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 similarities in business cycle turning points. We find four groups, or "clusters", of countries which experience idiosyncratic recessions relative to the global cycle. Additionally, we find the primary indicators of international recessions to be fluctuations in equity markets and geopolitical uncertainty. 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 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

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

innovation being the inclusion of time-varying transition probabilities (TVTP). TVTP models have two advantages over FTP alternatives. First, regimes can also 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 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 asset prices. This result reinforces the finding by Reinhart and Rogoff (2009) and Helbling, Kose, and Otrok (2011) of the importance of financial markets in propagating

[2]For example, Claessens, Kose, and Terrones (2008) find that recessions associated with negative 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.

recessions to a global level. Given these findings, we consider whether asset prices 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. 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. Let y_{nt} be the growth rate of real GDP for country n at time period t. Let 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_{0n}, and the average growth rate in recession is $\mu_{0n} + \mu_{1n}$. The multi-country regime-switching model is given by

$$\boldsymbol{y}_t = \boldsymbol{\mu}_0 + \boldsymbol{\mu}_1 \odot \boldsymbol{s}_t + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \overset{i.i.d}{\sim} N(\boldsymbol{0}, \boldsymbol{\Sigma}), \tag{1}$$

where $\boldsymbol{y}_t = [y_{1t}, \ldots, y_{Nt}]'$, $\boldsymbol{s}_t = [s_{1t}, \ldots, s_{Nt}]'$, $\boldsymbol{\mu}_0 = [\mu_{01}, \ldots, \mu_{0N}]'$, $\boldsymbol{\mu}_1 = [\mu_{11}, \ldots, \mu_{1N}]'$, 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.

We impose the identifying restrictions $\mu_{0n} \geq 0$ and $\mu_{1n} < 0$ for all n. These restrictions identify the business cycles states by ensuring that on average countries grow faster during expansions relative to recessions.[3] We also need the restrictions to avoid label switching between the two worldwide states and two growth rate parameters during estimation.

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

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.[4] In the case of full dependence, all countries follow the same cycle and can therefore be summarized by a single global regime indicator. In the case of full independence, each country's cycle is estimated separately from the others', assuming that each country's business cycle state offers no information for other countries' states. We opt for an intermediate assumption wherein we model a global business cycle but allow for deviations for K groups—or "clusters"—of countries. Following HO and FOS, we determine cluster composition endogenously through similarities in movements in economic growth as well as a set of country-specific characteristics that enter through the prior distribution.[5]

Define an aggregate latent regime variable $z_t \in \{1, \ldots, K, K+1, K+2\}$ indicating which cluster of countries is in recession at time t. Associated with each aggregate state

[3] We do not restrict the average growth rate in recessionary periods ($\mu_{0n} + \mu_{1n}$), thus allowing for the possibility of postive growth in recessions.

[4] Full independence implies that for two countries A and B, the business cycle regimes for each country $s_{A,t}$ and $s_{B,t}$ satisfy $\Pr(s_{A,t} = i, s_{B,t} = j) = \Pr(s_{A,t} = i) \Pr(s_{B,t} = j)$. Or equivalently, $\Pr(s_{A,t} = i | s_{B,t} = j) = \Pr(s_{A,t} = i)$. That is, the state of Country B's business cycle offers no information on the state of Country A's cycle.

[5] See also Frühwirth-Schnatter and Kaufmann (2008). The time-series clustering framework reduces these possible values to $K+2$ (where $K+2 << 2^N$), giving us a numerically tractable model.

$z_t = k$ is a $(N \times 1)$ vector $\boldsymbol{h}_k = [h_{1k}, \ldots, h_{Nk}]'$, 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.

Selecting the $K+2$ clusters to include out of the 2^N possible combinations is a model selection issue. We opt to always include the two "global" clusters: when all countries are simultaneously in either recession or expansion. *Ex ante*, we associate these global clusters with 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, $\boldsymbol{h}_{K+2} = [1, \ldots, 1]'$).

For the remaining aggregate regimes $z_t = 1, \ldots, K$, a group of countries is in recession while all remaining countries are in expansion. Membership of country n in cluster k—denoted by h_{nk}—is another unobserved variable, inferred from similar movements in economic growth as well as country-specific covariates which enter through a hierarchal prior specification. Following FOS, we restrict each country to be a member of one and only one idiosyncratic cluster (i.e., $\sum_{k=1}^{K} h_{nk} = 1$).[6]

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

$$\boldsymbol{m}_k = \boldsymbol{\mu}_0 + \boldsymbol{\mu}_1 \odot \boldsymbol{h}_k.$$

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 also a "black box" with constant regime duration. A framework where the expected duration

[6] This assumption uncovers the "strongest" comovement relationships across countries; whereas leaving cluster membership unrestricted would offer the flexibility to capture relatively weaker instances of economic comovement.

of a regime depends on current 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.[7] 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. Following Kaufmann (2015), we adopt a centered parameterization in order to identify the time-varying and time-invariant portions of the transition probabilities. Formally, the TVTP takes the multinomial logistic representation:

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

where $\boldsymbol{\gamma}^v_{ji}$ is a $(L \times 1)$ vector of coefficients for the transition covariates and γ_{ji} is the time-invariant transition parameter.[8] We set the arbitrary threshold vector $\bar{\boldsymbol{v}}$ to be the mean of the covariates. For identification purposes, we define the $K + 2$ state as the reference state, implying $\boldsymbol{\gamma}^v_{K+2,i} = \mathbf{0}_{L+1}$ and $\gamma_{K+2,i} = 0$ for all $i = 1, \ldots, K + 2$. 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.

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 $i \neq j$, $i \leq K$, and $j \leq K$ [see the discussion in HO]. Thus, individual clusters experience recessions relative to the world, but not directly following another cluster experiencing its own recession in the previous period.[9]

[7]Time-varying transition probabilities were first considered by Diebold, Lee, and Weinbach (1994), Filardo (1994), Filardo and Gordon (1998), and more recently by Kim, Piger, and Startz (2008), Kaufmann (2015), and Bazzi et al. (2016).

[8]Note that the framework with time-varying transition probabilities nests the simpler fixed transition probability setup. In the FTP case, $\boldsymbol{\gamma}^v_{ji} = \mathbf{0}$ for all i, j.

[9]This assumption focuses our attention on cluster deviations from the global business cycle (rather than between clusters) and significantly reduces the number of parameters to be estimated.

3 Estimation

We use the Bayesian technique of Gibbs sampling [Gefland and Smith (1990), Casella and George (1992), Carter and Kohn (1994)] to estimate the model. Gibbs sampling is a Markov-chain Monte Carlo (MCMC) technique which separates the model parameters and latent variables into blocks. Each block 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 $\boldsymbol{\theta}_n = \{\mu_{n0}, \mu_{n1}, \sigma_n^2\}$. The second 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, $\boldsymbol{x}_{nk}$:

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

with the normalizing assumption $\boldsymbol{\beta}_1 = \mathbf{0}$. This framework allows countries to endogenously cluster based on comovements in real GDP growth and country-specific covariates rather than imposing country groupings exogenously.

3.2 Posterior Inference

In this section, we give a brief overview of the posterior draws. Appendix A outlines the specifics of each sampling step in further detail. We draw each country's individual parameter set $\boldsymbol{\theta}_n = \{\mu_{n0}, \mu_{n1}, \sigma_n^2\}$ conditional on knowing all other countries' 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 $p(Y|\Theta_K)$ 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 et al (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 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.[10] The OE data runs from 1980:Q1 - 2016:Q4 which results in an unbalanced panel when grouped with the OECD dataset.[11]

[10] 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, Thailand, and Venezuela.

[11] 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.

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. 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.[12]

With the exception of the financial integration, oil rents, and supply chain variables, the measures that we use were used in FOS. Recent theoretical studies reached conflicting conclusions of how financial openness affects synchronization [see the discussion in Kalemi-Ozcan (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), Kalemli-Ozcan et al. (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

[12] 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 oil productions 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 WTO.

goods from other countries in their production process 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 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 regions. For details about the motivation for including the remaining covariates, we refer the reader to FOS.

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.[13] The bottom panel of Table 2 lists the sources for each transition covariate as well as any transformations made to the raw data.

The first transition covariate we examine is the term spread, which has been shown to forecast both output and business cycle turning points.[14] 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.[15]

We also include the return on a stock market index, measured as the log difference

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

[14]See Stock and Watson (1989), Estrella and Mishkin (1998), Kauppi and Saikkonen (2008), among many others. Wheelock and Wohar (2009) survey the literature on the relationship between the term spread and economic activity.

[15]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.

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 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 et al. (2009, 2012)]. Thus, we include the log difference of the Federal Reserve Bank of Dallas' Global Real Housing Price Index. Claessens et al. (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.[16] Increases in 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 of oil prices.[17]

Our final transition covariate is the historical Geopolitical Risk (GPR) Index from Caldara and Iacoviello (2017). The GPR Index is constructed based on the frequency that

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

[17] 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.

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.

5 Results

We approximate the joint posterior distribution of the model with 20,000 iterations of the Gibbs sampler after an initial burn-in period 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.[18]

Table 3 reports the estimates for each country's state-dependent growth rate (μ_{0n} and $\mu_{0n}+\mu_{1n}$) and standard deviation parameters (σ_n). As expected, developed countries tend to have lower growth rates in both expansion and 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

[18]Model selection results are available from the authors upon request.

associate a country with the cluster for which it has the highest posterior probability of inclusion.

Cluster 1 is comprised of Argentina, Brazil, Venezuela, and China, which has extensive trade with these South American countries. Cluster 2 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 3 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. Cluster 4 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 4.[19]

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. Explicitly, the marginal effect of covariate q on the probability of any given country being a member of cluster k is

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

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

[19]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) find a Southeast Asian cluster similar to the composition of Cluster 3 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.

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 North American countries being in Cluster 2, Asian countries in Cluster 3, and European countries in Cluster 4.

Beyond geographic proximity, a number of country-specific covariates influence cluster composition: the level of economic development (Cluster 1), openness to trade (Clusters 2 and 3), and language or cultural commonality (Clusters 2 and 4). For example, a country with a capital-output ratio one-standard-deviation below average (i.e., a high degree of industrialization) is *a priori* 29% less likely of being included in Cluster 1 than to a country with a capital-output ratio one-standard-deviation *above* average (i.e., a low 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.

5.2 Recession Timing and Determinants

The international business cycle state variable z_t—which determines the business cycle phase of all the countries—can take one of six possible values at any given time period. By definition, the first 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, 3, and 4) are in expansion.

5.2.1 Recession Timing

Figure 2 shows the posterior probabilities of being in a regime at any given time period.[20] The top panel shows the probability of global recession along with gray bars representing official NBER U.S. recession dates for the sake of comparison. Consistent with Kose and Terrones (2015) and Fushing et al. (2010), we find two instances of a global recession: (1) 1974:Q4-1975:Q1 (OPEC embargo) and (2) 2008:Q3-2009:Q1 (the recent global financial crisis).[21] 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 global events. The first oil crisis follows a recession in Cluster 2 (English-industrial) and the recent global financial crisis is both preceded and followed by a recession in Cluster 4 (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 2, we compare the recession timing of this cluster to the NBER recession dates.[22] One should not expect Cluster 2 recession dates to perfectly align with every NBER recession as the U.S is only one member of said cluster. Therefore, the NBER dates are not a exact benchmark, but are 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 1980, 1991, and early 2000s as cluster-wide. The latter dates are either not pervasive enough to warrant a cluster-wide recession, or a "stronger" recession occurs in another cluster during these periods.

Cluster 4'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

[20]We omit the global expansion regime since it can be calculated as the residual of all the other regimes.

[21]Using annual data on the growth rate of world GDP per capita, Kose and Terrones (2015) find additional global downturns during 1982 and 1991. Thus, their measure of the global cycle is a weighted average of output while our measure weights all countries equally. Using monthly data for individual countries, Fushing et al. (2010) find global downturns during 1980:04 and 2000:08 - 2001:05. However, they simply look at correlated movements, where we look at common movement in a large panel of countries in a single model.

[22]To get the complete recession timing of Cluster 2, we combine the Global Recession timing as well as the idiosyncratic recession timing of Cluster 2.

not a comparable accepted timeline of business cycle dates. However, Cluster 3's recession dates generally coincide with major economic events in Asia during the respective time period.[23]

Table 5 shows the estimated transition probabilities if the transition covariates were at their sample average. These estimates capture the time-invariant portion of the transition dynamics for the aggregate regime z_t. For example, the probability of being in a global expansion regime at time t (i.e., $z_t = 1$) is 0.89 given that the previous state was a global expansion and the transition covariates are at their average values. From a global expansion, the most likely recession will occur in Cluster 1. The global recession regime is not persistent (0.28) and there is a high probability of experiencing an idiosyncratic recession in Cluster 3 when exiting a global recession. Cluster 1 recessions are highly persistent (0.98) and tend to be followed by global expansion states. Similarly, Cluster 3 and Cluster 4 recessions are more likely to transition to global expansions whereas Cluster 2 recessions have a higher probability of turning into global recessions.

5.2.2 Determinants of Recession Timing

Our main methodological contribution is the addition of time-varying transition probabilities. This addition allows us to evaluate which of the transition variables discussed above precede changes in the aggregate business cycle state.

Table 6 displays the posterior mean of the marginal effects for each of the transition covariates; bold indicates that the 68% posterior coverage excludes zero. These marginal effects can be interpreted as how each covariate affects the transition probabilities.[24] The numbers in each panel show by how much the transition probability changes when the variable rises from one standard deviation below the mean to one standard deviation above.

[23] 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.

[24] The marginal effects are calculated as follows: Suppose covariate l is one standard deviation above its historical mean while all other covariates are at their respective historical means. We can then calculate the associated "high" transition probability p_{ji}^H. Similarly, we can calculate the "low" transition probability p_{ji}^L by assuming the covariate is one standard deviation below its historical mean. The marginal effect is the difference between the two probabilities: $\pi_{ji}^l = p_{ji}^H - p_{ji}^L$.

By far, the two most important transition covariates are the term spread and equity prices. A rising term spread increases global expansion persistence by 13 percent, suggesting that long global expansions are characterized by an upward sloping yield curve.[25] 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 regional recessions blossom into global recessions.

Equity returns have similar effects on cycle transitions. In particular, higher equity returns correlate with more persistent global expansions. They also increase the likelihood that regional recessions in industrialized countries (Clusters 2 and 4) 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 et al. (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.

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 4 recession.

Rising oil prices also increase the persistence of global expansions. While this may

[25] We are not suggesting causality of the covariates. Rather we are describing the transition dynamics through the covariates. A longer persistence of a global expansion could increase the term spread, thereby illustrating causality from the recession dynamics to the covariates.

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.

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 1) and Europe (Cluster 4), raising the likelihood a recession specific to each of these two regions by about 10 percentage points each. Geopolitical risk also increases the persistence of recessions in the English-speaking industrialized region (Cluster 2).

6 Forecasting

The previous section considered in-sample estimation of the model. One of the advantages of using 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.

6.1 Output Growth Forecasts

We compare the output growth forecasting ability of our time-series clustering framework to an AR(1) model, a two-regime univariate Markov-switching model, and the Markov-switching clustering model with fixed transition probabilities (MSC-FTP) from HO. The MSC-FTP provides a natural benchmark since the only difference from our model is the evolution of the state variable, which follows fixed transition probabilities in the MSC-FTP and time-varying transition probabilities in our model. This comparison allows us to test if the covariates influencing the time-varying transition probabilities have any additional forecasting value.

We conduct pseudo out-of-sample forecasts by using a subset of the entire data sample and iterate each model forward to create forecasts up until the end of the sample. We compute each model's mean-squared forecast error (MSFE) from the median posterior forecast for each period, which will be our criterion for a model's forecasting ability.

Explicitly, the complete process for computing a model's MSFE is:

1. Trim the sample to $\boldsymbol{Y}^{\boldsymbol{\tau_0}} = \{Y_1, ..., Y_{\tau_0}\}$ where $\tau_0 < T$.
2. Estimate each model using the smaller sample $\boldsymbol{Y}^{\boldsymbol{\tau_0}}$.
3. Compute each model's forecast for $\hat{Y}_{\tau_0+1|t}$.
4. Calculate the forecast error: $Y_{\tau_0+1} - \hat{Y}_{\tau_0+1|t}$.
5. Repeat steps 1 - 4 by iterating the sample one time-period forward: $\boldsymbol{Y}^{\boldsymbol{\tau_0+1}} = \{Y_1, ..., Y_{\tau_0}, Y_{\tau_0+1}\}$, ... , $\boldsymbol{Y}^{\boldsymbol{T-1}} = \{Y_1, ..., Y_{\tau_0}, Y_{T-1}\}$.
6. Compute the MSFE:

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

We estimate each model using 30,000 iterations of the Gibbs Sampler for each subsample. To computing the MSFE, we use the median posterior forecast for each shortened sample.[26] We choose τ_0 so that 60% of the data is in the initial pseudo sample.

Table 7 shows the MSFE for each country in the sample as well as the panel MSFE. For 19 of the 37 countries in the sample, the Markov-switching clustering framework with TVTP (MSC-TVTP) has a lower MSFE than any of the alternative models. Similarly, our model does better when forecasting the entire vector of countries, as indicated by the last row of the table. For 26 of the 37 countries, the MSC-TVTP forecasts output growth as good or 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.

There are two explanations for why our time-series clustering model with regime-switching improves on the forecasting ability of both the AR(1) and MS models. The

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

first advantage from our model is the information gained from common recessions, which allows for some feedback in the cross-section. The second advantage is the forward-looking nature of the transition covariates which signal an impending cluster-specific or global recession prior to movements in output growth. However, these features do not always improve the forecasting ability of our model over the alternative models for each country individually.

For nine of the countries in our sample, the simple AR(1) model provides the best forecast. For these countries, the information gained from last period's growth rate outweighs the gains from cross-sectional recessions and the transition covariates. We could sacrifice parsimony by including autoregressive terms in our time-series clustering framework which could potentially capture these dynamics. The univariate MS model is the best forecasting model only for three countries: China, India, and the Philippines. For these countries, the superiority of the univariate MS model can be explained by more country-specific recessions which are not captured in our limited clustering framework that is built to consider recessions across a large number of countries.

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, $\hat{\boldsymbol{s}}_{t+1|t}$, in a similar manner to the process outlined for obtaining output forecasts. However, we use the receiver operating characteristic (ROC) curve to conduct model comparison rather than MSFE. 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 metric for binary classification variables such as recession indicators. For observed recession dates, we use the OECD Composite Leading Indicators reference turning points.[27]

We consider three models that provide recession dating: (1) a two-regime univariate Markov-switching model (*MS*), (2) the MSC-FTP model from HO, and (3) this paper's

[27] 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.

MSC-TVTP model. However, we use global equity returns as the only transition covariate in the MSC-TVTP model due to their forward-looking nature and to eliminate any noise from the other covariates.

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. For 16 of the 29 countries with recession dates, the MSC-TVTP model forecasts recessions as good or better than either the MS or MSC-FTP model. For 12 of the countries, the univariate MS model is strictly 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 two countries (Canada and Japan), our model with time-varying transition probabilities has a larger AUROC than HO's model with fixed transition probabilities (i.e., MSC-FTP). This improved forecasting ability is solely due to the inclusion of equity returns influencing the transition probabilities. Due to the forward looking nature of equity returns, this improvement in forecasting recessions makes intuitive sense. However, since the returns are based on a global equity series and not country-specific, our TVTP model does not necessarily improve recession forecasting for every country, as illustrated by Canada and Japan.

7 Conclusion

In this paper, we analyzed the relationship between the world business cycle and the underlying cycles of groups of countries. We outlined a multivariate Markov-switching model with endogenously clustering and time-varying transition probabilities, allowing us to determine which country-characteristics determine business cycle synchronization and which macroeconomic shocks drive international business cycles.

We found four groups of countries that experience idiosyncratic recessions relative to global downturns. Geographic proximity appears to be an important determinant of synchronization across countries, but we also find important roles for trade openness, stage of development, and institutional factors such as linguistic diversity. This finding implies that studies on international business cycle synchronization need to consider a host of factors when grouping countries.

We analyzed the driving forces behind recession timing of these idiosyncratic clusters, and found asset prices to be a key indicator of the timing of global recessions. Additionally we found the European clusters to be highly sensitive to movements in housing and 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. Further investigation into the forecasting ability of our model showed that our time-series clustering model is better at forecasting output growth in aggregate as well as country-level recessions.

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A Estimation Details

This section gives the technical details of the Gibbs sampling technique utilized to estimate the model. The steps of the sampler are virtually identical to those outlined by HO with the exception of the TVTP parameter draw, which is outlined by Frühwirth-Schnatter and Frühwirth (2010) and Kaufmann (2015). There are four steps:

1. Draw the mean growth and variance parameters from $p(\boldsymbol{\theta}|\Theta_{-\boldsymbol{\theta}}, \boldsymbol{Y})$.

2. Draw the aggregate state vector from $p(\boldsymbol{Z}|\Theta_{-\boldsymbol{Z}}, \boldsymbol{Y})$.

3. Draw the transition probability parameters from $p(\boldsymbol{\gamma}|\Theta_{-\boldsymbol{\gamma}}, \boldsymbol{v})$.

4. Draw the cluster membership vector and prior hyperparameters from $p(\boldsymbol{H}|\Theta_{-\boldsymbol{H}}, \boldsymbol{Y}, \boldsymbol{x})$.

A.1 Conditional Likelihood

The likelihood conditional on the model parameters and latent variables is given by

$$p(\boldsymbol{Y}|\Theta) = \prod_{n=1}^{N} p(\boldsymbol{Y}_n|\boldsymbol{\theta}_n, \boldsymbol{Z}, h),$$

$$p(\boldsymbol{Y}_n|\boldsymbol{\theta}_n, \boldsymbol{Z}, h) = \prod_{t=1}^{T} p(y_{nt}|\boldsymbol{\theta}_n, z_t, h),$$

$$p(y_{nt}|\boldsymbol{\theta}_n, z_t, h) \propto \sigma_n^{-1} \exp\left\{\frac{-\left[y_{nt} - \boldsymbol{\mu}_n' \boldsymbol{w}\left(z_t, h\right)\right]^2}{2\sigma_n^2}\right\},$$

where

$$\boldsymbol{w}\left(z_t, h\right) = \left[1, h_{n,z_t}\right]'.$$

A.2 Draw $\boldsymbol{\theta}$ given $\Theta_{-\boldsymbol{\theta}}, \boldsymbol{Y}$

We draw $\boldsymbol{\theta}_n$ conditional on knowing all other countries' growth rate and error variance parameters. We then separate the draw of $\boldsymbol{\theta}_n$ into a step of drawing the error variance conditional on the growth rates, then drawing the growth rates conditional on the new draw of the error variance.

Country n's error variance is drawn from an inverse-gamma distribution:

$$\sigma_n^{-2} \sim \Gamma\left(\frac{\nu_0 + T}{2}, \frac{\tau_0 + \hat{\tau}}{2}\right),$$

where

$$\hat{\tau} = \sum_{t=1}^{T} \left[y_{nt} - \boldsymbol{\mu}_n' \boldsymbol{w}\left(z_t, h\right)\right]^2.$$

We draw the mean growth rate parameters for country n from a normal distribution:

$$\boldsymbol{\mu}_n \sim N\left(\boldsymbol{m}_n, \sigma_n^2 \boldsymbol{M}_n\right),$$

where

$$\boldsymbol{m}_n = \boldsymbol{M}_n \left[\boldsymbol{M}_0^{-1} \boldsymbol{m}_0 + \sum_{t=1}^{T} \boldsymbol{w}(z_t, h) y_{nt}\right],$$

and

$$\boldsymbol{M}_n = \left[\boldsymbol{M}_0^{-1} + \sum_{t=1}^{T} \boldsymbol{w}(z_t, h) \boldsymbol{w}(z_t, h)'\right]^{-1}.$$

A.3 Draw $\boldsymbol{Z}$ given $\Theta_{-\boldsymbol{Z}}, \boldsymbol{Y}$

Following HO, we have

$$p\left(\boldsymbol{Z} | \Theta_{-\boldsymbol{Z}}, \boldsymbol{Y}\right) \propto p(\boldsymbol{Y} | \Theta) p(\boldsymbol{Z} | \boldsymbol{\gamma}),$$

where the likelihood conditional on the model parameters and latent variables is given by

$$p(\boldsymbol{Y} | \Theta) = \prod_{n=1}^{N} p(\boldsymbol{Y}_n | \boldsymbol{\theta}_n, \boldsymbol{Z}, h),$$

$$p(\boldsymbol{Y}_n | \boldsymbol{\theta}_n, \boldsymbol{Z}, h) = \prod_{t=1}^{T} p(y_{nt} | \boldsymbol{\theta}_n, z_t, h),$$

$$p(y_{nt} | \boldsymbol{\theta}_n, z_t, h) \propto \sigma_n^{-1} \exp\left\{\frac{-\left[y_{nt} - \boldsymbol{\mu}_n' \boldsymbol{w}\left(z_t, h\right)\right]^2}{2\sigma_n^2}\right\},$$

$$\boldsymbol{w}\left(z_t, h\right) = \left[1, h_{n, z_t}\right]'.$$

Chib (1996) shows that

$$p\left(\boldsymbol{Z}|\Theta_{-\boldsymbol{Z}},\boldsymbol{Y}\right)=p\left(z_T|\boldsymbol{Y},\boldsymbol{\theta},\boldsymbol{\gamma},h\right)\prod_{t=1}^{T-1}p\left(z_t|z_{t+1},\dots,z_T,\boldsymbol{Y},\boldsymbol{\theta},\boldsymbol{\gamma},h\right).$$

Since z_{t+1} contains all information about z_t embodied by future z or y, we get

$$p\left(\boldsymbol{Z}|\Theta_{-\boldsymbol{Z}},\boldsymbol{Y}\right)=p\left(z_T|\mathcal{Y}_T,\boldsymbol{\theta},\boldsymbol{\gamma},h\right)\prod_{t=1}^{T-1}p\left(z_t|z_{t+1},\mathcal{Y}_t,\boldsymbol{\theta},\boldsymbol{\gamma},h\right),$$

where $\mathcal{Y}_t=\{y_{\tau n}:\tau\leq t;n=1,\dots,N\}$.

Implementing the filter outlined by Hamilton (1989), we calculate the filter density, $p\left(z_t|\mathcal{Y}_t,\boldsymbol{\theta},\boldsymbol{\gamma},h\right)$, for $t=1,\dots,T$. We then draw the terminal state, z_T, from the final filter density, $p\left(z_T|\mathcal{Y}_T,\boldsymbol{\theta},\boldsymbol{\gamma},h\right)$, and proceeding recursively we draw $z_{T-1},\dots,z_1$ from the updated filter densities:

$$p\left(z_t|z_{t+1},\mathcal{Y}_t,\boldsymbol{\theta},\boldsymbol{\gamma},h\right)=\frac{p_{z_{t+1},z_t}\left(\boldsymbol{v}_t\right)p\left(z_t|\mathcal{Y}_t,\boldsymbol{\theta},\boldsymbol{\gamma},h\right)}{\sum_{k=1}^{K+2}p_{z_{t+1},k}\left(\boldsymbol{v}_t\right)p\left(z_t=k|\mathcal{Y}_t,\boldsymbol{\theta},\boldsymbol{\gamma},h\right)}$$

where $p_{ji}\left(\boldsymbol{v}_t\right)$ are the time-varying transition probabilities.

A.4 Draw $\boldsymbol{\gamma}$ given $\Theta_{-\gamma},\boldsymbol{v}$

This step follows closely the sampler outlined by Kaufmann (2015). The estimation method assumes the state variable is determined by underlying state utility. Specifically, $z_t=j$ if and only if $U_{j,t}=\max_k U_{k,t}$, where

$$U_{k,t}=\boldsymbol{V}'_{k,t}\gamma_k+\eta_{k,t},\qquad k=1,\dots,K+2,$$

$$\boldsymbol{V}_{k,t}=\begin{cases}\left[\boldsymbol{v}_tI_{[z_{t-1}=1]},\dots,\boldsymbol{v}_tI_{[z_{t-1}=K+2]},I_{[z_{t-1}=1]},\dots,I_{[z_{t-1}=K+2]}\right]' & \text{if } k=1,2\\ \left[\boldsymbol{v}_tI_{[z_{t-1}=1]},\boldsymbol{v}_tI_{[z_{t-1}=2]},\boldsymbol{v}_tI_{[z_{t-1}=k]},I_{[z_{t-1}=1]},I_{[z_{t-1}=2]},I_{[z_{t-1}=k]}\right]' & \text{if } k=3,\dots,K+2\end{cases},$$

$$\boldsymbol{\gamma}_k=\begin{cases}\left[\boldsymbol{\gamma}^{v\prime}_{k1},\dots,\boldsymbol{\gamma}^{v\prime}_{kK+2},\gamma_{k1},\dots,\gamma_{kK+2}\right]' & \text{if } k=1,2\\ \left[\boldsymbol{\gamma}^{v\prime}_{k1},\boldsymbol{\gamma}^{v\prime}_{k2},\boldsymbol{\gamma}^{v\prime}_{kk},\gamma_{k1},\gamma_{k2},\gamma_{kk}\right]' & \text{if } k=3,\dots,K+2\end{cases},$$

and $\eta_{k,t}$ follows a Type 1 extreme value distribution.[28]

The random utility model (RUM) focuses on drawing these state utilities directly, whereas the difference in random utility model (dRUM) focuses on the differences in the latent state utilities. The dRUM representation as outlined by Kaufmann (2015) is

$$\omega_{k,t} = U_{k,t} - U_{-k,t}, \qquad k = 2, \ldots, K+2, \tag{4}$$

where $U_{-k,t} = \max_{j \neq k} U_{j,t}$, giving us the realization of the state variable

$$z_t = \begin{cases} 1 & \text{if } \max_{k=2,\ldots,K+2} \omega_{k,t} < 0 \\ j & \text{if } \omega_{j,t} = \max_{k=2,\ldots,K+2} \omega_{k,t} > 0 \end{cases}.$$

It follows that

$$U_{-k,t} = \log(\chi_{-k,t}) + \eta_{-k,t},$$

where

$$\chi_{k,t} = \exp(\boldsymbol{V}'_{k,t}\boldsymbol{\gamma}_k),$$

and

$$\chi_{-k,t} = \sum_{j \neq k} \chi_{j,t}.$$

Therefore, (4) can be rewritten as

$$\omega_{k,t} = \boldsymbol{V}'_{k,t}\boldsymbol{\gamma}_k + \eta_{k,t} - \log(\chi_{-k,t}) + \eta_{-k,t},$$

or

$$\omega_{k,t} = \boldsymbol{V}'_{k,t}\boldsymbol{\gamma}_k - \log(\chi_{-k,t}) + \epsilon_{k,t}, \qquad \epsilon_{k,t} \sim \textit{Logistic}.$$

Practically, there are three substeps to the sampling technique for $\boldsymbol{\gamma}_k$. The first

[28]The differences of $\boldsymbol{V}_{k,t}$ and $\boldsymbol{\gamma}_k$ across global ($k = 1, 2$) and idiosyncratic states ($k = 3, \ldots, K+2$) are due to the restriction on the transition probabilities, $p_{ji,t} = 0$ for all t where $i \neq j$, $i \leq K$, and $j \leq K$.

substep is to draw the latent state utility differences from

$$\omega_{k,t} = \log\left(\chi^*_{k,t} W_{k,t} + I_{[z_t=k]}\right) - \mathbf{log}\left(1 - W_{k,t} + \chi^*_{k,t} I_{[z_t \neq k]}\right),$$

where

$$\chi^*_{k,t} = \frac{\chi_{k,t}}{\chi_{-k,t}},$$

and

$$W_{k,t} \sim U(0,1).$$

In the second step, the logistic distribution of the errors, ϵ, is estimated by a mixture of normal distributions. The $M = 6$ components of the mixture are sampled from

$$p(R_{k,t} = r|\omega_{k,t}, \boldsymbol{\gamma}) \propto \frac{w_r}{s_r} \exp\left[-0.5\left(\frac{\omega_{k,t} - \boldsymbol{V}'_{k,t}\gamma_k + \log(\chi_{-k,t})}{s_r}\right)^2\right], \qquad r = 1, \ldots, 6,$$

where each component's weight, w_r, and standard deviation, s_r, are given in Table 1 of Frühwirth-Schnatter and Frühwirth (2010).

Lastly, we generate the new draw of $\boldsymbol{\gamma}_k$ from a normal posterior distribution:

$$\boldsymbol{\gamma}_k \sim N(g_k, \boldsymbol{G}_k),$$

where

$$g_k = G_k\left(\sum_{t=1}^{T} \frac{\boldsymbol{V}_{k,t}\left[\omega_{k,t} + \log(\chi_{-k,t})\right]}{s^2_{R_{k,t}}} + \boldsymbol{G}^{-1}_{0k} g_{0k}\right),$$

and

$$G_k = \left(\sum_{t=1}^{T} \frac{\boldsymbol{V}_{k,t}\boldsymbol{V}'_{k,t}}{s^2_{R_{k,t}}} + \boldsymbol{G}^{-1}_{0k}\right)^{-1}.$$

A.5 Draw H given $\Theta_{-\boldsymbol{H}}, \boldsymbol{Y}, \boldsymbol{x}$

Similar to the transition probability parameter draw, we draw the prior hyperparameters following the dRUM methodology outlined in Kaufmann (2015). The posterior for $\boldsymbol{\beta}_k$ follows a normal distribution

$$\boldsymbol{\beta}_k \sim N(\boldsymbol{b}_k, \boldsymbol{B}_k)$$

where

$$b_k = B_k \left(\sum_{n=1}^{N} \frac{\boldsymbol{x}_{k,n} \left[\omega_{k,n}^h + \log(\chi_{-k,n}^h) \right]}{s_{R_{k,n}^h}^2} + \boldsymbol{B}_{0k}^{-1} b_{0k} \right),$$

and

$$B_k = \left(\sum_{n=1}^{N} \frac{\boldsymbol{x}_{k,n} \boldsymbol{x}_{k,n}'}{s_{R_{k,n}^h}^2} + \boldsymbol{B}_{0k}^{-1} \right)^{-1}.$$

The differences in utility $\omega_{k,n}^h$, constants $\chi_{-k,n}^h$, and standard deviations $s_{R_{k,n}^h}$ are defined similarly as in the draw step for the transition parameters.

We draw the cluster membership variable h_{nk} country-by-country. For each country n, we draw h_{nk} by combining the conditional likelihood and prior:

$$\Pr\left(h_{nk} = 1 | \Theta_{-\boldsymbol{H}}, \boldsymbol{Y}, \boldsymbol{\beta}, \boldsymbol{x}\right) = \frac{p(\boldsymbol{Y}_n | h_{nk} = 1, \Theta_{-\boldsymbol{H}}) p(h_{nk} = 1 | \boldsymbol{\beta}, \boldsymbol{x})}{\sum_{j=1}^{K} p(\boldsymbol{Y}_n | h_{nj} = 1, \Theta_{-\boldsymbol{H}}) p(h_{nj} = 1 | \boldsymbol{\beta}, \boldsymbol{x})}.$$

B Tables and Figures

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_2	$N\left(g_{02}, \boldsymbol{G}_{02}\right)$	$g_{02} = \left[\mathbf{0}_{L(K+2)}, 0, 2, \mathbf{0}_K\right]$, $\boldsymbol{G}_{02} = 4\boldsymbol{I}_{(L+1)(K+2)}$	$\forall k$
γ_k	$N\left(g_{0k}, \boldsymbol{G}_{0k}\right)$	$g_{0k} = [\mathbf{0}_{3L}, 0, 0, 2]$, $\boldsymbol{G}_{0k} = 4\boldsymbol{I}_{3(L+1)}$	$k = 3, \ldots, K+2$
β_k	$N(b_{0k}, B_{0k})$	$b_0 = \mathbf{0}_{(Q+1)}, B_{0k} = \boldsymbol{I}_{(Q+1)}$	for $k = 1, ..., K$

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 (2017)	-	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 Rates and Variance Parameters

Country	μ_{0n}	$\mu_{0n} + \mu_{1n}$	σ_n
Argentina	3.42	-3.79	5.20
Australia	3.26	-0.59	1.77
Austria	2.95	-1.46	1.62
Belgium	2.74	-1.92	1.15
Brazil	3.52	-2.13	3.01
Canada	3.04	-2.70	1.47
Chile	5.01	-7.18	2.50
China	10.10	5.93	1.86
Denmark	2.36	-1.94	2.06
Finland	3.07	-1.84	2.57
France	2.59	-0.98	0.90
Germany	2.60	-1.65	1.72
Hong Kong	5.20	-6.23	3.27
India	6.31	1.05	2.13
Indonesia	5.96	-5.04	3.24
Ireland	5.08	-0.06	3.03
Italy	2.32	-2.48	1.49
Japan	2.95	-2.65	2.00
Korea	7.26	-0.29	3.13
Luxembourg	4.33	-1.52	2.53
Malaysia	6.40	-6.23	2.35
Mexico	3.74	-1.70	2.18
Netherlands	2.94	-1.89	1.94
New Zealand	2.99	-1.10	2.63
Norway	3.33	-0.19	2.41
Philippines	3.85	-1.96	3.88
Portugal	3.36	-3.76	2.09
Singapore	6.83	-4.73	3.05
South Africa	2.73	-2.43	1.75
Spain	3.24	-2.54	1.23
Sweden	2.79	-1.77	2.07
Switzerland	2.09	-4.69	1.24
Taiwan	6.05	-1.25	2.60
Thailand	5.59	-3.99	3.24
United Kingdom	2.75	-1.51	1.59
United States	3.10	-3.32	1.40
Venezuela	3.47	-5.55	6.02

This table shows the median posterior draw for each country n's average annualized quarterly real GDP growth rate in expansion (μ_{0n}) and recession ($\mu_{0n} + \mu_{1n}$) 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	0.00	**-0.61**	**0.44**	0.17
Financial Openness	-0.05	0.23	-0.21	0.02
Industrialization	**-0.29**	0.27	-0.16	0.18
Oil Production	0.10	-0.13	-0.04	0.07
Legal Systems	0.12	-0.16	0.00	0.03
Ethnolinguistic Index	-0.10	**0.49**	0.11	**-0.50**
Global Backward Linkages	-0.16	-0.07	-0.03	0.26
Asia	-0.02	**-0.49**	**0.68**	-0.18
Europe	**-0.11**	**-0.36**	**-0.17**	**0.63**
North America	**-0.07**	**0.29**	-0.08	**-0.13**
South America	0.07	0.04	-0.01	-0.10

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.	0.89	0.05	0.01	0.14	0.08	0.21
Current	*G. Rec.*	0.01	0.27	0.00	0.27	0.04	0.08
State	*Cluster 1*	0.05	0.07	0.98	-	-	-
(z_t)	*Cluster 2*	0.01	0.06	-	0.59	-	-
	Cluster 3	0.02	0.48	-	-	0.88	-
	Cluster 4	0.03	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*
Current State (z_t)	*G. Exp.*	**0.13**	-0.01	**-0.11**	0.05	0.14	**0.20**
	G. Rec.	0.00	**-0.30**	-0.02	**-0.40**	0.11	-0.03
	Cluster 1	**-0.07**	-0.04	**0.09**	-	-	-
	Cluster 2	**-0.04**	-0.02	-	0.36	-	-
	Cluster 3	-0.01	-0.01	-	-	-0.24	-
	Cluster 4	-0.01	**0.39**	-	-	-	-0.16

(b) Equity Returns

		Previous State (z_{t-1})					
		G. Exp.	*G. Rec.*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Current State (z_t)	*G. Exp.*	**0.17**	0.01	-0.02	**0.40**	-0.21	**0.47**
	G. Rec.	-0.01	**-0.51**	0.00	-0.10	-0.06	0.08
	Cluster 1	**-0.09**	0.05	0.01	-	-	-
	Cluster 2	**-0.03**	0.05	-	**-0.31**	-	-
	Cluster 3	-0.02	0.05	-	-	0.27	-
	Cluster 4	-0.02	**0.34**	-	-	-	**-0.55**

(c) Housing Prices

		Previous State (z_{t-1})					
		G. Exp.	*G. Rec.*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Current State (z_t)	*G. Exp.*	**0.18**	0.01	-0.01	0.06	-0.05	-0.07
	G. Rec.	0.00	-0.18	-0.05	0.20	-0.03	0.03
	Cluster 1	0.03	0.08	0.07	-	-	-
	Cluster 2	-0.01	0.08	-	-0.26	-	-
	Cluster 3	0.00	0.08	-	-	0.08	-
	Cluster 4	**-0.19**	-0.07	-	-	-	-0.10

(d) Oil Price Shock

		Previous State (z_{t-1})					
		G. Exp.	*G. Rec.*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Current State (z_t)	*G. Exp.*	**0.21**	0.01	**0.13**	0.03	0.02	**-0.16**
	G. Rec.	-0.01	0.08	0.00	-0.05	0.10	0.12
	Cluster 1	**-0.13**	0.10	**-0.12**	-	-	-
	Cluster 2	**-0.04**	0.06	-	0.03	-	-
	Cluster 3	-0.04	0.06	-	-	-0.12	-
	Cluster 4	0.01	-0.31	-	-	-	-0.04

(e) Geopolitical Risk

		Previous State (z_{t-1})					
		G. Exp.	*G. Rec.*	*Cluster1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Current State (z_t)	*G. Exp.*	**-0.18**	0.01	**0.02**	-0.08	**0.33**	**0.14**
	G. Rec.	0.00	0.03	0.01	**-0.45**	0.11	-0.02
	Cluster 1	**0.08**	0.05	**-0.04**	-	-	-
	Cluster 2	0.01	0.06	-	**0.53**	-	-
	Cluster 3	0.00	0.06	-	-	**-0.44**	-
	Cluster 4	**0.09**	-0.20	-	-	-	-0.13

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 $p_{t,ji}$. The marginal effects can be interpreted as the difference in transition probabilities when the covariate is realtively high and low (i.e., $\pi^l_{ji} = p^H_{t,ji} - p^L_{t,ji}$).

Table 7: Output Forecast Comparison

	AR(1)	*MS*	*MSC-FTP*	*MSC-TVTP*
Argentina	0.86	1.13	0.89	**0.83**
Australia	0.60	0.32	0.29	**0.28**
Austria	0.65	0.72	**0.55**	0.60
Belgium	**0.39**	0.78	0.47	0.53
Brazil	0.56	0.58	0.54	**0.51**
Canada	0.54	0.64	0.60	**0.51**
Chile	0.70	0.78	0.68	**0.63**
China	0.76	**0.60**	0.62	0.71
Denmark	0.68	0.73	**0.57**	**0.57**
Finland	0.67	1.02	0.57	**0.55**
France	**0.47**	0.74	0.72	0.74
Germany	**0.55**	0.89	0.58	0.57
Hong Kong	0.68	0.81	0.66	**0.53**
India	1.96	**1.17**	1.19	1.23
Indonesia	0.57	0.79	**0.48**	0.57
Ireland	2.60	3.71	1.80	**1.76**
Italy	**0.36**	0.74	0.77	0.68
Japan	**0.83**	1.07	1.11	1.02
Korea	**0.44**	0.64	0.73	0.72
Luxembourg	1.77	1.45	1.33	**1.20**
Malaysia	0.74	0.82	0.82	**0.73**
Mexico	**0.47**	0.85	0.55	0.49
Netherlands	0.46	0.57	0.35	**0.31**
New Zealand	0.65	0.45	**0.43**	0.52
Norway	0.96	1.12	0.93	**0.91**
Philippines	0.75	**0.21**	0.27	0.27
Portugal	**0.39**	0.57	0.62	0.60
Singapore	1.46	1.42	1.28	**1.16**
South Africa	0.49	0.41	0.40	**0.37**
Spain	**0.26**	0.45	0.56	0.51
Sweden	0.94	0.80	**0.53**	0.59
Switzerland	0.53	0.62	0.59	**0.49**
Taiwan	1.49	1.66	1.56	**1.39**
Thailand	1.74	1.50	1.28	**1.24**
United Kingdom	0.45	0.44	**0.42**	0.47
United States	0.61	0.69	0.71	**0.54**
Venezuela	1.91	1.63	1.55	**1.50**
Overall MSFE	30.91	33.49	27.97	**26.83**

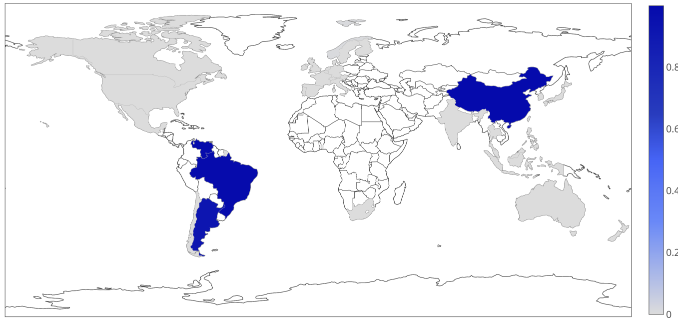
This table shows the mean squared forecast error for each country using four different models: a univariate autoregression (*AR(1)*), a univariate Markov-switching model (*MS*), the time-series clustering model of Hamilton and Owyang (2012) with fixed transition probabilities (*MSC-FTP*), and this paper's time-series clustering model with Markov-switching (*MSC-TVTP*). The forecast error for each country is normalized by the respective country's variance for the entire sample. The last row shows the MSFE when forecasting the entire vector of countries. Bold indicates the lowest MSFE across all of the models considered.

Table 8: Recession Forecast Comparison

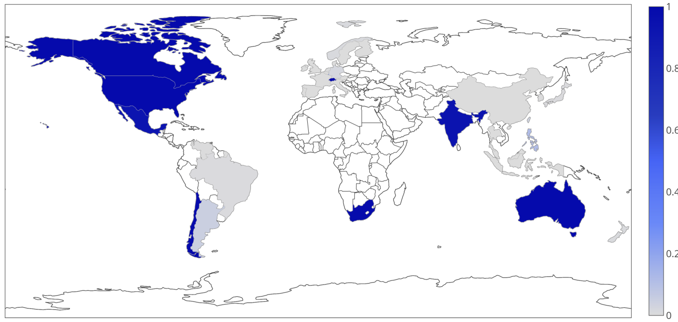
	MS	*MSC-FTP*	*MSC-TVTP**
Argentina	-	-	-
Australia	0.55	0.57	**0.58**
Austria	0.69	0.74	**0.75**
Belgium	0.68	0.74	**0.84**
Brazil	0.71	0.56	**0.73**
Canada	**0.70**	0.62	0.61
Chile	**0.74**	0.54	0.68
China	**0.82**	0.53	0.64
Denmark	**0.67**	0.64	0.66
Finland	**0.69**	0.65	**0.69**
France	**0.75**	0.60	0.74
Germany	0.71	0.78	**0.81**
Hong Kong	-	-	-
India	**0.72**	0.58	0.66
Indonesia	**0.62**	0.46	0.52
Ireland	0.56	0.70	**0.73**
Italy	0.71	0.76	**0.77**
Japan	0.59	**0.67**	0.62
Korea	**0.74**	0.54	0.55
Luxembourg	**0.70**	0.62	0.67
Malaysia	-	-	-
Mexico	**0.78**	0.67	0.73
Netherlands	0.75	0.72	**0.81**
New Zealand	0.57	0.55	**0.58**
Norway	0.58	0.57	**0.62**
Philippines	-	-	-
Portugal	0.70	0.63	**0.73**
Singapore	-	-	-
South Africa	0.77	0.61	**0.78**
Spain	0.71	0.81	**0.82**
Sweden	0.59	0.62	**0.69**
Switzerland	**0.74**	0.59	0.69
Taiwan	-	-	-
Thailand	-	-	-
United Kingdom	**0.60**	0.49	**0.60**
United States	**0.74**	0.58	0.70
Venezuela	-	-	-

This table shows the AUROC for each country using three models different models: a univariate Markov-switching model (*MS*) for each country, the time-series clustering model of Hamilton and Owyang (2012) with fixed transition probabilities (*MSC-FTP*), and this paper's time-series clustering model with time-varying transition probabilities (*MSC-TVTP*). In the *MSC-TVTP** model, equity returns (*ER*) is the transition covariate. Bold indicates a higher degree of accuracy in forecasting OECD recession dates.

Figure 1: Probability of Cluster Membership

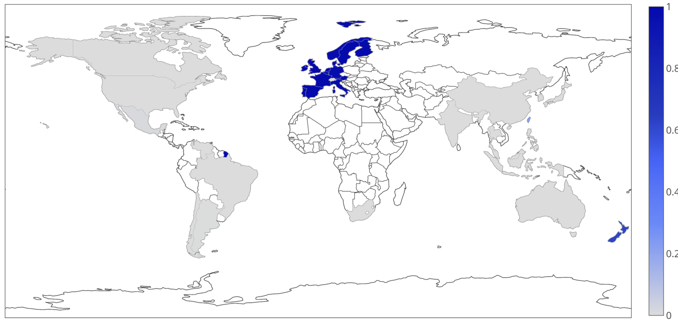


(a) Cluster 1



(b) Cluster 2

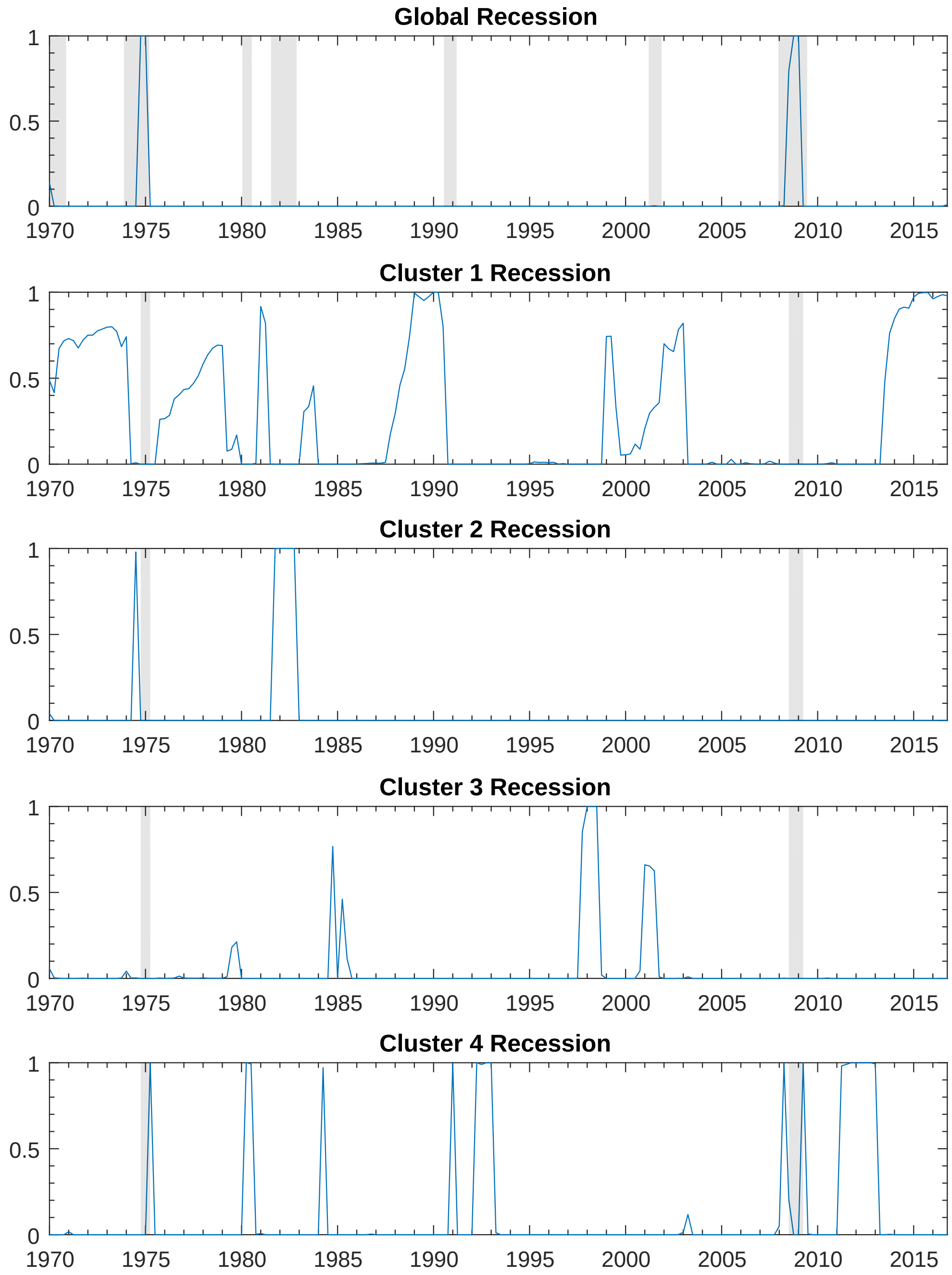
(c) Cluster 3



(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 bottom four panels represent the global recession dates from the top panel.