$ and β_{nG} and β_{ni} are the factor loadings.[3] We allow the error terms, ε_{nt}, to be serially correlated, following an AR(p_ε) process:

$$\varepsilon_{nt} = \psi_n(L)\varepsilon_{nt-1} + \epsilon_{nt},$$

where $\epsilon_{nt} \sim N\left(0, \sigma_n^2\right)$ and $E\left[\epsilon_{nt}\epsilon_{mt}\right] = 0$ for all $m \neq n$. We assume that each factor (including the global factor) follows an AR(p_F) process of the form:

$$F_{it} = \phi_i\left(L\right) F_{it-1} + e_{it}, \tag{2}$$

where $\phi_i\left(L\right)$ is a polynomial in the lag operator and $e_{it} \sim N\left(0, \omega_i^2\right)$, where we normalize $\omega_i^2 = 1$, as is common in the literature.

The restriction that each series can belong only to one cluster gives the panel description

[3] KOW estimate their model with a vector of country-level data, allowing them to include a country-level factor. Adding this feature or increasing the number of global factors is straightforward. We discuss the choice of M below.

of (1) a block structure that can be interpreted as regions.[4] For example, if the y_{nt}'s are country GDP, the interpretation of (1) is that country n belongs to the ith region. The diagonality of the variance-covariance matrix implies that comovements between series not in the same cluster arise solely from the global factor. Series within the same cluster, on the other hand, can comove via the global factor or the cluster factor. If we believe that some shocks affect all of the series while other shocks remain confined to the region or sector from which they originate, the model provides a framework with which we can perform regionally- or industrially-differentiated analysis [see Moench, Ng, and Potter (2013)].

In (1), we have *imposed* that series n belongs to cluster i, but what if we are unsure which series should move together? KOW assume that countries on the same continent comove; Moench, Ng, and Potter impose that within-sector data comove. While geographic proximity or industrial similarity may be a reason for the comovement between two countries, other causes (e.g., trade, demographics, level of industrialization) may also determine comovement. We, therefore, augment (1) to allow the clusters to be determined endogenously.

In endogenous clustering, the data choose the groupings.[5] We define a cluster indicator, $\gamma_{ni} = \{0, 1\}$, that signifies whether series n belongs to cluster i, retaining the restriction that a series can only belong to a single cluster—i.e., $\sum_i^M \gamma_{ni} = 1$. Then, we have

$$y_{nt} = \beta_{n0} + \beta_{nG} F_{Gt} + \sum_{i=1}^{M} \gamma_{ni} \beta_{ni} F_{it} + \varepsilon_{nt}. \tag{3}$$

The model preserves the restrictions on the comovement of the series; series in different clusters comove only through the global factor, while series belonging to the same cluster can comove apart from the global factor. However, in contrast to (1), we can now estimate the membership indicator, γ_{ni}, thereby allowing the data to determine the composition of the clusters.

[4] The restriction that each series belongs to a single cluster is straightforward to relax [see Frühwirth-Schnatter and Lopes (2010) and the sparse factor model of Carvalho, Lopes, and Aguilar (2010)].

[5] Lin and Ng (2012) estimate a panel threshold model and define clusters by the similarity of the coefficients. Bonhomme and Manresa (2015) use a "grouped fixed-effects" estimator that minimizes a least-squares criterion with respect to all possible groupings of the cross-sectional units. Our method's main idea is similar to theirs, but does not need to visit all possible clusters. Instead, we create a dynamic mixing environment that coverges to the highest likelihood clusters.

While KOW imposed a geographic structure to their clusters, estimation of the cluster membership allows us to incorporate other information that might lead countries to respond to the same common factor. For example, Norrbin and Schlagenhauf (1996) estimated the role of industrial similarity in international business cycles but find a limited role for industry-specific shocks in explaining the forecast-error variance of output across countries. McKinnon (1982) suggested coordinated monetary policies as a factor for synchronous cross-country business cycles, but Clark and van Wincoop (2001) found limited roles for both monetary and fiscal policies in the synchronization of business cycles across European countries. Finally, correlation between macroeconomic aggregates across countries could be due to unobservable innovations—e.g., common international shocks or country-specific shocks having spillover effects. Using structural vector autoregressions, Ahmed, Ickes, Wang, and Yoo (1993) concludes that spillovers from a country-specific labor supply shock are more important than common shocks in generating international business cycles.[6]

We can incorporate this additional information by assuming a multinomial logistic prior for the cluster membership indicator, γ_{ni}. Suppose there exists a vector, z_{ni}, of variables that may influence whether a series n belongs to cluster i. We assess the prior probability that series n belongs to cluster i as

$$\Pr\left[\gamma_{ni}=1|\mathbf{z}_{ni}\right]=\begin{cases}\exp\left(\mathbf{z}_{ni}^{'}\boldsymbol{\delta}_i\right)/\left[1+\sum\exp\left(\mathbf{z}_{ni}^{'}\boldsymbol{\delta}_i\right)\right] & i=1,...,M-1\\ 1/\left[1+\sum\exp\left(\mathbf{z}_{ni}^{'}\boldsymbol{\delta}_i\right)\right] & i=M\end{cases}, \tag{4}$$

for $n=1,...,N$ and where we have normalized $\delta_M=0$ for identification. Note also that the vector, z_{ni}, need not be composed of the same variables for each cluster i. As in Hamilton and Owyang (2012), we can think of the prior hyperparameters as population parameters signifying the clusters' relationships.

[6] See Baxter and Kouparitsas (2005) for a list of other potential determinants of business cycle comovements across countries.

3 Estimation

The endogenously clustered factor model outlined in the preceding section can be estimated using Bayesian techniques [see Gelfand and Smith (1990); Casella and George (1992); Carter and Kohn (1994)]. Bayesian methods allow us to estimate cluster membership directly using a reversible-jump Metropolis-Hastings step in the Gibbs sampler.[7]

The sampler is an MCMC algorithm that draws from the conditional distributions of each parameter block conditional on the previous draws from the remaining parameters. The sequence of draws from the conditional distributions converges to the joint posterior. Let $\mathbf{Y}$ represent the data, $\mathbf{\Theta}$ represent the full set of model parameters, and $\mathbf{F}$ represent the full set of factors. The model parameters and factors can be drawn in six blocks: (1) the group membership indicators, $\boldsymbol{\gamma}$, jointly with the intercept and the factor loadings, $\boldsymbol{\beta}$; (2) the innovation variances, $\boldsymbol{\sigma}^2$; (3) the innovation AR parameters, $\boldsymbol{\psi}$; (4) the factors, $\mathbf{F}$; (5) the set of factor AR parameters, $\boldsymbol{\phi}$; and (6) the logistic prior slope parameters, $\boldsymbol{\delta}$, a latent variable, $\boldsymbol{\xi}$, and the variance of the logistic, $\boldsymbol{\lambda}$. After initializing the sampler, the posterior distributions are computed with 10,000 iterations after 30,000 iterations are discarded for convergence.

For each series, the prior for factor loadings is normal, $\beta_n = [\beta_{n0}, \beta_{nG}, \beta_{ni}]' \sim N(\mathbf{b}_0, \mathbf{B}_0)$, and the innovation variances are inverse gamma, $\sigma_n^{-2} \sim \Gamma(\nu_0, \Upsilon_0)$. The factor and measurement error AR parameters also have normal priors, $\boldsymbol{\phi} \sim N\left(\mathbf{v}_0, \mathbf{V}_0^{-1}\right)$ and $\boldsymbol{\psi} \sim N\left(\mathbf{w}_0, \mathbf{W}_0^{-1}\right)$, respectively. The factors are assumed to have unit innovation variances. The logistic slope parameters have normal priors, $\boldsymbol{\delta} \sim N(\mathbf{d}_0, \mathbf{D}_0)$. The hyperparameters for the prior distributions are given in Table 1.

The primary difference between our paper and KOW lies in the joint draw of the membership indicator and the factor loadings. We provide details of this draw and a brief description of the draw of the factors. The draws of the variance, both sets of AR parameters, and all of the logistic parameters are straightforward and included in the Appendix.

[7] In principle, one could estimate each cluster combination model using classical techniques and determine the final cluster composition via some model selection criteria. However, this would mean estimating and comparing a very large number of possible models.

3.1 Generating $\boldsymbol{\gamma}, \boldsymbol{\beta} | \boldsymbol{\Theta}_{-\boldsymbol{\gamma},\boldsymbol{\beta}}, \mathbf{F}, \mathbf{Y}$

For efficiency reasons, we draw β_n and γ_n jointly for each n. The joint draw of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ can be written as

$$q\left(\beta_n^*, \gamma_n^* | \boldsymbol{\Theta}_{-\boldsymbol{\gamma},\boldsymbol{\beta}}, \mathbf{F}\right) = q\left(\gamma_n^* | \gamma_n, \boldsymbol{\Theta}_{-\boldsymbol{\gamma},\boldsymbol{\beta}}, \mathbf{Y}, \mathbf{F}\right) \pi\left(\beta_n^* | \boldsymbol{\Theta}_{-\boldsymbol{\gamma},\boldsymbol{\beta}}, \gamma_n^*, \mathbf{Y}, \mathbf{F}\right),$$

where we draw a candidate γ_n^* from $q\left(\gamma_n^* | \gamma_n, \boldsymbol{\Theta}_{-\boldsymbol{\gamma},\boldsymbol{\beta}}, \mathbf{Y}, \mathbf{F}\right)$, which may or may not depend on the past (accepted) value of γ_n. Then, conditional on the candidate γ_n^*, we draw a candidate β_n^* from its full conditional distribution $\pi\left(\beta_n^* | \boldsymbol{\Theta}_{-\boldsymbol{\gamma},\boldsymbol{\beta}}, \gamma_n^*, \mathbf{Y}, \mathbf{F}\right)$. This joint pair is then accepted or rejected.

Formally, let $\mathbf{X}_n^* = [\mathbf{1}_T, \mathbf{F}_G, \widetilde{\mathbf{F}}\gamma_n^*]$, where $\mathbf{1}_T$ is a $(T \times 1)$ vector of ones and $\widetilde{\mathbf{F}} = [\mathbf{F}_1, ..., \mathbf{F}_M]$ is the collection of cluster factors. Let $\overline{\mathbf{X}}_n^*$ and $\overline{\mathbf{Y}}_n^*$ represent the quasi-difference of $\mathbf{X}_n^*$ and $\mathbf{Y}_n$ [see Chib and Greenberg (1994)]. Then, the candidate β_n^* is drawn from

$$\beta_n | \boldsymbol{\Theta}_{-\beta_n,\boldsymbol{\gamma}_n}, \gamma_n^*, \mathbf{F}, \mathbf{Y} \sim N\left(\mathbf{b}_n^*, \mathbf{B}_n^*\right), \tag{5}$$

where $\mathbf{B}_n^* = \left(\mathbf{B}_0 + \sigma_n^{-2}\overline{\mathbf{X}}_n^{*\prime}\overline{\mathbf{X}}_n^*\right)^{-1}$, $\mathbf{b}_n^* = \mathbf{B}_n^*\left(\mathbf{B}_0^{-1}\mathbf{b}_0 + \sigma_n^{-2}\overline{\mathbf{X}}_n^{*\prime}\overline{\mathbf{Y}}_n^*\right)$.

Since we are drawing the β_n's from their full conditional densities – i.e., from $\pi\left(\beta_n^* | \gamma_n^*, \boldsymbol{\Theta}_{-\beta,\gamma}, \mathbf{F}, \mathbf{Y}\right)$, the value of β_n^* does not appear in the acceptance probability [see Troughton and Godsill (1997)]. In this case, for each n, the acceptance probability is

$$A_{n,\gamma} = \min\left\{1, \frac{|\mathbf{B}_n^*|^{1/2}}{|\mathbf{B}_n|^{1/2}} \frac{\exp\left(\frac{1}{2}\mathbf{b}_n^*\mathbf{B}_n^{*-1}\mathbf{b}_n^*\right)}{\exp\left(\frac{1}{2}\mathbf{b}_n\mathbf{B}_n^{-1}\mathbf{b}_n\right)} \frac{\pi\left(\gamma_n^*\right)}{\pi\left(\gamma_n\right)} \frac{q\left(\gamma_n | \gamma_n^*\right)}{q\left(\gamma_n^* | \gamma_n\right)}\right\}, \tag{6}$$

where $\mathbf{b}_n^*$ and $\mathbf{B}_n^*$ are defined as above and $\mathbf{b}_n$ and $\mathbf{B}_n$ are defined for γ_n, the value held over from the past draw.

To close this portion of the algorithm, we need to supply a proposal density for γ_n. We choose a symmetric density in which we draw a random element of γ_n and set this equal to 1 (setting all other elements equal to 0). The choice of the symmetric proposal makes the last term in (6) identically 1.[8]

[8] Troughton and Godsill (1997) point out that the γ proposal density must allow some nonzero probability

3.2 Generating $\mathbf{F}|\mathbf{\Theta}, \mathbf{Y}$

The factors are drawn recursively from the smoothed Kalman update densities using the techniques described in Kim and Nelson (1999). However, the signs of the factors are not uniquely identified from the loadings (e.g., switching the signs on both a factor and its loading produces an observationally equivalent system). For identification, KOW normalize the sign of the first factor loading in each group. Unlike KOW, we cannot restrict the sign of the first factor loading in each grouping as the clusters are not *a priori* known. We can, however, impose a sign on the first element (period 1) of each factor to resolve the sign identification issue. In some cases, this is not sufficient to avoid label switching (i.e., cases in which the sampler alternately draws F and $-F$). Thus, we also impose a normalization that selects either F or $-F$ depending on which is closest to the previous draw in mean squared distance. The draw of the factors is described in detail in Appendix A.

3.3 Choosing M

Choice of the optimal number of clusters is treated as a model selection problem. For a given support of the discrete number of clusters, $M \in \left\{\underline{M}, \overline{M}\right\}$, we estimate the full model and choose M based on a minimum entropy criteria:

$$\mathbf{E} = \sum_{n=1}^{N} \left[\log(\boldsymbol{\sigma}_n^2) + \frac{\left(\overline{\mathbf{Y}}_n^* - \overline{\mathbf{X}}_n^* \beta_n\right)' \left(\overline{\mathbf{Y}}_n^* - \overline{\mathbf{X}}_n^* \beta_n\right)}{\boldsymbol{\sigma}_n^2} \right], \tag{7}$$

where $\overline{\mathbf{Y}}_n^*$ and $\overline{\mathbf{X}}_n^*$ are the quasi-differenced values of the $\mathbf{Y}_n$ and $\mathbf{X}_n$, respectively.

4 The Effect of Misspecification

Allowing the data to determine the clusters rather than setting them in advance highlights a trade-off between the estimation uncertainty and potential misspecification. One would, therefore, want to evaluate the potential risks of each before proceeding with the difficult task

of revisiting the same model. That is, the probability that the candidate γ^* is equal to the last iteration's γ must be nonzero. If $\gamma^* = \gamma$, the acceptance probability is 1, but we still redraw β.

of estimating the clusters. To this end, we perform a set of Monte Carlo (MC) experiments designed to determine the extent to which the clusters must be misspecified to outweigh the uncertainty of estimating them.

We conduct 1000 MC replications by sampling 60 series of $T = 50$ evenly divided among 5 clusters. We generate the synthetic data following the system described with equations 1 and 2 with factors and error terms following an AR(3) process. The parameters used in the process are listed in the appendix, tables 12, 13 and 14. We begin by estimating the model with the (exogenous) correct cluster definitions and gradually increase the level of misspecification. We measure misspecification by the percentage of series exogenously allocated to the wrong cluster. Thus, a 1.7 percent misspecification refers to one series allocated to the wrong cluster with all other series correctly specified. We then estimate the clusters endogenously and compute an entropy measure (7) for each case. Higher entropy scores reflect poorer performance with relative entropy related to the familiar likelihood ratio statistic.[9]

Table 2 reports the results of the MC experiments. As expected, less misspecification is better than more misspecification. Interestingly, knowing the truth (zero misspecification) is statistically equivalent to estimating the truth (endogenous clustering), with the differences in the entropy scores likely due to variations in the small sample performances.[10] Thus, we conclude that in cases in which the truth is known, imposing the cluster composition is first best. However, if the cluster composition is not certain, allowing the data to determine the clusters reduces the risk of misspecification. It is important to note that, in these experiments, we give the best chance to pre-specification of the clusters by correctly setting the true number of clusters—that is, the only source of potential misspecification is incorrectly assigning a series n to the wrong cluster.

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[9] The entropy measure is calculated for each Gibbs iteration and the mean over all iterations is reported. Each MC replication is estimated with 40000 Gibbs iterations, with the first 30000 discarded for convergence.

[10] We also want to point out that when the simulated data was endogenously estimated for the 60 series (Obviously we know which series truely belongs to which cluster and that's how we conduct the comparisions.) the series correctly picked their clusters and hence it explains why we observe such lower entropy. It was almost equivalent to knowing the true clustering.

5 Re-evaluating International Business Cycles

We now reconsider the model proposed in KOW, in which geography is the sole determinant of cross-country comovements, by augmenting the model with a hierarchical prior that includes variables that may affect trade between countries.[11] By doing this, we can assess the sources of business cycle comovements.

5.1 Data

Our measure of business cycle activity is the annual constant-price chain-weighted real GDP growth rate (computed as the difference in the log of real GDP) from the 6.3 version of the Penn World Tables (PWT) [Heston, Summers, and Aten (2009)]. To maintain comparability, we choose the same 60 countries located in 7 regional blocks as in KOW.[12]

In addition to the real GDP data, our logistic prior requires covariate data, $\mathbf{Z}_i$. Our covariate dataset includes domestic and international variables as well as indices of the differences in legal and linguistic institutions. We have a total of seven covariates that inform the logistic prior: (1) the degree of economic openness, defined as the ratio of imports and exports to GDP; (2) investment share of real GDP; (3) an index of conflict resolution and sophistication of the legal system as captured by the manner in which lower courts facilitate landlords' collection of checks (and remedies for bounced checks); (4) an index of language diversity within each country; (5) an index of production dispersion relative to the rest of the world; (6) an index of export dispersion from each country's exporting partners; and (7) a similar index of import dispersion from each country's importing partners. The covariate data are summarized in Table 3.

Openness measures the size of trade as a fraction of GDP. This variable proxies the extent of a country's dependence on foreign economies and exposure to external shocks, without controls for the types of goods traded or the identities of trading partners, allowing us to

[11] KOW's business cycle data include other series in addition to real GDP, allowing them to estimate country factors. We focus on the comovements across countries by restricting the model to a single business cycle indicator. Extension to include country factors is left for future research.

[12] We use a later version of the PWT to extend our time sample. Ponomareva and Katayama (2010) discuss the hazards of comparing studies using different versions of the PWT. Table 6 in the appendix shows the 60 countries in the estimation along with the regional groupings imposed in KOW.

determine whether countries cluster based on the (relative) extent of their (direct) exposures to international shocks. The investment share of GDP is meant to capture the degree of industrialization; similar levels of industrialization may make countries susceptible to similar shocks inducing comovements.

The indices in (3) and (4) are included to test the extent to which institutions matter for clustering. Our institutional variables are the level of formality of the civil court system and the degree of linguistic diversity. Djankov, La Porta, Lopez-de-Silanes, and Shleifer (2003) construct the lower court system's *formalism* index in (3) which "measures substantive and procedural statutory intervention in judicial cases at lower-level civil trial courts" (p. 469). We hypothesize that trade flow between countries with similar conflict resolution processes in civil courts could be higher as individuals may prefer to form relationships in countries with familiar legal setups.

The ethnolinguistic index in (4) is from La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1999) and measures the degree of language diversity, the probability that two randomly selected individuals in a given country speak different languages, do not speak the official language, or do not speak the most widely used language.

Finally, Baxter and Kouparitsas (2003) construct the indices in (5)-(7) to analyze how the composition of a country's production and trade differ from the rest of the world and its trading partners. These indices are akin to variance measures with the exception that the export and import dispersions are weighted by sectoral export and import shares. A look at the trade dispersion indices, (6) and (7), reveals that they capture both the strengths of trading relations with different countries and the strength in the diversity of goods traded. Baxter and Kouparitsas find that industrialized nations have dispersions similar to the rest of the world (the average country) for all three indices, whereas developing countries systematically have higher values of dispersions. On the trade side, this is consistent with the fact that the bulk of trade of an industrialized nation is with other industrialized nations, while trade relations for developing nations are spread more evenly across developed and developing nations. By including these indices, we are allowing for the possibility that countries form clusters based on the similarities in their production structures (in terms of types of goods produced) and/or on the compositions of their trade (both in terms of the types of goods traded and the trading partners).

5.2 Full Sample Results

We first determine the optimal number of country-level factors by estimating the model for $M = 3, ..., 7$ and evaluating the average entropy for each M. The model with the highest probability is the model with three clusters.[13] The model with seven clusters—the specification that nests the one estimated by KOW—has one of the lowest likelihoods of the alternatives tested. In this case, the algorithm chooses nearly empty clusters at some Gibbs iterations, suggesting that seven clusters far exceeds the optimal number. Thus, we report the results for the specification with three regional factors and one global factor.[14] Because countries do not tend to fall into a single cluster, the data do not appear to support more than one global factor.

Figure 1 plots the median of the global factor along with its 16th and 84th percentiles; the shaded areas show NBER-defined recession dates defined as a year in which any quarter was in recession. While the NBER recessions are defined only for the U.S., they serve as reference points. The global factor roughly represents a world cycle with factor loadings for most countries being negative; the global factor spikes around 1975, 1982, 1998, and 2001. With the exception of 1998, these periods are roughly associated with U.S. NBER recessions.

Figure 2 shows the first cluster factor with its 68-percent probability bands and the NBER recessions. Figure 3 shows the posterior inclusion probabilities for this cluster. The darkest areas indicate countries which are very likely to be included in this cluster and yellow indicates countries that are very likely not associated with the cluster. Countries in white are not

[13] Choosing the optimal number of clusters with Bayes factors yields identical results. In this case, we estimated the model using a uniform prior for the clusters.

[14] The average acceptance rates for the MH steps across all iteration and observations are as follows: for γ draw it is 42%, factor errors, ϕ, have on average 78% and observation errors, ψ, have on average 71%. Since the $(\gamma, \beta\ )$ joint draw includes a random sample draw at each iteration for clusters, the acceptance rate is expected to be considrably smaller than the regular MH step. In particular, the model proposes a new cluster randomly at each iteration then accepts or rejects it. It mixes at each step unconditionally which results in lower acceptance on average.

included in our sample. Note, in particular, that cluster 1 does appear to demonstrate some regional/geographic properties. The cluster includes, with high probability, Japan and many of the countries in Europe. Other European countries—e.g., Iceland and Ireland—belong with more than 50 percent probability. Brazil, Thailand, and Pakistan also belong with more than 50 percent probability. Not all the European countries, however, appear to belong to this cluster. In particular, the U.K. and Denmark are excluded.

Figure 4 shows the second cluster factor. This factor clearly appears to decline around NBER recessions. Figure 5 shows why. The U.S. belongs to this cluster with probability 1; the cluster also includes Australia, Canada, Hong Kong, India, Malaysia, New Zealand, and the U.K. with very high posterior probability. Also included in this cluster are Denmark and many of the sub-Saharan African countries including South Africa.

Figure 6 shows the final factor and Figure 7 shows the composition of its cluster. Again, the cluster displays some regional/geographic characteristics with some notable exceptions. The cluster includes with high probability most of the countries in South America, with the exception of Brazil. Mexico, the Philippines, and a few African countries also belong to this cluster with high probability.

An explanation of the third cluster can be gleaned from its factor. We see that the 1997 Asian crisis is captured by the factor with the biggest dip in the past 40 years. The 1985 downturn corresponds with Singapore's economic crisis around that time. In 1985, Singapore experienced a drop in the demand for its oil and electronic products. Due to Singopore's geographical position, serving as a port of processing and transmitting goods, this crisis severely impacted its trading partners, such as Indonesia, Hong Kong and the Phillipines. The 2001 slump conincided with the dot-com bust that significantly reduced the exports which these East Asian-Pacific countries heavily relied upon (open trade and export led GDP growth are keys to economic development of these Oceanic countries). The region experienced lower growth rates and decelerated export during the dot-com bust. Supportive tables and maps are available in the appendix.

5.2.1 Variance Decompositions

One measure that can jointly capture the importance of both the factor and its loading can be obtained through a variance decomposition. Table 5 shows the percentage of each country's output volatility attributable to the global and regional factors and the idiosyncratic shock. Again, the results are not directly comparable with those of KOW, but a number of qualitative similarities and differences highlight the effect of estimating the clusters. KOW find that, in general, the global factor explains a greater portion of the volatility in more industrialized countries. Moreover, they conclude that the regional factors explain only a very small portion of macroeconomic fluctuations (about 3.6 percent, on average, of the output fluctuations of the 60 countries). Our results suggest a much larger role for the "regional" factor if a region is estimated by the countries' cyclical commonality. In fact, our cluster factors explain an average of 22.8 percent of the output fluctuations among the sample countries.

There are a few reasons this difference may not be surprising. First, KOW's sample differs from ours. Second, KOW's regional factors are defined as the common component for three series for each country. The inclusion of the additional two macroeconomic series could potentially contaminate the ability of their regional factor to explain output fluctuations. Third, imposing (rather than estimating) the regions may lead to the same misspecification discussed in the previous MC experiments above. When countries are included in a region with countries with which they do not actually share a common factor, the factor—and the associated loadings—may be biased.

Indeed, when the KOW model (exogenous model) is estimated with only output, the difference between the average variances explained by the regional factors in the two models is not as large: about 1.2 percentage points. The variance explained by the global factor in the exogenous model is about 4 percentage points lower. The largest difference, however, comes from the countries in the former British Commonwealth. In the purely geographic model that would place these countries in three separate regions, the regional factor would explain 36 percent of the variation in output for these countries (Australia, Canada, New Zealand, the U.K., and the U.S.). In the endogenous model that groups them together, the regional factor explains 57 percent of their output variation. This increase in explanatory power is important, especially given that these countries account for a substantial share of the total output of the 60 countries in the sample.

5.2.2 Explaining the clusters

Table 4 shows the posterior means for the logistic covariates along with the 16th and 84th percentiles of the posterior distributions. Our covariates are similar to the gravity variables found in the trade and international business cycle literatures. Using simultaneous equation methods to disentangle intra- and inter-industry trades, Imbs (2004) examined the relation between trade openness, financial integration, specialization, and business cycle synchronization and found that specialization has sizeable effects on business cycles. The paper used several "gravity variables" when measuring bilateral trade intensities and financial integration. Amongst these variables were a measure of distance between countries' capitals, an indicator of shared border, the log products of GDP, an indicator of common language, an assessment of accounting standards and a measure of the rule of law. Baxter and Kouparitsas (2005) included distances between countries and common languages as gravity variables in the investigation of business cycle comovements across countries. Finally, in the political economy literature, Castles and Obinger (2008), used hierarchical and k-means clustering approach to group 20 OECD countries along political, societal, and economic lines. The data used to form clusters include demographics, ethno-linguistic fractionalization, GDP per capita, and party system fractionalization.

In contrast to a purely continental approach such as that used in KOW, our results suggest that a country such as Mexico is much more likely to have cycles similar to its shared-language South American neighbors than its more geographically proximate neighbor, the U.S. These results suggest that common culture—either through linguistic or legal similarities—matter for cyclical commonality along with any iceberg costs usually associated with geographic proximity. The relevance of countries' legal systems and linguistic diversity is consistent with the notion that trade flows—and, therefore, business cycle comovements—are more likely across countries with similar institutions. Some economic indicators are also relevant in explaining our country clusters: The level of industrialization (proxied by a country's investment share of GDP) and the degrees of production, export and import dispersions all appear important in cluster determination.

We find similar clustering for the countries common to our and the Castles and Obinger (2008) samples. For instance, the countries in their English-speaking cluster are members of our second cluster; while countries in their Scandinavian and Southern-Northern European clusters comprise our first cluster. The similarities in both sets of clusters should not be much of a surprise given their gravity variables include GDP per capita, our cluster variable, and an indicator of common language, an important covariate that informs our clusters.

5.3 Cross-Validation Results

The in-sample results in the preceding section verify that the model performance declines as the degree of misspecification rises. One concern that arises is that estimating the clusters could lead to in-sample overfitting. For example, Billio et al (2016) also find linkages between countries but argue that for the results should be verified through forecasting experiments. Because our data sample is short, we cannot perform standard quasi-out-of-sample experiments; instead, we evaluate possible overfitting by testing the model using leave-one-out cross validation (LOOCV). LOOCV chooses a single time period to omit, estimates the model treating this period as missing, and evaluates the model performance in fitting the left out period. This experiment is iterated on all time periods.

We re-estimate our model using the same annual GDP data leaving out period $\widetilde{t}$, treating this observation as missing. We modify both the filter and the draws of the AR parameters to account for the fact that we do not know the data at time $\widetilde{t}$. These modifications are detailed in the appendix.

We then evaluate the fit of the fitted value of $\widehat{y_{\widetilde{t}}}$ relative to the true value $y_{\widetilde{t}}$ using the entropy measure above averaged across all Gibbs iterations. We sum this average for each $\widetilde{t} = 1, ..., T$. We compare these results to (1) the KOW clusters and (2) 20 sets of randomly specified clusters that are fixed ex ante. In the latter, we set $M = 7$, as in KOW, but choose the memberships randomly.

Consistent with the in-sample results, we find that the endogenously chosen clusters are associated with considerably lower entropy than the models with exogenously chosen, fixed clusters.[15] This result obtains regardless of whether the clusters are chosen geographically (KOW) or randomly and suggests that, at least in the PWT data, possible concerns about overfitting are outweighed by the benefit of choosing the clusters.

6 Conclusions

Much research has been done on measuring the comovement of business cycle variables across countries. Limited by the potential proliferation of the estimated parameters, these empirical models typically (1) compare business cycles which are estimated country-by-country; (2) use models of relatively few countries (e.g., bilateral analyses); and/or (3) impose the structure of the correlations *ex ante*. One application of the third approach (that of KOW) estimates a factor model in which the correlation structure across countries is assumed to be determined by geographic proximity—that is, countries that share a continent also share a common unobserved factor.

In this paper, we allow the data to determine which countries share common factors. Our model allows for a number of possible alternative country characteristics that can affect how countries are grouped. In MC experiments, we show that misspecifying the regions can affect the fit of the model. In the data, we find evidence that sharing a common geographic region is one component but not the *only* determinant of country groupings. These results, therefore, verify some of the underlying rationale behind KOW's selection of using a shared continent as the basis of defining a region. However, while there do appear to be some localized comovements (e.g., South America and Europe), these comovements stretch beyond what would be narrowly considered geographic regions and exclude some countries that would

[15] The random assignment, on average, beats the geographic clusters by about 10%; however, we note that the data used here differ substantially from the original KOW dataset, both in vintage of the PWT and because we use only one business cycle indicator.

ordinarily be associated by continent. In particular, continental Europe appears to share a common cyclical component with Japan but not with the U.K., and the majority of South American countries appear to share a cycle with Mexico but less so with Brazil. One cluster consisting of the U.S., U.K., and some other former British Commonwealth countries belies geography or proximity as the driving force behind the cyclical commonality and suggests other fundamental forces linking the countries.

Priors for Estimation

Parameter	Prior Distribution	Hyperparameters	
β_n	$N(\mathbf{b}_0, \mathbf{B}_0)$	$\mathbf{b}_0 = \mathbf{0}_3$; $\mathbf{B}_0 = \mathbf{I}_3$	$\forall n$
σ_n^{-2}	$\Gamma\left(\frac{\nu_0}{2}, \frac{\Upsilon_0}{2}\right)$	$\nu_0 = 6$; $\Upsilon_0 = 0.1$	$\forall n$
γ_n	*Logistic*		$\forall n$
$\boldsymbol{\phi}_i$	$N(\mathbf{v}_0, \mathbf{V}_0)$	$\mathbf{v}_0 = \mathbf{0}_{p_F}, \mathbf{V}_0 = \frac{1}{2}\mathbf{I}_{p_F}$	$\forall i$
$\boldsymbol{\psi}_n$	$N(\mathbf{w}_0, \mathbf{W}_0)$	$\mathbf{w}_0 = \mathbf{0}_{p_\varepsilon}, \mathbf{W}_0 = \mathbf{\frac{1}{2}}\mathbf{I}_{p_\varepsilon}$	$\forall n$
δ_i	$N(\mathbf{d}_0, \mathbf{D}_0)$	$\mathbf{d}_0 = \mathbf{0}_7$; $\mathbf{D}_0 = \mathbf{2} \times \mathbf{I}_7$	$\forall i$

Table 1: Priors. Notes: n denotes the series, where N is the total number of series; i indicates the cluster, where M is the total number of cluster factors; and the p's denote the maximum number of lags in the error and factor lag polynomials.

Degree of Cluster Misspecification

	60%	40%	20%	6.7%	5%	3.4%	1.7%	*None*	*Endogenous*
Entropy	3372.2	3339.4	3302.7	3299.76	3295.30	3291.49	3289.98	3288.80	3287.45

Table 2: Monte Carlo Results. Notes: The table reports the median entropy for 1000 Monte Carlo replications with sample size of 50 periods. Each sample contains 60 series, 5 cluster factors, and 1 global factor. The column headings indicate the percent of the series in the exogenous clusters that is misallocated. 'None' indicates the exogenously clustered model with no misspecification. 1 misallocated series (of 60) equates to 1.66 percent misspecification, and so on. The last column shows the median entropy for the model estimated with clusters determined endogenously.

Covariate Data

Purpose	**Variable**	**Mnemonic**
Trade	Openness	OPEN
Industrialization	Investment Share of GDP	KI
Formalism Index	Collection of Bounced Checks	CHECK
Linguistic Diversity within a Country	Ethnolinguistic Fraction	LIN
Production Dispersion	Production Dispersion versus World	ProDisp
	Export Dispersion versus Export Partners	ExDisp
	Import Dispersion versus Import Partners	ImDisp

Table 3: Covariate Data.

Logistic Coefficients

Variable	Cluster 2	Cluster 3
Openness	-0.19	0.46
	(-0.77 0.39)	(-0.11 1.01)
Investment Share of GDP	-0.49	**-1.21**
	(-1.12 0.14)	(-1.82 -0.54)
Collection of Bounced Checks	**-1.86**	**2.47**
	(-2.47 -1.24)	(1.82 3.09)
Ethnolinguistic Fraction	**0.99**	**-0.89**
	(0.29 1.71)	(-1.48 -0.31)
Production Dispersion versus World	**-1.61**	**-1.24**
	(-2.89 -0.34)	(-2.48 -0.03)
Export Dispersion versus Export Partners	**-1.47**	-0.93
	(-2.82 -0.16)	(-2.26 0.41)
Import Dispersion versus Import Partners	**-1.90**	**-1.42**
	(-3.21 -0.61)	(-2.76 -0.07)

Table 4: Posterior means for each covariate in clusters 2 and 3. Notes: The first cluster (Cluster 1) covariate coeffients are normalized to zero. Values in bold indicate coefficients for which zero is not within the 68 percent coverage interval. The numbers in parentheses indicate the 16th and 84th percentiles of the posterior distributions.

Variance Decompositions: Posterior Means (%)

	Global	Cluster	Idio.		Global	Cluster	Idio.
Argentina	0.1	21.7	78.2	Japan	22	8.9	69.1
Australia	6.5	49.7	43.8	Kenya	0	4.4	95.6
Austria	21.4	49.2	29.3	Korea	60.3	0.9	38.7
Bangladesh	0.6	0.1	99.3	Luxembourg	7.9	36.9	55.2
Belgium	21.6	66.2	12.2	Malaysia	72.3	0.7	27
Bolivia	3.1	19.5	77.4	Mexico	7.1	19	73.8
Brazil	5	24.8	70.3	Morocco	0	0.2	99.8
Cameroon	7.4	3.7	88.9	Netherlands	12.4	44.3	43.3
Canada	6.5	77.9	15.6	New Zealand	0.9	25.2	73.9
Chile	20.6	11.8	67.6	Norway	3.9	21.8	74.2
Colombia	22.2	27.3	50.5	Pakistan	0.2	11.6	88.2
Costa Rica	0.9	28	71.2	Panama	3.9	9.3	86.8
Ivory Coast	0.7	2.5	96.8	Paraguay	0	7.8	92.2
Denmark	9.6	33.4	57	Peru	0.6	16.5	82.9
Dom. Republic	4.7	10.2	85.1	Philippines	11.9	15	73.1
Ecuador	1.1	25.5	73.5	Portugal	23.8	34.3	42
El Salvador	0.6	23.1	76.3	Senegal	15.7	0.1	84.2
Finland	5.5	40.8	53.7	Singapore	55.1	0.3	44.5
France	12.5	73.2	14.3	South Africa	1	0.1	98.9
Germany	31.9	16.7	51.4	Spain	0.7	22.1	77.2
Greece	14	18.5	67.5	Sri Lanka	5.2	16.9	77.9
Guatemala	30.9	18.1	51	Sweden	8.6	59.6	31.8
Honduras	0.5	19.3	80.2	Switzerland	4.8	69.9	25.3
Hong Kong	36.4	7	56.5	Thailand	57	3.9	39.2
Iceland	0	14.1	85.9	Trinidad & Tobago	10.2	5.7	84.1
India	1.5	7.1	91.4	United Kingdom	14.5	52.5	32.9
Indonesia	58.8	0.3	40.9	United States	24.6	64.3	11.1
Ireland	21.8	14.6	63.6	Uruguay	2.3	18.6	79.1
Italy	22.6	53.4	24	Venezuela	0.4	21	78.5
Jamaica	2.5	0	97.5	Zimbabwe	0	0.6	99.4

Table 5: Variance Decompositions. Notes: Each row shows the variation in GDP growth that is attributable to the global, cluster and idiosyncratic factors. In calculation of the variance share of clusters, members are assumed to belong to a cluster if they pick the said cluster majority of the Gibbs run. In other words, the modal values for the indicator function are used to determine the cluster to which a country belongs, then the variance attributable to that specified cluster is calculated.

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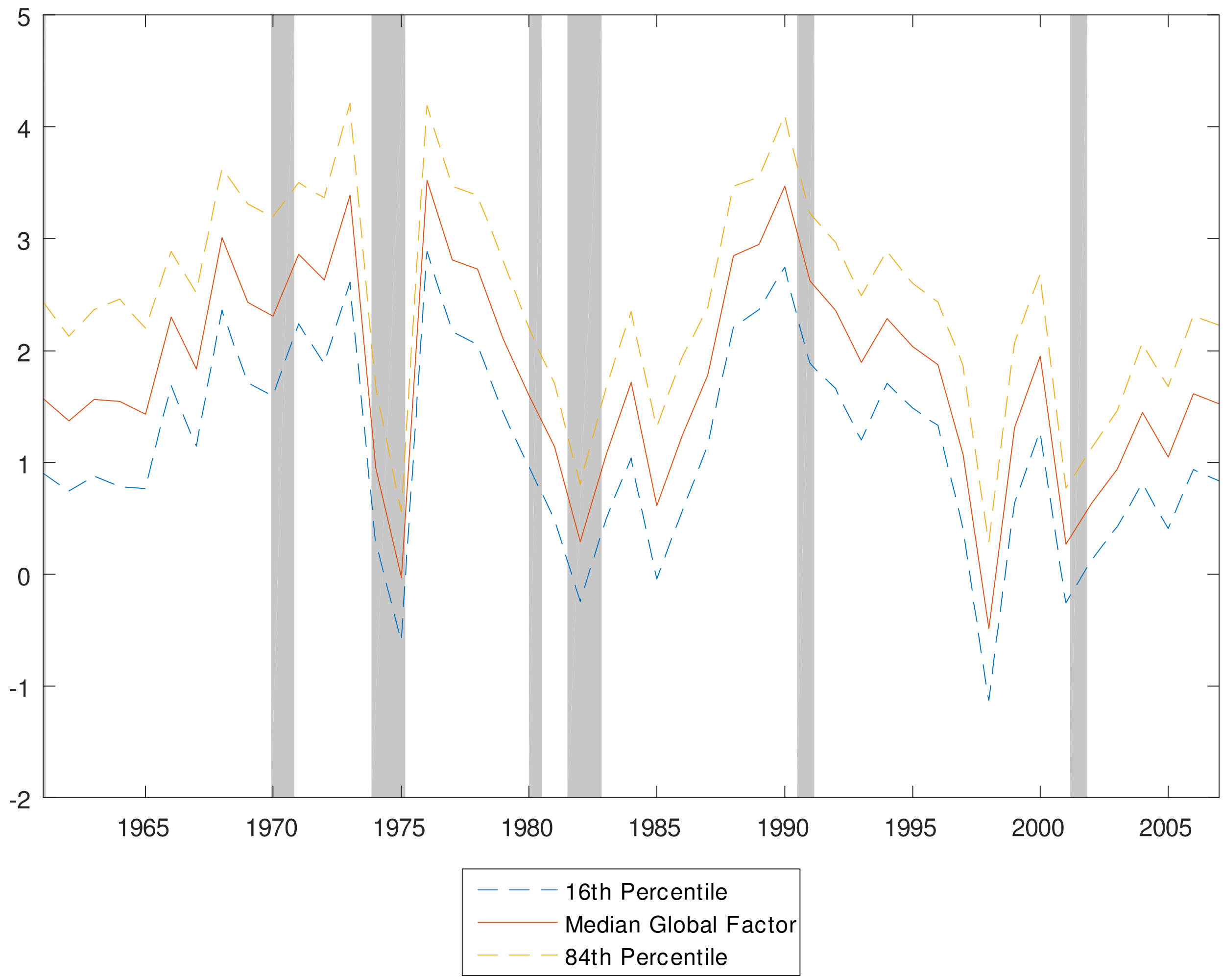

Figure 1: Global Factor. The red solid line is the median of the posterior distribution of the global factor. Dashed lines represent the 16th and 84th percentiles. Shaded regions are annual NBER recessions, where a recession is defined as a year in which any quarter was in recession according to the Business Cycle Dating Committee turning points.

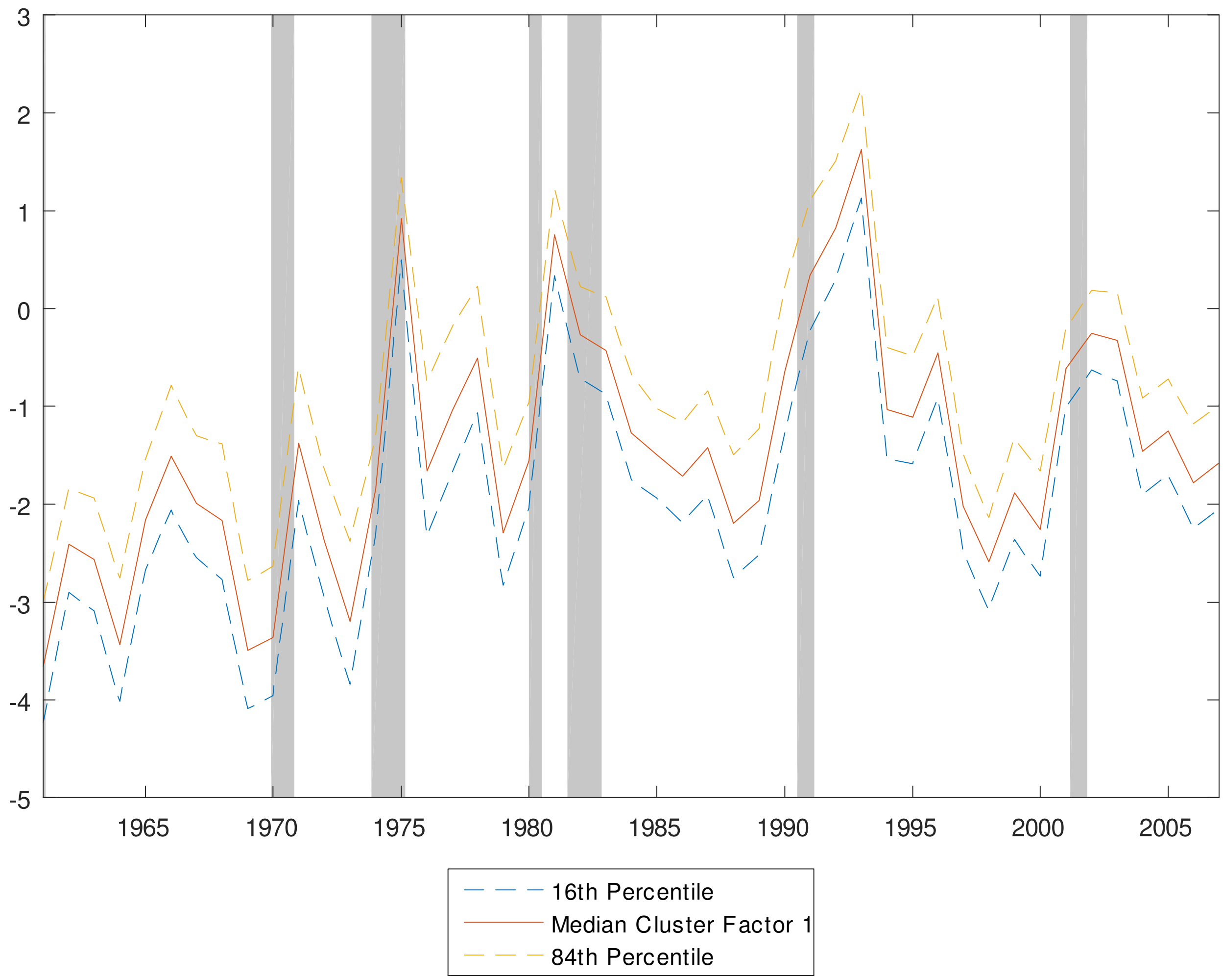

Figure 2: Cluster 1 Factor. The red solid line is the median of the posterior distribution of Cluster 1's factor. Dashed lines represent the 16th and 84th percentiles. Shaded regions are annual NBER recessions, where a recession is defined as a year in which any quarter was in recession according to the Business Cycle Dating Committee turning points.

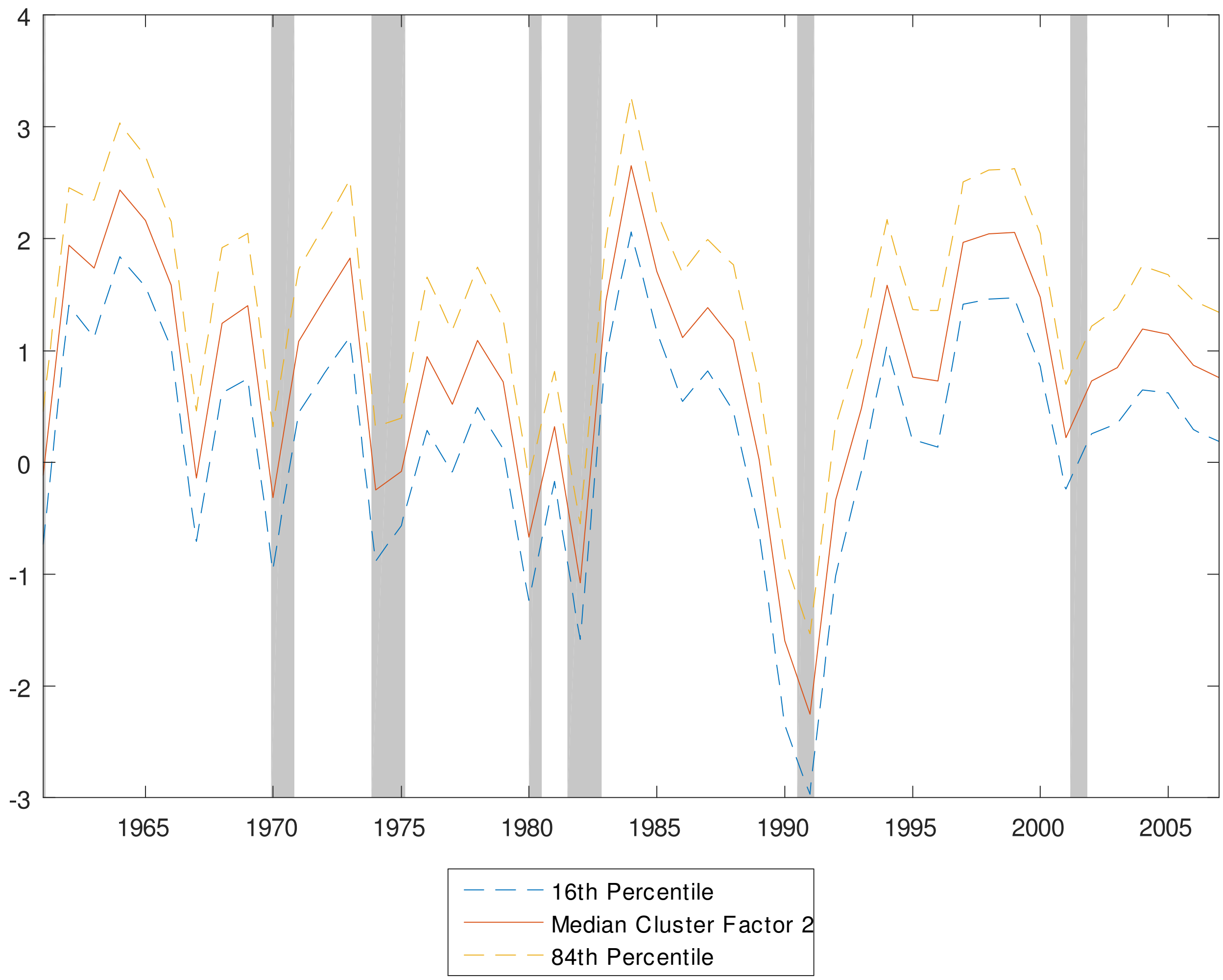

Figure 3: Cluster 2 Factor. The red solid line is the median of the posterior distribution of Cluster 2's factor. Dashed lines represent the 16th and 84th percentiles. Shaded regions are annual NBER recessions, where a recession is defined as a year in which any quarter was in recession according to the Business Cycle Dating.

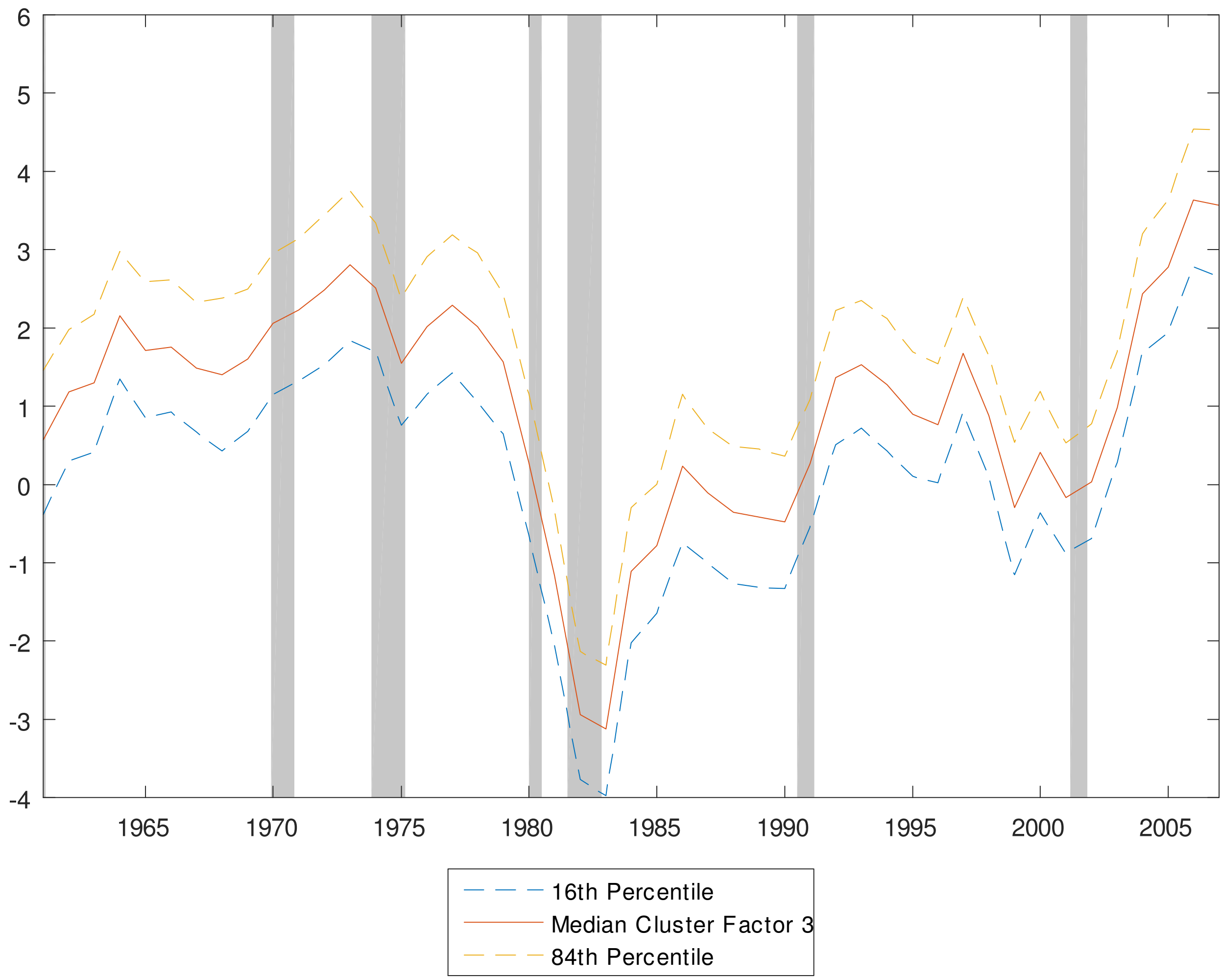

Figure 4: Cluster 3 Factor. The red solid line is the median of the posterior distribution of Cluster 3's factor. Dashed lines represent the 16th and 84th percentiles. Shaded regions are annual NBER recessions, where a recession is defined as a year in which any quarter was in recession according to the Business Cycle Dating Committee turning points.

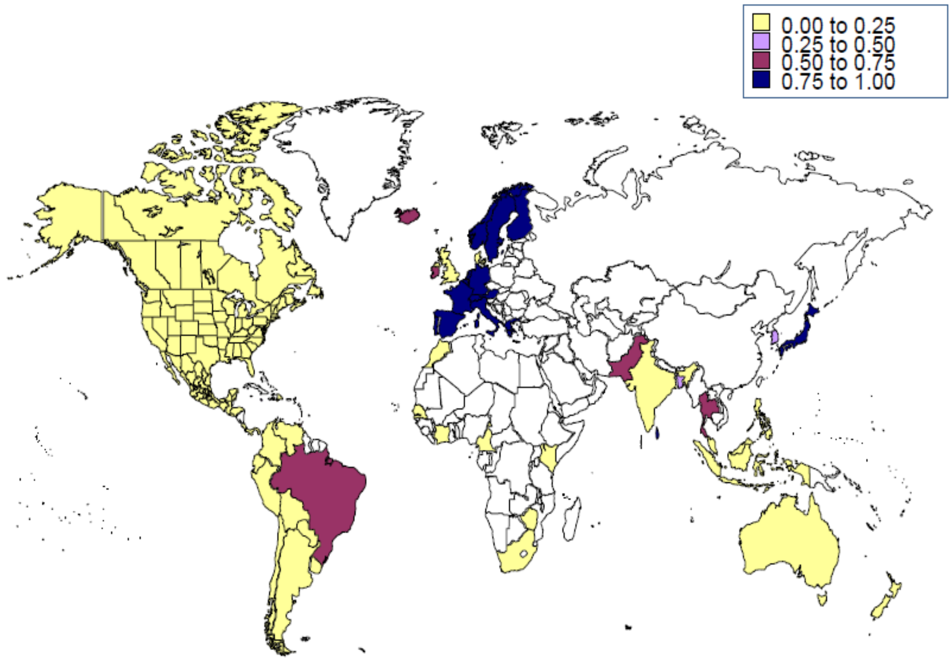

Figure 5: Cluster 1 Composition. The map shows the posterior probabilities of countries included in Cluster 1. Countries in white are omitted from the sample.

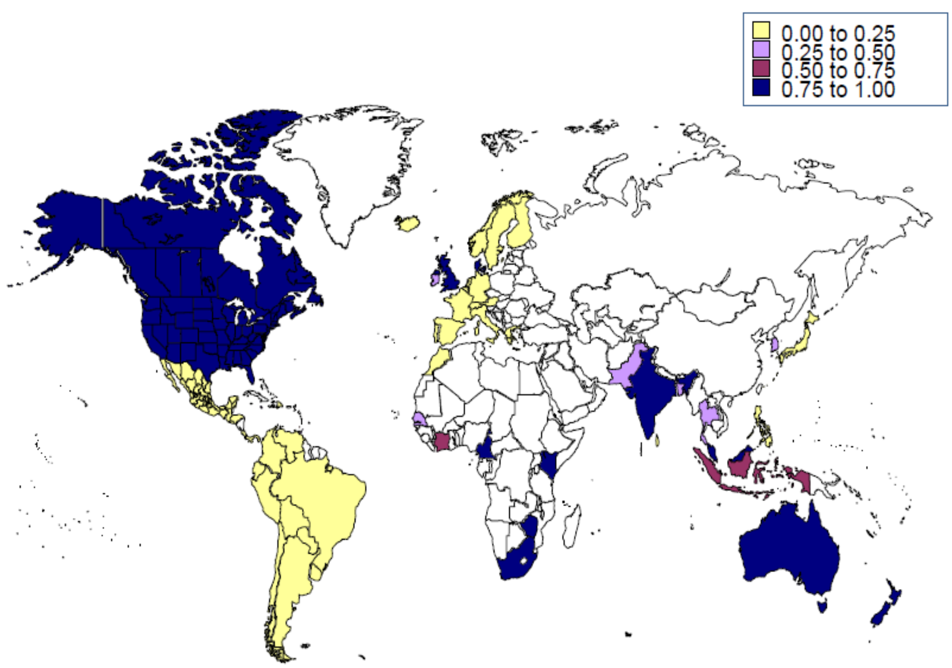

Figure 6: Cluster 2 Composition. The map shows the posterior probabilities of countries included in Cluster 2. Countries in white are omitted from the sample.

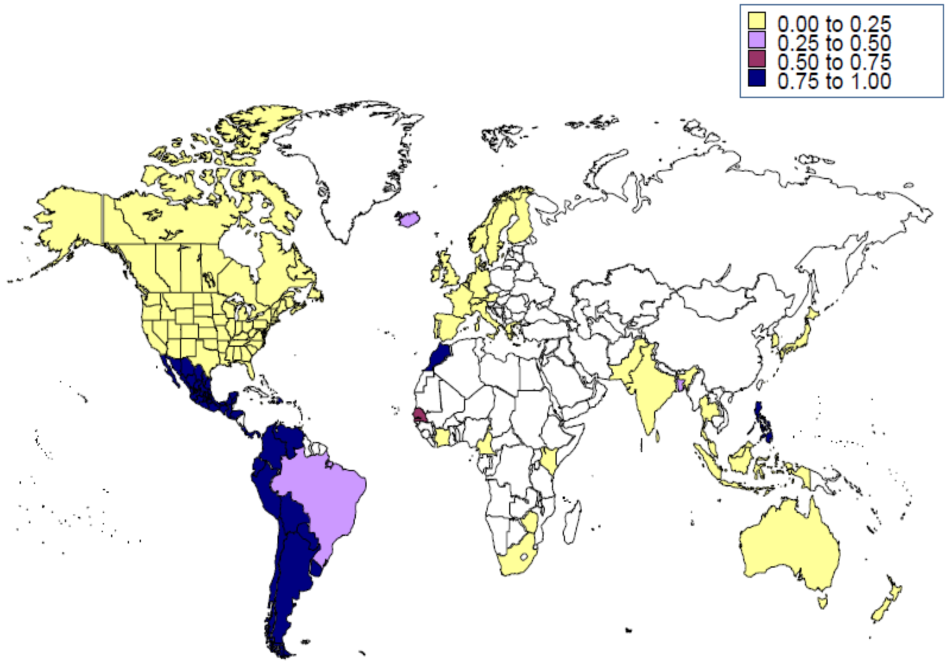

Figure 7: Cluster 3 Composition. The map shows the posterior probabilities of countries included in Cluster 3. Countries in white are omitted from the sample.

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