Regime-switching Models of the Business Cycle

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ABSTRACT

DANIEL SOQUES: Regime-switching Models of the Business Cycle.
(Under the direction of Neville Francis)

A popular way to describe the business cycle is as a movement between distinct phases of expansion and recession. During expansions, output growth and employment are relatively high, whereas recessions are characterized by sluggish output growth and high unemployment. Hamilton (1989) used regime-switching models to describe this evolution of the business cycle. In this dissertation, I extend the model of Hamilton (1989) to address a number of prevalent macroeconomic questions regarding business cycle comovement.

First, in joint work with Neville Francis and Michael T. Owyang, we assess the leading role played by U.S. in the global economy by analyzing if U.S. output growth informs the timing of business cycle turning points of other nations. We find that the U.S. economic growth influences both the timing and duration of business cycle phases for Canada, Germany, the United Kingdom, and, to a lesser extent, Mexico. Conversely, we find no relationship between U.S. output growth and the business cycles of France, Italy, and Japan.

In the second paper, again with Neville Francis and Michael T. Owyang, 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 three groups of countries which experience idiosyncratic recessions relative to the global business cycle. Additionally, we find the primary indicator of international recessions to be large movements in asset prices.

In a third paper with James D. Hamilton and Michael T. Owyang, we extend Hamilton and Owyang (2012) which examined the comovements of state-level business cycles using a clustered Markov-switching approach. Here, we consider whether industries also comove and, if so, whether this comovement is limited to subsectors within a single industry classification. We find four industry clusters, with their composition implying some degree of propagation of recessions up the production chain.

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CHAPTER 1

DOES THE UNITED STATES LEAD FOREIGN BUSINESS CYCLES?

1.1 Introduction

The U.S. is the largest of the world's economies. In 2012, the U.S. accounted for 22.4 percent of the world's gross domestic product (GDP) and 35.1 percent of the world's total market capitalization.[1] The importance of the U.S. to the global economy was highlighted during the recent Great Recession of 2007-2009. A financial shock originating for the most part in the U.S. led to a worldwide downturn, which had detrimental and lasting effects on both developed and emerging economies. This dynamic is summarized by the phrase, "when the U.S. sneezes, the rest of the world catches a cold."

Given this role as a global economic leader, a number of recent studies investigate the spillover effects of the U.S. economy onto other nations. Arora and Vamvakidis (2004) use a fixed-effects panel regression and find that U.S. economic growth has positive effects on the rest of the world, especially for developing countries. Helbling et al. (2007) use multiple methodologies to determine the effect of the U.S. economy on other countries. By conducting an event study, they find that U.S. recessionary periods coincide with global downturns. They also use simple regressions while controlling for potential common unobserved shocks and country-specific effects and find that a 1-percentage-point decline in U.S. growth leads to an average 0.16-percentage-point drop in output growth across their sample of countries, with Canada, Latin America, and Caribbean countries being the most strongly influenced. Lastly, they use the more dynamic approach of structural vector autoregressions (SVARs) to allow for both foreign and domestic effects, where they find U.S. growth significantly impacts growth in Latin America, the Newly Industrialized Economies

[1] Source: World Bank.

(Hong Kong, Korea, Singapore, and Taiwan), and the Association of Southeast Asian Nations (Indonesia, Malaysia, the Philippines, and Thailand). Antonakakis (2012) uses a dynamic measure of correlation to examine the synchronization of G7 business cycles across a long time-series (1870 to 2011). They find U.S. recessions have positive effects on business cycle comovements after the 1971 breakdown of the Bretton-Woods system, with an increased level of synchronization during the Great Recession.

The goal of this paper is to assess the influence that U.S. output growth has on the business cycles of other nations. In particular, we ask if U.S. economic growth signals economic turning points in other countries. In our setting, we cannot identify which structural innovations (shocks) drive spillovers from the U.S. to other countries, or if the proximate shock leading to the turning point is global in nature. Rather, we are merely interested in the comovement between U.S. output and economic downturns of other countries. However, we do analyze the timing of when the U.S. affects other countries. So, we could appeal to other studies as to what the driving forces were during a given time period.[2]

Despite the inability of our model to offer a complete characterization of these shocks, our study should be of relevant interest to policymakers and others interested in the dependence of foreign business cycles on the U.S. economy. Our results imply that the trajectory of U.S. output growth informs both the timing and duration of economic turning points in certain foreign economies. Proper analysis of these cross-country linkages give policymakers, both in the U.S. and abroad, a better understanding of the trade-offs faced when conducting independent and coordinated actions.

Since our focus is on economic turning points, we use the regime-switching model of Hamilton (1989) with time-varying transition probabilities (TVTP) as outlined by Goldfield and Quandt (1973), Diebold et al. (1994), and Filardo (1994). This framework allows us to not only identify economic turning points, but also the degree to which U.S. output growth influences the evolution

[2]For analysis of the specific mechanisms (trade openness, financial market linkages, etc.) by which the U.S. transmits shocks to the rest of the world, see Calvo, Leiderman and Reinhart (1993), Kose and Yi (2001), Uribe and Yu (2006), Mackowiak (2007), Edwards (2010), Bayoumi and Bui (2010), and Kim, Wagan and Akbar (2013).

of the underlying state—recession or expansion—of a nation's economy. We consider regime-switching models with both two (recession and expansion) and three states (recession, low-growth expansion, and high-growth expansion).

Our panel of countries includes the Canada, France, Germany, Italy, Japan, Mexico, and the United Kingdom (U.K.), covering the time period 1960:Q2 - 2013:Q4. We find that U.S. output growth informs the timing and duration of recessions for Canada, Germany, the U.K., and, to a lesser extent, Mexico. For the remaining countries (France, Italy, and Japan), we find no relationship between U.S. output growth and business cycle turning points.

The paper proceeds as follows: Section 2.2 details the regime-switching model. Section 1.3 describes the data and outlines the estimation methodology. Section 2.5 presents our results. Section 2.6 concludes.

1.2 Model

Burns and Mitchell (1946) characterized the business cycle as distinct phases of expansion and recession. As defined by the National Bureau of Economic Research (NBER), a recession is a wide-spread decline in economic activity typically lasting from a few months to over a year. On the other hand, expansions are characterized by positive growth in economic activity and, typically, longer durations.

Models of a country's business cycle are typically estimated with that country's data alone. Regime shifts are characterized by sudden and persistent shifts in the growth rate of the economic indicators, usually domestic GDP. In this paper, we are interested in contagion of economic outcomes across countries. To this end, we will augment the standard business cycle model to account for possible contagion by a dominant country—in this case, the U.S.

The model we adopt is based on the business cycle model of Hamilton, who characterizes the cycle as a two-state process with random regime changes. In his framework, the mean growth rate of a country's output, y_t, depends on a latent state variable, $s_t = \{1, 2\}$. The state of the economy at any time is either "recession" ($s_t = 1$) or "expansion" ($s_t = 2$). Assuming no autoregressive terms for simplicity, this model is given by

$$y_t = \begin{cases} \mu_1 + \varepsilon_t, & \text{if } s_t = 1 \text{ (recession)} \\ \mu_2 + \varepsilon_t, & \text{if } s_t = 2 \text{ (expansion)} \end{cases},$$

where the error variance, $\varepsilon_t \sim N(0, \sigma^2)$, is constant across states. Consistent with the NBER's definition of the business cycle, we restrict the average growth rate of output to be positive during expansionary periods ($\mu_2 > 0$) and negative during recessionary periods ($\mu_1 < 0$).

In principle, we could include any number of states K in the model in order to better match certain features of business cycles. For example, Kim and Piger (2000), Kim and Murray (2002), and Billio et al. (2013) include three-states in their regime-switching model of the business cycle. Additional states can reflect persistent differences in business cycle characteristics such as fast versus slow growth expansion regimes or deep versus shallow recessions. The generalized K-state model is given by

$$y_t = \begin{cases} \mu_1 + \varepsilon_t & \text{if } s_t = 1, \\ \mu_2 + \varepsilon_t & \text{if } s_t = 2, \\ \quad\vdots & \quad\vdots \\ \mu_K + \varepsilon_t & \text{if } s_t = K, \end{cases}$$

with the identifying restriction $\mu_1 < \mu_2 < \ldots < \mu_K$. We consider both a two-state ("recession" and "expansion") and a three-state ("recession", "low-growth expansion", and "high-growth expansion") model for each country. We normalize the states such that $\mu_1 < 0 < \mu_2 < \mu_3$. This provides econometric identification as well as an interpretations for future discussion.

1.2.1 Transition Probabilities

The NBER's Business Cycle Dating Committee provides ex post historical dates for which the U.S. is in expansion or recession. Many other countries do not have "official" business cycle turning points. The model leaves the state of the economy unobserved, and, therefore, requires an assumption about the evolution process of the state variable. Ideally, a model of economic business cycles matches two features of the data: (1) both expansions and recessions are highly persistent, and (2) expansions have longer average durations than recessions.

A standard assumption of regime-switching models is to assume the state variable follows a first-order Markov process with *fixed* transition probabilities (FTPs) [e.g., as in Hamilton (1989)]. The Markov property imposes that the current value of the state variable, s_t, is a function of its previous value, s_{t-1}. In the two-state model, the transition matrix governing the Markov process is represented as

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix},$$

with FTPs

$$p_{ji} = \Pr\left[s_t = j | s_{t-1} = i\right], \tag{1.1}$$

where the columns of P each sum to 1 (i.e., $\sum_j p_{ji} = 1$ for $i = 1, 2$). Thus, if a country was in expansion last period ($s_{t-1} = 2$), the probability that it remains in expansion this period ($s_t = 2$) is p_{22}, and the probability that the economy enters a recession this period ($s_t = 1$) is $p_{12} = 1 - p_{22}$. Similarly, given that a country was in recession last period ($s_t = 1$), the probability that it remains in recession this period ($s_t = 1$) is p_{11}, and the probability the economy recovers and enters expansion this period ($s_t = 2$) is $p_{21} = 1 - p_{11}$.

Persistence is generated in the Markov process when the diagonal elements of the transition matrix are greater than the off-diagonal elements. Previous studies typically find the persistence probability of expansion, p_{22}, to be greater than the persistence probability of recession, p_{11}, coinciding with the observation that the average duration of expansions is greater than that for recessions. For example, Hamilton (1989) found a persistence probabilities for the U.S. of approximately 0.90 for expansions and 0.75 for recessions, implying expected durations of 10 quarters for expansions and 4 quarters for recessions, similar to those defined by the NBER.

Because we are interested in how U.S. output growth informs economic turning points of other nations, we extend Hamilton's model to allow a foreign (U.S.) output growth rate to directly affect the evolution of the underlying economic state of other nations.[3] We assume the Markov process

[3] We assume that the foreign output growth rate, in this case, is exogenous and unaffected by the domestic regime.

is governed by *time-varying* transition probabilities (TVTP), which are functions of exogenous covariates and last period's state. In our case, we use the one-period lag of U.S. output growth, y_{t-1}^{US}, as the single covariate which influences the switching process. The time-varying transition matrix in the two-state model is

$$P_t = \begin{bmatrix} p_{11,t} & p_{12,t} \\ p_{21,t} & p_{22,t} \end{bmatrix},$$

with TVTP

$$p_{ji,t} = \Pr\left[s_t = j | s_{t-1} = i, y_{t-1}^{US}\right] = \frac{\exp\left(\alpha_{ji} + \beta_{ji} y_{t-1}^{US}\right)}{\sum_{k=1}^{2} \exp\left(\alpha_{ki} + \beta_{ki} y_{t-1}^{US}\right)}.$$

Here, α_{ji} is the time-invariant parameter and β_{ji} is the coefficient on lagged U.S. output growth. The FTP model is nested under the TVTP framework if the covariate has no effect under each state realization (i.e., $\beta_{ji} = 0$ for $i = 1, 2$ and $j = 1, 2$). Note that the time-invariant parameter α_{ji} and the coefficient β_{ji} depend on both the previous state ($s_{t-1} = i$) and the potential current state ($s_t = j$) thereby reflecting the Markov property. Also, this parameterization allows U.S. output growth to have asymmetric effects since we assume the coefficient is state dependent (i.e., $\beta_{j1} \neq \beta_{j2}$ for $j = 1, 2$ and $\beta_{1i} \neq \beta_{2i}$ for $i = 1, 2$). In order to identify the transition parameters, we must normalize one of the state's transition parameters to be zeros. For the two-state model, we use state 2: $\alpha_{2i} = 0$ and $\beta_{2i} = 0$ for $i = 1, 2$.

For the general K-state model, the time-varying transition matrix is

$$P_t = \begin{bmatrix} p_{11,t} & p_{12,t} & \cdots & p_{1K,t} \\ p_{21,t} & p_{22,t} & & \\ \vdots & & \ddots & \\ p_{K1,t} & & & p_{KK,t} \end{bmatrix},$$

with TVTP

$$p_{ji,t} = \Pr\left[s_t = j | s_{t-1} = i, \mathbf{x}_t\right] = \frac{\exp\left(\alpha_{ji} + \beta_{ji} y_{t-1}^{US}\right)}{\sum_{k=1}^{K} \exp\left(\alpha_{ki} + \beta_{ki} y_{t-1}^{US}\right)}, \tag{1.2}$$

where we can impose the identification restrictions on state K: $\alpha_{Ki} = 0$ and $\beta_{Ki} = \mathbf{0}$ for $i = 1, 2, \ldots, K$. We collect the unrestricted transition parameters into the $[2K \times (K-1)]$ matrix $\Gamma = [\gamma_1, \ldots, \gamma_{K-1}]$, where $\gamma_i = [\alpha_{i1}, \ldots, \alpha_{iK}, \beta_{i1}, \ldots, \beta_{iK}]'$ for $i = 1, \ldots, K-1$.

1.2.2 Determining the Effects of U.S. Output Growth

The effect of U.S. output growth on other countries' turning points appears to be summarized by the coefficient β_{ji} in the transition equations. However, interpreting these coefficients in the logistic framework of TVTP is less straightforward than in a simple linear regression model. One of the ways to assess the effect of U.S. output growth on the transition dynamics is by looking at the *marginal effect* of a change in y^{US}_{t-1} on each transition probability $p_{ji,t}$ for $j = 1, \ldots, K$ and $i = 1, \ldots, K$. We calculate the marginal effect of y^{US}_{t-1} on $p_{ji,t}$ by taking the partial derivative of (1.2) with respect to y^{US}_{t-1}:

$$\frac{\partial p_{ji,t}}{\partial y^{US}_{t-1}} = p_{ji,t} \left(\beta_{ji} - \bar{\beta} \right),$$

where $\bar{\beta} = \sum_k p_{ki,t} \beta_{ji}$ is the probability weighted mean of the coefficient across states.

In the two-state model, the marginal effect of a change in y^{US}_{t-1} on the probability of recession ($s_t = 1$) simplifies to

$$\frac{\partial p_{1i,t}}{\partial y^{US}_{t-1}} = \beta_{1i} p_{1i,t} (1 - p_{1i,t}),$$

which depends on the previous period's state. Determining the sign of this marginal effect is straightforward because it is irrespective of the value of y^{US}_{t-1} and therefore time-invariant. If $\beta_{1i} < \beta_{2i} = 0$, then the probability of experiencing a recession (expansion) next period falls (rises) as lagged U.S. output growth rises. We expect to find this relationship for countries that tend to comove with the U.S. economy. Conversely, if $\beta_{1i} > \beta_{2i} = 0$, then the probability of experiencing a recession (expansion) next period rises (falls) as lagged U.S. output growth rises. We expect to find this relationship for countries that move opposite ("decouple") from the U.S. economy. If $\beta_{1i} = \beta_{2i} = 0$, then the marginal effect is zero and lagged U.S. output growth does not influence the transition probabilities. Therefore, no relationship exists between U.S. output growth and economic turning points for the country under consideration.

Unlike the sign, the magnitude of the marginal effect in the two-state model is time-varying because it depends on the value of y^{US}_{t-1}. For example, assume parameter values $\alpha_{11} = -1$ and $\beta_{11} = -1$ in a simple two-state version of our model ($K = 2$). First, consider the case where U.S. output growth is two-standard-deviations above its historical mean ($y^{US}_{t-1} = 2$). Then, the marginal effect of further changes in y^{US}_{t-1} on the persistence probability of recession is -0.05. However, if U.S. output growth is relatively low at two standard deviations below its historical mean ($y^{US}_{t-1} = -2$), then the absolute magnitude of this marginal effect quadruples to -0.20. Thus, the current status of the U.S. economy informs not only the probability of recession in the country of interest, but also the current degree of influence U.S. output growth has over this probability.

In the general K-state model, both the sign and magnitude of the marginal effects depend on the value of y^{US}_{t-1}. In order to fully assess the effect of U.S. output growth at different points in time, we calculate the marginal effects over a range of possible values of y^{US}_{t-1}.

1.3 Data and Estimation

1.3.1 Data

We use the seasonally-adjusted, annualized quarter-to-quarter growth rate of real GDP as our measure of economic activity growth (y_t) for each country. We use the data from the Quarterly National Accounts database provided by Organisation for Economic Co-operation and Development (OECD). The countries included in our sample are the U.S.' G7 counterparts (Canada, France, Germany, Italy, Japan, and the U.K.) and Mexico, given its geographic proximity and economic relationship with the U.S. Our time-series covers 1960:Q2 to 2013:Q4 for Canada, Germany, Italy, Japan, and the U.K., 1970:Q2 to 2013:Q4 for France, and 1980:Q2 to 2013:Q4 for Mexico. Table B.1 provides summary statistics for our sample.

For the transition covariate, y^{US}_{t-1}, we use the one period lag of U.S. output growth from the OECD's Quarterly National Accounts database, covering the time period 1960:Q1 to 2013:Q3. To simplify the interpretation of the results, we standardize the time series of U.S. output growth to have zero mean and unit variance. Thus, $y^{US}_{t-1} = 0$ implies the U.S. is at its historical average growth rate over our sample period, approximately 3.04%. Similarly, $y^{US}_{t-1} = c$ means the U.S. is growing at c standard deviations away from its historical average growth rate. For example, $y^{US}_{t-1} = 2$ implies that U.S. output grew at 9.80% last period since the standard deviation of U.S.

output growth from 1960:Q1 to 2013:Q2 is approximately 3.38.

Figure B.1 plots the time-series of real GDP growth for a subset of our sample (Canada, Germany, and Japan). Grey bars represent U.S. recession dates as defined by the NBER's Business Cycle Dating Committee and are included only for reference. For each country, real GDP growth tends to fall during periods of U.S. recession, implying some connection between U.S. and other countries' growth.

1.3.2 Estimation

We estimate both the two- and three-state models using the Gibbs sampler, a Markov-chain Monte Carlo algorithm used in a Bayesian environment. Rather than drawing from the full joint posterior distribution directly, the Gibbs sampler draws each of the four parameter blocks from their individual conditional posterior distribution given the draws for the other blocks. First, we partition the parameters and latent variables into four blocks: (1) the average growth rates $\mu = [\mu_1, \dots, \mu_K]'$; (2) the error variance σ^2; (3) the transition probability parameters Γ; and (4) the time-series of the latent state variable, $\mathrm{s} = [s_1, \dots, s_T]'$. We run the sampler for 100,000 iterations, discarding the first 50,000 to achieve convergence.

Prior distributions for the parameters of the two- and three-state model are given in Tables B.2 and B.3, respectively. In each case, we use conjugate prior distributions. Following Kim and Nelson (1999), the steps to draw the average growth rate and error variance parameters are straightforward. The conditional posterior distribution for the vector of average growth rates, μ, is multivariate normal and the posterior for the error variance, σ^2, is inverse-Gamma.

The transition probability parameters can be rewritten as a differences in random utility model (dRUM) as outlined by Frühwirth-Schnatter and Frühwirth (2010) and Kaufmann (2011). Under the dRUM, we assume each state has a continuous, latent utility value. Conditional on knowing the state at each point in time, the observed state is the one with the highest utility. The conditional posterior distribution of the transition parameter vector, γ_i, is multivariate normal for each state $i = 1, \dots, K-1$. The unobserved state variable is drawn using the filter from Hamilton (1989) with the smoothing algorithm from Kim (1994). For the general K-state model, we use the multi-state extension of the filter as outlined by Kaufmann (2011).

Choosing between using two states ("recession" and "expansion") and three states ("recession", "low-growth expansion", and "high-growth expansion") is a model selection problem. We use Bayesian Information Criterion (BIC) to choose which model is best suited for each country. BIC is calculated as

$$BIC = -2\log[L(\Theta, \mathbf{s}, \mathbf{y}, \mathbf{y}^{US})] + N\log(T)$$

where N is the number of parameters in the model, T is the number of time-series observations, and $L(\Theta, \mathbf{s}, \mathbf{y}, \mathbf{y}^{US})$ is the value of the likelihood function given model parameters $\Theta = \{\mu, \sigma^2, \alpha, \beta\}$, the state vector $\mathbf{s}$, and the data $\mathbf{y} = [y_1, \ldots, y_T]$ and $\mathbf{y}^{US} = \left[y_0^{US}, \ldots, y_{T-1}^{US}\right]$. BIC accounts for the likelihood of the data, while penalizing models with a large number of parameters. BIC was shown by Raftery (1995) and Kass and Raftery (1995) to approximate the Bayes factor of competing models, and thus provides an adequate solution to our model selection issue. The BIC is calculated at each iteration of the Gibbs sampler and the optimal model for each country is the one which minimizes the median BIC calculation.

1.4 Results

Table B.4 gives the model selection results for each country. The two-state model is preferred for Germany, Japan, and Mexico, while the three-state model is chosen for Canada, France, Italy, and the U.K. These results suggest a more stable expansion output growth rate for the former countries, while the latter countries appear to have both low and high growth expansions.

We present the estimated mean growth rate and variance parameters for each country in Table B.5. Germany, Japan, and Mexico each have much higher error variance than the other countries in sample, possibly due to the lack of third state in their optimal model to capture high-growth dynamics. The lack of two expansion states also explains the higher estimated mean expansionary growth rate for these countries since it is capturing episodes of both high- and low-growth.

We discuss the remaining results in two subsections. The first outlines the estimated recession timing for each country across time. The second subsection assesses the ability of U.S. output growth to inform business cycle turning points for each country.

1.4.1 Timing of Business Cycle Phases

Figure B.2 presents the probability implied by our model that a country is in a state of recession at each time period in our sample. In technical terms, these are the posterior probability of recession, $\Pr[s_t = 1|\Omega_T]$ for each country conditional on Ω_T, the information at time t. For each t, $\Pr[s_t = 1|\Omega_T]$ is the percentage of Gibbs iterations for which a recession state is drawn at each time period. Although all of the countries in our sample experience some similar recessions (e.g., the first oil crisis of the mid 1970's and the Great Recession of 2007-2009), there are substantive differences in the timing of entering recessions as well as their durations. For example, we find that most countries enter recession after the NBER determined that the Great Recession of 2007-2009 in U.S. already began. Although some countries (e.g., Canada, Mexico, and the U.K.) exit this recession with the U.S., others (e.g., Italy and Japan) experience lasting effects of the global downturn leading to a "double-dip" recession.

For completeness, we plot the posterior probability of expansion in Figure B.3. Countries following the two-state model (Germany, Japan, and Mexico) have a single expansion state and therefore a single posterior probability of expansion, whereas countries following the three-state model (Canada, France, Italy, and the U.K.) have two expansion states (low- and high-growth). For the latter, we include the posterior probabilities of the low-growth expansion state in Figure B.3 and we plot separately the posterior probabilities for the high-growth state in Figure B.4.

Consistent with the empirical literature on business cycles, we find the expansion state(s) to be highly persistent with longer average duration(s) than the recession state. The high-growth expansion state accounts for periods of relatively high-growth prior to 1985, the beginning of the period known as the Great Moderation. For France, the high-growth expansion state also captures two notable economic periods: the movement away from dirigisme in the late 1980s, and the beginning of Euro integration in the late 1990s.

1.4.2 Does U.S. output growth drive business cycles?

The focus of this paper is on whether U.S. output growth informs economic turning points of other nations.[4] In our modelling framework, this relationship is captured in the transition dynamics of the state variable. Table B.6 displays the median posterior draws for the transition probability parameters for all the countries in our sample. As we noted in Section 1.2.2, the coefficients β_{ji} in the transition equations suggest how U.S. output growth influences the state dynamics of the country of interest. They are not, however, the sole determinants of the (marginal) effect of a change in lagged U.S. output growth on the transition probabilities on the business cycle of a given country. Because the marginal effects depend on both the value of lagged U.S. output growth y_{t-1}^{US} and the previous state of the economy s_{t-1}, we calculate them across all possible combinations of s_{t-1} and y_{t-1}^{US}.[5] We do this for each iteration of the Gibbs sampler, thereby constructing the posterior distribution for each of the marginal effects.

Figures B.5 through B.11 display the marginal effect of a change in lagged U.S. output growth on each of the transition probabilities. The horizontal axis for each figure reflects different values for U.S. output growth, negative four to positive four standard deviations from its historical average. The vertical axis plots the marginal effect of a change in U.S. output growth on the respective transition probability conditional on the value for y_{t-1}^{US} and the previous state s_{t-1}. In each figure, the blue line represents the posterior median of the marginal effect and the shaded region represents the 68% coverage of the posterior distribution.

A positive marginal effect implies that an increase in lagged U.S. output growth increases the respective transition probability $p_{ji,t} = \Pr(s_t = j | s_{t-1} = i, y_{t-1}^{US})$. Conversely, a negative marginal effect implies that an increase in lagged U.S. output growth decreases the respective transition probability. That is, for countries that comove with the U.S., we expect to find a positive (negative)

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[4] Note that we cannot infer causality of the business cycle in the structural sense, but rather we assess if U.S. output acts as an informative indicator of other countries' turning points. Therefore, countries for which our model indicates that U.S. output growth is not a significant indicator does not imply a lack of structural mechanisms which propagate shocks between the two nations.

[5] We consider values for y_{t-1}^{US} between negative four standard deviations and positive four standard deviations of its historical mean. This corresponds to a range of -10.5 to 16.6, which includes the historical minimum (-8.7) and maximum (15.3) values of U.S. output growth.

marginal effect of y^{US}_{t-1} on the probability of transitioning to an expansion (recession) and the persistence of expansion (recession). For countries that decouple from the U.S., we expect to find a negative (positive) marginal effect of y^{US}_{t-1} on the probability of transitioning to an expansion (recession) and the persistence of expansion (recession).

For each country, we assess the ability of U.S. output growth to inform (1) the timing of entering a recession, (2) the persistence or duration of a recession, and (3) transitions between states of low- and high- growth expansion (for countries following the three-state model). We assess the first dynamic by looking at the marginal effect of U.S. output growth on the transition probability from expansion ($s_{t-1} = 2$ or 3) to recession ($s_{t-1} = 1$), so the relevant transition probabilities are $p_{12,t}$ and $p_{13,t}$. For recession persistence, we see if U.S. output influences the transition probability of staying in recession this period ($s_t = 1$) given the economy was in recession last period ($s_{t-1} = 1$) with relevant transition probability $p_{11,t}$.We analyze the the last aspect by looking at both the persistence probability of both low- ($p_{22,t}$) and high-expansion ($p_{33,t}$) states in addition to the transition probabilities between the two expansion states ($p_{23,t}$ and $p_{32,t}$).

The three countries for which U.S. output growth has the most influence are Canada, Germany, and the U.K.. For these countries, lagged U.S. output growth influences both the timing of entering a recession as well as the duration of a recession. The results show that each of these countries comove with the U.S.: higher U.S. output growth implies a lower probability of recession, and lower output growth implies a higher probability of recession ($\uparrow y^{US}_{t-1} \Rightarrow \downarrow p_{1i,t}, \uparrow p_{2i,t}$ for all i). Figure B.7 presents the marginal effects for Germany, which follows the simpler two-state model. For Germany, the marginal effect of U.S. output growth is largest (in absolute terms) at low levels of y^{US}_{t-1}, or when the U.S. is likely in a state of recession. Therefore when the U.S. economy is in dire circumstances (as signalled by low output growth), Germany is more susceptible to any further movements in U.S. output relative to more "normal" economic times.

In addition to informing the timing and duration of recessions, U.S. output growth also influences the transition dynamics of low- and high-growth expansion for Canada, as seen in Figure B.5. When U.S. growth is relatively low (i.e., below its historical mean), increases in U.S. output growth imply a higher persistence of low-growth expansion ($\uparrow p_{22,t}$). However, when U.S. growth is relatively high (i.e., above its historical mean), increases in U.S. output growth decrease the persistence of low-growth expansion and increase the probability of transitioning to high-growth expansion ($\uparrow p_{32,t}$) -as well as the persistence probability of high-growth expansion ($\uparrow p_{33,t}$). This result reflects the strong economic relationship between Canada and the U.S. since it not only informs the timing of recessions but also the timing of varying degrees of expansion.

For Mexico, lagged U.S. output growth informs the duration of recession but not the timing of entering recession. When U.S. output growth falls, the persistence probability of recession in Mexico rises ($\uparrow p_{11,t}$) implying a longer expected duration of recession. The lack of U.S. output growth influencing the timing of Mexico entering recession could be due to the fact that Mexico experienced idiosyncratic recessions unrelated to the U.S. (e.g. the 1994 Mexican peso crisis), which tended to be shorter than coincident recessions with the U.S. (e.g. the recession of the early 1980's and the Great Recession of 2007-2009).

The results for France, Italy, and Japan suggest that lagged U.S. output growth does not influence the timing or duration of recession for these countries. For France and Italy, increases in U.S. output growth increase the persistence probability of high-growth expansion ($\uparrow p_{33,t}$), but only at low-levels of U.S. output growth.

Recent studies on business cycle synchronization offer two possible explanations of our results: stage of development and common language. Regarding the first explanation, Kose et al. (2012) find that emerging market economies and advanced economies have decoupled during the globalization period but countries inside each respective group have converged. This finding is consistent with our result that the U.S. is more informative for the business cycles of advanced countries like Canada, Germany, and the U.K., and less so for the developing country in our sample, Mexico.

Another plausible explanation is that countries with a common language tend to have similar business cycles.[6] We find that U.S. output growth informs the business cycles for each of the countries in our sample with English as the *de facto* or official language.

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[6]See Artis et al. (2011) and Francis et al. (2012), Ductor and Leiva-Leon (2014).

1.5 Conclusion

In this paper, we assessed whether U.S. economy drives business cycle turning points of other nations. We extended the nonlinear business cycle model of Hamilton (1989) to allow U.S. output growth to influence the probability of a country moving between states of expansion and recession. We found that the U.S. does inform the timing and duration of recessions for Canada, Germany, the U.K., and, to a lesser extent, Mexico. Additionally, we found no informative relationship between U.S. output growth and the business cycles of France, Italy, and Japan.

It is important to keep in mind that the results here suggest only that the U.S. does not appear to lead France, Italy, and Japan. If these countries business cycles react intraquarter to fluctuations in U.S. output, they would show up as a false negative in the estimation. Further, if a common world shock affects the U.S. before other countries, the result might be a false positive. However, our analysis provides a framework for approaching the question of Granger causality across business cycles.

CHAPTER 2

BUSINESS CYCLES ACROSS SPACE AND TIME

2.1 Introduction

Recent evidence suggests the presence of an overarching world business cycle with a number of underlying regional business cycles.[1] For instance, all countries experience global shocks, such as the financial crisis of 2009, but only a subset of countries experience idiosyncratic regional shocks, such as the European debt crisis which began in 2011. This paper seeks to answer a number of questions regarding how the world business cycle interacts with less-pervasive business cycles that are isolated to a subset of countries: How has this relationship between global and regional cycles evolved over time? What factors determine business cycle similarities across countries? What drives international turning points?

One way to model the business cycle is as a movement between distinct latent states of expansion and recession [see Burns and Mitchell (1946)].[2] Distinguishing periods of recession can be done through a simple rule such as two consecutive periods of economic contraction, or through richer statistical methods. For example, Hamilton (1989) outlined a two-state Markov-switching model of the U.S. economy and found similar recession dates to those outlined by the NBER. Since that seminal paper, numerous studies have implemented Markov-switching frameworks to estimate

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[1] Kose, Otrok, and Whiteman (2003, 2008) determined that both regional and global factors account for a relatively large portion of the variation in economic growth across countries. Bordo and Helbling (2011) conducted historical analysis of international business cycle synchronization over the past , and similarly found an increase in the importance of global shocks over time. On the other hand, Kose, Otrok, and Prasad (2012) and Hirata, Kose, and Otrok (2012) found a decline in the importance of global factors, but an increase in business cycle comovement within both emerging and developing economies.

[2] Alternatively, there is a large literature on modelling business cycles through dynamic factors as opposed to looking at business cycle phases. See Kose, Otrok, and Whiteman (2003, 2008), Kose, Otrok, and Prasad (2012), Hirata, Kose, and Otrok (2012), and Francis, Owyang, and Savaşçin (2012), among others.

business cycle phases for multiple economies and compare common movements *ex post*.[3] Typically these studies assume independence across economies where individual cycles are estimated separately from one another in a univariate setting. These univariate Markov-switching models therefore do not lend themselves to properly analyze the comovement and interaction of multiple economies.

Hamilton and Owyang (2012, henceforth HO) constructed a regional business cycle model to consider a large number of economies inside of a single Markov-switching framework. In their application, they 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 implement time-series clustering by assuming that states tend to move together in a small number of endogenously-determined groupings determined by historical employment growth rates and other state-specific characteristics, such as industry composition. They find evidence that all states tend to experience national downturns, but the specific timing of entering or exiting recession differs depending on the shock which initially led to the downturn.

A shortfall of HO's model is that they assume the underlying business cycle regime evolves according to fixed transition probabilities (FTP). Markov-switching models with FTP (e.g., Hamilton, 1989; HO) assume the current regime is a function of only the previous regime(s), and may miss vital information (contained in macroeconomic data) signalling business cycle turning points. For example, the probability of a global recession should rise when there is a financial crisis. To reflect this, the variables driving the time-variation of the transition probabilities should contain financial statistics informing the model of an impending downturn.

We adopt the framework of HO and apply it to countries rather than states, with the primary methodological innovation being the inclusion of time-varying transition probabilities (TVTP). Markov-switching models with TVTP have two particular advantages over standard fixed transition alternatives. First, the economic regime is a function of both the previous regime as well as past macroeconomic conditions. We can therefore include a set of covariates which inform the

[3]See Owyang, Piger, and Wall (2005), Owyang, Piger, Wall, and Wheeler (2008) and Altuğ and Bildirici (2012), among others.

model of the timing of regime switches. The second advantage of using TVTP is that the expected duration of a given state is also time-varying. This feature is more intuitive than models with constant expected duration (i.e., models with FTP) because recessions tend to have different lengths depending on the economic climate and their proximate causes. For example, economists expect that a recession caused by a negative financial shock will last longer than a recession due to say a contractionary oil shock. Similarly, the expected length of a recession should depend on the relative magnitudes of the underlying shocks. For example, a large shock to oil prices implies a longer expected recession relative to a much smaller oil price shock.

Since it is infeasible to include every variable believed to influence international turning points, the choice of which variables to include in the switching process is crucial to the model's implications. For this study, we choose four variables which economic theory and previous empirical studies determined to have predictive ability and substantive relationships with previous recessions. These include term spreads, oil price shocks, global stock market returns, and global house price movements.

We use the Bayesian technique of Gibbs sampling to perform posterior inference. Our dataset includes 37 countries, covering the time period of 1970:Q3 - 2013:Q2. In that time frame, we find two instances of global recession: the first oil crisis in 1974 - 1975 and the global financial crisis of 2008 - 2009. We find three groups of countries, or "clusters," which tend to experience their own independent timing of recessions. As previous studies suggest, geographic proximity is an important factor in determining the groupings of these countries.[4] However, we find that trade openness, industrialization, and similar institutional factors, such as linguistic diversity are also important.

From the TVTP setup, our results suggest that the primary drivers of international turning points are movements in asset prices. 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

[4]We should note this result comes from analyzing the cluster compositions *ex post* and finding a tendency of countries to cluster based on geographic proximity. We plan on testing this by including continent dummies in the prior specification.

fluctuations in asset prices. This result reinforces the finding by Reinhart and Rogoff (2009) and Helbling et al (2011) of the importance of financial markets in propagating recessions to a global level.

The outline of the paper is as follows: Section 2.2 outlines the model. Section 2.3 explains the estimation technique. Section 2.4 describes the data. Section 2.5 presents the estimation results and findings. Section 2.6 concludes the paper.

2.2 Model

The central framework of our model is the multivariate regime-switching framework of Hamilton and Owyang (2012, HO). We assume each economy's growth rate depends on a latent regime indicator which takes one of two possible states at each time period. These states represent the business cycle, with alternating phases of expansion and recession. In expansion states, the economy grows at a relatively higher average rate than in recession states.

Standard regime-switching models (e.g., Hamilton, 1989; HO) assume the regime indicator follows a first-order Markov process with *fixed transition probabilities* (FTP). Here, the probability of the current period's state (i.e., expansion or recession) depends upon last period's state, allowing the model to capture regime persistence. For example, Hamilton (1989) found in a simple one-country model that expansionary periods tend to be followed by expansionary periods and recessionary periods tend to be followed by recessionary periods. This characteristic matches the dating of recessions by the NBER's Business Cycle Dating Committee.

However, the regime-switching model with FTP has a number of shortcomings. First, the evolution of the regime is an implicit probabilistic process. The model is parsimonious and tractable, but operates as a "black box" with underlying dynamics that may be of interest to researchers and policymakers. Second, regime persistence is constant across time periods. A framework wherein the expected duration of a regime (e.g., a recession) is a function of current economic conditions is more appealing. Therefore, we assume the switching process for the aggregate regime variable follows *time-varying transition probabilities* (TVTP).[5] In the model with TVTP, the underlying

[5] Time-varying transition probabilities were first considered by Diebold, Lee, and Weinbach (1994), Filardo (1994), Filardo and Gordan (1998), and more recently by Kim, Piger, and Startz (2008), Kaufmann (2011), and Bazzi et al.

transition probabilities are a function of exogenous transition covariates, in addition to the previous state. In our application, the transition covariates are measures of global shocks and economic conditions informing the timing of business cycle turning points. The inclusion of TVTP in the regime-switching process allows us to consider what shocks tend to drive groups of countries into and out of recession.

In addition to the modeling assumptions placed on the transition dynamics, we must also consider the interaction of business cycles across countries. Typically, regime-switching models which consider multiple countries assume either full dependence or full independence across country business cycles. In the case of full dependence, all countries follow the same cycle and can therefore be summarized by a single, global regime indicator. Conversely in the case of full independence, each country's cycle is estimated separately from the others' and assumes 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 while allowing for deviations for groups of countries, or what we call "clusters". Following HO and Francis, Owyang, and Savaşçin (2012, henceforth FOS), we determine cluster composition endogenously through similar movements in economic growth as well as a set of country-specific characteristics which enter through the prior distribution.

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

$$\mathbf{y}_t = \mu_0 + \mu_1 \odot \mathbf{s}_t + \varepsilon_t, \qquad \varepsilon_t \overset{i.i.d}{\sim} N(\mathbf{0}, \mathbf{\Sigma}), \tag{2.1}$$

where $\mathbf{y}_t = [y_{1t}, \ldots, y_{Nt}]'$, $\mathbf{s}_t = [s_{1t}, \ldots, s_{Nt}]'$, $\mu_0 = [\mu_{01}, \ldots, \mu_{0N}]'$, $\mu_1 = [\mu_{11}, \ldots, \mu_{1N}]'$, and $\varepsilon_t = [\varepsilon_{1t}, \ldots, \varepsilon_{Nt}]'$. The symbol $\odot$ represents element-by-element multiplication.

We assume the error vector ε_t is independent of the state vector, s_τ, for all time periods (i.e.

(2014).

$E[\varepsilon_t'\mathbf{s}_\tau] = 0 \,\forall\, \tau$). Additionally, we assume the covariance matrix is diagonal : $\mathbf{\Sigma}=$ 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 $\mathbf{s}_t$ in our model.

2.2.1 Clustering

Each country's regime indicator can take one of two possible values at any given time period (0 for expansion or 1 for recession). When the number of countries (N) is large, the regime vector $\mathbf{s}_t$ can take 2^N possible values. Left unrestricted, the model cannot be feasibly estimated due to the number of possible combinations the regime vector can take and the resulting parameter proliferation problem. One potential solution is to assume all of the country cycles are fully dependent, and therefore follow the same global business cycle. Conversely, we could assume full independence across country cycles and estimate each individual country's regime variable independent of the others'.[6]

Instead we opt for an assumption between the case of full dependence and full independence. We restrict the number of possible values for the regime vector through a *time-series clustering* framework.[7] Clustering assumes there are a number of unobserved groupings – or, "clusters" – of countries which experience similar business cycle turning points apart from the global cycle. Country-members of each respective group experience idiosyncratic recessionary periods while non-members are in expansion. It is important to note that this assumption abstracts away from business cycle turning points isolated to a single country or a small group of countries. Therefore, recessions must be substantially pervasive across countries in order to show up in our model. This assumption is justified by the recent empirical evidence from Kose et al. (2012), which suggests that a large portion of economic growth is due to both global and regional factors.

[6]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, $\Pr(s_{A,t} = i | s_{B,t} = j) = \Pr(s_{A,t} = i)$.

[7]See Frühwirth-Schnatter and Kaufmann (2008), HO, FOS, and Hernández-Murillo et al. (2013). The time-series clustering framework reduces these possible values to $K+2$ (where $K+2 << 2^N$), giving us a numerically tractable model.

Assume there is 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 $z_t = k$ is a $(N \times 1)$ vector $\mathbf{h}_k = [h_{1k}, \ldots, h_{Nk}]'$, 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 recession, $\mathbf{h}_{K+1} = [1, \ldots, 1]'$) and $z_t = K+2$ (all countries in expansion, $\mathbf{h}_{K+2} = [0, \ldots, 0]'$).

For the remaining aggregate regimes $z_t = 1, \ldots, K$, a group of countries is in recession while simultaneously all remaining countries are in expansion. These regimes are associated with what we call "idiosyncratic" clusters since one group of countries experiences an idiosyncratic recession in relation to the rest of the countries in our sample when these regimes are realized. Country membership h_{nk} in each of the idiosyncratic clusters is an unobserved variable determined endogenously. We infer cluster membership 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., $\sum_{k=1}^{K} h_{nk} = 1$). This assumption stands in contrast to the model of HO, which did not restrict U.S. states to a single cluster, but allowed for each state to be a member of either one cluster, multiple clusters, or none of the clusters. Our assumption uncovers the "strongest" comovement relationships across countries, whereas leaving cluster membership unrestricted offers the flexibility to capture relatively weaker instances of economic comovement.

We rewrite (2.1) as a mixture model with $K+2$ components:

$$\mathbf{y}_t | z_t = k \sim N(\mathbf{m}_k, \mathbf{\Sigma}) \text{ for } k = 1, \ldots, K+2, \tag{2.2}$$

where

$$\mathbf{m}_k = \mu_0 + \mu_1 \odot \mathbf{h}_k.$$

2.2.2 Evolution of the Regime

We assume the switching process for the aggregate regime variable z_t follows *time-varying transition probabilities* (TVTP). The underlying transition probabilities are a function of a set of transition covariates $\mathbf{v}_t = [v_{1t}, \ldots, v_{Lt}]'$ in addition to the realization of last period's state z_{t-1}. Following Kaufmann (2011), we adopt a centered parameterization in order to properly identify the time-varying and time-invariant portions of the transition probabilities. Formally, the TVTP takes the multinomial logistic representation:

$$p_{ji,t} = \Pr(z_t = j | z_t = i, \mathbf{v}_t) = \frac{\exp\left[(\mathbf{v}_t - \bar{\mathbf{v}})\,\gamma_{ji}^v + \gamma_{ji}\right]}{\sum_{k=1}^{K+2} \exp\left[(\mathbf{v}_t - \bar{\mathbf{v}})\,\gamma_{ki}^v + \gamma_{ki}\right]}, \tag{2.3}$$

where γ_{ji}^v 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 $\bar{\mathbf{v}}$ to be the mean of the covariates. For identification purposes, we define state $K+2$ as the reference state, implying $\gamma_{K+2,i}^v = \mathbf{0}_{L+1}$ 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.

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.[9] We also need the restrictions to avoid label switching between the two worldwide states and two growth rate parameters during estimation.

In order to identify the idiosyncratic clusters, we must impose restrictions on the transitions of the aggregate state variable, z_t. Following HO, we deny transitions from one idiosyncratic state to a different idiosyncratic state by imposing $p_{ji,t} = 0$ for all t where $i \neq j$, $i \leq K$, and $j \leq K$.

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

[9] Notice that 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.

Thus, individual clusters experience idiosyncratic recessions relative to the world, but not directly following another cluster experiencing its own idiosyncratic recession in the previous period. 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.

2.3 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 their conditional posterior distributions rather than directly drawing 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 be estimated. The first block is the entire set of growth and variance parameters, $\theta = \{\theta_1, \ldots, \theta_N\}$, where $\theta_n = \{\mu_{n0}, \mu_{n1}, \sigma_n^2\}$. The second block is the aggregate state time series, $\mathbf{Z} = \{z_1, \ldots, z_T\}$. The third block consists of the entire set of transition probability parameters, $\gamma = \{\gamma_1, \ldots, \gamma_{K+2}\}$, where $\gamma_j = \left[\gamma_{j1}^{v\prime}, \gamma_{j1}, \ldots, \gamma_{jK+2}^{v\prime}, \gamma_{jK+2}\right]'$ represents the entire set of transition parameters governing the transition probabilities to state j. The fourth block, $\mathbf{H} = \{\beta, \xi, \lambda, h\}$, includes the cluster membership indicators, $h = \{\mathbf{h}_1, \ldots, \mathbf{h}_{K+2}\}$, as well as the set of hyperparameters and latent variables determining the prior for cluster association, $\beta = \{\beta_1, \ldots, \beta_{K+2}\}$, $\xi = \{\xi_1, \ldots, \xi_{K+2}\}$, and $\lambda = \{\lambda_1, \ldots, \lambda_{K+2}\}$.[10]

2.3.1 Priors

We must define prior distributions for the parameters. These distributions are given in Table B.7. The mean growth rate parameters have a normal prior distribution. The variance parameters have an inverse-Gamma prior distribution. Following Kaufmann (2011), the transition parameters have a normal prior distribution.

Following Frühwirth-Schnatter and Kaufmann (2008), HO, Francis, Owyang, and Savaşçin

[10]Note: $\xi_k = [\xi_{1k}, \ldots, \xi_{Nk}]'$ and $\lambda_k = [\lambda_{1k}, \ldots, \lambda_{Nk}]'$.

(2012), and Hernández-Murillo et al. (2013), 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, $\mathbf{x}_{nk}$:

$$p(h_{nk}) = \begin{cases} \frac{\exp(x'_{nk}\beta_k)}{1+\exp(x'_{nk}\beta_k)} & \text{if } h_{nk} = 1 \\ \frac{1}{1+\exp(x'_{nk}\beta_k)} & \text{if } h_{nk} = 0 \end{cases} . \tag{2.4}$$

This assumption allows countries to endogenously cluster based on comovements in real GDP growth and country-specific covariates rather than imposing country groupings exogenously. Following Holmes and Held (2006) and HO, we rewrite (2.4) under the assumption that cluster membership is determined by an underlying latent variable ξ_{nk} with associated variance λ_{nk}:

$$h_{nk} = \begin{cases} 1 & \text{if } \xi_{nk} > 0 \\ 0 & \text{else} \end{cases} ,$$

where

$$\xi_{nk} | \beta_k, \lambda_{nk} \sim N\left(\mathbf{x}'_{nk}\beta_k, \lambda_{nk}\right)$$

$$\lambda_{nk} = 4\psi_{nk}^2$$

$$\psi_{nk} \sim KS,$$

where KS represents the distribution of the Kolmogorov-Smirnov test statistic.

2.3.2 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 $\theta_n = \{\mu_{n0}, \mu_{n1}, \sigma_n^2\}$ 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, $\mathbf{Z}$, 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 mutiple-state extension of the filter – outlined by HO – with the inclusion of TVTP as in Kaufmann (2011).

We utilize the difference random utility model (dRUM) outlined by Frühwirth-Schnatter and Frühwirth (2010) and Kaufmann (2011) to sample the transition probability parameters ,γ. The dRUM is a data augmentation method that gives us a linear regression of γ_j with logistic errors. The logistic errors can be approximated by a mixture of normal distributions, so that the posterior distribution for γ_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, $\mathbf{P} = \{P_1, \ldots, P_T\}$.

Cluster membership and the associated prior hyperparameters are drawn in four substeps. We first draw the coefficients in the prior, β_k , from a normal distribution conditional on knowing the other model parameters and prior hyperparameters. Following Holmes and Held (2006), we draw the latent variable ξ_{nk} from a truncated logistic distribution. We then draw the variance of this distribution, λ_{nk}, conditional on this new draw of ξ_{nk}. Country n's idiosyncratic cluster membership indicator, h_{nk}, is drawn conditioned on the membership indicators for the other countries and the new parameter draws. After incorporating the hierarchical prior, cluster membership depends on similarity in fluctuations across countries' economic growth rates.

2.3.3 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 $p\left(Y|\Theta\right)$ 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 et al. (2013) 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. McLachlan and Peel (2010) find through simulations that BIC may overrate models with a large number of clusters. Thus, we also calculate the Integrated Classification Criterion (ICL-BIC) which penalizes models for both complexity and the presence of overlapping clusters. Since these information criterion are decreasing with the likelihood and increasing in the penalty factors (complexity and/or overlapping clusters), the optimal number of clusters is the model with the smallest BIC or ICL-BIC.

2.4 Data

We use quarterly real GDP growth as our indicator of economic activity for each country. Our sample includes 37 countries[11] covering the time period 1970:Q3 - 2013:Q2. 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.[12] The OE data runs from 1980:Q1 - 2013:Q2 which results in an unbalanced panel when grouped with the OECD dataset.[13]

In order to control for the Great Recession, we allow for a structural break in the average growth rates beginning in the first quarter of 2008 through the third quarter of 2009. We represent this break by rewriting (2.2) as:

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

[11]Countries included in our sample include Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Hong Kong, India, Indonesia, Ireland, Italy, Japan, Korea, Luxembourg, Malaysia, Mexico, Netherland, New Zealand, Norway, Philippines, Portugal, Singapore, South Africa, Spain Sweden, Switzerland, Taiwan, Thailand, United Kingdom, United States, and Venezuela.

[12]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.

[13]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.

where

$$\mathbf{m}_k^* = (\mu_0 + D_t\mu_0^*) + (\mu_1 + D_t\mu_1^*) \odot \mathbf{h}_k.$$

and D_t is a dummy variable which is equal to 1 during the Great Recession time period (2008:Q1 - 2009:Q3) and 0 otherwise. This specification controls for the potential structural break during this time period by allowing for lower average growth rates.

In addition to the data for real GDP growth, the model also requires data on two sets of covariates: (1) country-specific covariates influencing the prior distribution of cluster membership, and (2) transition covariates driving the regime-switching process.

2.4.1 Cluster Covariates

The cluster covariates are country-specific variables which potentially inform business cycle synchronization across countries by influencing the prior distribution on cluster membership. We consider six variables: (1) the degree of trade openness, (2) financial integration, (3) the degree of industrialization, (4) oil rents, (5) a formalism index, (6) an ethnolinguistic index, and (7) continent dummies. The top panel of Table B.8 lists the sources for each cluster covariate as well as any transformations made to the raw data.

The degree of trade openness of a country is measured as total trade as a percentage of its GDP using data from Penn World Tables 8.0. A country with a high degree of trade openness is more exposed to foreign demand and supply shocks, leading to a higher degree of synchronization with its trading partners. However, economic theory also suggests that countries with a high degree of trade openness may have more divergent cycles due to production specialization (Imbs, 2004). We do not separate these channels, but rather examine how trade openness influences synchronization inside of our different clusters of countries.

We measure financial openness as the sum of total foreign assets and total foreign liabilities as a percentage of GDP, with data provided by Lane and Milesi-Ferretti (2007). Recent theoretical studies reached conflicting conclusions of how financial openness affects synchronization [See discussion in Kalemi-Ozcan (2013)]. On one hand, an idiosyncratic negative shock to productivity will lead to lower domestic investment and financial outflows to unaffected foreign economies, implying lower levels of synchronization. On the other hand, a negative shock affecting all countries will lead to a reduction in investment in all economies, implying higher levels of synchronization. Empirical studies have also been unable to resolve the question of how financial openness affects business cycle synchronization, since different papers have found it can increase, decrease, or have no impact on synchronization [See Imbs (2010), Kalemli-Ozcan et al. (2013), and Davis (2014)]. In this paper, we leave this channel unrestricted. A higher degree of financial openness may be a characteristic of synchronization between one group of countries, whereas another cluster may be characterized by countries with relatively lower levels of financial integration.

Investment share of GDP reflects the degree of industrialization of a country, with a high investment share of GDP reflecting an emerging or developing economy that is experiencing catch-up growth. As noted by Kose et al. (2012), countries at a similar stage of development tend to experience a higher degree of synchronization especially during the time period considered in our sample.

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 who 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.

We also include two gravity measures to capture similarities in institutions across countries. The literature has shown that countries with similar institutions may be inclined to have more similar business cycle timing.[14] The first is a formalism index provide by Djankov et al. (2003) which measures the degree of formality of the civil court system. Economic agents inside countries which have similar methods for solving legal disputes may be more likely to conduct business with each other, and have a higher degree of economic integration. The second gravity metric is an ethnolinguistic index from La Porta et al. (1999) which measures the degree of language diversity. Similar to legal systems, countries that share a common language will be more likely to trade with

[14] See Imbs (2004), Baxter and Kouparitsis (2005), and Francis et al. (2012).

each other and therefore be more synchronized.

Continent dummies capture geographic proximity and common movements across regions. We include dummies for Asia, Europe, North America, and South America, and leave the remaining countries (Australia, New Zealand, and South Africa) without a continent dummy variable.

2.4.2 Transition Covariates

By construction of the model, the transition covariates are macroeconomic variables which inform the model when business cycle turning points occur. Whereas the cluster covariates measured country-specific factors which influence synchronization, the transition covariates inform the regime-switching process of (lagged) economic conditions. We place our focus on four covariates which economic theory and empirical evidence have shown to have predictive ability for business cycle turning points. While the cluster covariates reflect country-specific characteristics, the transition covariates reflect global economic conditions. The transition covariates we use are (1) an interest rate term spread, (2) a measure of oil price movements, (3) stock market returns, and (4) housing price growth. We use the one-period lag of each variable to meet sufficient conditions proposed by Filardo (1998) that the covariates be uncorrelated with the state variable. The bottom panel of Table B.8 lists the sources for each transition covariate as well as any transformations made to the raw data.

Numerous studies show the term spread's ability to forecast output and instances of recession.[15] One notable explanation is that term spread movements could be reflecting changes in monetary policy.[16] A contractionary monetary policy shock – i.e. an increase in the short-term interest rate – will mitigate both inflation and inflation expectations. However, the short-term interest rate is expected to fall back to its original level in the future, thereby implying some downward pressure on the long-term interest rate. The short-rate increases by relatively more than the long-term rate,

[15] See Harvey (1988), Stock and Watson (1989), Dueker (1997), Estrella and Mishkin (1998), Hamilton and Kim (2002), Kauppi and Saikkonen (2008), Katayama (2010), among many others. Stock and Watson (2003) and Wheelock and Wohar (2009) survey the literature on the relationship between the term spread and economic activity.

[16] See Estrella (2005).

leading to a fall in the term spread – a flattening of the yield curve – prior to the decrease in economic activity implied by the contractionary policy shock. Another plausible explanation outlined by Harvey (1988) is related to agents' expectation of future economic growth. When agents foresee an economic downturn, they desire to smooth their future consumption stream. Agents sell short-term bonds and buy long-term bonds, thereby inverting the yield curve and decreasing the term spread. We use the difference between the 10-year and 3-month U.S. Treasury security yields as our term spread metric.[17]

Our second transition covariate is a measure of oil price movements. Hamilton (2003) and Barsky and Kilian (2004) survey the primary channels through which oil price shocks can lead to recessions.[18] On the supply side of the economy, a spike in the price of oil increases input costs for firms, thereby decreasing productivity and driving down output. On the demand side, an oil price shock decreases household consumption and savings since consumers' demand for oil tends to be inelastic. Additionally, countries have heterogenous responses to an oil price shock depending on if they are a net exporter or importer of oil. If a group of countries is a net exporter of oil, then the increase in income due to rising oil prices may outweigh the aforementioned costs incurred by households and non-oil-producing firms. In our model, this would be represented by a negative coefficient for oil price growth in the transition probability of these oil-producing countries experiencing an idiosyncratic recession. Therefore, when the price of oil rises, the probability of this cluster of countries experiencing a recession goes down. Conversely, clusters comprised of countries which are net-importers of oil should have a higher probability of recession when the price of oil rises.

We use the world price of oil from the IMF's International Financial Statistics as our measure of oil prices.[19] To gauge movements in this price, we use the net oil price increase formulated

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

[18]Also, see Raymond and Rich (1997), Kilian (2008), and Engemann, Kliesen, and Owyang (2011).

[19]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.

by Hamilton (1996, 2003), which accounts for both the asymmetry of oil price shocks and the evolution of the price of oil over the previous year. 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.

Our third covariate is the return on a stock market index, which we measure 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) and Katayama (2010) 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.

Our fourth and final transition covariate is the growth in global housing prices, as measured by the log difference of the Federal Reserve Bank of Dallas' Global Real Housing Price Index. A number of recent studies find a significant link between housing and business cycle turning points.[20] One potential reason for this relationship is that housing reflects a large portion of consumer wealth. Therefore, household behavior reacts strongly to declines in housing wealth and induces a relatively large shortfall in aggregate demand. Also, 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.

2.5 Results

We approximate the joint posterior distribution of the model with 50,000 iterations of the Gibbs sampler after an initial burn-in period of 50,000 iterations. 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 $K = 3$ idiosyncratic clusters minimizes both BIC and

[20]See Leamer (2007), Owyang and Ghent (2010), Claessens et al. (2010, 2012), Hirata et al. (2014).

ICL-BIC, with $K = 5$ clusters being the second-best model.[21]

Table B.9 reports the estimates for each country's state-dependent growth rate (μ_{0n} and μ_{1n}) and variance parameters (σ_n^2). As expected, developed countries tend to have lower growth rates in both expansion and recession compared to the emerging and developing economies in our sample, but also smaller volatility. For some of the rapidly developing countries (e.g., 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.

2.5.1 Cluster Composition

Figure B.12 is a choropleth map showing the posterior probabilities of cluster membership for cluster 1. Countries with red shading have a high posterior probability of membership , while countries in yellow have a low probability. Countries in white are not included in our sample. Cluster 1 is comprised solely of European countries. In fact, Switzerland is the only European country in our sample with a low probability of membership in cluster 1.

Figure B.14 shows the cluster membership probabilities for cluster 2. Countries with high probabilities of membership include Australia, Canada, Chile, India, South Africa, Switzerland, and the U.S. Besides Chile and Switzerland, these countries were all former British territories. Other countries with relatively high membership probabilities (i.e., greater than 0.50) include Brazil, China, and Mexico.

Lastly, Figure B.16 shows the cluster membership probabilities for cluster 3. This cluster is comprised of mostly Southeastern Asian countries, including Hong Kong, Indonesia, Japan, Malaysia, New Zealand, Singapore, Taiwan, and Thailand. Other countries with relatively high probabilities of membership are Argentina, Korea, and the Philippines.

These cluster results coincide with previous studies, such as Castles and Obinger (2008), FOS, and Ductor and Leiva-Leon (2015), which each found a European and English-speaking group of countries. Additionally, Ductor and Leiva-Leon (2015) find a Southeast Asian cluster similar to the composition of cluster 3 from our results. These similarities are not unexpected given that these

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

previous studies also use real GDP as a cluster variable (or in some instances, a gravity variable) in determining country groupings.

In our model, cluster membership is not only determined by similar GDP growth rates, but also a set of country-specific characteristics which enter through the prior distribution. This assumption allows 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 discrete derivative, δ_{qk}, for each cluster covariate q and idiosyncratic cluster k. Explicitly, this derivative is given by

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

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. The discrete derivative measures the amount the prior probability of cluster membership changes with respect to a single covariate (i.e., country-specific characteristic) while holding all other covariates at their respective averages. For example, suppose two countries had average country characteristics with the exception of a sole cluster covariate q. For one country, the covariate q is one standard deviation above the mean value ($\bar{x}_q + \sigma_q$), while for the other country, this covariate is one standard deviation below ($\bar{x}_q - \sigma_q$). The discrete derivative δ_{qk} is the difference between the implied (prior) probabilities of these two countries being included in cluster k.

Table B.10 gives the posterior median of the discrete derivative, δ_{qk}, for each cluster characteristic. We find that a country with a relatively high degree of trade openness (i.e., one standard deviation above the sample mean) would have a prior probability 0.36 lower of being included in cluster 2 relative to a country with a relatively low degree of trade openness (i.e., one standard deviation below the sample mean), *ceteris paribus*. Similarly, a country with a high degree of trade openness has a 0.39 higher probability of being in cluster 3 relative to a country that trades relatively less. For cluster 1, a lower enthnolinguistic index increases the probability of membership. For cluster 2, lower trade openness is the only significant country characteristic which influences the prior membership probability. Finally, we find that many of the country characteristics influence the prior probability of membership in cluster 3, including a higher degree of trade openness, a lower stage of development[22], less domestic oil production, and more financial integration. These results imply that a number of factors apart from geography influence country comovement. Therefore, simply imposing country groupings based on geographic proximity overlooks these important economic relationships which need to be accounted for in models of international business cycles.

Another way to analyze how the country characteristics affect cluster groupings is by looking at the implied probabilities of membership based solely on the cluster covariates. These membership probabilities differ from the ones previously presented (i.e., the probabilities presented in Figures B.12, B.14, and B.16) in that those probabilities take into account comovement in output growth across countries as well as the country characteristics entering the prior We present the probabilities implied only by the cluster covariates for each cluster in Figures B.13, B.15, and B.17.

For cluster 1, we see from Figure B.13 that the prior information places a high weight on most European countries, some South American countries (e.g., Argentina, Brazil, and Chile), and Japan. After considering output growth, Figure B.12 infers that the cluster becomes more refined to solely European countries.

Figure B.15 shows that the prior information for cluster 2 implies a relatively high membership probability on Canada, India, South Africa, the U.K., and the U.S. When output growth is also included, the cluster membership probabilities shown in Figure B.14 on all of these countries rises to the highest quintile (except the U.K., which clusters with its European counterparts in cluster 1). Additionally, Australia and Chile are added, implying the country characteristics entering the prior distribution offer little to explain why these two countries cluster with the other members in cluster 2. Finally, the prior information for cluster 3 from Figure B.17 shows a high weight on the Southeast Asian countries, China, New Zealand, and Venezuela. Accounting for output growth, the cluster profile centers on the Southeast Asian countries and New Zealand, while adding Argentina

[22]Industrialization is measured by the capital-income ratio. Typically, developing countries have a higher capital-income ratio than their developed counterparts. Therefore, this cluster is comprised of developed countries by our industrialization metric.

and Japan, as seen in Figure B.16. These results imply that although our cluster covariates are accounting for some of the reasons for comovement, there are also other factors unaccounted for in our set of covariates for which some countries comove with others. Next, we analyze the degree to which certain shock processes affect comovement due to countries having a similar degree of exposure.

2.5.2 Recession Timing and Its Determinants

The optimal model according to BIC indicated $K = 3$ idiosyncratic clusters. Added to the two global regimes (all countries in expansion, or all countries in recession), this implies the optimal model can take one of six possible aggregate regimes at any given time period. The first two regimes correspond to global expansion ($z_t = 1$) and recession ($z_t = 2$), during which all countries are simultaneously in an economic upturn or downturn, respectively. The remaining three regimes ($z_t = 3, 4, 5$) are idiosyncratic regimes wherein one cluster of countries is in recession while the remaining countries experience expansion. For example, regime 3 ($z_t = 3$) implies the countries in cluster 1 are in recession while all other countries in the sample are in expansion.

Figure B.18 shows the posterior probabilities of being in each regime at each time period. These probabilities are computed as the percentage of MCMC iterations for which a regime is drawn. For each time period, we deem the regime to be the modal draw. These probabilities are useful because they offer us an explicit timing of the interaction between the global business cycle and the endogenously-determined cluster cycles. For instance it allows us to answer questions about whether global recessions were preceded or followed by idiosyncratic recessions of particular country clusters.

The top panel of Figure B.18 shows the probability of global recession. We also include gray bars representing official NBER recession dates for the U.S. for comparison. We find two instances of a global recession: (1) 1974:Q4-1975:Q1 and (2) 2008:Q2-2009:Q2. This first global recession is commonly associated with the first major oil crisis, while the second coincides with the recent global financial crisis. These results are in line with those of Kose et al (2012) and Fushing et al.

(2010), which both find global recessions during these time periods.[23]

The bottom three panels of Figure B.18 show the probability of an idiosyncratic recession in one of the endogenously-determined clusters. Here, the gray bars reflect the timing of global recessions implied by our model. We should note that two periods of global recession are preceded by idiosyncratic recessions. The first oil crisis follows a recession in cluster 2 (the English-speaking cluster), and the global financial crisis follows a recession in cluster 3 (the Southeast Asian cluster). The timing of the first global recession is easily understood by looking at the sharp drop in equity values across the member countries of cluster 2 which occurred prior to the global propagation of the oil crisis. The timing of the global financial crisis is more puzzling since the common narrative is that the crisis began in the U.S. The reason is that output growth in the other countries in cluster 2 did not yet begin to experience a significant downturn compared to the Southeast Asian countries which comprised cluster 3. By the fourth quarter of 2008, the crisis had spread enough to be labelled a global recession according to our model. This result highlights the regional aspect of our model rather than looking at the effects on individual countries.

We now compare the estimated recession timing for each cluster with the actual recession histories of the specific country-groupings. Figure B.19 shows the probability that cluster 1 experiences either a global recession (the blue line) or an idiosyncratic recession (the orange line). Since this cluster is primarily comprised of the European countries in our sample, a natural benchmark is the recession dating according to the CEPR Business Cycle Dating Committee, which is represented by the gray bars. It is clear that our estimated timing of recession for the European cluster (cluster 1) covers many of the recession dates outlined by the CEPR.

Figure B.20 displays a similar comparison for the estimated recession dates for cluster 2, where

[23]There are some notable differences in global recession timing across these two previous studies and ours. Kose et al. (2012) finds additional global downturns during 1982 and 1991. Fushing et al. (2010) finds downturns during 1980:04 and 2000:08 - 2001:05.

These differences can be attributed to differences in data and methodology. Kose et al. (2012) use annual data to construct a timing of the global business cycle. Therefore, they are only able to identify business cycle turning points at an annual frequency whereas we can do so at a quarterly frequency. To classify recessions, they look solely at the peaks and troughs in the growth rate of world GDP per capita and reinforce these dates by looking at the movement of other macroeconomic aggregates around these points (similar to the NBER and CEPR dating methods). Fushing et al. (2010) use monthly data on an individual country basis. However, they simply look at correlated movements, where we look at common movement in a large panel of countries in a single model.

the blue line again represents the posterior probability of a global recession and the orange line represents the probability of an idiosyncratic recession for cluster 2. The gray bars reflect US recession dates according to the NBER's Business Cycle Dating Committee, which are used for comparison since this cluster includes the US and its main trading partners. Again, our estimated timing of recession matches up well with that of the NBER. The relatively low probability of recession for the early 1990's recession reflects the weakness of this recession to propagate internationally. Also, our dating misses the early 1980's and early 2000's recession given that the recession effects are relatively more prevalent in cluster 1 and cluster 3, respectively.[24]

For cluster 3, there does not exist an accepted timeline of business cycle dates for the Asian countries included in that cluster. Instead, we match our estimated recession dates to major economic events in Asia during those time periods. Table B.11 lists the estimated idiosyncratic recession dates for cluster 3 and the associated economic event(s) in the region. Again, we find our results are consistent with documented recessions or downturns in this region.

Ultimately, we would like to determine how common shocks affect the timing of recessions across country groupings. Does a specific shock lead to a recession in a certain cluster, or is a single, common shock responsible for differences in recession timing? Table B.12 displays the posterior mean of the discrete derivatives for each of the transition covariates, with bold indicating that 68% of the posterior distribution does not include zero. These discrete derivatives can be interpreted as how each transition covariate (e.g., term spread movements, global house prices, equity returns, and oil price shocks) affects the regime dynamics of the model (i.e., how z_t evolves across time). Specifically, the derivatives are calculated as follows: Suppose covariate l is one standard deviation above its historical mean while all other covariates are at their respective 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 discrete derivative is the difference between the two probabilities: $\delta_{ji}^l = p_{ji}^H - p_{ji}^L$. To give a concrete example, the $\delta_{11}^2 = 0.19$ given in the first column and first row in

[24] Recall, only one idiosyncratic cluster can be in recession at a time. Therefore, our model does not allow for overlapping recessions across two idiosyncratic clusters.

the top panel of Table B.12 implies that the persistence probability of the global expansion regime (i.e., the probability a global expansion regime continues into the current period given that the previous period was a global expansion) is 0.19 larger when global house price growth is one standard deviation above its historical mean compared to when it is one standard deviation below. Therefore, long global expansions are characterized by relatively robust growth in house prices.

In addition to house price growth, the length of global expansions appears to be driven by increases in oil prices. This result seems counter-intuitive since large increases in oil prices are commonly attributed to supply-side recessions. However, this positive relationship comes from the steady rise in oil demand during good economic times (i.e., global expansions) rather than the negative effects of sharp oil supply shocks of the 70's and 80's.

The persistence of global recession periods is negatively related to equity returns. This result follows from the fact that both of the global recessions in our sample are characterized by large losses in values of equities. Interestingly, we do not find a similar role for house price growth during periods of recessions. Rather, house prices appear to be an indicator of transitions between global expansion and idiosyncratic cluster recessions. Conditional on being in a state of global expansion, a large loss in global housing wealth increases the probability of transitioning to a recession in cluster 1 or 3.

The dynamics of cluster 1 depend heavily upon the state of asset prices. The persistence of an idiosyncratic recession in cluster 1 is characterized by large losses in both global house and equity prices, whereas recoveries of cluster 1 into global expansion are similarly characterized by growth in housing and equities. When transitioning from global recession to a recession in cluster 1, we find countries outside of cluster 1 tend to enter recovery from a global recession as global equities recover, whereas cluster 1 countries tend to lag and stay in recession. The sensitivity of cluster 1 to asset prices may be a function of the fact that the member countries for the most part have developed financial markets. Since they are well-integrated to global asset markets, these countries are more exposed to downturns in financial wealth.

Our results suggest that recessions in cluster 2 are caused by a variety of shocks. In a global expansion regime, the probability of cluster 2 entering a recession increases with either (1) an inversion of the yield curve, (2) large losses in equity markets, or (3) oil price increase shocks. When cluster 2 is in recession, the probability of the idiosyncratic recession propagating to a global level goes up as the yield curve continues to invert, whereas the probability of entering a global expansion is positively related to equity price growth. After accounting for the members of cluster 2 (US and its trading partners along with China and its trading partners), these results suggest cluster 2 is not exposed to any one shock in particular but rather comovement occurs due to one of the major economies (US or China) falling into recession.

Similar to cluster 1, the probability of cluster 3 entering a recession is also dependent on falling house and equity prices. The persistence of recession in cluster 3 correlates with (1) an inverting yield curve, (2) increases in equity markets, or (3) oil price increase shocks. If global housing and equity markets continue to deteriorate, then the probability rises of an idiosyncratic recession in cluster 3 spreading to the global level. Conversely, a normalization of the yield curve and/or the absence of oil price increase shocks increases the probability of recovering and entering a global expansion. The sensitivity of cluster 3 is not surprising given its composition of Asian countries and the numerous financial crises associated with that region.

Overall, we find that recession timing across the clusters and the world depends largely on movements in asset (house and equity) prices. Following Reinhart and Rogoff (2009) and Helbling et al. (2011), this suggests that financial frictions are one of the main contributing factors in propagating recessions to a global level. Potential explanations for this result include 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.

2.6 Conclusion

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

We found three 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.

Finally, 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 and Asian clusters to be highly sensitive to movements in housing and equity price movements, while a cluster comprised of US and China was open to a variety of global shocks

CHAPTER 3

BUSINESS CYCLE COMOVEMENTS IN INDUSTRIAL SUBSECTORS

3.1 Introduction

Business cycles are often thought of as the transitions between two distinct economic regimes, expansion and recession (e.g., Burns and Mitchell, 1946). The notion of regimes, albeit statistically convenient, stems from the idea that these phases are asymmetric. For example, Morley and Piger (2009) show that expansions tend to be slow and steady while recessions are typically short but deep. In economic models, the statistical characterization of the business cycle regimes has taken many forms. In particular, Hamilton (1989) proposed that transitions between phases of the business cycle follow a first order Markov process. This paper spawned a rather substantial literature analyzing, among other things, differences in the cycle across time.

Recently, some studies have considered differences in the business cycle across space – that is, the U.S. business cycle can be decomposed into regional, state, or city cycles. Within the context of Markov-switching models, Owyang, Piger, and Wall (2005, OPW) found that states' business cycles, though similar to the national cycle, may exhibit both idiosyncratic timing and growth rates. OPW show that state cycles, when estimated independent of one another, may experience recessions earlier, later, or not at all relative to the nation.[1] Building on this work, Hamilton and Owyang (2012, HO) proposed a model in which states' business cycles moved together forming a national cycle.[2] HO also simultaneously allows a small number of clusters of states to move apart from the national cycle. Thus, states may have heterogeneity in their turning points with respect to the national cycle or experience recessions completely unrelated to the national cycle.

[1] Owyang, Piger, Wall, and Wheeler (2008) also studied the business cycles of cities. Their results as to the potential variety of the timing of the turning points were consistent with those for states in the previous paper.

[2] Stock and Watson (2010) also reinvestigated the notion that aggregate cycles can be identified by examining a large number of disaggregate series.

HO found two groups of states that enter recessions before the nation, a group of states that stayed in recession after the nation recovered, and a group of states that experienced recessions unrelated to the nation. In addition, HO found that a state's industrial mix was an important determinant of the cluster to which the state belonged.

The literature studying the comovements between industrial sectors is substantial. Murphy, et al (1989); Cooper and Haltiwanger (1990); and Christiano and Fitzgerald (1998) are among the many the studies which have documented industrial comovements. [results here] Carlino and Defina (2004) compare the comovement between pairs of industrial sectors using a cohesion index. Comin and Phillipon (2005) attribute the decline in aggregate volatility to a decline in the sychronization of industries. Hornstein (2000) shows that industries comove both within and across sectors. See Kim and Kim (2006) for a relatively recent survey.

Because industrial mix appears to be an important determinant of the comovement of states' economies, this paper investigates the business cycle linkages between disaggregate industries. We consider 84 of the the four-digit NAICS industrial sectors during the period 1972 - 2014 to determine (1) whether comovements occur, (2) whether they are a pervasive feature of the U.S. business cycle, (3) whether they are limited to industries within a single classification – i.e., do subsectors in the same broad classification move together more than subsectors across industrial classes, and (4) whether they are determined by industries' relative position in the prodcution stream.

The model we propose is similar to that of HO. We assume there exists a national business cycle in which all sectors move together. Some industrial sectors, however, may belong to particular clusters which may differ from the national cycle by entering or leaving their own "idiosyncratic" recessions. The number of possible clusters is small relative to the number of total industrial sectors and is chosen by Bayesian information criterion. While the framework is similar in flavor to the original HO paper, we do not rely on industry-level covariates as we did in HO to inform our prior as to which industries cluster together. Instead, we adopt a uniform prior which weights each industry's cluster inclusion probability equally.[3] Additionally, our model differs from HO in that we decompose each industry's IP growth into trend and cycle components through an unobserved components framework.

The balance of the paper is laid out in the following order: Section 2 presents the empirical model of clustered Markov switching. Section 3 outlines the estimation via the Gibbs sampler and describes the disaggregated industrial data. We pay particular attention to the estimation of the aggregate regimes and the cluster inclusion probabilities as informed by the Dirichlet prior. Section 4 discusses the empirical findings. Section 5 concludes.

3.2 The Empirical Model

Let $\mathbf{y}_t$ denote an $(N \times 1)$ vector of the log of observed industrial production levels at date t, where N is the number of industries. Let $\mathbf{Y}_t = (\mathbf{y}_t, \mathbf{y}_{t-1}, ..., \mathbf{y}_1)'$ denote the history of observations through date t. We model $\mathbf{y}_t$ as having two unobserved components, trend and cycle:

$$\mathbf{y}_t = \tau_t + \mathbf{c}_t$$

where $\tau_t = (\tau_{1t}, \tau_{2t}, ..., \tau_{Nt})'$ and $\mathbf{c}_t = (c_{1t}, c_{2t}, ..., c_{Nt})'$. We model the trend component as a random walk with drift:

$$\tau_t = \delta + \delta^* I(t > t^*) + \tau_{t-1} + \eta_t$$

where δ is the $(N \times 1)$ vector of drift parameters, and η_t is an $(N \times 1)$ vector of permanent innovations. We allow for a structural break in the drift parameter at some specified time period t^*. Let $E(\eta_t \eta_t') = \tilde{\mathbf{\Sigma}}$, reflecting potential cross-industry correlations in the shocks to trend.

We assume the cyclical component is an AR(p) with a Markov-switching intercept:

$$\mathbf{c}_t = \mu_t + \sum_{l=1}^{p} \phi_l \mathbf{c}_{t-l} + \varepsilon_t$$

where μ_t is the $(N \times 1)$ vector of time-varying average growth, ϕ_l is the $(N \times N)$ diagonal matrix

[3] We also place a small prior probability on the possibility that an industry is unassociated with all of the aggregate clusters.

of AR coefficients, and ε_t is an $(N \times 1)$ vector of transitory innovations with $E(\varepsilon_t \varepsilon_t') = \mathbf{\Sigma}$. For each industry n, we assume the roots of $\phi_n(L) = \phi_1 L + \ldots + \phi_p L^p$ lie strictly outside the unit circle.

Let $\mathbf{s}_t$ be an $(N \times 1)$ vector of recession indicators (so $s_{nt} = 1$ when industry n is in recession and $s_{nt} = 0$ when industry n is in expansion). Suppose that

$$\mu_t = \mu_0 + \mu_1 \odot \mathbf{s}_t, \tag{3.1}$$

where the nth element of the $(N \times 1)$ vector $\mu_0 + \mu_1$ is the average cycle IP growth in industry n during recession, the nth element of the $(N \times 1)$ vector μ_0 is the average cycle IP growth in industry n during expansion, and $\odot$ represents the Hadamard product.

In order for the model to be identified, we must set one of the regime-dependent growth rates to be 0 (ie., either $\mu_0 = 0$ or $\mu_0 + \mu_1 = 0$ must be imposed). Following Kim and Nelson (1999) and Sinclair (2010), we assume $\mu_0 = 0$ and $\mu_1 < 0$. Under these restrictions, the model follows Friedman's plucking model, where expansions are periods when the cycle is near trend and recessions are periods when the cycle is "plucked" downward from trend.

In the most general case, each industry n has both a set of expansion and recession growth rates (μ_{0n}, μ_{1n}) and its own regime process $\widetilde{\mathbf{s}}_{nt} = \{s_{n1}, .., s_{nt}\}$. The most degenerate case is one in which each industry has the same set of expansion and recession growth rates (i.e., $\mu_{0n} = \mu_{0m}$ and $\mu_{1n} = \mu_{1m}$ for all n, m combinations) and the same business cycle (i.e., $\widetilde{\mathbf{s}}_{nt} = \widetilde{\mathbf{s}}_{mt}$ for all n, m combinations and for all time t). We are interested in an intermediate version of these models in which industries can be clustered together based on the timing of their business cycles. That is, we are interested in a model in which N industries take on $\kappa << N$ different regime processes and have N different steady-state expansion and recession growth rates. In this case, the national (aggregate) regime consists of the compilation of the individual industrial regimes, the relationship between which is specified next.

Let Z_t signify the time-t aggregate regime and let $\mathbf{H}$ denote an $(N \times K)$ matrix whose elements are all zeros and ones and K is the allowed possible number of aggregate permutations (regimes).

The row n, column k element of $\mathbf{H}$ is one if industry n is in a recession when the aggregate regime is k. In the simplest possible model (this is the degenerate case above), $K = 2$, with the first column being all zeros (every industry is in expansion together when in regime $k = 1$) and the second column is all ones (every industry is in recession together when in regime $k = 2$). A natural first alternative is $K = 3$, where the third column just has ones for the manufacturing subsectors (all manufacturing subsectors are in recession together when in regime $k = 3$; all other industries are in expansion during this period). For purposes of discussion, we refer to the regimes in which all industries move together as "national" regimes and refer to regimes in which some industries are in recession but others are not as "idiosyncratic" regimes.

The aggregate regime is assumed to follow a K-state Markov process with $(K \times K)$ transition matrix $\mathbf{P}$. In principle, we could model a world in which Z_t is allowed to transition to and from any aggregate regime. However, for identification, we additionally assume that the transition probabilities across idiosyncratic regimes are zero. This restriction prohibits two separate sets of industries from experiencing idiosyncratic recessions in consecutive periods. In other words, a set of industries can only enter and exit recession through the regime in which all industries are either in or out of recession. As an example, the "manufacturing" cluster cannot enter recession directly after the "transportation" cluster without all industries experiencing either a recession or recovery first.

Thus, we can redefine the regime-dependent cyclical growth rate as

$$\mu_t = \mu(Z_t = k) = \mu_0 + \mu_1 \odot \mathbf{h}_k \tag{3.2}$$

for $\mathbf{h}_k$, the kth column of $\mathbf{H}$. In principle, we can estimate each element of $\mathbf{H}$ without restriction. However, we can map this framework into the clustered time series framework of Frühwirth-Schnatter and Kaufmann (2008) by assuming that any industry can enter only a single non-degenerate aggregate regime.[4] That is, apart from the regimes in which all industries are either in recession ($k = 1$) or expansion ($k = 2$), industries may only be in recession for one

[4]We allow for an industry to not be a member of any aggregate regime with a small prior probability (0.01).

aggregate regime ($k \geq 3$). Formally,

$$\sum_{k=3}^{K} h_{nk} \leq 1 \text{ for all } n. \tag{3.3}$$

Under this assumption, we can define a number of unique industrial clusters $\kappa = K - 2$.

3.3 Estimation

The full set of latent variables and parameters includes the series of trend components $\tau^T = (\tau_1^{'}, \tau_2^{'}, ..., \tau_T^{'})'$, the series of cycle components $\mathbf{c}^T = (\mathbf{c}_1^{'}, \mathbf{c}_2^{'}, ..., \mathbf{c}_T^{'})'$, the trend growth rates $\tilde{\delta}$ =$[\delta, \delta^*]$, the trend variance parameters $\tilde{\Sigma}$, the recession growth rates μ_1, the cycle AR coefficients Φ, the cycle variance parameters $\mathbf{\Sigma}$, the transition probabilities $\mathbf{P}$, the series of aggregate state posterior regimes $\mathbf{Z^T} = (Z_1, Z_2, ..., Z_T)'$, the matrix defining the clusters $\mathbf{H}$, and the number of clusters κ. For now, assume that the number of clusters κ is determined exogenously and is suppressed in the notation. Then, there are five blocks of parameters to be sampled: the trend and cycle components, $\{\tau^T, \mathbf{c}^T\}$, each industry's cycle parameter set $\theta_n = \{\mu_{1n}, \sigma_n^2, \phi_n(L)\}$, each industry's trend parameter set $\tilde{\theta}_n = \{\delta_n, \delta_n^*, \tilde{\sigma}_n^2\}$, the aggregate business cycle $\mathbf{Z^T}$ and its associated transition matrix $\mathbf{P}$, and the matrix $\mathbf{H}$ determining the cluster membership.

3.3.1 Priors

Each of the intercept parameters in θ_n and $\tilde{\theta}_n$ is assumed to have a normal prior distribution. The conditional variances for each industry is assumed to have an inverse Gamma prior distribution. The transition probabilities for the aggregate regime process are assumed to have a Dirichlet prior distribution given the fixed number of regimes. The fixed number of regimes is determined by the number of clusters. Each industry n's membership in any cluster is $\frac{1}{\kappa}(1 - p_0)$, where κ is the total number of clusters and p_0 is the prior probability that an industry does not belong to any cluster. Prior hyperparameters are shown in Table B.13.

3.3.2 Drawing $\mathbf{c^T}, \tau^{\mathbf{T}} | \tilde{\delta}, \tilde{\Sigma}, \mu_1, \mathbf{\Sigma}, \mathbf{H}, \mathbf{Z}, \mathbf{Y_T}$

The unobserved components model has the following state-space representation:

$$\begin{aligned} \Delta \mathbf{y}_t &= \delta + \delta^* I(t > t^*) + \mathbf{A}\mathbf{x}_t + \eta_t, \\ \mathbf{x}_t &= \mathbf{M}_t + \mathbf{F}\mathbf{x}_{t-1} + \tilde{\varepsilon}_t, \end{aligned}$$

where $\Delta \mathbf{y}_t = \mathbf{y}_t - \mathbf{y}_{t-1}$, $\mathbf{x}_t = [\mathbf{c}_t', \mathbf{c}_{t-1}']'$, $\tilde{\varepsilon}_t = [\varepsilon_t', \mathbf{0}_{1xN}]'$, and matrices

$$\begin{aligned} \mathbf{F} &= \begin{bmatrix} \phi_1 & \phi_2 \\ \mathbf{I}_N & 0 \end{bmatrix}, \\ \mathbf{A} &= \left[\mathbf{I}_N, -1\mathbf{I}_N\right], \\ \mathbf{M}_t &= \left[\mu_t', \mathbf{0}_{1xN}\right]', \end{aligned}$$

where μ_t is defined as in equation 3.2. We carry out the forward-backward filter of Carter and Kohn (1994) to obtain a draw of $\mathbf{x}^T$, and therefore $\mathbf{c}^T$. The corresponding draw of the trend component is then $\tau_t = \mathbf{y}_t - \mathbf{c}_t$ for all $t = 1, \ldots, T$.

3.3.3 Drawing $\tilde{\delta}, \tilde{\Sigma} | \mathbf{P}, \mathbf{Y_T}, \tau^{\mathbf{T}}$

Given the draw for τ^T, we can draw each industry's trend parameters $(\delta_n, \delta_n^*, \tilde{\sigma}_n^2)$ independent of the other industries. Premultiplying the trend equation by $\tilde{\sigma}_n^{-1}$, we get

$$\Delta \tilde{\tau}_{nt} = \tilde{\sigma}_n^{-1}\delta_n + \tilde{\sigma}_n^{-1} I(t > t^*)\delta_n^* + \tilde{\eta}_{nt},$$

where $\Delta \tilde{\tau}_{nt} = \tilde{\sigma}_n^{-1}(\tau_{nt} - \tau_{nt-1})$, $I(t > t^*)$ is the indicator function of when t is greater than the structural break date of t^*, and $\tilde{\eta}_{nt} \sim N(0, 1)$. We stack equations for $t = 1, ..., T$, to get

$$\Delta \tilde{\tau}_n^T = \mathbf{W}_n^T \tilde{\delta}_n + \tilde{\eta}_n^T,$$

where $\Delta\tilde{\tau}_n^T = [\Delta\tilde{\tau}_{n2},\ldots,\Delta\tilde{\tau}_{nT}]'$, $\mathbf{W}_n^T = [W_{n2},\ldots,W_{nT}]'$, $W_{nt} = [\tilde{\sigma}_n^{-1},\tilde{\sigma}_n^{-1}I(t > t^*)]'$, and $\tilde{\delta}_n = [\delta_n,\delta_n^*]'$. The posterior distribution of the drift parameters is

$$\tilde{\delta}_n|\tilde{\sigma}_n^2,\tau_n^{\mathbf{T}} \sim N(\mathbf{d}_{n1},\mathbf{D}_{n1}),$$

where

$$\begin{aligned}\mathbf{d}_{n1} &= \mathbf{D}_1^{-1}(\mathbf{D}_0^{-1}\mathbf{d}_0 + \mathbf{W}_n^{T\prime}\Delta\tilde{\tau}_n^T),\\ \mathbf{D}_{n1} &= (\mathbf{D}_0^{-1} + \mathbf{W}_n^{T\prime}\mathbf{W}_n^{T\prime}).\end{aligned}$$

The posterior distribution for the trend variance is therefore

$$\tilde{\sigma}_n^2|\tilde{\delta}_n,\tau_n^{\mathbf{T}} \sim IG\left(\frac{\tilde{\nu}_0 + T}{2},\frac{\tilde{s}_0 + \hat{\eta}_n^{T\prime}\hat{\eta}_n^T}{2}\right),$$

where IG represents the inverse-gamma distribution, $\hat{\eta}_n^T = (\hat{\eta}_{n1},\hat{\eta}_{n2},\ldots,\hat{\eta}_{nT})'$ and $\hat{\eta}_{nt} = \Delta\tau_{nt} - \delta_n - I(t > t^*)\delta_n^*$.

3.3.4 Drawing $\mu,\mathbf{\Sigma}|\mathbf{Z^T},\mathbf{H},\mathbf{c^T}$

The industries' cycle parameters (μ_{1n},σ_n^2) are conditional independent of each other once $\mathbf{c}^T$, $\mathbf{P}$, $\mathbf{Z^T}$, and $\mathbf{H}$ are drawn. Let

$$\varsigma_{nt} = \begin{cases} 1 & \text{if } h_{nz_t} = 1 \\ 0 & \text{otherwise} \end{cases}.$$

Premultiplying the cycle equation by σ_n^{-1}, we have

$$c_{nt}^* = \mu_{1n}\varsigma_{nt}^* + \varepsilon_{nt}^*, \tag{3.4}$$

for $c_{nt}^* = \sigma_n^{-1}(c_{nt} - \phi_1 c_{nt-1} - \phi_2 c_{nt-2})$, $\varsigma_{nt}^* = \sigma_n^{-1}\varsigma_{nt}$ and $\varepsilon_{nt}^* = \sigma_n^{-1}\varepsilon_{nt}$ so that $\varepsilon_{nt}^* \sim N(0,1)$. Stacking the equations for $t = 1,...,T$, we get

$$\widetilde{\mathbf{c}}_{nT}^* = \widetilde{\mathbf{X}}_{nT}^*\mu_{1n}+\widetilde{\varepsilon}_{nT}^*,$$

where $\widetilde{\mathbf{X}}^*_{nT} = (\varsigma^*_{n1}, \varsigma^*_{n2}, \ldots, \varsigma^*_{nT})'$. Hence, we have the posterior distribution for each industry n:

$$\mu_{1n}|\mathbf{Z_T}, \mathbf{\Sigma}, \mathbf{H}, \mathbf{c}_n^{\mathbf{T}} \sim N(m_1, M_1),$$

where

$$\begin{aligned} m_1 &= M_1^{-1}\left(M_1^{-1} m_1 + \widetilde{\mathbf{X}}^{*\prime}_{nT}\widetilde{\mathbf{c}}^*_{nT}\right), \\ M_1 &= \left(M^{-1} + \widetilde{\mathbf{X}}^{*\prime}_{nT}\widetilde{\mathbf{X}}^*_{nT}\right). \end{aligned}$$

The posterior distribution of the cycle variance is given by

$$\sigma_n^{-2}|\mathbf{Z}_T, \mu_{1n}, \mathbf{H}, \mathbf{c}_n^{\mathbf{T}} \sim IG\left(\frac{\nu_0 + T}{2}, \frac{s_0 + \widetilde{\varepsilon}'_{nT}\widetilde{\varepsilon}_{nT}}{2}\right)$$

where $\widetilde{\varepsilon}_{nT} = (\tilde{\varepsilon}_{n1}, \tilde{\varepsilon}_{n2}, \ldots, \tilde{\varepsilon}_{nT})'$ and $\tilde{\varepsilon}_{nt} = c_{nt} - \phi_1 c_{nt-1} - \phi_2 c_{nt-2} - \varsigma_{nt}$.

3.3.5 Drawing $\mathbf{Z}^{\mathbf{T}}, \mathbf{P}|\mu_0, \mu_1, \mathbf{\Omega}, \mathbf{H}, \mathbf{c}^{\mathbf{T}}$

Conditional on $\mathbf{H}$, the aggregate regime process can be drawn by a method similar to a K-state Markov process [see Kim and Nelson (1999)]. This relies on drawing the vector $\mathbf{Z}^{\mathbf{T}}$ from the conditional distribution

$$p\left(\mathbf{Z}^{\mathbf{T}}|\mathbf{P}, \theta, \mathbf{H}, \mathbf{c}^{\mathbf{T}}\right) = p\left(Z_{\mathbf{T}}|\mathbf{c}^{\mathbf{T}}\right)\prod_{t=1}^{T-1} p\left(Z_{\mathbf{t}}|Z_{\mathbf{t+1}}, \mathbf{c}^{\mathbf{t}}\right),$$

where $p(\mathbf{Z_t}|\mathbf{Y_t})$ can be obtained from a modification of the Kalman filter [see Hamilton (1989)] and

$$p\left(Z_{\mathbf{t}}|Z_{\mathbf{t+1}}, \mathbf{c}^{\mathbf{t}}\right) \propto p\left(Z_{\mathbf{t+1}}|Z_{\mathbf{t}}\right) p\left(Z_{\mathbf{t}}|\mathbf{c}^{\mathbf{t}}\right).$$

Recognizing that $p(Z_{\mathbf{t+1}}|Z_{\mathbf{t}})$ is simply a transition probability, the regime probabilities can be written as

$$\Pr\left[Z_{\mathbf{t}} = i | Z_{\mathbf{t+1}}, \mathbf{c^t}\right] = \frac{p\left(Z_{\mathbf{t+1}} | Z_{\mathbf{t}} = i\right) p\left(Z_{\mathbf{t}} = i | \mathbf{c^t}\right)}{\sum_{j=1}^{K} p\left(Z_{\mathbf{t+1}} | Z_{\mathbf{t}}\right) p\left(Z_{\mathbf{t}} | \mathbf{c^t}\right)},$$

and each $Z_{\mathbf{t}}$ can be generated using a random draw from a uniform distribution.

Conditional on $\mathbf{Z^T}$, the transition probabilities $\mathbf{P}$ can be drawn from a Dirichlet posterior in which the hyperparameters are determined by the number of observed transitions between regimes [see Kim and Nelson (1999)].

3.3.6 Drawing $\mathbf{H} | \mu_0, \mu_1, \mathbf{\Omega}, \mathbf{Z_T}, \mathbf{P}, \mathbf{Y_T}$

As in Frühwirth-Schnatter and Kaufmann (2008), we assume that the prior distribution for the clusters is Dirichlet with hyperparameters β_0. Then, the posterior cluster probabilities can be computed as

$$\Pr\left[h_{nk} = 1 | \mathbf{c}_n^{\mathbf{T}}, \mathbf{Z^T}, \theta_n\right] \propto p\left(\mathbf{c}_n^{\mathbf{T}} | \mathbf{Z^T}, \theta_n, h_{nk} = 1\right) \times \Pr\left[h_{nk} = 1 | \beta_{-n}\right],$$

where $p\left(\mathbf{c}_n^{\mathbf{T}} | \mathbf{Z^T}, \theta_n, h_{nk} = 1\right)$ is the likelihood associated with the drawn parameters and $h_{nk} = 1$. The probability $\Pr\left[h_{nk} = 1 | \beta_{-n}\right]$ is the posterior Dirichlet density with updated hyperparameters β_{-n}, where β_{-n} reflects the number of industries in each cluster excluding industry n.

3.3.7 Choosing the Number of Clusters

The optimal number of clusters is determined by Bayesian Information Criterion (BIC),which Kass and Raftery (1995) showed to be a good approximation of Bayes factors. We run the Gibbs Sampler for $K = 2, \ldots, 8$ idiosyncratic clusters and choose the model which minimizes the BIC.

3.3.8 Data

The business cycle indicator of interest is the annualized, seasonally-adjusted quarterly industrial production at the four-digit NAICS industry level provided by the Federal Reserve Board of Govenors. Our sample includes 83 industries covering the time period 1972:Q1 - 2014:Q4.

3.4 Empirical Results

According to the information criterion, the optimal model contains four idiosyncratic clusters ($K = 4$). Figure B.21 presents the recessionary experiences of the four clusters and the aggregate depicted through their posterior recession probabilities. Recall that, at each period, the economy can reside in a single (aggregate) regime, preventing overlapping cluster recessions. Table B.14 shows the transition probabilities for the aggregate regime. While some transitions are restricted ex ante (these are shown by zeros in bold), the estimated model yields more transition restrictions than imposed. Table B.15 lists each industry included in our sample along with its four-digit NAICS code and the posterior cluster membership probabilities.[5]

While there are a number of periods in which clusters of industries experience idiosyncratic recessions, Figure B.21 shows that the aggregate recessions are broadly consistent with the NBER-defined national recessions, which are indicated by grey shading. For the most part, each industry cluster exhibits a unique recessionary behavior relative to the aggregate. For example, industries in group 2 lead the aggregate into recessions by a few months. These harbinger industries include textile manufacturing, wood products, wholesale trade, and some services, suggesting that the incidence of most recessions occurs upstream and propagates down. Similarly, group 1 includes mining, paper products, computer and electronic products, iron and steel products, and some transportation (rail and ship building), suggesting downturns moving down the prodution stream. This group experiences an isolated recession only during the early 2000's after the aggregate recession of 2001 and leading up to the Great Recession.

The third group is comprised of energy, food, chemical products, medical equipment and some transportation industries. This group tends to stay in prolonged recession following national recessions, implying a longer recovery time for these industries. The fact that many of the sectors included in this group are necessities (food, energy, and medicine) may be indicative of overall consumer behavior following a national downturn.

Lastly, membership in group 4 is not very strong across industries given by the low inclusion probability. One potential explanation for this is that there is only one idiosyncratic recession captured by this cluster. Therefore, this group may be picking up common movements during this single time period rather than a long-term relationship across industry business cycles.

[5]Estimation results for all model parameters are available from the authors upon request.

3.5 Conclusion

In a previous paper, we examined the cross-state patterns for the propagation of recessions. We found that some states led the nation into recession, some states lagged the nation in recovery, and some – particularly energy intensive states – experienced downturns not experienced by the rest of the nation. We noted these state clusters could be, in large part, characterized by their industrial mix.

In this paper, we investigated the business cycle properties of the industries themselves and found that industries behave in much the same manner as the states. Industries upstream in the production processs often led others into recession. Energy, raw materials, and textiles sectors also were prone to experience prolonged recessions unrelated to aggregate recessions, indicating that robust growth in other sectors can offset downturns in these industries (perhaps caused by declines in the prices of the raw commodity). Future avenues of research include testing to see if similar broad industry classification as well as connected production (as measured through input-output matrices) are significant determinants of two industries being in the same grouping.

APPENDIX 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 (2011) and Kaufmann (2011). There are four steps:

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

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

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

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

A.1 Conditional Likelihood

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

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

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

$$p(y_{nt}|\theta_n,z_t,h)\propto\sigma_n^{-1}\exp\left\{\frac{-\left[y_{nt}-\mu_n'\mathbf{w}\left(z_t,h\right)\right]^2}{2\sigma_n^2}\right\},$$

where

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

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

We draw θ_n conditional on knowing all other countries' growth rate and error variance parameters. We then separate the draw of θ_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

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

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

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

where

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

and

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

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

Following HO, we have

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

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

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

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

$$p(y_{nt}|\theta_n, z_t, h) \propto \sigma_n^{-1} \exp\left\{\frac{-\left[y_{nt} - \mu_n' \mathbf{w}\left(z_t, h\right)\right]^2}{2\sigma_n^2}\right\},$$

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

Chib (1996) shows that

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

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

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

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

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

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

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

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

The estimation method assumes the state variable is determined by underlying state utilities given by

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

$$z_t=j\Leftrightarrow U_{j,t}=\max_k U_{k,t},$$

where $v_{k,t}$ follows a Type 1 extreme value distribution, and

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

and

$$\gamma_k = \begin{cases} \left[\gamma_{kk}^{v\prime}, \gamma_{kk}, \gamma_{kK+1}^{v\prime}, \gamma_{kK+1}, \gamma_{kK+2}^{v\prime}, \gamma_{kK+2}\right]' & \text{if } k = 1, \ldots, K \\ \left[\gamma_{k1}^{v\prime}, \gamma_{k1}, \ldots, \gamma_{kK+2}^{v\prime}, \gamma_{kK+2}\right]' & \text{if } k = K+1, K+2 \end{cases}.$$

The differences of $\mathbf{V}_{k,t}$ and γ_k across global ($k = K+1, K+2$) and idiosyncratic states ($k = 1, \ldots, K$) is due to the restriction on the transition probabilities, $p_{ji,t} = 0$ for all t where $i \neq j$, $i \leq K$, and $j \leq K$.

The random utility model (RUM) focuses on drawing these state utilities directly, whereas the dRUM uses the differences in these latent state utilities. The dRUM representation is outlined by Kaufmann (2011) as

$$\omega_{k,t} = U_{k,t} - U_{-k,t}, \qquad k = 2, \ldots, K+2, \tag{A.1}$$

where

$$U_{-k,t} = \max_{j \neq k} U_{j,t},$$

giving us the value 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

$$\chi_{k,t} = \exp\left(\mathbf{V}_{k,t}'\gamma_k\right),$$

and

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

Therefore, (A.1) can be rewritten as

$$\omega_{k,t} = \mathbf{V}_{k,t}'\gamma_k + \eta_{k,t} - \log(\chi_{-k,t}) + \eta_{-k,t},$$

or

$$\omega_{k,t} = \mathbf{V}'_{k,t}\gamma_k - \log(\chi_{-k,t}) + \epsilon_{k,t}, \qquad \epsilon_{k,t} \sim Logistic.$$

Practically, there are three substeps to the sampling technique for γ_k. The first substep is to draw the latent state utility differences from

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

where

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

and

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

Next, we must estimate the logistic distribution of the errors, ϵ, by a mixture of normal distributions with $M = 6$ components. The components are sampled from

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

where the component weights, w_r, and component standard deviation, s_r, are given in Table 1 of Frühwirth-Schnatter and Frühwirth (2010).

Finally, we can generate the new draw of γ_k from a normal posterior distribution:

$$p(\gamma_k|\mathbf{Z}, \boldsymbol{\omega}, \mathbf{R}) = N(g_k, \mathbf{G}_k),$$

where

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

and

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

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

We draw the latent variables for cluster determination for state k, $H_k = \{\beta_k, \xi_k, \lambda_k, \mathbf{h}_k\}$, conditional on knowing all other state's cluster variables, $H_{-k} = \{H_j : j = 1, \ldots, K, j \neq k\}$.

Draw β_k

The posterior for β_k follows a normal distribution

$$\beta_k \sim N(\mathbf{b}_k, \mathbf{B}_k)$$

where

$$\mathbf{b}_k = \mathbf{B}_k \left(\mathbf{B}_0^{-1} \mathbf{b}_0 + \mathbf{X}_k' \mathbf{W}_k^{-1} \xi_k \right),$$

$$\mathbf{B}_k = (\mathbf{B}_0 + \mathbf{X}_k' \mathbf{W}_k^{-1} \mathbf{X}_k),$$

$$\mathbf{W}_k = \text{diag}\left(\lambda_{1k}, \ldots, \lambda_{Nk}\right),$$

$$\mathbf{X}_k = \left[x_{1k}', \ldots, x_{Nk}'\right]'.$$

Draw ξ_k

The latent variables which determine cluster membership are calculated by

$$\xi_{nk} = \mathbf{x}_{nk}' \beta_k - \log\left(u_{nk}^{-1} - 1\right),$$

where

$$u_{nk} = \begin{cases} \frac{1}{1+\exp\left(\mathbf{x}_{nk}'\beta_k\right)} u_{nk}^* & \text{if } h_{nk} = 0 \\ \frac{1}{1+\exp\left(\mathbf{x}_{nk}'\beta_k\right)} + \frac{\exp\left(\mathbf{x}_{nk}'\beta_k\right)}{1+\exp\left(\mathbf{x}_{nk}'\beta_k\right)} u_{nk}^* & \text{if } h_{nk} = 1 \end{cases},$$

and

$$u_{nk}^* \sim U\left[0, 1\right].$$

Draw λ_k

A candidate for λ_{nk} is calculated as

$$\lambda_{nk} = \begin{cases} \frac{r_{nk}}{v_{nk}} & \text{if } u_{nk} \leq \frac{1}{1+v_{nk}} \\ r_{nk} v_{nk} & \text{otherwise} \end{cases}$$

where

$$r_{nk}^2 = \left(\xi_{nk} - \mathbf{x}_{nk}' \beta_k\right)^2,$$

$$v_{nk} = 1 + \frac{w_{nk}^2 - \sqrt{w_{nk}^2 \left(4 r_{nk} + w_{nk}^2\right)}}{2 r_{nk}},$$

$$w_{nk} \sim N\left(0, 1\right),$$

$$u_{nk} \sim U\left(0, 1\right).$$

We follow the methodology of Holmes and Held (2006) to either accept the candidate, or repeat this step until acceptance occurs.

Draw h_k

For each country n, we draw h_{nk} by combining the conditional likelihood and prior:

$$\Pr\left(h_n = k | \Theta_{-\mathbf{H}}, \mathbf{Y}, \beta, \xi, \lambda\right) = \frac{p(\mathbf{Y}_n | h_n = k, \beta, \xi, \lambda, \theta, \mathbf{z}) p(h_{nk} = k)}{\sum_{j=1}^{K} p(\mathbf{Y}_n | h_n = j, \beta, \xi, \lambda, \theta, \mathbf{z}) p(h_{nk} = j)}. \tag{A.2}$$

APPENDIX B

TABLES AND FIGURES

Country	**Coverage**	**Mean ($\bar{y}$)**	**Variance (σ_y^2)**	**Correlation with U.S. ($\rho_{x,y}$)**
Canada	1960:Q2 - 2013:Q4	3.19	11.89	0.52
France	1970:Q2 - 2013:Q4	2.09	5.24	0.32
Germany	1960:Q2 - 2013:Q4	2.44	19.56	0.27
Italy	1960:Q2 - 2013:Q4	2.47	17.13	0.24
Japan	1960:Q2 - 2013:Q4	3.93	28.22	0.21
Mexico	1980:Q2 - 2013:Q4	2.39	28.53	0.26
U.K.	1960:Q2 - 2013:Q4	2.45	15.43	0.26
U.S.	1960:Q1 - 2013:Q3	3.04	11.42	-

Table B.1: Sample Statistics

Parameter	**Prior Distribution**	**Hyperparameters**
$\mu = [\mu_1, \mu_2]'$	$N\left(\mathbf{m}_0, \sigma^2\mathbf{M}_0\right)$	$\mathbf{m}_0 = [3, -3]$, $\mathbf{M}_0 = \mathbf{I}_2$
σ^{-2}	$\Gamma\left(\frac{\upsilon_0}{2}, \frac{\tau_0}{2}\right)$	$\upsilon_0 = 1$, $\tau_0 = 1$
$\gamma = [\alpha_1, \alpha_2, \beta_1, \beta_2]'$	$N\left(\mathbf{g}_0, \mathbf{G}_0\right)$	$\mathbf{g}_0 = \mathbf{0}_4$, $\mathbf{G}_0 = 2\mathbf{I}_4$

Table B.2: Prior Distributions for the Two-state Model

Parameter	**Prior Distribution**	**Hyperparameters**
$\mu = [\mu_1, \mu_2, \mu_3]'$	$N\left(\mathbf{m}_0, \sigma^2\mathbf{M}_0\right)$	$\mathbf{m}_0 = [-2, 2, 6]$, $\mathbf{M}_0 = \mathbf{I}_2$
σ^{-2}	$\Gamma\left(\frac{\upsilon_0}{2}, \frac{\tau_0}{2}\right)$	$\upsilon_0 = 1$, $\tau_0 = 1$
$\gamma_k = [\alpha_{k1}, \alpha_{k2}, \alpha_{k3}, \beta_{k1}, \beta_{k2}, \beta_{k3}]'$	$N\left(\mathbf{g}_0, \mathbf{G}_0\right)$	$\mathbf{g}_0 = \mathbf{0}_6$, $\mathbf{G}_0 = 2\mathbf{I}_6$

Table B.3: Prior Distributions for the Three-state Model

Country	Two-state Model	Three-state Model
Canada	1112.2	**1057.6**
France	769.1	**746.3**
Germany	**1238.0**	1259.9
Italy	1195.2	**1174.2**
Japan	**1026.3**	1048.6
Mexico	**806.8**	855.9
UK	1166.1	**1161.2**

Table B.4: Bayesian Information Criterion

Parameter	Canada	France	Germany	Italy	Japan	Mexico	U.K.
μ_1	-2.90	-3.25	-2.86	-2.57	-3.74	-4.60	-2.99
μ_2	2.66	1.49	3.19	1.69	3.21	3.66	2.82
μ_3	6.78	4.10	-	6.60	-	-	8.15
σ^2	5.19	2.44	15.53	8.97	16.22	17.21	8.46

Table B.5: Estimates for the Average Growth Rate and Variance Parameters - Median posterior draws for the state-dependent growth rates, μ_i, and the variance, σ^2.

	Parameter	Canada	France	Germany	Italy	Japan	Mexico	U.K.
$p_{11,t}$	α_{11}	-0.17	0.76	$\mathbf{-1.17}$	1.12	-0.49	0.20	$\mathbf{1.06}$
	β_{11}	$\mathbf{-1.35}$	$\mathbf{-0.81}$	$\mathbf{-1.12}$	-0.52	-0.25	$\mathbf{-0.91}$	$\mathbf{-0.81}$
$p_{12,t}$	α_{12}	$\mathbf{-1.10}$	$\mathbf{-1.46}$	$\mathbf{-2.73}$	-0.59	$\mathbf{-2.91}$	$\mathbf{-2.78}$	$\mathbf{-0.84}$
	β_{12}	$\mathbf{-2.49}$	$\mathbf{-1.00}$	$\mathbf{-1.40}$	$\mathbf{-1.36}$	-0.29	-0.50	$\mathbf{-1.27}$
$p_{13,t}$	α_{13}	$\mathbf{-2.23}$	$\mathbf{-3.13}$	-	$\mathbf{-2.35}$	-	-	0.36
	β_{13}	$\mathbf{-1.44}$	$\mathbf{-0.96}$	-	-0.35	-	-	-0.26
$p_{21,t}$	α_{21}	-0.73	0.09	-	-0.18	-	-	0.54
	β_{21}	-0.46	$\mathbf{-0.87}$	-	0.39	-	-	0.82
$p_{22,t}$	α_{22}	$\mathbf{2.51}$	$\mathbf{2.94}$	-	$\mathbf{3.58}$	-	-	$\mathbf{3.16}$
	β_{22}	$\mathbf{-1.53}$	-0.45	-	-0.54	-	-	-0.02
$p_{23,t}$	α_{23}	0.06	$\mathbf{-2.25}$	-	$\mathbf{-2.30}$	-	-	0.90
	β_{23}	$\mathbf{-1.03}$	-0.31	-	-0.65	-	-	0.08

Table B.6: Estimates for the Transition Probability Parameters - Median posterior draws for the parameters governing the transition probabilities, $p_{ji,t} = \Pr[s_t = j | s_{t-1} = i, y_{t-1}^{US}]$. α_{ji} captures the time-invariant portion of the transtion probability, and β_{ji} is the coefficient on lagged U.S. output growth. Bold indicates that 0 lies outside the 68$\%$ posterior coverage.

Parameter	*Prior Distribution*	*Hyperparameters*	
μ_n	$N\left(\mathbf{m}_0, \sigma_n^2 \mathbf{M}_0\right)$	$\mathbf{m}_0 = [1, -2]'$, $\mathbf{M}_0 = 2\mathbf{I}_2$	$\forall n$
σ_n^{-2}	$\Gamma\left(\frac{v_0}{2}, \frac{\tau_0}{2}\right)$	$v_0 = 1$, $\tau_0 = 1$	$\forall n$
γ_2	$N\left(g_{02}, \mathbf{G}_{02}\right)$	$g_{02} = \left[\mathbf{0}_{L(K+2)}, -2, 2, \mathbf{0}_K\right]$, $\mathbf{G}_{0k} = \mathbf{I}_{(L+1)(K+2)}$	$\forall k$
γ_k	$N\left(g_{0k}, \mathbf{G}_{0k}\right)$	$g_{0k} = [\mathbf{0}_{3L}, -2, 0, 2]$, $\mathbf{G}_{0k} = 2\mathbf{I}_{3(L+1)}$	$k = 3, \ldots, K+2$
β_k	$N(b_{0k}, B_{0k})$	$b_0 = \mathbf{0}_{(Q+1)}$, $B_{0k} = \mathbf{I}_{(Q+1)}$	$\forall k$

Table B.7: Prior Specifications for Estimation

Variable	*Raw Statistic*	*Source*	*Transformation*
Cluster Covariates			
Trade Openness	Exports and Imports (% of GDP)	Penn World Tables 8.0	Average 1950-2011
Financial Openness	Foreign Assets and Liabilities (% of GDP)	Lane and Milesi-Ferretti (2007)	Average 1970-2011
Industrialization	Capital-Income Ratio	Penn World Tables 8.0	Average 1950-2011
Oil Production	Oil Rents (% of GDP)	World Bank WDI	Average 1970-2011
Legal Systems	Formalism Index	Djankov et al. (2003)	-
Language	Ethnolingusitic Index	La Porta et al. (1999)	-
Transition Covariates			
Net Oil Price Increase	Commodity Prices, Crude Oil (Petroleum)	IMF IFS	NOPI (See Hamilton 1996, 2003)
Equity Returns	MSCI World Index	MSCI	Log first-difference
Term Spread	10-Year Treasury Constant Maturity Rate,	FRED	Difference between
	3-Month Treasury Bill: Secondary Market Rate	FRED	10-year and 3-month rate
Housing Prices	Real House Price Index	FRB Dallas	Log first-difference

Table B.8: Covariate Data Sources - 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.

Country	μ_{0n}	$\mu_{0n} + \mu_{1n}$	σ_n^2
Argentina	0.81	-0.78	6.36
Australia	0.84	-0.28	0.81
Austria	0.78	-0.15	0.61
Belgium	0.70	-0.36	0.35
Brazil	0.73	-0.63	1.89
Canada	0.82	-0.61	0.50
Chile	1.34	-1.51	1.75
China	2.37	1.27	2.77
Denmark	0.62	-0.36	1.31
Finland	0.83	-0.36	1.53
France	0.68	-0.14	0.19
Germany	0.68	-0.37	0.69
Hong Kong	1.50	-1.36	2.58
India	1.54	0.56	0.95
Indonesia	1.55	-0.91	2.91
Ireland	1.21	0.36	1.56
Italy	0.63	-0.44	0.55
Japan	0.80	-0.10	1.04
Korea	1.89	0.36	2.33
Luxembourg	1.08	-0.33	1.69
Malaysia	1.71	-0.92	1.54
Mexico	0.96	-0.16	1.23
Netherlands	0.75	-0.45	0.98
New Zealand	0.75	-0.40	1.96
Norway	0.87	0.15	1.35
Philippines	0.93	-0.36	4.12
Portugal	0.89	-0.80	1.20
Singapore	1.95	-1.22	2.06
South Africa	0.73	-0.57	0.78
Spain	0.84	-0.37	0.41
Sweden	0.73	-0.32	1.16
Switzerland	0.51	-0.87	0.38
Taiwan	1.60	-0.12	1.64
Thailand	1.55	-0.71	3.75
United Kingdom	0.73	-0.19	0.66
United States	0.83	-0.64	0.49
Venezuela	0.72	-0.85	10.51

Table B.9: Growth Rates and Variance Parameters - The median posterior draw for the average GDP growth rate and variance parameters of each country. μ_{0n} is the average growth rate for country n during a period of expansion. $\mu_{0n} + \mu_{1n}$ is the average growth rate of country n during a period of recession. σ_n^2 is the regime-independent variance for country n's average annualized growth rate across the entire sample.

Cluster Covariate	Raw *Metric*	*Cluster 1*	*Cluster 2*	*Cluster 3*
Trade Openness	Total Trade (% of GDP)	0.04	**-0.42**	**0.38**
Industrialization	Capital-Income Ratio	-0.07	-0.12	**0.19**
Legal Systems	Formalism Index	0.06	-0.02	-0.03
Language	Ethnolinguistic Index	**-0.17**	0.12	0.04
Oil Production	Oil Rents	0.04	0.10	-0.14
Financial Openness	Foreign Assets & Liabilities (% of GDP)	-0.05	-0.06	0.11
Asia	Continent Dummies	0.03	**-0.37**	**0.34**
Europe		**0.24**	**-0.14**	**-0.10**
North America		-0.08	0.14	-0.06
South America		-0.08	0.11	-0.03

Table B.10: Hyperparameters for the Prior Distribution of Cluster Membership - This table displays the posterior medians of the logistic coefficients (β_k) determining the prior distribution of cluster membership. Bold indicates parameters for which the 68% posterior coverage interval does not include zero. The table also includes the discrete derivatives (δ_k) implied by the median coefficients.

Estimated Recession Dates for Cluster 3	*Economic Event(s) in Asia*
1984:Q4 - 1985:Q3	Plaza Accord; Lack of export demand from US recession
1997:Q4 - 1998:Q3	Asian Financial Crisis
2001:Q1 - 2001:Q3	Tech Recession
2003:Q3	SARS Epidemic
2008:Q2 - 2008:Q3	Global Financial Crisis
2010:Q3	USD appreciation and tight regional monetary policy

Table B.11: Cluster 3 Recession Dates and Major Events in Asia - The first column of this table shows the estimated (idiosyncratic) recession dates for cluster 3 as implied by the posterior regime probabilities. The second table lists the associated major economic events in Asia during these time periods.

Term Spread		Previous State (z_{t-1})				
		Global Expansion	*Global Recession*	*Cluster 1*	*Cluster 2*	*Cluster 3*
Current State (z_t)	*Global Expansion*	0.03	0.06	0.11	0.01	**0.33**
	Global Recession	0	-0.22	-0.01	**-0.40**	0.05
	Cluster 1	-0.02	0.10	-0.11	-	-
	Cluster 2	**-0.02**	0.03	-	0.39	-
	Cluster 3	0.01	0.04	-	-	**-0.37**

Housing Prices		Previous State (z_{t-1})				
		Global Expansion	*Global Recession*	*Cluster 1*	*Cluster 2*	*Cluster 3*
Current State (z_t)	*Global Expansion*	**0.20**	-0.05	**0.29**	0.14	0.15
	Global Recession	0	0.04	**0.16**	0.31	**-0.09**
	Cluster 1	**-0.13**	0.01	**-0.45**	-	-
	Cluster 2	-0.01	-0.02	-	**-0.44**	-
	Cluster 3	**-0.06**	0.03	-	-	-0.06

Equity Returns		Previous State (z_{t-1})				
		Global Expansion	*Global Recession*	*Cluster 1*	*Cluster 2*	*Cluster 3*
Current State (z_t)	*Global Expansion*	**0.07**	-0.07	**0.65**	**0.31**	-0.16
	Global Recession	0	**-0.53**	0.05	-0.10	**-0.10**
	Cluster 1	0.01	**0.49**	**-0.70**	-	-
	Cluster 2	-0.02	0.06	-	-0.21	-
	Cluster 3	**-0.06**	0.04	-	-	**0.26**

Oil Price Shock		Previous State (z_{t-1})				
		Global Expansion	*Global Recession*	*Cluster 1*	*Cluster 2*	*Cluster 3*
Current State (z_t)	*Global Expansion*	**0.09**	-0.04	-0.10	-0.05	**-0.32**
	Global Recession	-0.01	0.06	0.05	-0.09	-0.08
	Cluster 1	-0.01	-0.11	0.05	-	-
	Cluster 2	**-0.04**	0.04	-	0.14	-
	Cluster 3	-0.03	0.06	-	-	**0.40**

Table B.12: Transition Covariates Effects - This table shows the effects of external shocks on the transition process of the aggregate regime z_t. We present the discrete derivatives δ^i_{ji} for each covariate on each transition probability $p_{t,ji}$. The derivatives can be interpreted as the difference in transition probabilities when the covariate is realtively high and low (i.e., $\delta^l_{ji} = p^H_{t,ji} - p^L_{t,ji}$).

Parameter	Prior Distribution	Hyperparameters	
μ_{1n}	$N\left(m, \sigma^2 M\right)$	$m = -2\ ;\ M = \mathbf{1}$	$\forall n$
σ_n^{-2}	$\Gamma\left(\frac{\nu}{2}, \frac{\iota_0}{2}\right)$	$\nu_0 = 10\ ;\ \iota_0 = 1$	$\forall n$
$\tilde{\sigma}_n^{-2}$	$\Gamma\left(\frac{\tilde{\nu}_0}{2}, \frac{\tilde{\iota}_0}{2}\right)$	$\tilde{\nu}_0 = 100\ ;\ \tilde{\iota}_0 = 0.1$	$\forall n$
$\mathbf{P}$	$\mathbf{D}\left(\alpha\right)$	$\alpha_i = 0$	$\forall i$
$\tilde{\delta}_n$	$N\left(\mathbf{d}_0, \mathbf{D}_0\right)$	$\mathbf{d}_0 = [2, 0]'\ ;\ \mathbf{D}_0 = \mathbf{I}_2$	$\forall n$
ϕ_n	$N\left(\mathbf{g}, \mathbf{G}\right)$	$\mathbf{g} = \mathbf{0}_p\ ;\ \mathbf{G} = \mathbf{I}_p$	$\forall n$
h_{nk}	$\Pr(h_{nk} = 1) = \frac{1}{\kappa}(1 - p_0)$	$p_0 = 0.01$	$\forall n, k$

Table B.13: Priors for Estimation

		Previous State (z_{t-1})					
		Agg. Exp.	*Agg. Rec.*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Current State (z_t)	*Agg. Exp.*	0.789	0	0.13	0.12	0	0
	Agg. Rec.	0	0.68	0	0.30	0.11	0.08
	Cluster 1	0	0.03	0.87	**0**	**0**	**0**
	Cluster 2	0.17	0.11	**0**	0.55	**0**	**0**
	Cluster 3	0	0.16	**0**	**0**	0.89	**0**
	Cluster 4	0.03	0	**0**	**0**	**0**	0.92

Table B.14: Transition Probabilities - This table shows the posterior median draw of the transition probabilities for the aggregate state variable (Z_t). Zeros in bold indicate transitions that were restricted ex ante.

Industry	*NAICS*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Apparel	315	**0.48**	0.47	0.01	0.02
Leather and allied product	316	0.19	**0.65**	0.09	0.05
Printing and related support activities	323	0.32	**0.59**	0.05	0.03
Petroleum and coal products	324	0.22	0.13	**0.59**	0.04
Logging	1133	**0.44**	0.16	0.38	0.01
Oil and gas extraction	2111	**0.93**	0.06	0.00	0.01
Coal mining	2121	**0.41**	0.25	0.30	0.04
Metal ore mining	2122	**0.54**	0.31	0.11	0.03
Nonmetallic mineral mining and...	2123	0.24	**0.68**	0.03	0.04
Support activities for mining	2131	**0.35**	0.25	0.34	0.02
Electric power generation, transmission...	2211	0.06	0.11	**0.78**	0.05
Natural gas distribution	2212	**0.60**	0.34	0.03	0.02
Animal food	3111	0.30	**0.32**	0.30	0.07
Grain and oilseed milling	3112	**0.43**	0.14	0.36	0.06
Sugar and confectionery product	3113	**0.46**	0.38	0.12	0.04
Fruit and vegetable preserving and...	3114	0.30	0.26	**0.35**	0.09
Dairy product	3115	0.27	0.16	**0.32**	0.23
Animal slaughtering and processing	3116	0.13	0.19	**0.62**	0.06
Bakeries and tortilla	3118	0.45	**0.46**	0.02	0.07
Other food	3119	0.10	**0.54**	0.32	0.02
Beverage	3121	0.08	0.07	**0.84**	0.01
Tobacco	3122	**0.45**	0.38	0.09	0.04
Fiber, yarn, and thread mills	3131	0.33	**0.48**	0.14	0.03
Fabric mills	3132	0.31	**0.62**	0.05	0.02
Textile and fabric finishing and fabric...	3133	0.34	**0.60**	0.01	0.05
Textile furnishings mills	3141	0.32	**0.64**	0.01	0.02
Other textile product mills	3149	0.13	**0.79**	0.01	0.06
Sawmills and wood preservation	3211	0.16	**0.76**	0.05	0.02
Veneer, plywood, and engineered...	3212	0.14	**0.75**	0.01	0.10
Other wood product	3219	0.12	**0.78**	0.01	0.07
Pulp, paper, and paperboard mills	3221	**0.46**	0.24	0.27	0.01
Converted paper product	3222	**0.47**	0.28	0.15	0.08
Basic chemical	3251	0.15	0.10	**0.68**	0.06
Resin, synthetic rubber, and artificial and...	3252	0.23	0.34	**0.40**	0.02
Pesticide, fertilizer, and other agricultural...	3253	0.31	0.14	**0.52**	0.02
Pharmaceutical and medicine	3254	0.05	0.05	**0.88**	0.02
Paint, coating, and adhesive	3255	0.45	**0.49**	0.02	0.03
Soap, cleaning compound, and toilet...	3256	0.04	0.07	**0.83**	0.05
Plastics product	3261	0.27	**0.65**	0.01	0.05
Rubber product	3262	**0.45**	0.28	0.00	0.26
Clay product and refractory	3271	**0.51**	0.37	0.02	0.07

Table B.15: Cluster Composition - This table shows the posterior cluster inclusion probabilities for each industry. The second column lists the four-digit classification level according to the NAICS.

Industry	*NAICS*	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Glass and glass product	3272	0.24	**0.59**	0.01	0.15
Cement and concrete product	3273	0.16	**0.75**	0.01	0.07
Lime and gypsum product	3274	0.28	**0.62**	0.04	0.06
Other nonmetallic mineral product	3279	0.21	**0.35**	0.18	0.24
Alumina and aluminum production...	3313	0.32	**0.36**	0.27	0.03
Nonferrous metal (except aluminum)...	3314	**0.56**	0.16	0.21	0.06
Foundries	3315	0.33	**0.47**	0.01	0.16
Forging and stamping	3321	0.35	**0.55**	0.01	0.04
Cutlery and handtool	3322	**0.50**	0.19	0.08	0.21
Architectural and structural metals	3323	0.10	**0.84**	0.01	0.03
Hardware	3325	0.23	**0.72**	0.00	0.04
Spring and wire product	3326	0.31	**0.56**	0.01	0.11
Machine shops; turned product; ...	3327	0.30	**0.61**	0.01	0.04
Coating, engraving, heat treating,...	3328	0.30	**0.46**	0.02	0.16
Other fabricated metal product	3329	0.15	**0.73**	0.05	0.03
Agriculture, construction, and mining...	3331	**0.33**	0.18	0.28	0.15
Industrial machinery	3332	0.26	**0.56**	0.01	0.12
Ventilation, heating, air-conditioning, and...	3334	0.16	**0.80**	0.01	0.01
Metalworking machinery	3335	0.44	**0.44**	0.04	0.05
Engine, turbine, and power transmission...	3336	**0.59**	0.19	0.02	0.18
Computer and peripheral equipment	3341	**0.61**	0.30	0.04	0.04
Communications equipment	3342	**0.57**	0.32	0.03	0.07
Audio and video equipment	3343	**0.52**	0.41	0.03	0.03
Semiconductor and other electronic...	3344	0.39	**0.43**	0.03	0.13
Navigational, measuring, electromedical...	3345	**0.43**	0.28	0.25	0.02
Electric lighting equipment	3351	0.13	**0.82**	0.02	0.02
Household appliance	3352	0.25	**0.67**	0.03	0.03
Electrical equipment	3353	0.35	**0.50**	0.05	0.06
Other electrical equipment and...	3359	0.43	**0.53**	0.00	0.02
Motor vehicle	3361	0.21	**0.64**	0.01	0.14
Motor vehicle body and trailer	3362	0.24	**0.46**	0.04	0.25
Motor vehicle parts	3363	0.28	**0.48**	0.01	0.22
Aerospace product and parts	3364	0.21	0.26	**0.50**	0.02
Railroad rolling stock	3365	**0.33**	0.23	0.26	0.17
Ship and boat building	3366	**0.42**	0.17	0.37	0.02
Other transportation equipment	3369	0.14	0.12	**0.67**	0.07
Household and institutional furniture...	3371	0.26	**0.65**	0.02	0.06
Medical equipment and supplies	3391	0.07	0.08	**0.80**	0.04
Newspaper, periodical, book, and...	5111	0.14	**0.66**	0.17	0.02
Iron and steel products	3311,2	**0.55**	0.21	0.16	0.07
Commercial and service industry....	3333,9	0.36	**0.39**	0.16	0.03
Office and other furniture	3372,9	0.13	**0.84**	0.01	0.01

Table B.15: Cluster Composition (continued) - This table shows the posterior cluster inclusion probabilities for each industry. The second column lists the four-digit classification level according to the NAICS.

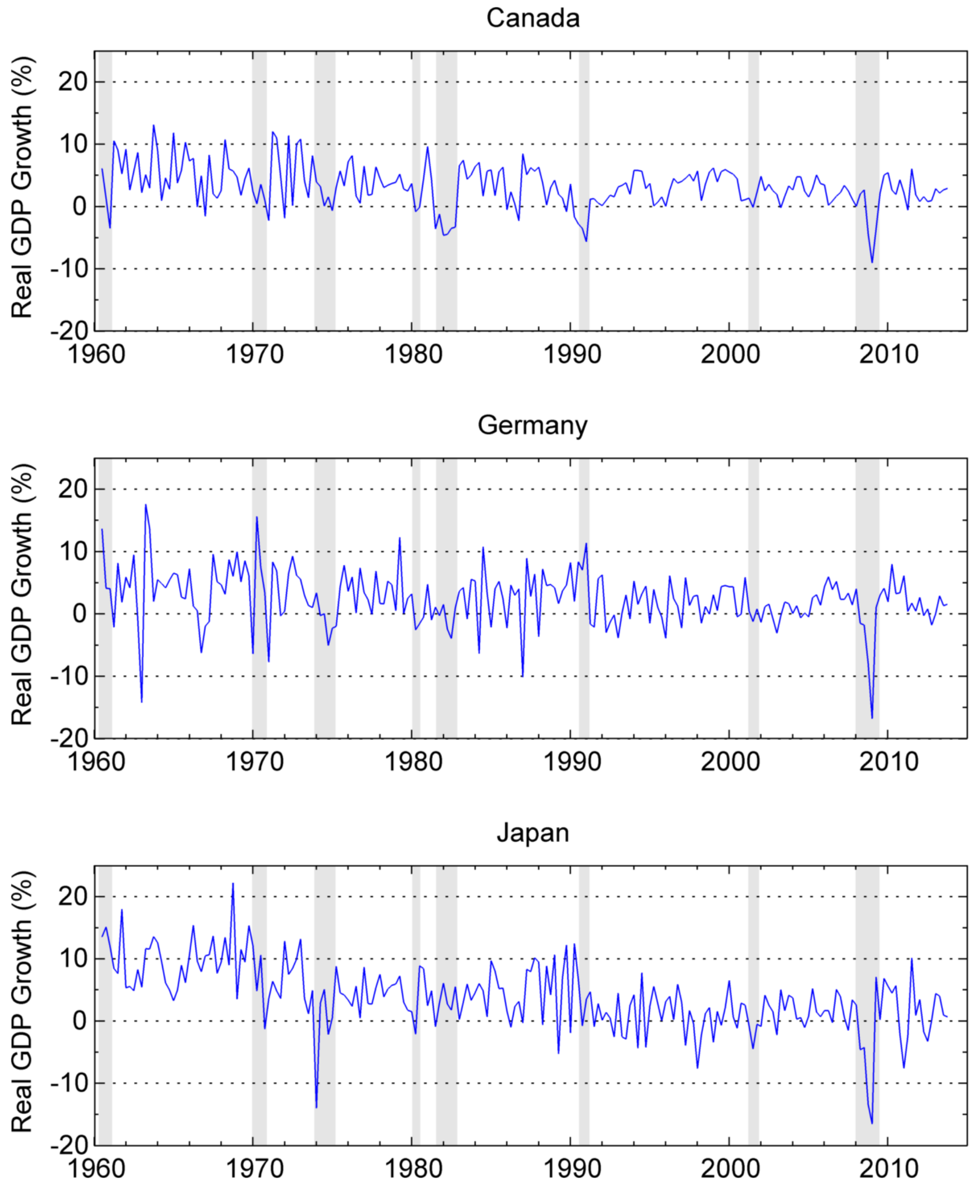

Figure B.1: Real GDP Growth for Canada, Germany, and Japan

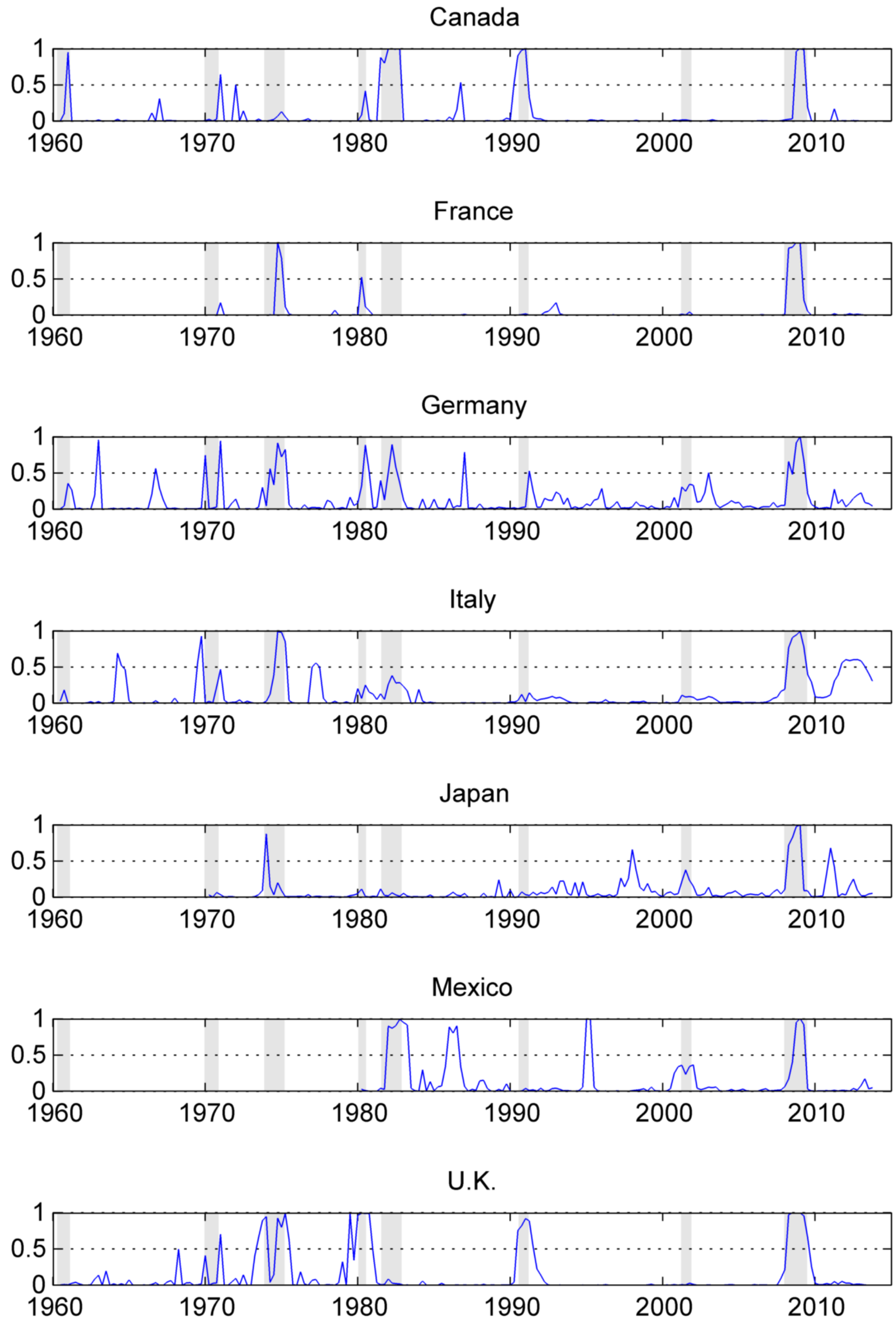

Figure B.2: Posterior Recession Probabilities - The posterior recession probabilities for each country are calculated as the percentage of MCMC draws for which a recession is drawn ($s_t = 1$). Gray bars represent NBER recession dates for the U.S.

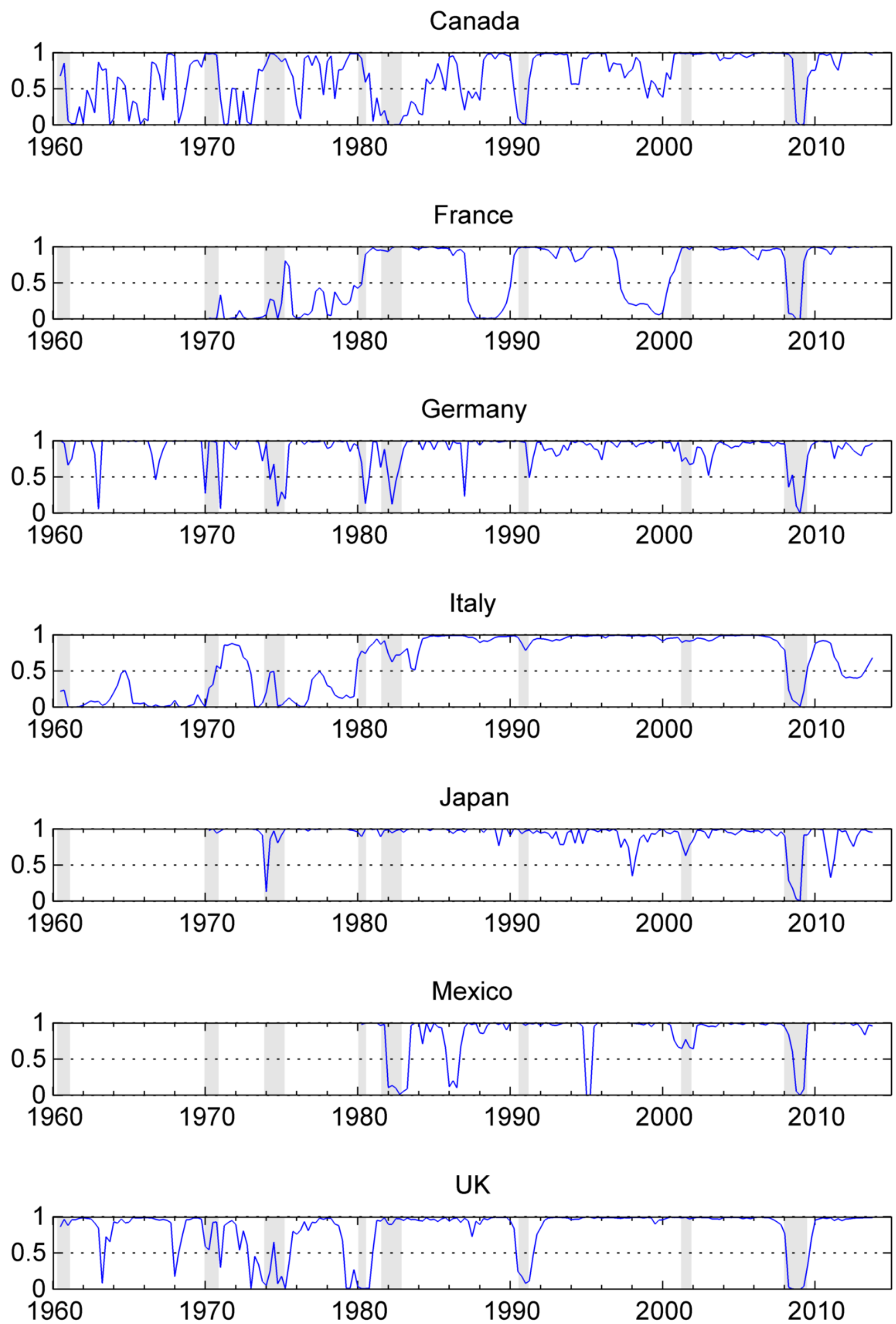

Figure B.3: Posterior Expansion Probabilities - The posterior expansion probabilities for each country are calculated as the percentage of MCMC draws for which an expansion is drawn ($s_t = 2$). For countries following the three-state model, these are the posterior probabilities of the low-growth rate expansion state. Gray bars represent NBER recession dates for the U.S.

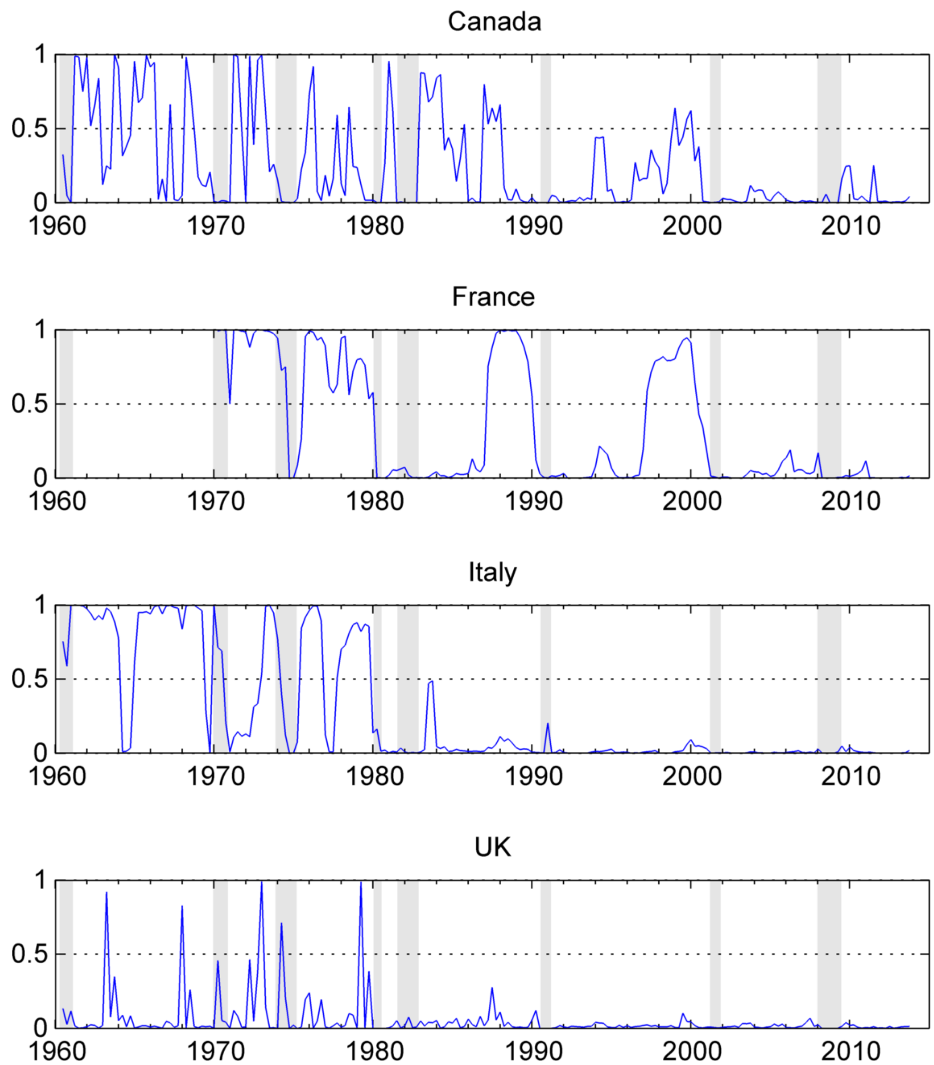

Figure B.4: Posterior High-Growth Expansion Probabilities - The posterior high-growth expansion probabilities for countries following the three-state model are calculated as the percentage of MCMC draws for which a high-growth expansion is drawn ($s_t = 3$). Gray bars represent NBER recession dates for the U.S.

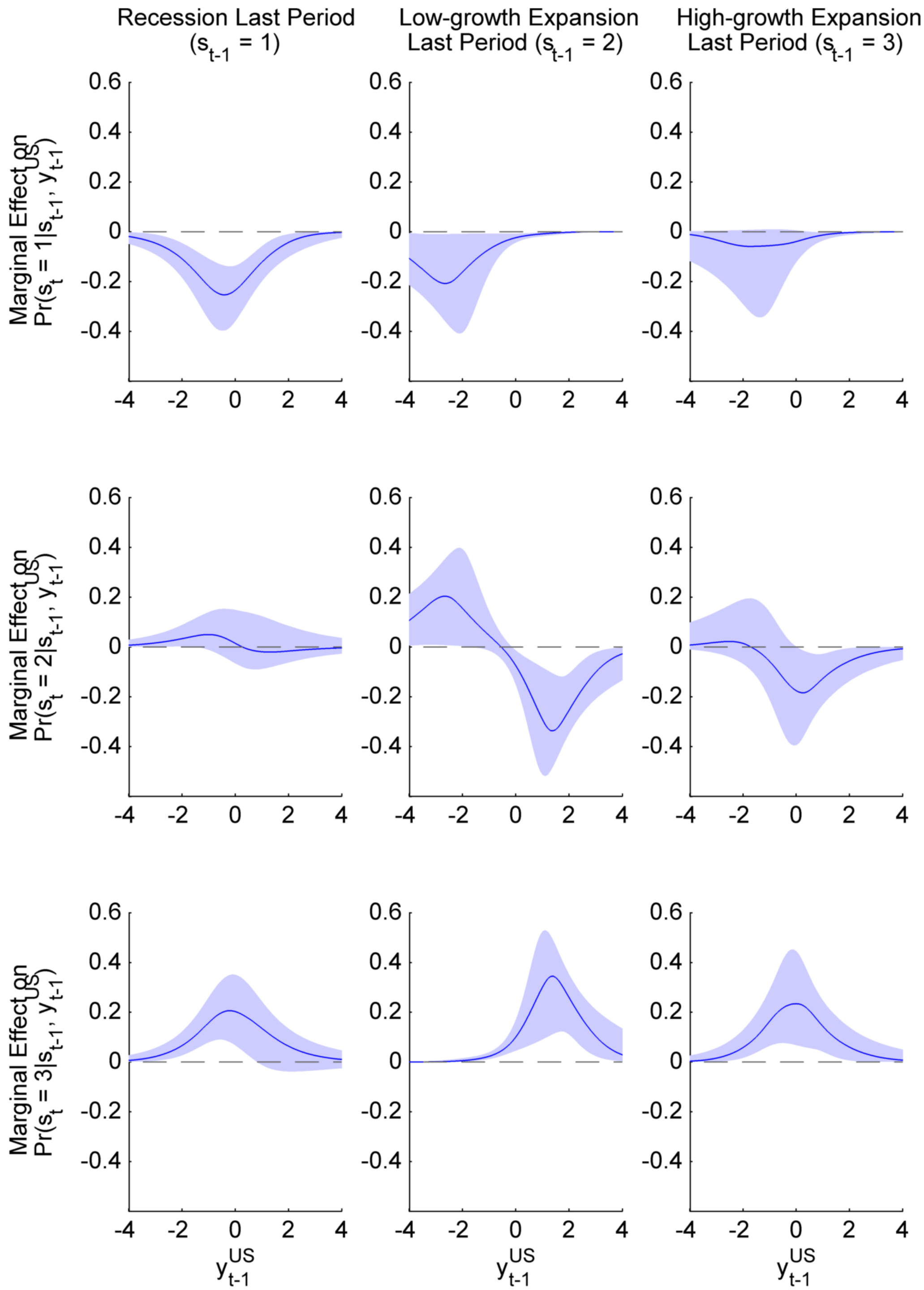

Figure B.5: Marginal Effects on the Transition Probabilities for Canada - The blue line represents the posterior median of the marginal effect of a change in U.S. output growth on the transition probability given the values for lagged U.S. output growth (y_{t-1}^{US}) and the past state (s_{t-1}). The shaded region reflects the 68% coverage of the posterior distribution.

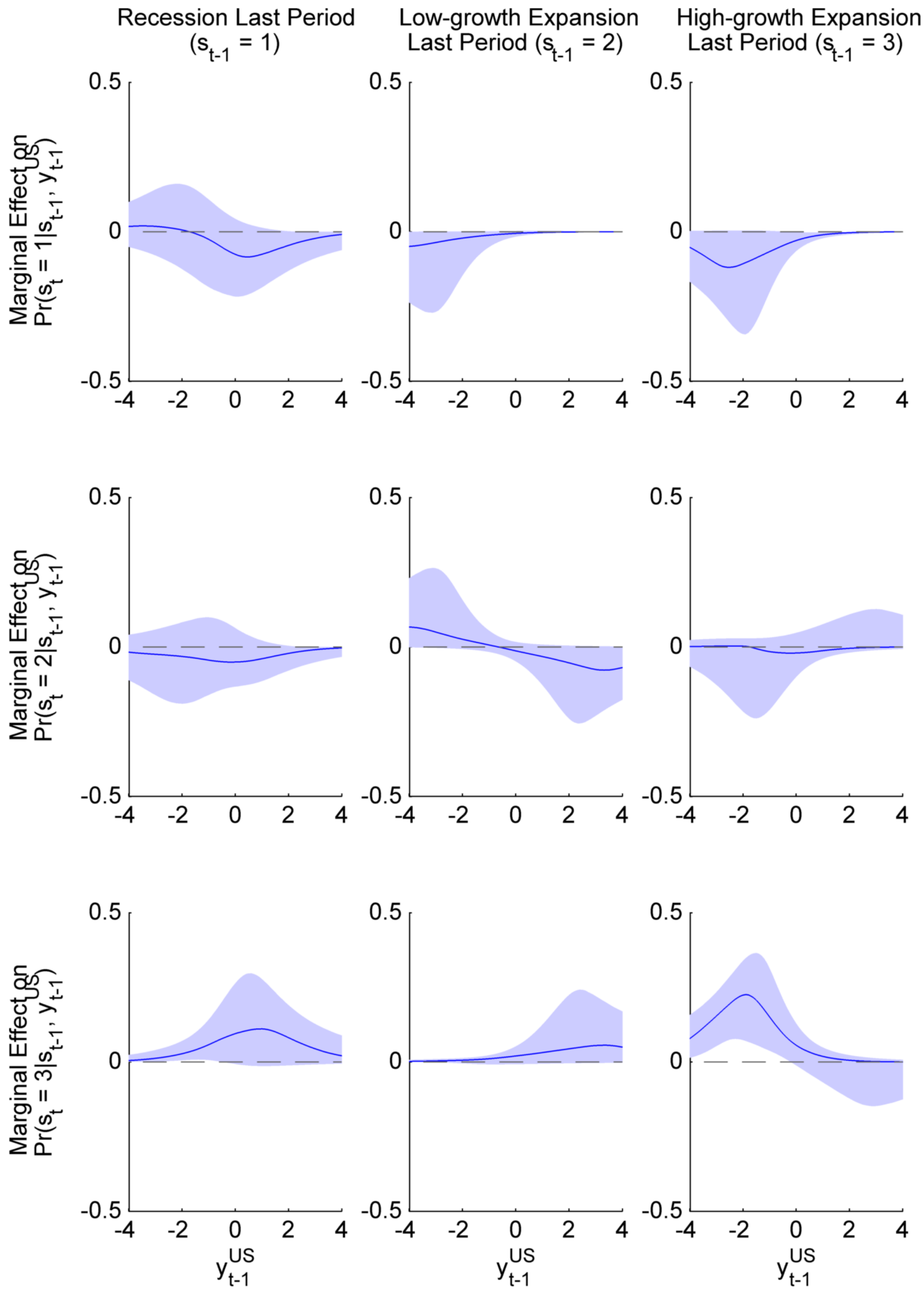

Figure B.6: Marginal Effects on the Transition Probabilities for France - The blue line represents the posterior median of the marginal effect of a change in U.S. output growth on the transition probability given the values for lagged U.S. output growth (y_{t-1}^{US}) and the past state (s_{t-1}). The shaded region reflects the 68% coverage of the posterior distribution.

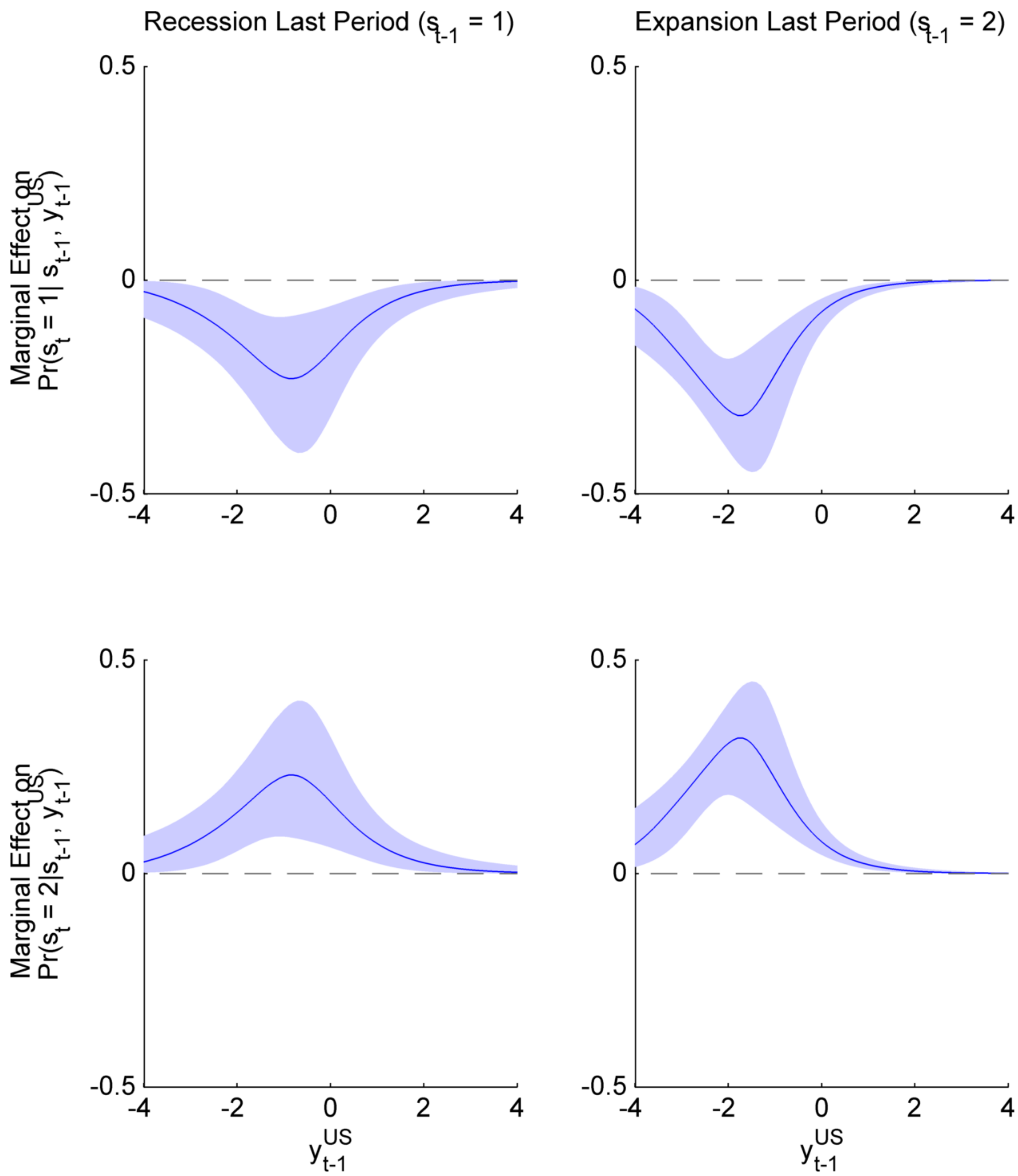

Figure B.7: Marginal Effects on the Transition Probabilities for Germany - The blue line represents the posterior median of the marginal effect of a change in U.S. output growth on the transition probability given the values for lagged U.S. output growth (y_{t-1}^{US}) and the past state (s_{t-1}). The shaded region reflects the 68% coverage of the posterior distribution.

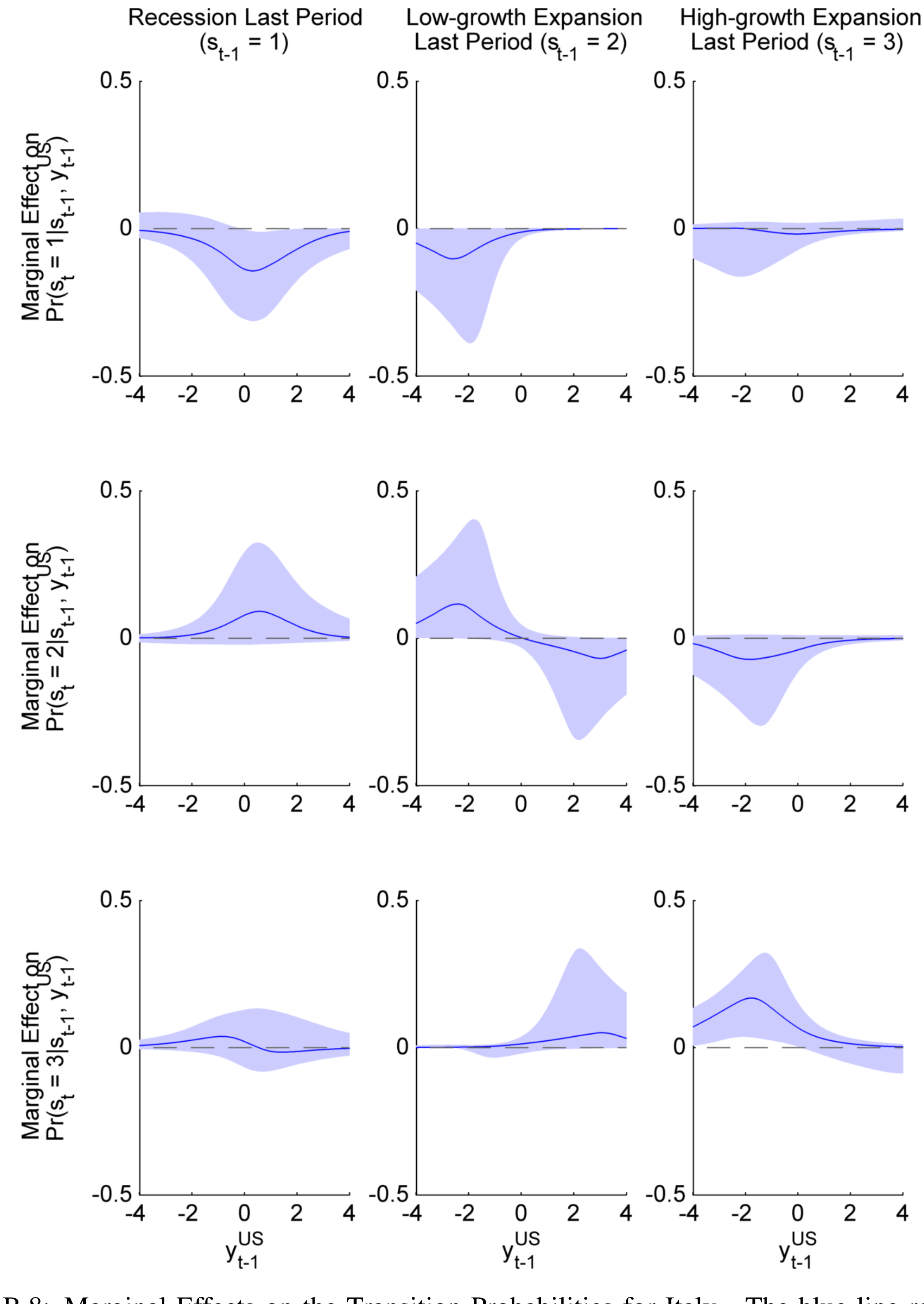

Figure B.8: Marginal Effects on the Transition Probabilities for Italy - The blue line represents the posterior median of the marginal effect of a change in U.S. output growth on the transition probability given the values for lagged U.S. output growth (y_{t-1}^{US}) and the past state (s_{t-1}). The shaded region reflects the 68% coverage of the posterior distribution.

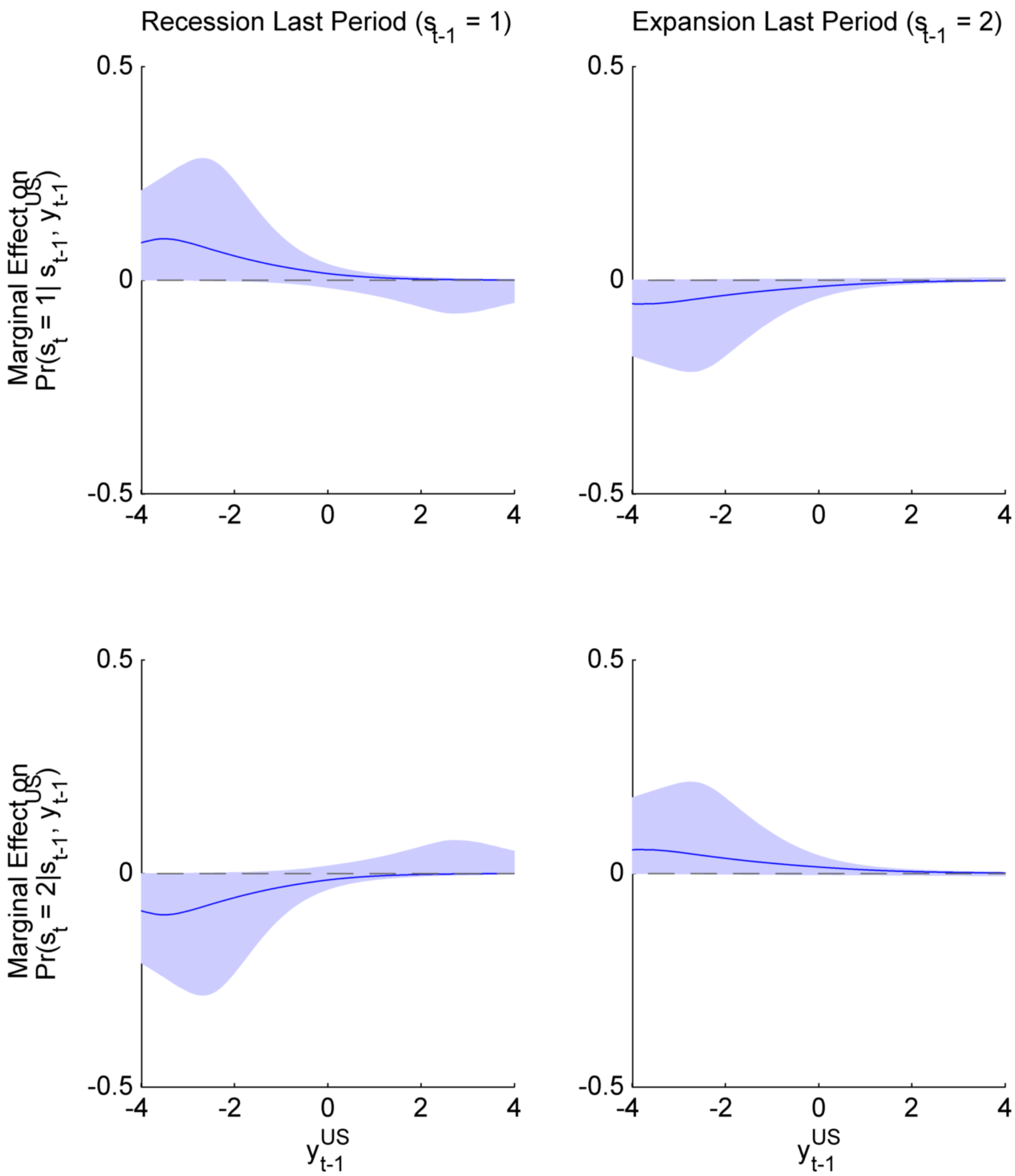

Figure B.9: [Marginal Effects on the Transition Probabilities for Japan - The blue line represents the posterior median of the marginal effect of a change in U.S. output growth on the transition probability given the values for lagged U.S. output growth (y^{US}_{t-1}) and the past state (s_{t-1}). The shaded region reflects the 68% coverage of the posterior distribution.

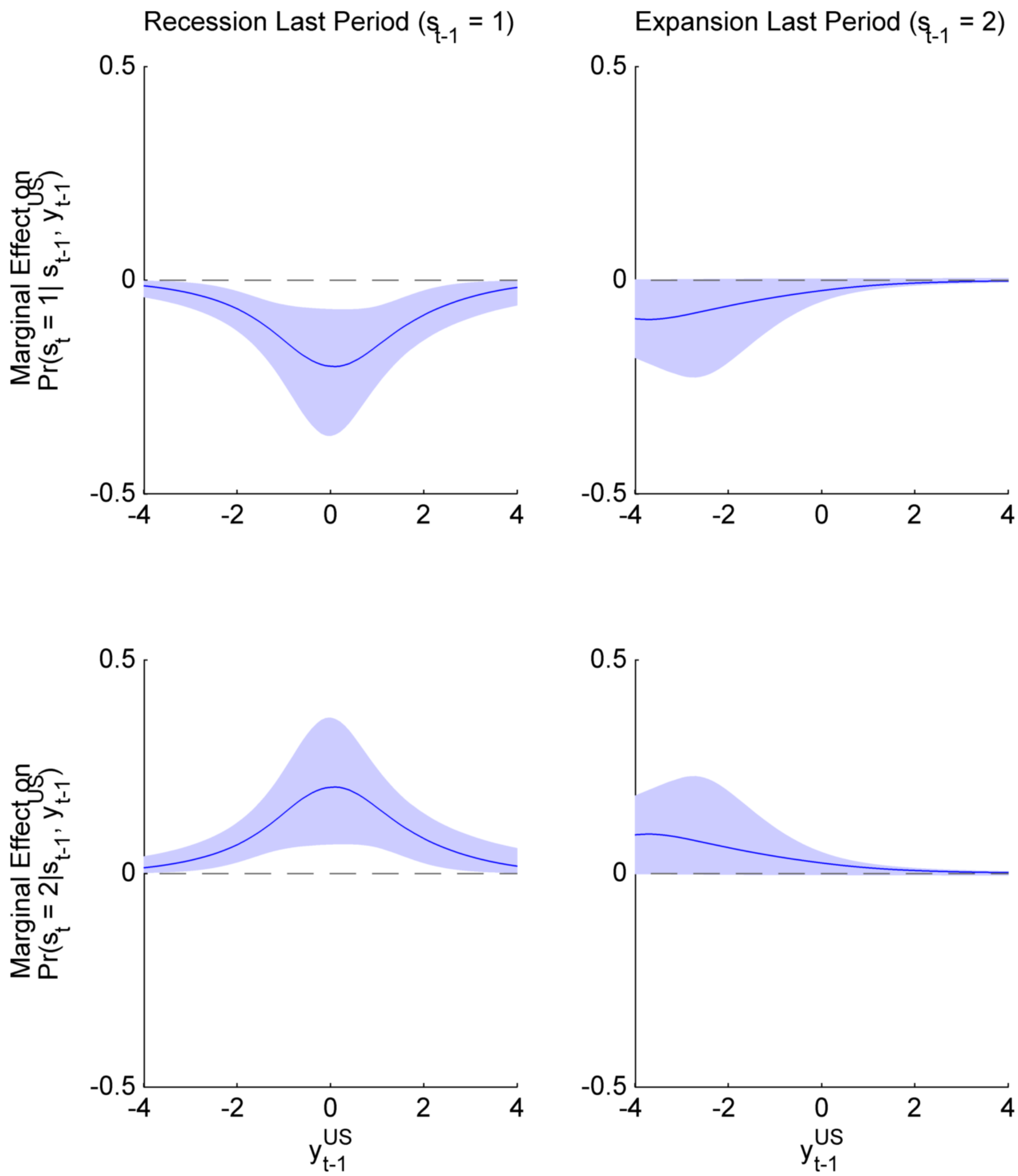

Figure B.10: Marginal Effects on the Transition Probabilities for Mexico - The blue line represents the posterior median of the marginal effect of a change in U.S. output growth on the transition probability given the values for lagged U.S. output growth (y_{t-1}^{US}) and the past state (s_{t-1}). The shaded region reflects the 68% coverage of the posterior distribution.

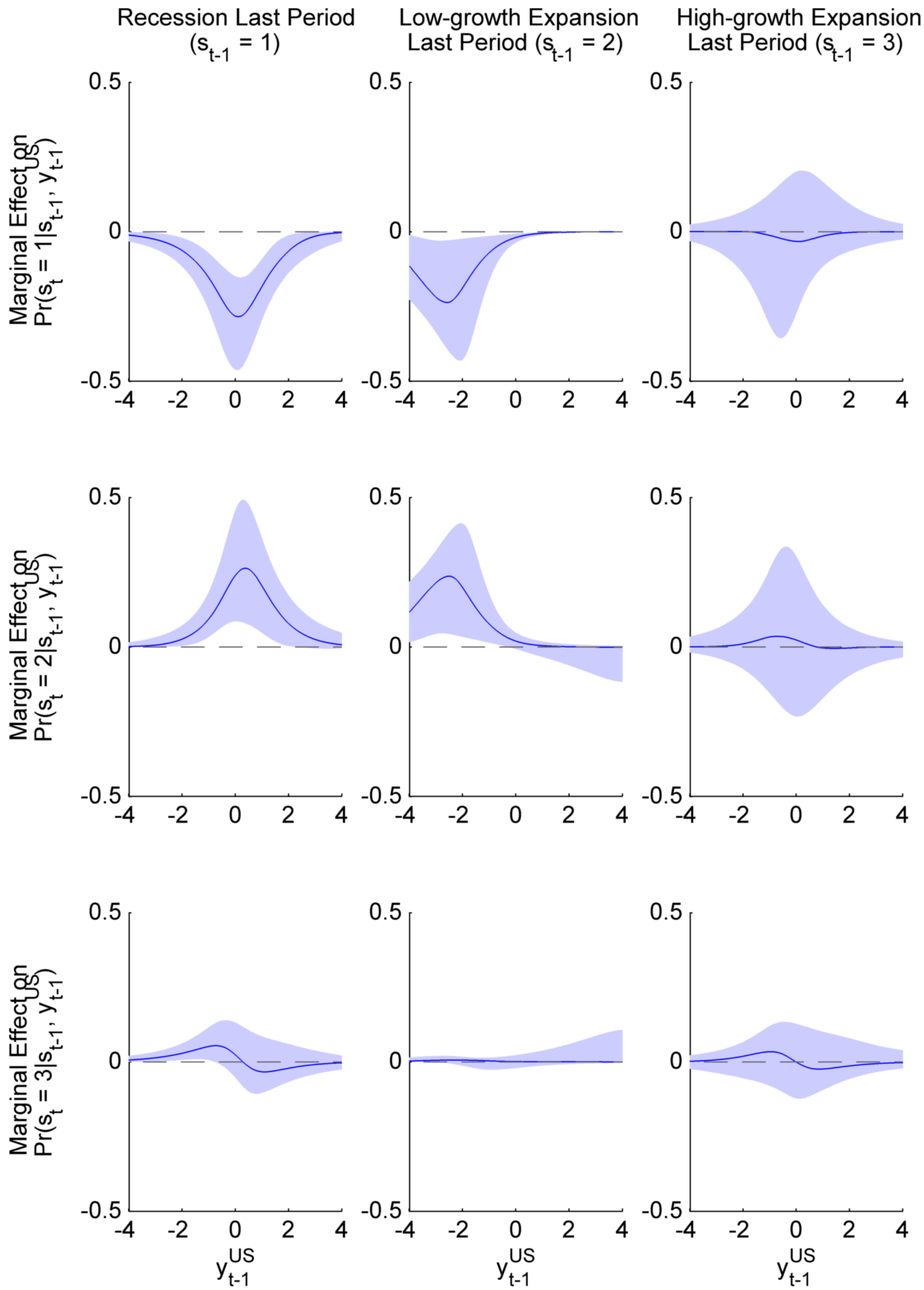

Figure B.11: Marginal Effects on the Transition Probabilities for the U.K. - The blue line represents the posterior median of the marginal effect of a change in U.S. output growth on the transition probability given the values for lagged U.S. output growth (y^{US}_{t-1}) and the past state (s_{t-1}). The shaded region reflects the 68% coverage of the posterior distribution.

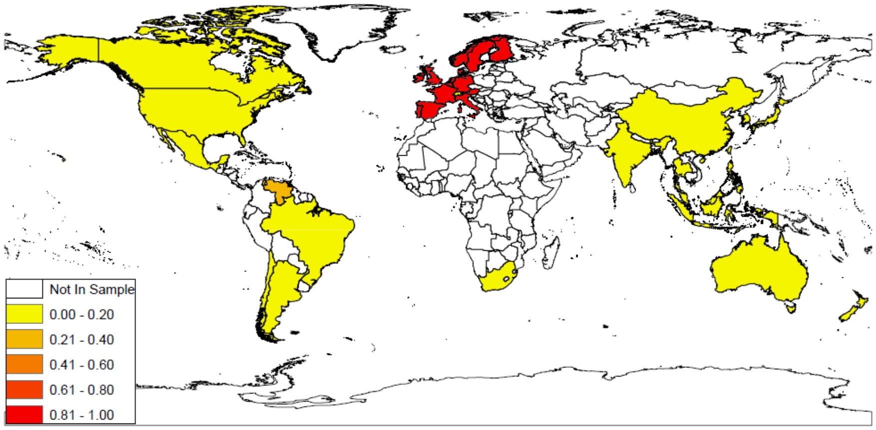

Figure B.12: Probability of Membership in Cluster 1 - This map presents the posterior probabilities of cluster 1 membership based on the country-specific characteristics (e.g., trade openness, industrialization, etc.) along with the full time series of output growth.

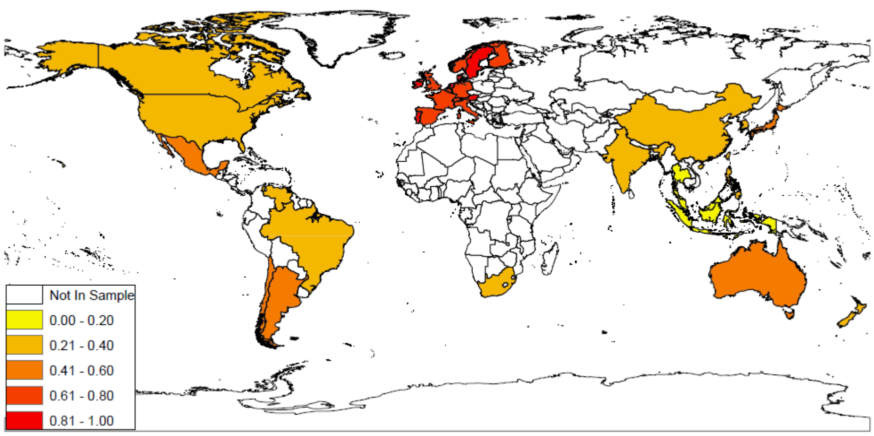

Figure B.13: Probability of Membership in Cluster 1 Due to Cluster Covariates - This map presents the probabilities implied by the country-specific characteristics (e.g., trade openness, industrialization, etc.) and the posterior median for the multinomial logistic coefficients.

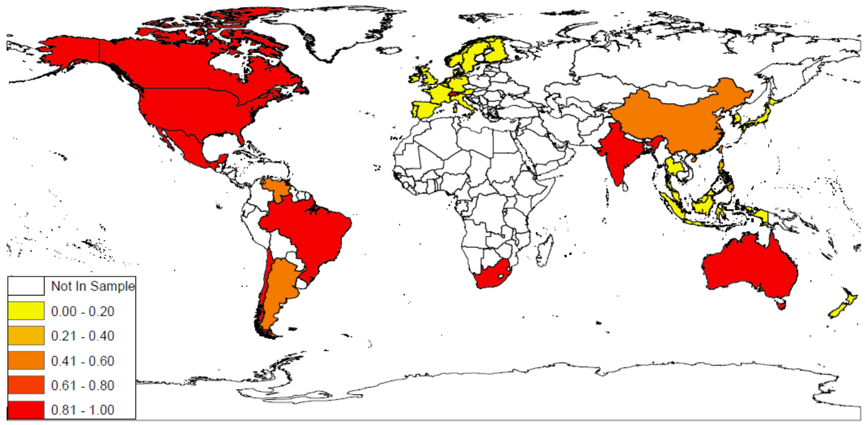

Figure B.14: Probability of Membership in Cluster 2 - This map presents the posterior probabilities of cluster 2 membership based on the country-specific characteristics (e.g., trade openness, industrialization, etc.) along with the full time series of output growth.

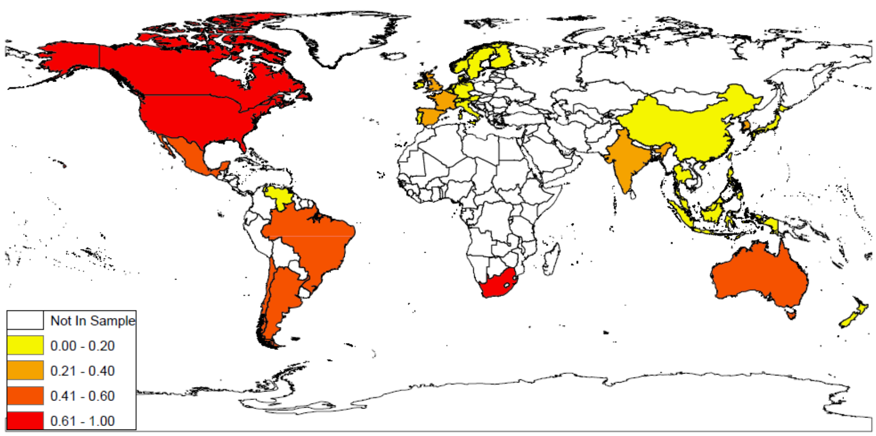

Figure B.15: Probability of Membership in Cluster 2 Due to Cluster Covariates - This map presents the probabilities implied by the country-specific characteristics (e.g., trade openness, industrialization, etc.) and the posterior median for the multinomial logistic coefficients.

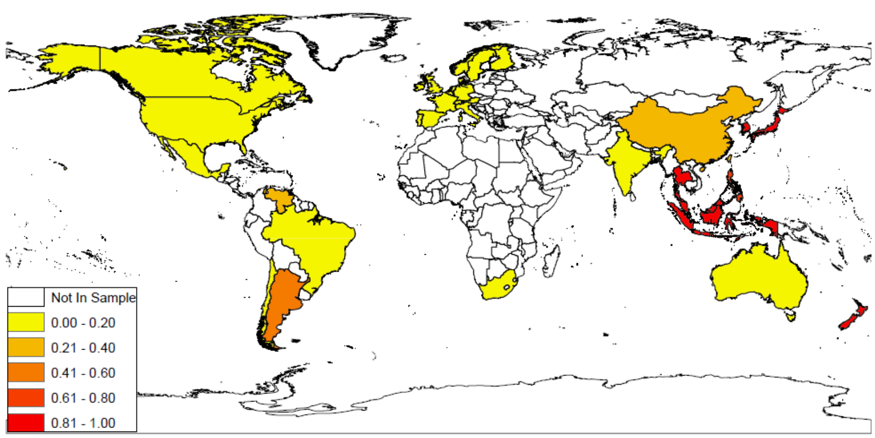

Figure B.16: Probability of Membership in Cluster 3 - This map presents the posterior probabilities of cluster 3 membership based on the country-specific characteristics (e.g., trade openness, industrialization, etc.) along with the full time series of output growth.

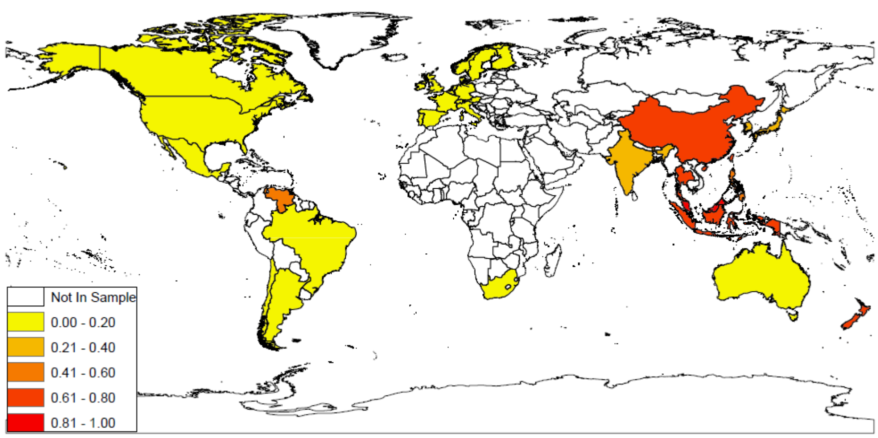

Figure B.17: Probability of Membership in Cluster 3 Due to Cluster Covariates - This map presents the probabilities implied by the country-specific characteristics (e.g., trade openness, industrialization, etc.) and the posterior median for the multinomial logistic coefficients.

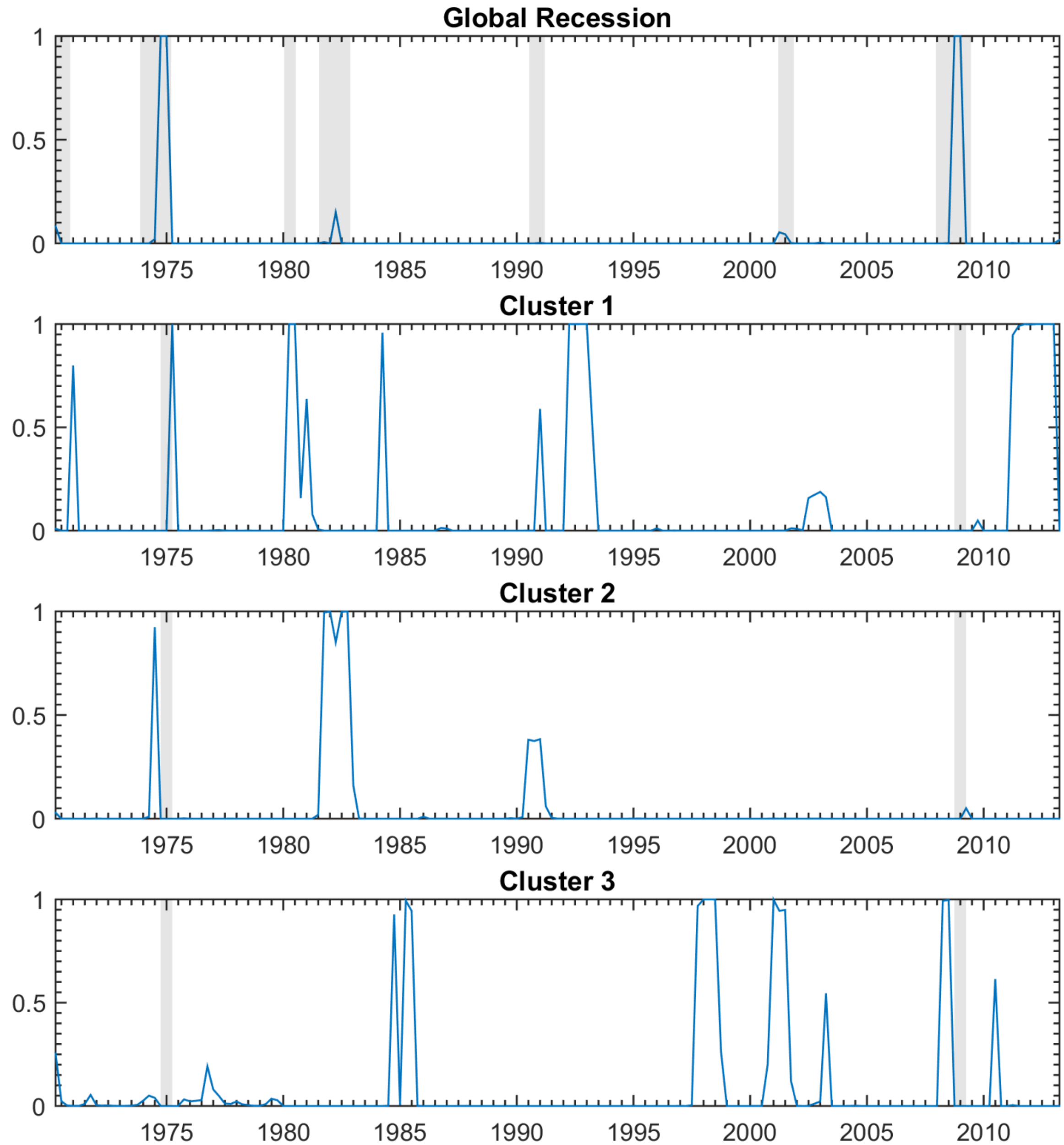

Figure B.18: Posterior Recession Probabilities for Global Clusters- This figure shows the mean posterior probability of recession for the world (top panel) as well as each idiosyncratic cluster (bottom panels). Gray bars represent NBER recession dates for the U.S. (top panel) and the estimated aggregate recession dates (bottom panels).

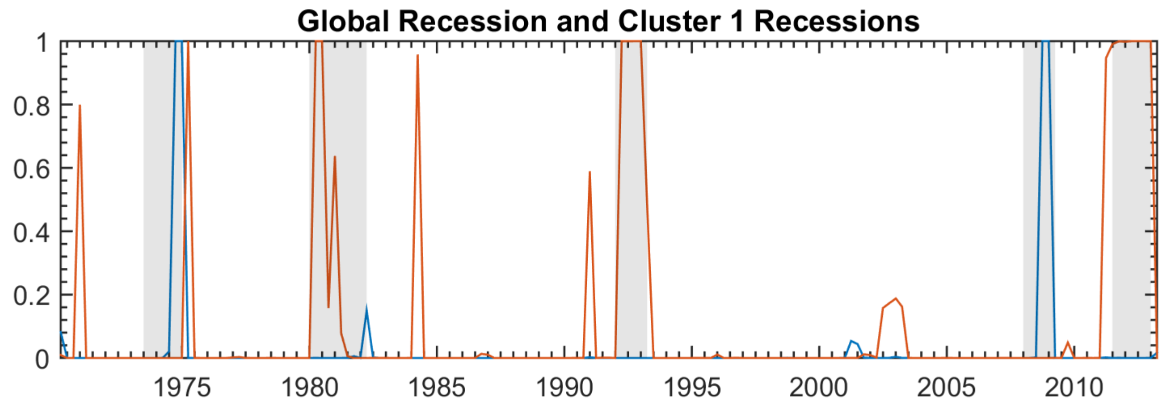

Figure B.19: Cluster 1 Recessions and the Euro Area Business Cycle - This figure shows probability that the countries in cluster 1 are in recession. The blue line represents the posterior probability of a global recession, and the orange line represents the posterior probability of an idiosyncratic recession for cluster 1. Gray bars represent recession dates as outlined by the CEPR Euro Area Business Cycle Dating Committee.

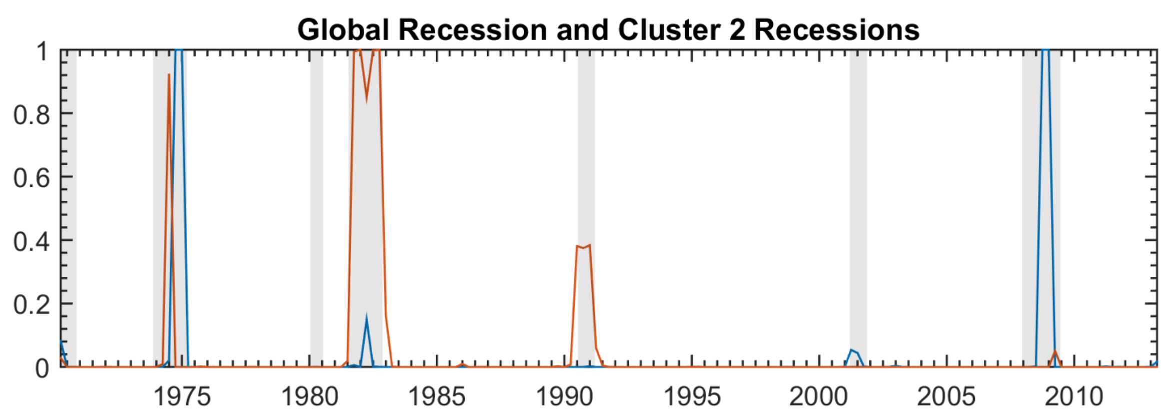

Figure B.20: Cluster 2 Recessions and the US Business Cycle - This figure shows probability that the countries in cluster 2 are in recession. The blue line represents the posterior probability of a global recession, and the orange line represents the posterior probability of an idiosyncratic recession for cluster 2. Gray bars represent recession dates as outlined by the NBER's Business Cycle Dating Committee .

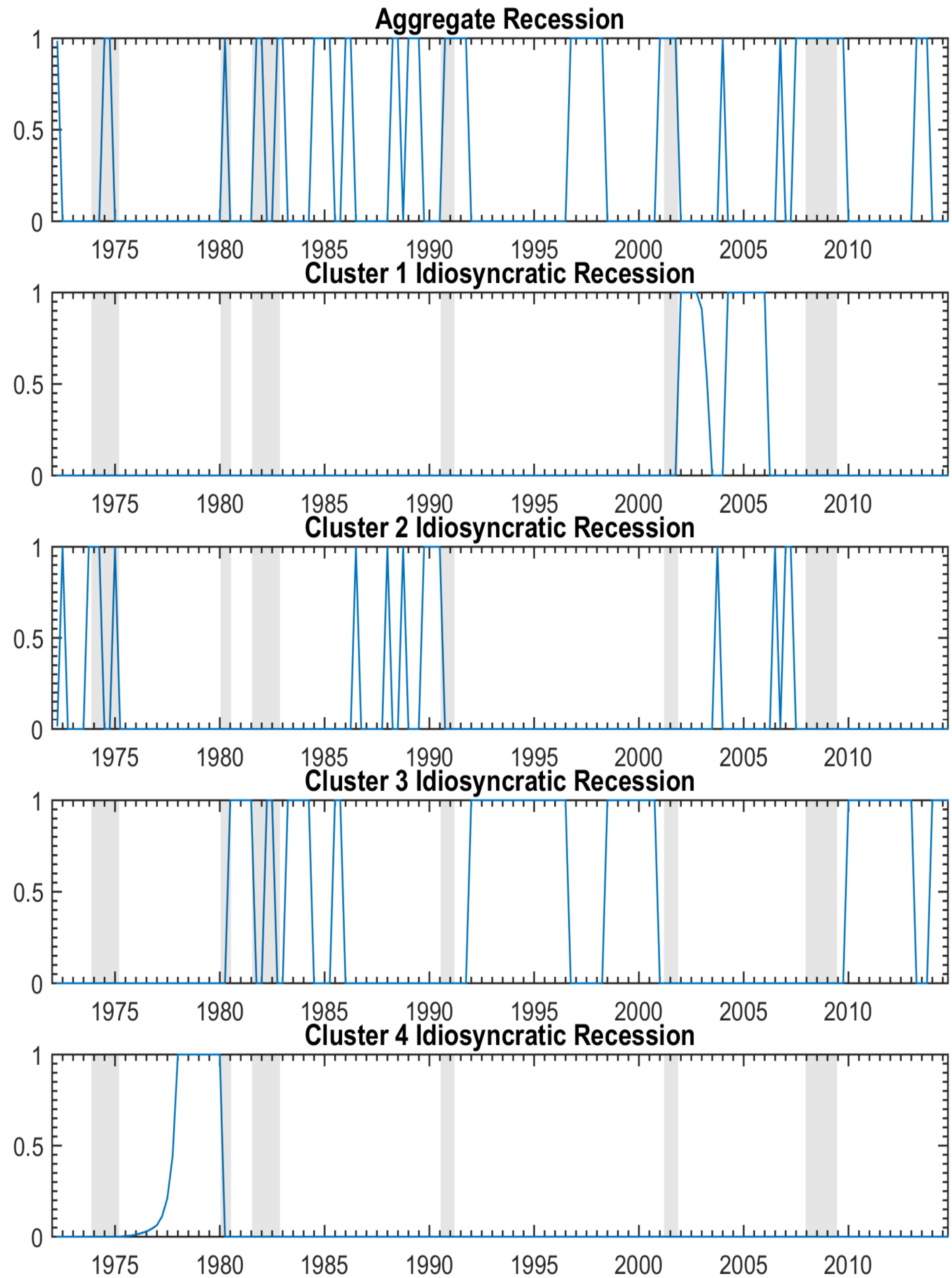

Figure B.21: Posterior Regime Probabilities for Industry Clusters - This figure shows the posterior probability of being in a regime at any point in time. The top panel shows the probability of being in a national recession, and the bottom panels show the probability of being in an idiosyncratic recession for each respective cluster. Gray bars represent recession dates as defined by the NBER's Business Cycle Dating Committee.

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