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Business Cycles Across Space and Time*

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Abstract

We study the comovement of international business cycles in a time series clustering model with regime-switching. We extend the framework of Hamilton and Owyang (2012) to include time-varying transition probabilities to determine what drives the simultaneous business cycle turning points. We find four groups, or "clusters,"of countries that experience idiosyncratic recessions relative to the global cycle. Additionally, we find the primary indicators of international recessions to be fluctuations in the term spread, equity markets, and geopolitical risk. In out-of-sample forecasting exercises, we find that our model is an improvement over standard benchmark models for forecasting both aggregate output growth and country-level recessions.

Keywords: Markov-switching, time-varying transition probabilities, cluster analysis

JEL Codes: C11, C32, E32, F44

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1 Introduction

While business cycle dating has generally focused on the movement between expansion and recession phases in a single country [e.g., Burns and Mitchell (1946); Hamilton (1989)], recent evidence suggests the presence of an overarching world cycle with a number of underlying regional cycles. Shocks, then, can be either global—affecting all (or most) countries (e.g., the financial crisis of 2009)—or regional—affecting a small subset of countries (e.g., the European debt crisis which began in 2011). For example, Kose, Otrok, and Whiteman (2003, 2008) conclude that both regional and global factors account for much of the cross-country variation in growth. Similarly, Bordo and Helbling (2011) find an increase in the importance of global shocks over time.

Typically, individual cycles are estimated separately in a univariate setting and any co-movement is determined *ex post* [e.g., Owyang, Piger, and Wall (2005) for U.S. states].[1] Hamilton and Owyang (2012, henceforth HO), on the other hand, construct a model to jointly analyze the U.S. national business cycle and its interaction with state-level business cycles. To alleviate the parameter proliferation problem associated with using a large cross-section, HO organize states into regions determined both by commonality in economic fluctuations and similarity of state-specific characteristics such as industry composition. In the HO model, the business cycle phases evolve according to fixed transition probabilities (FTP), where future regimes depend only on the current regime(s) and may omit macroeconomic or financial information signalling turning points. For example, the probability of a global recession rises during a financial crisis; FTP models, however, do not incorporate information from financial variables that may signal an impending downturn. Moreover, because the transition probability does not vary over time, FTP models are relatively ineffective at forecasting turning points.

We consider the factors that drive international turning points, while simultaneously taking advantage of the fact that countries move together. We adopt the framework of HO and apply it to countries rather than states, with the primary methodological innovation

[1] An exception is Billio et al. (2016), which accounts for cycle endogeneity by including country-specific regime indicators in time-varying transition probabilities.

being the inclusion of time-varying transition probabilities (TVTP). TVTP models have two advantages over FTP alternatives. First, regimes in TVTP models can depend on lags of macro and financial conditions, meaning we can include transition variables which inform the model of the timing of regime switches. Second, the expected duration of the regimes will be time-varying, as recession lengths depend on the economic climate and their proximate causes.[2]

We estimate the model using a quarterly panel of output growth for 37 countries. Within this framework, our paper has the dual focus of using several cross-country covariates to form regional "clusters" [see also Francis, Owyang, and Savaşçin (2017, henceforth FOS)] and using a set of time-series covariates to inform the transitions between business cycle phases. The cluster covariates include the degree of trade and financial openness, stage of development, oil dependency, geographic proximity, and gravity measures of linguistic diversity and legal systems. We consider five transition covariates that previous studies determined to have predictive ability for recessions: the term spread, oil prices, global stock market returns, global house price movements, and geopolitical uncertainty.

We find four clusters that experience regional recessions with different timing than the global recessions. As previous studies suggest, geographic proximity is an important factor in determining the groupings of these countries. However, we find that trade openness, industrialization, and similar institutional factors, such as linguistic diversity, are also important.

We find two instances of global recession in our time sample: the first oil crisis in 1974-1975 and the global financial crisis of 2008-2009. Our results suggest that international turning points are primarily related to movements in the term spread, equity returns, and geopolitical risk. We do not find that any one cluster is particularly exposed to a single type of shock, but rather idiosyncratic recession timing across all clusters depends upon fluctuations in these three factors. This result reinforces the previous findings by Reinhart and Rogoff (2009) as well as Helbling, Kose, and Otrok (2011) that financial markets are

[2]For example, Claessens, Kose, and Terrones (2009) find that recessions associated with financial shocks last longer than recessions due to other contractionary shocks. Additionally, the expected length of a recession may depend on the relative magnitudes of the underlying shocks.

important in propagating recessions to a global level. Given these findings, we consider whether equity returns are predictive for either global or idiosyncratic recessions. We perform a set of out-of-sample forecasting experiments, where we evaluate the model's ability to predict output growth and recessions one period ahead. For most countries in our sample, our model does better than standard benchmark models when forecasting aggregate output growth as well as idiosyncratic recessions dates.

The outline of the paper is as follows: Section 2 outlines the model. Section 3 explains the estimation technique. Section 4 describes the data. Sections 5 and 6 present the in-sample and out-of-sample forecasting results, respectively. Section 7 concludes the paper.

2 Model

The central framework of our multi-country regime-switching model is based on HO, where each country's output growth rate depends on a latent binary indicator representing expansions and recessions. In expansion, an economy grows at a relatively higher average rate than in recession. Let N be the number of countries considered in the model; y_{nt} be the growth rate of real GDP for country n at time period t; and s_{nt} be country n's business cycle regime indicator: $s_{nt} = 1$ if in recession, and $s_{nt} = 0$ if in expansion. Country n's average growth rate in expansion is μ_n, and the average growth rate in recession is $\mu_n + \Delta\mu_n$. The multi-country regime-switching model is given by

$$\boldsymbol{y}_t = \boldsymbol{\mu} + \Delta\boldsymbol{\mu} \odot \boldsymbol{s}_t + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \overset{i.i.d}{\sim} N(\mathbf{0}, \boldsymbol{\Sigma}), \tag{1}$$

where $\boldsymbol{y}_t = [y_{1t}, \ldots, y_{Nt}]'$, $\boldsymbol{s}_t = [s_{1t}, \ldots, s_{Nt}]'$, $\boldsymbol{\mu} = [\mu_1, \ldots, \mu_N]'$, $\Delta\boldsymbol{\mu} = [\Delta\mu_1, \ldots, \Delta\mu_N]'$, and $\boldsymbol{\varepsilon}_t = [\varepsilon_{1t}, \ldots, \varepsilon_{Nt}]'$. The symbol $\odot$ represents element-by-element multiplication. The vector of regimes evolves according to a Markov-switching process with time-varying transition probabilities that we discuss in more detail below.

2.1 Clustering

Because each country can be in one of two states in any given time period, $\boldsymbol{s}_t$ can take 2^N possible values. When N is large, estimating the countries' regime processes jointly can become intractable depending on the assumed interaction between s_{nt} and s_{mt}. Thus, multi-country regime-switching models often assume either full dependence or full independence across countries' business cycles. In the case of full dependence, all countries follow the same cycle and are summarized by a single global regime indicator. In the case of full independence, each country's cycle is estimated separately, assuming that country n's business cycle state offers no information for country m's state, $m \neq n$. We opt for an intermediate assumption where we model a global business cycle but allow for deviations for K groups—or "clusters"—of countries. Following HO and FOS, the cluster composition is estimated relying on similarities in countries' business cycles as well as country-specific characteristics that enter through the prior.[3]

Define an aggregate latent regime variable, $z_t \in \{1, \ldots, K, K+1, K+2\}$, indicating the cluster of countries in recession at time t. Associated with each aggregate state $z_t = k$ is a $(N \times 1)$ vector $\boldsymbol{h}_k = [h_{1k}, \ldots, h_{Nk}]'$ of binary indicators, where $h_{nk} = 1$ when country n is a member of cluster k and $h_{nk} = 0$ when country n is not a member of cluster k. Thus, we refer to h_{nk} as a cluster membership indicator. We restrict each country to be a member of one and only one idiosyncratic cluster (i.e., $\sum_{k=1}^{K} h_{nk} = 1$).[4]

For the aggregate regimes $z_t = 1, \ldots, K$, a group of countries is in recession while all remaining countries are in expansion. That is, $s_{nt} = 1$ if $z_t = k$ and $h_{nk} = 1$. In addition to recessions of the K clusters, the $K+2$ regimes include two "global" clusters: when all countries are simultaneously in either recession or expansion. *Ex ante*, we define these global clusters as the aggregate regimes $z_t = K+1$ (all countries in expansion, $\boldsymbol{h}_{K+1} = [0, \ldots, 0]'$) and $z_t = K+2$ (all countries in recession, $\boldsymbol{h}_{K+2} = [1, \ldots, 1]'$).

[3] See also Frühwirth-Schnatter and Kaufmann (2008). The time-series clustering framework reduces the model dimension ($K + 2 << 2^N$), giving us a numerically tractable model.

[4] This assumption uncovers the "strongest" comovement relationships across countries and yields well-defined regions. The alternative specification (i.e., overlapping clusters) is considered in the Web Appendix.

We rewrite (1) as a mixture model with $K+2$ components:

$$\boldsymbol{y}_t|\,(z_t = k) \sim N(\boldsymbol{m}_k, \boldsymbol{\Sigma}) \text{ for } k = 1, \ldots, K+2, \tag{2}$$

where

$$\boldsymbol{m}_k = \boldsymbol{\mu} + \Delta\boldsymbol{\mu} \odot \boldsymbol{h}_k.$$

2.2 Evolution of the Regime

Standard regime-switching models [e.g., Hamilton (1989)] assume that s_{nt} follows a first-order Markov process with *fixed transition probabilities* (FTP). Because the current period's state probabilities depend only on last period's state, the regime evolves as an independent probabilistic process, making the model parsimonious and tractable but providing little insight into the variables that may indicate or cause a switch in regime. Additionally, the FTP framework assumes a constant expected regime duration. A framework where the expected duration of a regime depends on economic or financial conditions may be more appealing both for explaining the cycle and for forecasting.

We assume the regime-switching process is characterized by *time-varying transition probabilities* (TVTP) that are functions of exogenous covariates $\boldsymbol{v}_t = [v_{1t}, \ldots, v_{Lt}]'$ in addition to the previous state.[5] In our application, the transition covariates are measures of global shocks and economic conditions which signal business cycle turning points. Including TVTP in the regime-switching process allows us to consider which shocks tend to drive groups of countries into and out of recession. We adopt a centered parameterization in order to identify the time-varying and time-invariant portions of the transition probabilities [see Kaufmann (2015)]. Formally, the TVTP takes the multinomial logistic representation:

$$p_{ji,t} = \Pr(z_t = j | z_{t-1} = i, \boldsymbol{v}_t) = \frac{\exp\left[(\boldsymbol{v}_t - \bar{\boldsymbol{v}})\,\boldsymbol{\gamma}^v_{ji} + \gamma_{ji}\right]}{\sum_{k=1}^{K+2} \exp\left[(\boldsymbol{v}_t - \bar{\boldsymbol{v}})\,\boldsymbol{\gamma}^v_{ki} + \gamma_{ki}\right]}, \tag{3}$$

[5] Time-varying transition probabilities were first considered by Diebold, Lee, and Weinbach (1994) and Filardo (1994) as well as more recently by Kim, Piger, and Startz (2008), Kaufmann (2015), and Bazzi et al. (2017).

for all $i, j = 1, ..., K+2$, where $\boldsymbol{\gamma}_{ji}^{v}$ is a $(L \times 1)$ vector of coefficients for the transition covariates and γ_{ji} is the time-invariant transition parameter.[6] We set the arbitrary threshold vector $\bar{\boldsymbol{v}}$ to be the mean of the covariates. For identification purposes, we define the $(K+2)^{\text{th}}$ state as the reference state, implying $\boldsymbol{\gamma}_{K+2,i}^{v} = \mathbf{0}_L$ and $\gamma_{K+2,i} = 0$ for all $i = 1, \ldots, K+2$.[7] We compile the transition probabilities at time period t in the transition matrix P_t, where $p_{ji,t}$ is the element in the jth row and ith column.

2.3 Model Restrictions

Before estimating the model, we impose a number of restrictions. These restrictions are included to simplify computation, add economic interpretation, and facilitate estimation. We can relax some of these restrictions; when applicable, we refer the reader to the robustness section of the Web Appendix or note where the results are available upon request from the corresponding author.

First, we make a number of assumptions regarding the error vector, ε_t. We assume the error vector is independent of the state vector, s_τ, for all time periods (i.e., $E[\varepsilon_t' s_\tau] = 0 \ \forall \ \tau$). Additionally, we assume the covariance matrix is diagonal: $\Sigma = \text{diag}(\sigma_1^2, \ldots, \sigma_N^2)$. This latter assumption implies that coincident recessions are the only channel through which economic growth is deterministically correlated across countries. Therefore, business cycle synchronization shows up as similar recession timing reflected in the regime vector s_t in our model.[8]

Second, we assume that the average growth rates for each country (μ_n and $\mu_n + \Delta\mu_n$) are time invariant and invariant to the type of recession (global or cluster). If one were interested in relaxing this assumption, Eo and Kim (2016) show how to estimate a model in which the mean growth rate in a recession is drawn at each occurrence. A simpler

[6]Note that time-varying transition probabilities nest fixed transition probabilities when $\boldsymbol{\gamma}_{ji}^{v} = \mathbf{0}$ for all i, j.

[7]We could choose any state to be the reference (or baseline) state since it is necessary only for identification. For further discussion, see p.120 - 121 in Frühwirth-Schnatter and Frühwirth (2010).

[8]In the Web Appendix, we consider the alternative model where the off-diagonal terms in Σ are allowed to be nonzero. The results for this less restrictive specification are broadly similar to the baseline (restricted) model with the exception of the composition of Cluster 1. Additionally, in-sample fit of the alternative model is considerably worse than the baseline model according to BIC due to the the additional $N(N-1)/2$ free parameters. In general, loosening this restriction does not improve out-of-sample forecasting ability of either output-growth or recessions for most of the countries in our sample.

alternative would be to allow different mean growth rates for cluster recessions and global recessions.[9]

Third, we impose the restrictions $\mu_n \geq 0$ and $\Delta\mu_n < 0$ for all n to ensure that, on average, countries have non-negative growth during expansions and grow faster during expansions relative to recessions. The latter restriction also prevents label switching during estimation.[10]

Finally, to identify the clusters, we impose restrictions on the transitions of the aggregate state variable, z_t. We exclude transitions from one cluster recession to a different cluster recession by imposing $p_{ji,t} = 0$ for all t where $i \neq j$ and both i and j are smaller than $K + 1$ [see the discussion in section 3.9 of HO]. Thus, individual clusters experience recessions relative to the world but not directly following another cluster experiencing its own recession in the previous period.[11]

3 Estimation

We estimate the model using Gibbs sampling [Gelfand and Smith (1990), Casella and George (1992)]. Gibbs sampling is a Markov-chain Monte Carlo (MCMC) technique which separates the model parameters and latent variables into blocks. In each block, the parameter of interest is drawn from its conditional posterior distribution rather than directly from the unconditional joint posterior density. This method is particularly useful in instances where it is difficult or infeasible to sample directly from the full joint posterior distribution, as is the case with our model.

We have a total of four blocks to estimate. The first block is the entire set of growth and variance parameters, $\boldsymbol{\theta} = \{\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_N\}$, where $\boldsymbol{\theta}_n = \{\mu_n, \Delta\mu_n, \sigma_n^2\}$. The second

[9]We estimated the model with different growth rates for global and cluster recessions. These results are available upon request from the corresponding author.

[10]The restriction prevents a draw $\Delta\mu > 0$ that relabels $s_{nt} = 1$ as the expansion (higher growth) state. Across a large number of Gibbs draws, prevalent reclassification biases the posterior regime probabilities downward and biases the mean growth rates toward zero. We do not restrict the average growth rate in recessionary periods to be strictly negative.

[11]This assumption also reduces the dimension of the matrix of transitions between regimes. In small samples, this matrix, used to estimate the transition probabilities, could be sparse if left unrestricted. In this case, the transition probabilities would default to the prior. However, the results are robust to relaxing this restriction [see the results in the Web Appendix].

block is the aggregate state time series, $\boldsymbol{Z} = \{z_1, \ldots, z_T\}$. The third block consists of the entire set of transition probability parameters, $\boldsymbol{\gamma} = \left\{\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_{K+2}\right\}$, where $\boldsymbol{\gamma}_j = \left[\boldsymbol{\gamma}_{j1}^{v\prime}, \ldots, \boldsymbol{\gamma}_{jK+2}^{v\prime}, \gamma_{j1}, \ldots, \gamma_{jK+2}\right]'$ represents the entire set of transition parameters governing the transition probabilities to state j. The fourth block, $\boldsymbol{H} = \{\boldsymbol{\beta}, \boldsymbol{h}\}$, includes the cluster membership indicators, $\boldsymbol{h} = \{\boldsymbol{h}_1, \ldots, \boldsymbol{h}_{K+2}\}$, as well as the hyperparameters determining the prior distributions of cluster association, $\boldsymbol{\beta} = \{\boldsymbol{\beta}_1, \ldots, \boldsymbol{\beta}_{K+2}\}$. Let $\boldsymbol{\Theta} = \{\boldsymbol{\theta}, \boldsymbol{Z}, \boldsymbol{\gamma}, \boldsymbol{H}\}$ represent all parameters and latent variables to be estimated in the model.

3.1 Priors

Prior distributions for the parameters are given in Table 1. The mean growth rate parameters have a normal prior distribution. The variance parameters have an inverse-Gamma prior distribution. As in Kaufmann (2015), the transition parameters have a normal prior distribution.

We assume that country n's prior probability of membership in idiosyncratic cluster $k = 1, \ldots, K$ depends on a $(Q \times 1)$ country-specific cluster covariate vector, $\boldsymbol{x}_n$:

$$p(h_{nk}) \propto \exp(\boldsymbol{x}_n' \boldsymbol{\beta}_k)$$

with the normalizing assumption $\boldsymbol{\beta}_1 = \boldsymbol{0}$. This framework allows countries to endogenously cluster based on comovements in real GDP growth and country-specific covariates rather than imposing country groupings exogenously. We initialize cluster membership randomly and find that the posterior probabilities are consistent across different runs of the sampler.

3.2 Posterior Inference

In this section, we give a brief overview of the posterior draws.[12] We draw each country's individual parameter set $\boldsymbol{\theta}_n = \{\mu_n, \Delta\mu_n, \sigma_n^2\}$ conditional on knowing all other countries'

[12]We provide further details of each sampling step in an online appendix.

parameter values. The posterior distribution for a country's mean growth rates is multivariate normal, while the posterior for a country's variance is inverse-Gamma. This sampling step is standard for Markov-switching models [see Kim and Nelson (1999)].

The latent state vector, $\boldsymbol{Z}$, is drawn conditional on the other model parameters. We implement the filter outlined by Hamilton (1989) with smoothed transition probabilities from Kim (1994). We combine the multiple-state extension of the filter—outlined by HO—with the inclusion of TVTP as in Kaufmann (2015).

We utilize the difference random utility model (dRUM) outlined by Frühwirth-Schnatter and Frühwirth (2010) and Kaufmann (2015) to sample the transition probability parameters, $\boldsymbol{\gamma}$. The dRUM is a data augmentation method that gives us a linear regression of $\boldsymbol{\gamma}_j$ with logistic errors. The logistic errors can be approximated by a mixture of normal distributions, so that the posterior distribution for $\boldsymbol{\gamma}_j$ is normal conditional on knowing the state vector and the other states' transition parameters. After drawing the entire set of transition parameters, we calculate the transition probabilities at each point in time and obtain the entire time series of transition matrices, $\boldsymbol{P} = \{P_1, \ldots, P_T\}$.

Cluster membership and the associated prior hyperparameters are drawn in two substeps. We first draw the coefficients in the prior, $\boldsymbol{\beta}_k$, from a normal distribution conditional on knowing the other model parameters and prior hyperparameters. Country n's idiosyncratic cluster membership indicator, h_{nk}, is drawn conditioned on the membership indicators for the other countries and the new hyperparameter draws. After incorporating the hierarchical prior, cluster membership depends on similarity in fluctuations across countries' economic growth rates.

3.3 Choosing the Number of Clusters

Determining the optimal number of idiosyncratic clusters, K, is a model selection problem. Ideally, we would calculate the marginal likelihood $p\left(Y|\Theta_K\right)$ across a number of potential idiosyncratic clusters. HO implement cross-validation to approximate the marginal likelihood of different models. Cross-validation is computationally intensive since it involves testing the out-of-sample fit of each model to approximate its marginal likelihood.

Hernández-Murillo, Owyang, and Rubio (2017) determine the optimal number of clusters based on Bayesian Information Criterion (BIC), which was shown by Kass and Raftery (1995) to well-approximate the marginal likelihood.

We calculate BIC at each MCMC iteration with the associated draws for the parameters and latent variables. Since these information criterion are decreasing with the likelihood and increasing in the penalty factors, the optimal number of clusters is the model with the smallest median BIC draw.

4 Data

We use annualized quarterly real GDP growth as our indicator of economic activity for each country. Our sample includes 37 countries covering the time period 1970:Q3 - 2016:Q4. For a majority of the advanced economies, we use the OECD's Quarterly National Accounts dataset. We supplement this with Oxford Economics' (henceforth OE) Global Economic Databank, which provides real GDP data for many of the developing and emerging economies of our sample.[13] The OE data runs from 1980:Q1 - 2016:Q4 which results in an unbalanced panel when grouped with the OECD dataset.[14]

In addition to the data for real GDP growth, the model also requires data on two sets of covariates: (1) cross-country covariates informing cluster membership, and (2) time-series covariates informing the regime-switching process.

4.1 Cluster Covariates

The cluster covariates are country-specific variables that inform business cycle synchronization across countries by influencing the prior distribution on cluster membership.[15]

[13] The OECD provides data for Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, United Kingdom, and the United States. The OE dataset includes Argentina, Brazil, Chile, China, Hong Kong, India, Indonesia, Malaysia, Mexico, Philippines, Singapore, South Africa, Taiwan, Thailand, and Venezuela.

[14] Previous studies on international business cycles use data from the Penn World Tables which would allow us to include a larger subset of countries. However, this data is only available at an annual frequency which may miss important business cycle movements occurring on a quarterly basis.

[15] Because the clusters can change across Gibbs iterations, we cannot use covariates that depend either on the cluster composition or the relationship between two (or more) countries. We only use time-

We consider eight variables: (1) the degree of trade openness, (2) financial openness, (3) the degree of industrialization, (4) the importance of oil rents, (5) legal systems, (6) an ethnolinguistic index, (7) supply chain linkages, and (8) continent dummies. The top panel of Table 2 lists the sources, transformations, and summary statistics for each cluster covariate.[16]

With the exception of the financial integration, oil rents, and supply chain variables, all other measures were used in FOS. Recent theoretical studies reached conflicting conclusions of how financial openness affects synchronization [see the discussion in Kalemi-Ozcan, Papaioannou, and Peydró (2013)]. Negative productivity shocks could lower domestic investment and financial outflows, causing desynchronization. On the other hand, a negative shock that affects all countries could reduce investment in all economies, raising synchronization. Empirical results have also varied, finding increases, decreases, or no impact on synchronization [see Imbs (2010); Kalemi-Ozcan, Papaioannou, and Peydró (2013); and Davis (2014)].

Oil rents as a share of GDP measure the oil wealth of a nation and the degree to which its economy is dependent upon oil production. The output of economies that are heavily dependent on oil production will be subject to the same commodity price shock, and therefore may experience a higher degree of business cycle synchronization.

The supply chain affects countries that depend on raw materials and intermediate goods from other countries in their production processes and are subject to shocks emanating from these import-supplying countries. Similarly, a country with a high degree of backward linkages will spread domestic shocks to countries from which they source their imports.

Continent dummies capture geographic proximity and common movements across

invariant, country-specific covariates.

[16]Trade openness is total trade share of GDP using data from Penn World Tables 8.0 [Feenstra, Inklaar, and Timmer (2015)]. Financial openness is the sum of total foreign assets and liabilities as a percentage of GDP [Lane and Milesi-Ferretti (2007)]. Industrialization is measured by the investment share of GDP. Oil rents are measured by the oil production share of GDP. The legal system is an index of formality of the civil court system [Djankov et al. (2003)]. Language diversity is measured by an ethnolinguistic index from La Porta et al. (1999). Backward supply-chain linkages is measured by the percent of imports that are used in a country's exports, computed using data from the OECD and the World Trade Organization (WTO).

regions. We include dummies for Asia, Europe, North America, and South America, and leave Africa and Oceania as the reference groups. We do so because our sample only includes three countries (Australia, New Zealand, and South Africa) from these two latter regions. For details about the motivation for including the remaining covariates, we refer the reader to FOS.

In order to facilitate computation of marginal effects, the cluster covariates are standardized to have mean zero and unit standard deviation.

4.2 Transition Covariates

While the cluster covariates influence synchronization, the transition covariates inform the regime-switching process. We consider one lag of each of five covariates that may have predictive ability for business cycle turning points: (1) an interest rate term spread, (2) stock market returns, (3) housing price growth, (4) a measure of oil price movements, and (5) geopolitical uncertainty.[17] The bottom panel of Table 2 lists the sources for each transition covariate as well as any transformations made to the raw data.

The term spread has been shown to forecast both output and business cycle turning points.[18] The term spread's predictive power lies in its ability to capture both contractionary monetary policy raising short rates [Estrella (2005)] and market expectations on the long end of the yield curve [Harvey (1988)]. We use the difference between the 10-year and 3-month U.S. Treasury security yields as our measure of the term spread.[19]

We also include global equity returns, measured as the log difference of the MSCI World stock market index. Stock market returns reflect shocks to consumer wealth and financial health. Decreases in consumer wealth due to lower equity values depress consumption, thereby increasing the probability of entering a recession. Similarly, deteriorations in financial health increase uncertainty about future economic conditions which decreases investment. Estrella and Mishkin (1998) show the predictive ability of stock

[17] Because conventional TVTP models [e.g., Filardo (1998)] require that the transition covariates be uncorrelated with the state variable, we use lags of these data.

[18] See Stock and Watson (1989), Estrella and Mishkin (1998), among many others. Wheelock and Wohar (2009) survey the literature on the relationship between the term spread and economic activity.

[19] Ideally, we would prefer to use a world interest rate spread. Because no such rate is available, we use the U.S. term spread as a proxy for a "global" term spread.

market returns in predicting U.S. recessions. Nyberg (2010) found that stock market returns had predictive power for recessions in both the U.S. and Germany.

Because housing is a large portion of consumer wealth, household behavior reacts strongly to declines in housing wealth and induces a relatively large shortfall in aggregate demand. Recent studies have shown a link between housing and business cycle turning points [e.g., Leamer (2007), Claessens, Kose, and Terrones (2009, 2012)]. Thus, we include the log difference of the Federal Reserve Bank of Dallas' Global Real Housing Price Index. Claessens, Kose, and Terrones (2012) found that business cycles associated with housing busts tend to have longer recessions and slower recoveries, which in our model comes through the persistence probability of the regimes.

Previous studies have examined how oil price fluctuations are related to the timing of recessions.[20] Rising oil prices increase input costs for firms and decrease household consumption. To account for the asymmetric effects of oil price shocks, we compute the increase in net oil prices suggested by Hamilton (1996, 2003). If the current oil price exceeds the maximum price over the previous four quarters, the shock is calculated as the log difference between the two prices. Conversely, if the current oil price is less than the maximum price over the previous four quarters, the shock is set to zero. As our measure of oil prices, we use the world price of oil from the IMF's International Financial Statistics to measure oil prices.[21]

Our final transition covariate is the historical Geopolitical Risk (GPR) Index from Caldara and Iacoviello (2018). The GPR Index is constructed based on the frequency that words associated with geopolitical tensions are mentioned in three newspapers (*New York Times*, *Chicago Tribune*, and *Financial Times*) to capture economic crises, significant political events, wars, and other risks associated with geopolitical turmoil. An increase in the GPR index signals heightened uncertainty, which could lead to a reduction of spending and investment, and therefore a higher chance of an economic downturn.

[20] Hamilton (2003) and Barsky and Kilian (2004) survey the primary channels through which oil price shocks can lead to recessions.

[21] The IMF's world price of oil is a weighted average of U.K. Brent (light), Dubai (medium), and West Texas Intermediate (heavy). Prior to 1983, Alaska North Slope (heavy) was used in place of West Texas Intermediate.

Similar to the clustering covariates, the transition covariates are standardized to have mean zero and unit standard deviation.

5 Results

The joint posterior distribution of the model is approximated using 20,000 iterations of the Gibbs sampler after an initial burn-in of 30,000 iterations. In order to diagnose convergence, we calculated running means and autocorrelation functions of the parameter draws. We consider models with differing numbers of idiosyncratic clusters $K = 2, \ldots, 7$, and calculate the posterior median of the information criterion for each one. The model with $K = 4$ idiosyncratic clusters minimizes BIC, with $K = 3$ clusters being the second-best model.[22]

Table 3 reports the estimates for each country's state-dependent growth rate (μ_n for expansions and $\mu_n + \Delta\mu_n$ for recessions) and standard deviation parameters (σ_n). As expected, developed countries tend to have lower growth rates in expansion and less negative growth rates in recession compared to the emerging and developing economies (in particular, the Asian countries) in our sample, but also tend to have less volatility. For some of the rapidly developing countries (China and India), the mean growth in recession is greater than zero, implying a recessionary period in these countries is characterized by relatively slower, but still positive, economic growth compared to expansions.

5.1 Cluster Composition

Figure 1 depicts choropleth maps showing the posterior probabilities of membership for each cluster. Countries with relatively darker shading have a high posterior probability of membership in the cluster associated with the figure. To ease exposition, we will often associate a country with the cluster for which it has the highest posterior probability of

[22] We also estimate the integrated complete likelihood (ICL) criterion first outlined by Biernacki, Celeux, and Govaert (2000) for each model. The ICL includes an entropy measure that accounts for how well the data is partitioned into clusters. Similar to the BIC results, the optimal number of clusters based on ICL is $K = 4$ with $K = 3$ being second-best. Model selection results are available from the authors upon request.

inclusion.

Cluster 1 includes a number of former British territories—Australia, Canada, India, South Africa, and the U.S., as well as Chile, Mexico, and Switzerland. The inclusion of Chile, Mexico, and Switzerland is most likely due to their high degrees of trade and close economic relationships with the U.S. Cluster 2 is comprised of Argentina, Brazil, Venezuela, and China, which has extensive trade with these South American countries. Cluster 3 includes only European countries: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom. Switzerland is the only European country in our sample not included in Cluster 3. Cluster 4 consists of mainly Asian countries: Hong Kong, Indonesia, Japan, Korea, Malaysia, New Zealand, the Philippines, Singapore, Taiwan, and Thailand. China and India are the only Asian countries that are not members of Cluster 3.[23]

In our model, cluster membership is also informed by the prior, allowing us to determine which country characteristics are important in determining cluster composition. Due to the multinomial logistic representation of this prior, we translate the coefficients β_{qk} into the corresponding marginal effects, δ_{qk}, for each cluster covariate q and idiosyncratic cluster k. The marginal effect of covariate q on the probability of any given country being a member of cluster k is

$$\begin{aligned}\delta_{qk} = \Pr\left(h_k = 1 | x_q = \bar{x}_q + \sigma_q,\ x_{-q} = \bar{x}_{-q}, \beta_{qk}\right) \\ - \Pr\left(h_k = 1 | x_q = \bar{x}_q - \sigma_q,\ x_{-q} = \bar{x}_{-q}, \beta_{qk}\right), \quad (4)\end{aligned}$$

where $\bar{x}_q = \sum_{n=1}^{N} x_{nq}$ is the average covariate value across all countries, and σ_q is the standard deviation of cluster covariate q. This marginal effect measures the change in the prior probability of cluster membership resulting from a single covariate (i.e., a

[23] These cluster results coincide roughly with previous studies, such as Castles and Obinger (2008), FOS, and Ductor and Leiva-Leon (2016), who each found a European and English-speaking group of countries. Additionally, Ductor and Leiva-Leon (2016) found a Southeast Asian cluster similar to the composition of Cluster 4 from our results. These similarities are not unexpected given that these previous studies also use real GDP as a cluster variable (or, in some instances, a gravity variable) in determining country groupings. Additionally, the cluster compositions are relatively robust to using samples of different time periods.

country-specific characteristic), holding all other covariates at their respective averages.

Table 4 shows the posterior median of the marginal effects for each cluster characteristic. In addition to the country-specific covariates, we include continent dummies to control for the fact that countries may cluster simply based on geographic proximity. We find that geographic proximity is an important factor for European countries being in Cluster 3 and Asian countries in Cluster 4.

Beyond geographic proximity, a number of country-specific covariates influence cluster composition: the level of economic development (Cluster 2 and 3), openness to trade (Clusters 1 and 4), language or cultural commonality (Clusters 1, 3, and 4), and global supply linkages (Clusters 2 and 3). For example, a country with a capital-output ratio one-standard-deviation above average (i.e., a low degree of industrialization) is *a priori* 24% more likely of being included in Cluster 2 than a country with a capital-output ratio one-standard-deviation *below* average (i.e., a high degree of industrialization). These results reinforce the findings of FOS, which imply that a number of country-specific factors apart from geography influence business cycle comovement. Therefore, simply imposing country groupings based on geographic proximity overlooks these important economic relationships which need to be accounted for in theoretical and empirical models of international business cycles.[24]

5.2 Recession Timing and Determinants

The aggregate state variable, z_t, determines the business cycle phase of all the countries and takes one of six possible values for any time period. By definition, the last two regimes correspond to global expansion ($z_t = 5$) and recession ($z_t = 6$), during which all countries are simultaneously in an economic upturn or downturn, respectively. The remaining four regimes ($z_t = 1, 2, 3, 4$) are characterized by one cluster of countries in recession while the other countries experience expansion. For example, $z_t = 1$ implies the countries in Cluster 1 are in recession while all other countries in the sample (Clusters 2,

[24]We consider two alternative specifications for the prior: (i) a flat prior for clusters and (ii) including only continent as a cluster covariate. Both alternatives have higher BIC than the model with endogenous clusters and all covariates. These results suggest that geography alone is not the best metric for sorting countries into regions. Results are available in the Web Appendix.

3, and 4) are in expansion.

5.2.1 Recession Timing

Figure 2 shows the posterior probabilities of being in a regime for any time period.[25] The top panel shows the probability of global recession along with gray bars representing the NBER U.S. recession dates for comparison. We find two instances of a global recession: (1) 1974:Q4-1975:Q1 (OPEC embargo) and (2) 2008:Q3-2009:Q1 (the Great Recession).[26] The bottom four panels of Figure 2 show the probabilities of recessions for the four clusters. In these four panels, the gray bars correspond to our model's global recessions. Note that the cluster recessions can be related to the global recessions, as regions either lead or follow many of the global events. The first global recession follows a recession in Cluster 1 (English-industrial) and the second global recession is both preceded and followed by a recession in Cluster 3 (the European cluster).

We can compare our estimated business cycle turning points to other established dating methods. Given that the U.S. is in Cluster 1, we compare the recession timing of this cluster to the NBER recession dates.[27] One should not expect Cluster 1 recession dates to perfectly align with every NBER recession as the U.S. is only one member of the cluster. Therefore, the NBER dates are not an exact benchmark but can be used to check which U.S. recessions coincided with cluster-wide recessions. The model identifies common recession dates in the mid-1970s, 1982-83, and the Great Recession of 2008-2009, but does not classify the recessions of 1979-80, 1991, and early 2000s as cluster-wide. The latter recessions may not have been pervasive enough to warrant a cluster-wide recession.

Cluster 3's recessions are consistent with the CEPR's Euro Area Business Cycle Dating Committee, with false positives in 1984 and 1991. For the Asian countries, there is not a comparable accepted timeline of business cycle dates. However, Cluster 4's reces-

[25] We omit the global expansion regime because it is the residual of the other regime probabilities.

[26] These results are generally consistent with Kose and Terrones (2015) and Fushing et al. (2010). Using annual data on the growth rate of world GDP per capita, Kose and Terrones (2015) find additional global downturns during 1982 and 1991. Their measure is a weighted average of output while ours weights all countries equally. Using monthly data, Fushing et al. (2010) find global downturns during 1980:04 and 2000:08 - 2001:05.

[27] To get the complete recession timing of Cluster 1, we combine the global recessions with the Cluster 1 recessions.

sion dates generally coincide with major economic events in Asia during the respective time period.[28]

Table 5 shows the estimated transition probabilities when the covariates are at their sample averages. For example, if the current regime is a global expansion and the transition covariates are at their average values, the probability of staying in a global expansion regime next period is 93 percent. While the transition probabilities will depend on the values of the covariates, the table illuminates some connections between the regimes, even when the covariates are at their sample averages. From a global expansion, the most likely recession will occur in either Cluster 2 or 4. The global recession regime is not persistent (0.28). Recovery from a global recession does not always happen simultaneously for all countries: a Cluster 3 recession occurs with high probability when exiting the global recession. These Cluster 3 recessions are highly persistent (0.89) and tend to be followed by global expansion states. Similarly, Cluster 2 and Cluster 4 recessions are more likely to transition to global expansions, whereas Cluster 1 recessions have a higher probability of turning into global recessions.

5.2.2 Determinants of Recession Timing

The addition of time-varying transition probabilities allows us to evaluate which of the transition covariates presage business cycle turning points. We calculate marginal effects for each transition covariate using equation (3). For each Gibbs draw, the marginal effect we report is the difference in the transition probabilities when the mth covariate changes from one standard deviation below to one standard deviation above its historical mean, holding the other transition variables at their historic means:

$$\pi^l_{ji} = Pr(z_t = j | z_{t-1} = i, [v_{mt} = \bar{v}_{mt} + \sigma_m, \boldsymbol{v}_{-mt} = \bar{\boldsymbol{v}}_{-mt}]) \\ - Pr(z_t = j | z_{t-1} = i, [v_{mt} = \bar{v}_{mt} - \sigma_m, \boldsymbol{v}_{-mt} = \bar{\boldsymbol{v}}_{-mt}]). \quad (5)$$

[28]The model identifies recessions in Asia associated with the effects of the Plaza Accord and lackluster export demand from the U.S. in the mid-1980s, the well-known 1997-1998 Asian Financial Crisis, and the lack of foreign demand during the Tech Recession of 2001.

Table 6 displays the posterior mean of the marginal effects for each of the transition covariates; bold indicates that the 68-percent posterior coverage excludes zero. These marginal effects can be interpreted as the change in the turning point probability induced by a two-standard-deviation change in the covariate of interest on the transition probabilities. Because they are standardized, the relative importance of the transition covariates can be obtained directly from the table. However, causality from the transition covariates to the business cycle should not be inferred.

A rising term spread increases global expansion persistence by 6 percentage points, suggesting that long global expansions are characterized by an upward sloping yield curve. The negative signs in the second row of panel 1 show that a falling term spread increases the persistence of global contractions and raises the likelihood that a regional recession in Cluster 1 blossoms into a global recession.

Equity returns have similar effects on cycle transitions. In particular, higher equity returns increase the likelihood that regional recessions in industrialized countries (Clusters 1 and 3) transition back into global expansions. Thus, localized bad outcomes are mitigated in the presence of rising equities. The sensitivity of the industrialized countries to equity prices may be attributed to the fact that the member countries for the most part have developed financial markets. Because they are well-integrated to global asset markets, these countries are more exposed to downturns in financial wealth. Conversely, falling equities make transitions back to global expansion less likely. When equities fall, these regional recessions become more persistent. Moreover, if the world slips into global recession, falling equity prices make the recession last longer.

Consistent with Reinhart and Rogoff (2009) and Helbling, Kose, and Otrok (2011), the importance of equity returns suggests that financial frictions are one of the main contributing factors in propagating recessions to a global level. This result can be obtained from models such as the financial accelerator model of Bernanke and Gertler (1989), which suggest that the effect of financial shocks on the real economy become amplified as falling global asset prices deteriorate international firms' balance sheets.

Other covariates have mixed influence. For example, house price growth has two significant effects on the global cycle. In particular, higher house price growth prolongs global expansions and lowers the probability of transitioning from global expansion to a Cluster 3 recession. Rising oil prices also increase the persistence of global expansions. While this may appear counterintuitive, the positive relationship comes from the steady rise in oil demand during global expansions rather than the negative effects of sharp oil supply shocks of the 1970s and 80s.[29] Rising geopolitical risk raises the probability of transitioning out of global expansions. Geopolitical risk, however, does not increase the likelihood of global recessions. Instead, these risks appear concentrated in South America (Cluster 2) and Europe (Cluster 3), raising the likelihood of a recession specific to either of these two regions by 6 percentage points each. Geopolitical risk also increases the persistence of recessions in the English-speaking industrialized region (Cluster 1).

These results suggest that certain covariates inform particular directions of the business cycle switching. Falling housing prices, increased geopolitical risks, and a falling term spread signal a transition out of a global expansion regime. Prolonged global recessions are signaled by a fall in the term spread and losses in global equity markets.

6 Forecasting

The previous section considered in-sample estimation of the model. In addition to relating economic data to business cycle turning points, another advantage of the TVTP model is that the transition covariates can be used for forecasting. In this section, we consider whether the model has predictive ability out of sample. We consider two dimensions over which the model may have predictive ability: one-quarter-ahead forecasts of GDP growth and one-quarter-ahead forecasts of recessions.[30]

[29]One potential issue is the choice of net oil price increase as a covariate. For robustness, we replace this oil price metric with a broad index of commodity inflation from the CRB. The results are qualitatively similar with regards to recession timing and the effects of the other transition covariates. However, we find that the persistence of the global recession regime is significantly and positively related to commodity inflation whereas the global expansionary regime is no longer significantly related to commodity inflation as it is when we use net oil price increase.

[30]Because our data have been revised, these are not true psuedo-real-time experiments. One solution might be to consider multi-step-ahead forecasts rather than one-step-ahead forecasts.

6.1 Output Growth Forecasts

We compare the output growth forecasting ability of our model (MSC-TVTP) to four benchmarks: (i) an AR(1) model; (ii) a two-regime univariate Markov-switching model; (iii) a Global VAR model similar to the one first outlined by Pesaran et al. (2004),[31] and (iv) the Markov-switching clustering model with fixed transition probabilities (MSC-FTP) from HO.[32] Being the fixed transition probabilities version of our model, the MSC-FTP is a natural benchmark, allowing us to assess forecasting value of adding time-varying transition probabilities.

We conduct pseudo out-of-sample forecasts and compute each model's mean-squared forecast error (MSFE) from the median posterior forecast for each period. At each forecast origin, $\tau < T$, we estimate the models using data $\boldsymbol{Y^\tau} = \{Y_1, ..., Y_\tau\}$, compute each model's forecast for $\hat{Y}_{\tau+1|\tau}$, and compute the forecast error $Y_{\tau+1} - \hat{Y}_{\tau+1|\tau}$. We repeat this experiment for forecast origins, $\tau = \tau_0, ..., T-1$ to obtain the MSFE for each country:

$$MSFE = \frac{1}{T - \tau_0} \sum_{t=\tau_0}^{T-1} \left(Y_{t+1} - \hat{Y}_{t+1|t}\right)^2,$$

where we have suppressed the country index. We estimate each model using 30,000 iterations of the Gibbs Sampler for each subsample. When computing the MSFE, we use the median posterior forecast for each shortened sample.[33] We choose τ_0 to be 1998Q1 so that 60% of the data is in the initial pseudo-sample.

Table 7 shows the MSFE for each model and for each country in the sample, as well as the panel MSFE. We normalize the MSFE for each alternative model by the MSFE of our baseline model, so that a relative MSFE above one indicates our model has a lower MSFE than the alternative model. Out of the 37 countries in our sample, our model

[31]For the Global VAR, we use flat weights across the other countries in the sample when constructing the foreign variables for each country. Additionally, we must truncate the sample period to begin in 1980:Q1 to ensure a balanced panel

[32]We considered adding more lags of output growth or more lags of the transition covariates. Adding a lag of output improved the forecast output growth forecasts but worsened recession forecasts. Additional lags of the transition covariates generally did not improve forecasting ability of either output growth or recessions compared to the baseline model. These results are available in the Web Appendix.

[33]See Frühwirth-Schnatter (2006), Section 12.4.2 and Geweke and Whiteman (2006) for an overview of Bayesian forecasting methods.

outperforms the AR, MS, GVAR, and MSC-FTP models for 28, 30, 25, and 26 countries, respectively. The last row shows the sum of the MSFE of the entire vector of countries relative to our model, which outperforms each alternative model.

To test if our model forecasts significantly better than the alternatives, we implement tests of equal predictive accuracy. For the AR, MS, and GVAR models, we report the outcomes of a one-sided Diebold and Mariano (2002) test with the null hypothesis is that our model has the same predictive accuracy as the other model and the alternative hypothesis is that our model performs better. Since the MSC-FTP model is a nested alternative of our model, we use the test of Clark and West (2007) which is a one-sided test that has the same null and alternative hypotheses. As indicated by the stars in table 7, our model significantly outperforms the AR, MS, GVAR, and MSC-FTP models for 14, 20, 11, and 17 countries, respectively.

Two reasons may explain the forecasting advantages exhibited by our model. First, the transition covariates allow our model to be forward-looking. This is particularly true when comparing our MSC-TVTP model to the nested MSC-FTP model. For the 26 countries where our model performs better than the MSC-FTP, the sole explanation for this difference is the information contained in the transition covariates of global or cluster-specific recessions. Second, our model exploits the information gleaned from the common recessions across the cross-section. Because it relies on information in the cross-section, it improves the forecasting ability of our model over the alternative models for individual countries.

Despite our model's head-to-head performance against each alternative specification, it is important to note our framework's limitations since it is the best predictor for only 14 countries (based on having the smallest MSFE). The AR(1) yields the best forecast for eight countries. In these cases, output may be better explained by a persistent, mean-reverting process where cross-sectional information about recessions is uninformative. It is possible that including AR terms in our model could improve forecasting for these countries. The univariate MS model is the best forecasting model for only two countries: India and the Philippines. These countries may experience more country-specific recessions not captured in our limited clustering framework that is built to consider recessions across a large number of countries. Finally, the Global VAR dominates for eight of the countries in our sample. For these countries, a linear model with cross-country spillovers is a better predictor than a model with simultaneous recessions.

6.2 Recession Forecasts

We now consider the ability of our model to forecast recessions one quarter ahead. We obtain out-of-sample recession forecasts, $\hat{\boldsymbol{s}}_{t+1|t}$ using the recursive window method described above. In place of the linear MSFE metric, we use the receiver operating characteristic (ROC) curve to compare models. As explained by Berge and Jordà (2011), the ROC curve alleviates the need to specify an explicit forecast loss function and is a more appropriate measure for binary classification variables such as recession indicators. For observed recession dates, we use the OECD Composite Leading Indicators reference turning points.[34] We compare our model to two benchmark models: (i) a two-regime univariate Markov-switching model (*MS*) and (ii) the MSC-FTP model from HO. However, we use global equity returns as the only transition covariate in the MSC-TVTP model due to their forward-looking nature.[35]

Table 8 presents the recession forecasting results. Specifically, we report the area under the ROC curve (AUROC), which measures the forecast accuracy for a binary classification model. A maximum AUROC of 1 implies that the model correctly identifies recessions with no false positives. A model with an AUROC of 0.5 implies the model is no better than a coin flip at calling recessions. Similar to the MSFE results, we normalize the AUROC for each competing model by the AUROC for the baseline model. For 22 of the 29 countries with recession dates, the MSC-TVTP model forecasts recessions better than the univariate MS model. Our model does even better compared to the MSC-FTP model as it performs better for 26 countries.

[34] OECD recession dates are not available for 8 of the 37 countries in our sample: Argentina, Hong Kong, Malaysia, Philippines, Singapore, Taiwan, Thailand, and Venezuela. We do not consider these countries in the recession forecasting exercise.

[35] We also tested the model including all transition covariates. For most countries in our sample, using only equity returns improved forecasting ability for recessions. However, we find the model with all transition covariates forecasts output growth better than the model with only equity returns.

We use DeLong's test to see if our model significantly forecasts recessions better than each of the two alternative models [see DeLong, DeLong, and Clarke-Pearson (1988)]. The null under DeLong's test is that the AUROC of the baseline model is equal to the respective alternative model's AUROC, while the alternative hypothesis is that AUROC for our model is strictly greater. The stars in table 8 indicate significance at either the 1, 5, or 10% significance level. Compared to the MS and MSC-FTP models, our model performs significantly better for 6 and 11 countries, respectively.

Again, we note the limitations of our model's forecasting ability compared to the alternative frameworks. For 7 of the countries, the univariate MS model performs better than the MSC-TVTP model. Since country-specific recessions are not captured by our model, the univariate MS model dominates in cases in which a country experiences shocks that cause a significant fall in output growth without spreading to its cluster or the rest of the world.

For all but three countries (Australia, Japan, and Portugal), our model with time-varying transition probabilities has a larger AUROC than MSC-FTP. This improved forecasting ability arises from the inclusion of equity returns influencing the transition probabilities and is consistent with some of the literature on news shocks and business cycles. Specifically, Beaudry and Portier (2006) identify news shocks about future TFP shocks, suggesting that asset prices may be indicators of future turning points. However, since the returns are based on a global equity series and are not country-specific, our TVTP model does not necessarily improve recession forecasting for every country, as illustrated by these three countries.

7 Conclusion

We analyzed the relationship between the world business cycle and the cycles of smaller groups of countries using a multivariate Markov-switching model with endogenous clustering and time-varying transition probabilities. The model is estimated with a hierarchical prior that determines which country characteristics lead to business cycle synchronization and which macroeconomic shocks drive international business cycles.

Four groups of countries experience recessions relative to global downturns. While geographic proximity is perhaps the most important determinant of synchronization across countries, but there exist important roles for trade openness, stage of development, supply linkages, and institutional factors such as linguistic diversity. This finding implies that the study of international business cycle synchronization needs to consider a host of factors when grouping countries.

The drivers of transitions between regimes are fluctuations in the term spread, equity returns, and geopolitical risks. Specifically, the term spread and equity prices tend to be key indicators of the timing of global recessions. Additionally, the European cluster is responds to equity price movements, while a cluster comprised of the U.S. and other English-speaking countries was open to a variety of global shocks, including geopolitical uncertainty. Our model also has predictive ability over other alternatives for forecasting output and recessions for a number of countries.

Our model includes a number of restrictions that may affect both its forecasting ability and the economic interpretation of the in-sample results. First, contemporaneous correlation in the baseline model is restricted to obtain only from transitions in the global regime variable. Second, transitions between idiosyncratic cluster recessions are ruled out. We do this because we believe that deterministic transitions between recessions in one group of countries to another is unlikely, Moreover, transition from one group recession to another via one period of world expansion or recession is still permissible. However, we recognize that this limitation may not be palatable in other applications. Neither of these restrictions appears to result in substantive qualitative differences from a more unrestricted model. However, the more unrestricted model may outperform the baseline forecast of output growth but generally fares worse when forecasting recessions.

This study motivates a number of avenues for future research. First, the cluster associations were held constant across the full sample estimation of our model. Allowing countries cluster association to evolve could show how international comovement has changed across time. Second, we only consider five transition covariates in our application, whereas a number of other potential factors could indicate switches in the global business cycle. One could consider a large number of potential covariates using a stochastic search variable selection method or a similar variable selection method. Lastly, we only considered output growth in our model. Including a number of additional economic indicators in a multivariate setting might fine-tune the identification of recessionary periods.

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Table 1: Prior Specifications for Estimation

Parameter	*Prior Distribution*	*Hyperparameters*	
$\boldsymbol{\mu}_n$	$N\left(\boldsymbol{m}_0, \sigma_n^2 \boldsymbol{M}_0\right)$	$\boldsymbol{m}_0 = [1, -2]'$, $\boldsymbol{M}_0 = 2\boldsymbol{I}_2$	$\forall n$
σ_n^{-2}	$\Gamma\left(\frac{v_0}{2}, \frac{\tau_0}{2}\right)$	$v_0 = 1$, $\tau_0 = 1$	$\forall n$
γ_{K+1}	$N\left(g_{02}, \boldsymbol{G}_{02}\right)$	$g_{0K+1} = \left[\mathbf{0}_{L(K+2)}, \mathbf{0}_K, 2, 0, \right]$, $\boldsymbol{G}_{0K+1} = 4\boldsymbol{I}_{(L+1)(K+2)}$	
γ_k	$N\left(g_{0k}, \boldsymbol{G}_{0k}\right)$	$g_{0k} = [\mathbf{0}_{3L}, 2, 0, 0]$, $\boldsymbol{G}_{0k} = 4\boldsymbol{I}_{3(L+1)}$	$k = 1, \ldots, K$
β_k	$N(b_{0k}, B_{0k})$	$b_0 = \mathbf{0}_{(Q+1)}, B_{0k} = \boldsymbol{I}_{(Q+1)}$	for $k = 1, ..., K$

8 Tables and Figures

Table 2: Covariate Data Sources

Variable	*Raw Statistic*	*Source*	*Transformation*	*Mean*	*SD*
Cluster Covariates					
Trade Openness	Exports and Imports (% of GDP)	Penn World Tables 8.0	Average 1950-2011	63	55
Financial Openness	Foreign Assets and Liabilities (% of GDP)	Lane and Milesi-Ferretti (2007)	Average 1970-2011	4.63	14.66
Industrialization	Capital-Income Ratio	Penn World Tables 8.0	Average 1950-2011	0.22	0.05
Oil Production	Oil Rents (% of GDP)	World Bank WDI	Average 1970-2011	2.39	5.19
Legal Systems	Formalism Index	Djankov et al. (2003)	-	3.23	1.11
Language	Ethnolingusitic Index	La Porta et al. (1999)	-	0.24	0.23
Backward Linkages	Import Content of Exports (%)	OECD-WTO	Average 1995-2011	24.79	9.71
Geographic Proximity	Continent Dummies	-	-	-	-
Transition Covariates					
Term Spread	10-Year Treasury Constant Maturity Rate,	FRED	Difference between	1.73	1.22
	3-Month Treasury Bill: Secondary Market Rate	FRED	10-year and 3-month rate		
Equity Returns	MSCI World Index	MSCI	100 × Log first-difference	1.54	7.29
Housing Prices	Real House Price Index	FRB Dallas	100 × Log first-difference	0.88	2.93
Net Oil Price Increase	Commodity Prices, Crude Oil (Petroleum)	IMF IFS	NOPI (See Hamilton 1996, 2003)	3.93	11.78
Geopolitical Risks	Geopolitical Risk Index	Caldara and Iacoviello (2018)	-	90.83	50.08

This table presents the data sources and transformations for both the cluster covariates (top panel) and transition covariates (lower panel). The first column lists the covariate being measured. The second lists the raw statistic used to measure each covariate. The third column lists the data source, and the fourth column details any transformations made to the raw data.

Table 3: Growth Rate and Variance Parameters

Country	μ_n	$\mu_n + \Delta\mu_n$	σ_n
Argentina	3.14	-4.14	5.23
Australia	3.26	-0.59	1.76
Austria	2.95	-1.45	1.62
Belgium	2.74	-1.94	1.15
Brazil	3.31	-2.39	3.04
Canada	3.04	-2.69	1.47
Chile	5.01	-7.17	2.51
China	9.96	5.58	1.85
Denmark	2.36	-1.94	2.06
Finland	3.07	-1.86	2.57
France	2.59	-0.97	0.90
Germany	2.60	-1.65	1.72
Hong Kong	5.24	-6.14	3.27
India	6.31	1.08	2.13
Indonesia	5.97	-4.93	3.24
Ireland	5.06	-0.05	3.03
Italy	2.32	-2.48	1.49
Japan	2.96	-2.81	1.99
Korea	7.25	-0.04	3.14
Luxembourg	4.35	-1.37	2.53
Malaysia	6.41	-6.10	2.36
Mexico	3.74	-1.69	2.18
Netherlands	2.94	-1.89	1.94
New Zealand	3.00	-1.11	2.63
Norway	3.33	-0.13	2.41
Philippines	3.86	-1.91	3.87
Portugal	3.35	-3.75	2.09
Singapore	6.85	-4.81	3.04
South Africa	2.73	-2.44	1.75
Spain	3.24	-2.53	1.23
Sweden	2.79	-1.77	2.07
Switzerland	2.09	-4.67	1.24
Taiwan	6.07	-1.29	2.59
Thailand	5.59	-3.94	3.24
United Kingdom	2.75	-1.51	1.59
United States	3.10	-3.32	1.40
Venezuela	3.17	-5.61	6.08

This table shows the median posterior draw for each country n's average annualized quarterly real GDP growth rate in expansion (μ_n) and recession ($\mu_n + \Delta\mu_n$) as well as each country's standard deviation (σ_n).

Table 4: Marginal Effects of the Cluster Covariates

Cluster Covariate	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Trade Openness	**-0.25**	-0.12	0.09	**0.28**
Industrialization	-0.15	**0.24**	**-0.27**	0.17
Legal Systems	-0.05	0.10	0.01	-0.06
Ethnolinguistic Index	**0.21**	-0.05	**-0.37**	**0.21**
Financial Openness	-0.02	0.00	0.13	-0.11
Oil Production	-0.03	0.08	-0.11	0.06
Global Backward Linkages	-0.11	**-0.16**	**0.25**	0.02
Asia	-0.07	-0.14	-0.29	**0.50**
Europe	**-0.16**	**-0.09**	**0.43**	**-0.18**
North America	0.08	0.01	-0.08	-0.01
South America	0.00	0.12	-0.11	-0.02

This table displays the marginal effect (δ_k) of each country-specific factors on the prior probability of inclusion in the endogenous clusters. Numbers presented are posterior medians, and bold indicates parameters for which the 68% posterior coverage interval does not include zero. The marginal effects can be interpreted as the difference in the prior probability of cluster membership when the covariate is relatively high and low.

Table 5: Estimated Transition Matrix

		Previous State (z_{t-1})					
		G. Exp.	*G. Rec.*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
	G. Exp.	0.93	0.05	0.14	0.09	0.08	0.22
Current	*G. Rec.*	0.00	0.28	0.27	0.05	0.03	0.07
State	*Cluster 1*	0.01	0.06	0.59	-	-	-
(z_t)	*Cluster 2*	0.02	0.06	-	0.86	-	-
	Cluster 3	0.01	0.48	-	-	0.89	-
	Cluster 4	0.02	0.06	-	-	-	0.71

This table displays the posterior mean draw for the transition probabilities if all transition covariates were at their respective average. Transitions between idiosyncratic clusters are restricted to 0 by assumption.

Table 6: Transition Covariates Effects

(a) Term Spread

		Previous State (z_{t-1})					
		G. Exp.	*G. Rec.*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
	G. Exp.	**0.06**	-0.01	0.04	**-0.17**	**0.22**	0.13
Current	*G. Rec.*	0.00	**-0.36**	**-0.38**	0.03	-0.03	0.09
State	*Cluster 1*	**-0.02**	-0.02	0.34	-	-	-
(z_t)	*Cluster 2*	-0.02	-0.02	-	0.14	-	-
	Cluster 3	-0.01	0.43	-	-	-0.18	-
	Cluster 4	-0.01	-0.02	-	-	-	-0.22

(b) Equity Returns

		Previous State (z_{t-1})					
		G. Exp.	*G. Rec.*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
	G. Exp.	0.06	0.02	**0.42**	-0.02	**0.51**	-0.27
Current	*G. Rec.*	0.00	**-0.54**	-0.10	0.01	0.13	-0.05
State	*Cluster 1*	-0.01	0.05	-0.32	-	-	-
(z_t)	*Cluster 2*	-0.02	0.04	-	0.01	-	-
	Cluster 3	-0.01	**0.39**	-	-	**-0.63**	-
	Cluster 4	-0.01	0.05	-	-	-	0.31

(c) Housing Prices

		Previous State (z_{t-1})					
		G. Exp.	*G. Rec.*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
	G. Exp.	**0.16**	0.02	0.05	-0.10	0.08	-0.06
Current	*G. Rec.*	0.00	-0.26	0.21	**-0.18**	0.05	-0.05
State	*Cluster 1*	-0.01	0.09	-0.26	-	-	-
(z_t)	*Cluster 2*	0.02	0.09	-	0.28	-	-
	Cluster 3	**-0.16**	-0.01	-	-	-0.12	0.00
	Cluster 4	0.00	0.08	-	-	-	0.11

(d) Oil Price Shock

		Previous State (z_{t-1})					
		G. Exp.	*G. Rec.*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
	G. Exp.	**0.18**	0.02	0.03	**0.23**	-0.13	0.05
Current	*G. Rec.*	-0.01	0.13	-0.05	0.03	0.17	0.10
State	*Cluster 1*	**-0.04**	0.07	0.02	-	-	-
(z_t)	*Cluster 2*	**-0.09**	0.07	-	**-0.26**	-	-
	Cluster 3	0.00	-0.35	-	-	-0.04	-
	Cluster 4	-0.05	0.07	-	-	-	-0.15

(e) Geopolitical Risk

		Previous State (z_{t-1})					
		G. Exp.	*G. Rec.*	*Cluster1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
	G. Exp.	**-0.13**	0.01	-0.08	0.04	**0.12**	**0.39**
Current	*G. Rec.*	0.00	0.06	**-0.46**	-0.03	-0.04	0.11
State	*Cluster 1*	0.01	0.05	**0.54**	-	-	-
(z_t)	*Cluster 2*	**0.06**	0.05	-	-0.01	-	-
	Cluster 3	**0.06**	-0.23	-	-	-0.09	-
	Cluster 4	0.00	0.05	-	-	-	**-0.50**

This table shows the effects of external shocks on the transition process of the aggregate regime z_t. We present the marginal effects π^i_{ji} for each covariate on each transition probability $p_{t,ji}$. Explicitly, these marginal effects are calculated as in equation (5).

Table 7: Output Forecast Comparison

	AR(1)	*MS*	*GVAR*	*MSC-FTP*
Argentina	**1.04**	**1.36*****	**1.11***	0.94
Australia	**1.96*****	**1.04**	**1.25***	**1.11**
Austria	**1.18**	**1.31***	0.84	**1.03****
Belgium	0.82	**1.62*****	**1.27**	**1.02*****
Brazil	**1.07**	**1.10**	**1.03**	**1.01**
Canada	**1.04**	**1.22**	0.96	0.97
Chile	**1.13**	**1.26*****	**1.08**	**1.04*****
China	0.95	0.75	0.65**	0.78
Denmark	**1.27****	**1.36*****	0.98	**1.02****
Finland	**1.24***	**1.90*****	**1.77****	0.98
France	0.67	**1.06**	0.86	**1.09****
Germany	**1.09**	**1.76**	**1.33**	**1.08*****
Hong Kong	**1.33***	**1.57*****	**1.37**	**1.14**
India	**1.67*****	1.00	**1.11***	**1.01***
Indonesia	**1.07**	**1.46***	**1.55***	**1.03***
Ireland	**1.50*****	**2.14*****	**2.22***	**1.04*****
Italy	0.57	**1.18**	0.73	**1.09****
Japan	0.84	**1.09**	**1.13**	1.00
Korea	0.62	0.92	0.77	0.92
Luxembourg	**1.45*****	**1.19***	**1.15***	**1.01**
Malaysia	**1.10**	**1.22***	**1.12**	**1.04***
Mexico	**1.00**	**1.80*****	**1.42***	**1.02**
Netherlands	**1.66*****	**2.02*****	**1.38*****	**1.15*****
New Zealand	**1.41*****	0.98	**1.33*****	0.95
Norway	**1.05**	**1.23*****	0.89	1.00
Philippines	**2.87*****	0.81	**1.07**	**1.01**
Portugal	0.66	0.95	0.75*	**1.06****
Singapore	**1.31***	**1.27****	**1.16**	**1.10***
South Africa	**1.48*****	**1.26***	0.86	**1.17*****
Spain	0.47	0.82	0.62	**1.09***
Sweden	**1.62*****	**1.38**	**1.28**	0.92
Switzerland	**1.11**	**1.31***	**1.03**	0.98
Taiwan	**1.06**	**1.19****	0.99	**1.03**
Thailand	**1.44**	**1.25**	**1.21**	**1.05**
United Kingdom	0.97	0.95	0.83	**1.01***
United States	**1.12**	**1.26****	**1.02**	**1.11**
Venezuela	**1.20**	**1.02**	**1.30**	0.94
Overall	**1.18*****	**1.27*****	**1.16*****	**1.02**

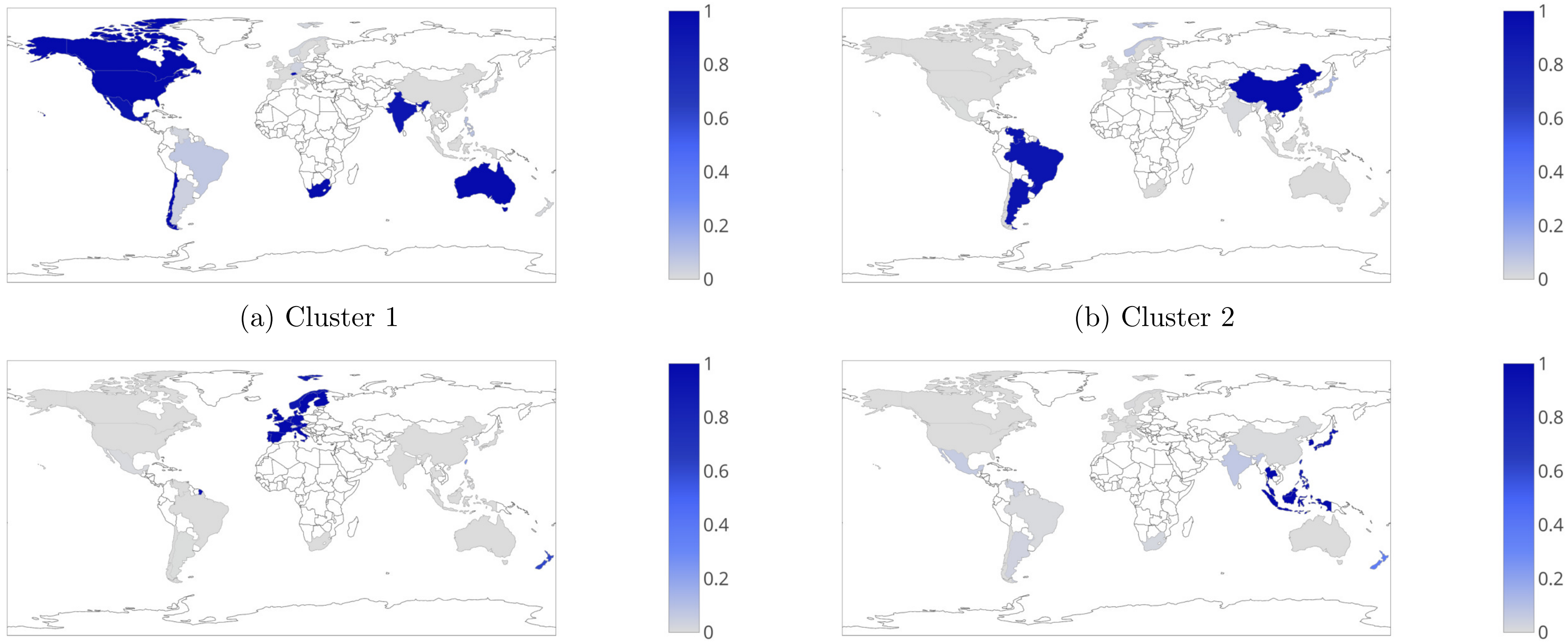
This table shows the relative mean squared forecast error (MSFE) for each country using four different models: a univariate autoregression (*AR(1)*), a univariate Markov-switching model (*MS*), a Global VAR model (*GVAR*), and the time-series clustering model of Hamilton and Owyang (2012) with fixed transition probabilities (*MSC-FTP*) . Each model's MSFE is normalized by the MSFE of this paper's time-series clustering model with Markov-switching (*MSC-TVTP*). The last row shows the relative MSFE when forecasting the entire vector of countries. Bold indicates the respective model has a higher MSFE than the MSC-TVTP model. Stars represent significant results from a Diebold-Mariano test (first three columns) or Clark-West test (last column) of equal predictive accuracy. *** $p < 0.01$, **$p < 0.05$, *$p < 0.01$

Table 8: Recession Forecast Comparison

	MS	*MSC-FTP*
Argentina	-	-
Australia	**1.30**	0.95
Austria	**1.50*** **	**1.09**
Belgium	**1.16***	**1.23*** **
Brazil	**1.06**	**1.24*** **
Canada	**1.04**	**1.09**
Chile	0.98	**1.30*** **
China	0.79	**1.09**
Denmark	**1.03**	**1.04**
Finland	0.97	**1.20** **
France	1.00	**1.20** **
Germany	**1.29**	**1.12***
Hong Kong	-	-
India	**1.03**	**1.09**
Indonesia	**1.14**	**1.08**
Ireland	**1.39**	**1.12***
Italy	**1.20**	**1.18** **
Japan	**1.02**	0.88
Korea	0.75	**1.02**
Luxembourg	0.96	**1.07**
Malaysia	-	-
Mexico	**1.04**	**1.28*** **
Netherlands	**1.45*** **	**1.10**
New Zealand	**1.14**	**1.02**
Norway	**1.15**	**1.09**
Philippines	-	-
Portugal	**1.01**	0.97
Singapore	-	-
South Africa	**1.01**	**1.09**
Spain	**1.16**	**1.01**
Sweden	**1.81*** **	**1.10**
Switzerland	**1.02**	**1.34*** **
Taiwan	-	-
Thailand	-	-
United Kingdom	0.92	**1.33*** **
United States	**1.06**	**1.09**
Venezuela	-	-

This table shows the relative area under the receiver operating characteristic curve (AUROC) for each country using two different models: a univariate Markov-switching model (*MS*) for each country and the time-series clustering model of Hamilton and Owyang (2012) with fixed transition probabilities (*MSC-FTP*). Specifically, the table reports the AUROC from the baseline model – this paper's time-series clustering model with Markov-switching – with equity returns as the transition covariate divided by each respective model's AUROC. Each model's AUROC is normalized by the AUROCBold indicates the MSC-TVTP model has a higher AUROC than the respective model. Stars represent significant results from DeLong's test of equal predictive accuracy. *** $p < 0.01$, **$p < 0.05$, *$p < 0.01$

Figure 1: Probability of Cluster Membership



(a) Cluster 1

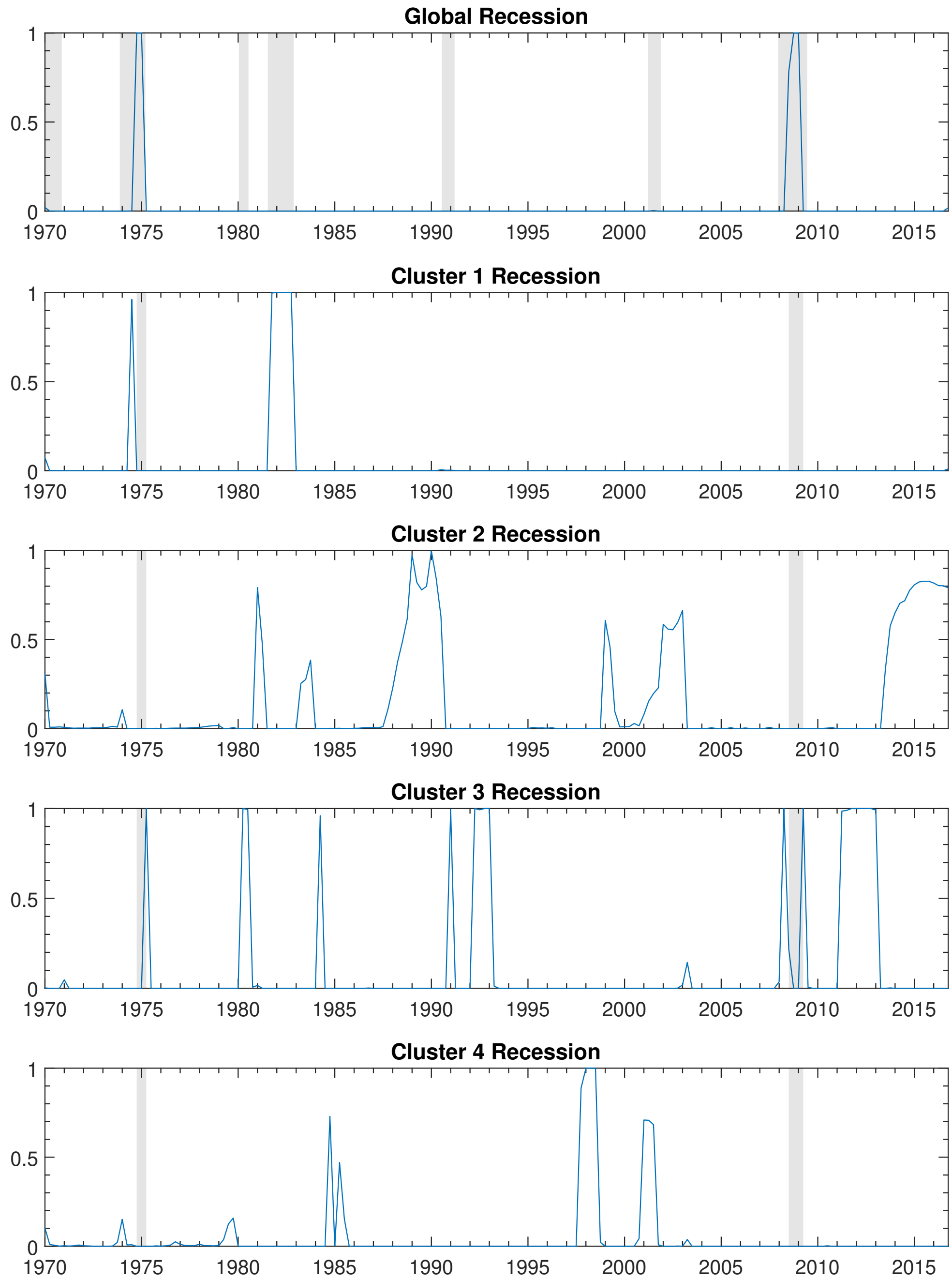
(b) Cluster 2

(c) Cluster 3

(d) Cluster 4

This figure presents the posterior probabilities of cluster membership based on the country-specific characteristics (i.e., trade openness, industrialization, etc.) as well as comovement across the full time-series of output growth. Countries in white are not included in the sample.

Figure 2: Recession Probabilities



This figure shows the mean posterior probability of recession for the world (top panel) as well as each idiosyncratic cluster (bottom four panels). The gray bars in the top panel reflect official NBER U.S. recession dates. The gray bars in the bottom four panels represent the global recession dates from the top panel.