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Industrial Connectedness and Business Cycle Comovements

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Abstract

While aggregate shocks account for most business cycle fluctuations, sectoral shocks have become relatively more important since the 1980s. Previous studies show that sectoral shocks propagate through industry supply chains. Typically, sectors are defined by similarities in function and/or market. While some industries have supply chains within their own sector (vertical), others have supply chains across a number of sectors (horizontal). Similarity in these supply chain characteristics appear to be a determining factor in how industries comove. Using industrial production data of 82 four-digit NAICS industries over the period 1972 to 2019, this comovement is analyzed in a panel Markov-switching model incorporating a number of features relevant for sub-national analysis: (i) industry-specific trends that differentiate cyclical downturns from secular declines; (ii) a national-level business cycle; and (iii) factors that represent industrial comovement. While national-level shocks are typically still the most important driver of cyclical fluctuations, endogenously clustering by industry comovement highlights the role of sectoral shocks.

Keywords: Keywords: cluster analysis, Markov-switching JEL Codes: C32; E32

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1. Introduction

Recent study of the aggregate business cycle is increasingly focusing on the interaction between its disaggregate components—state (Owyang et al., 2005; Leiva-Leon, 2017), regional (Hamilton & Owyang, 2012), and even city (Owyang et al., 2008). A portion of this literature has investigated the interaction and comovements of industries [see Murphy et al. (1989); Cooper & Haltiwanger (1990); and Kim & Kim (2006) for a survey]. Previous studies have found comovement both within and across sectors (Christiano & Fitzgerald, 1998; Hornstein, 2000) that is linked to aggregate (Chang & Hwang, 2015) and state (Carlino & DeFina, 2004) business cycles. However, the role of this comovement may be changing: Comin & Philippon (2005) attribute the Great Moderation to a decline in the synchronization of industries, and Camacho & Leiva-Leon (2019) find that industries have business cycles different from the aggregate.

The literature debates the importance of aggregate versus sectoral shocks for explaining the business cycle. Foerster et al. (2011), Garin et al. (2018), and Li & Martin (2019) find that aggregate shocks are more important than industry or sector shocks; Atalay (2017) finds industry shocks can account for half of aggregate volatility. However, there is little agreement on what constitutes a "sector." For example, Garin et al. (2018) estimates a principal component from the 12 sectors that make up the bulk of the aggregate IP index, and Li & Martin (2019) estimate a factor model from real output for 16 nonfarm private sectors. On the other hand, Foerster et al. (2011) considers aggregate and industry factors for 117 industries, roughly corresponding to four-digit NAICS industries. The former papers suggest two levels of comovement: one at the aggregate level and one at the NAICS sectoral level. The latter paper restricts comovements to the aggregate level, albeit with multiple factors that could represent sectors.

We reinvestigate industrial comovements allowing a variety of possible correlation structures at different levels of disaggregation. We consider a model with three types of shocks: (i) an aggregate binary shock that affects all industries at once; (ii) cluster shocks that affect only subsets of industries; and (iii) an industry shock. One of the primary differences between our model and those employed by the rest of the literature on industrial comovement is that we will determine cluster membership—the sets of industries that comove—endogenously.

Instead of defining a sector as a NAICS two-digit industry, we allow common fluctuations across NAICS four-digit industries to form clusters. Thus, we define industrial groupings that maximize the explained volatility attributed to the cluster level, which is our analog to a sector. Moreover, because we do not limit our examination to within-NAICS-sector comovements, our model may suggest whether similarities in industries' production networks determine their comovements. If clusters form from industries with within-sector supply chains, cycles may be viewed as being driven by sector-specific shocks. On the other hand, if clusters form from industries with cross-industry production networks, cycles may be driven by wide-ranging disruptions in supply chains.

Examining the comovement of industries differs substantially from examining state or regional comovement [as in Hamilton & Owyang (2012) or González-Astudillo (2019)]. Because the latter are diversified economies in a common currency zone, they tend to have positive growth rates during expansions and negative growth rates during recessions. This stylized fact allows routine identification of the business cycle phases: Expansions occur during periods of positive growth and recessions occur during periods of negative growth. This means of identification, however, is not as useful at the industry level because some industries experience long periods of secular decline. Thus, it is important to characterize both the trend and the cycle terms simultaneously.

We consider industrial production of 82 four-digit NAICS industries over the period 1972 to 2019 to determine (i) whether comovements occur, (ii) whether they are a pervasive feature of the U.S. business cycle, and (iii) whether they are limited to industries within a single sector or whether they are determined by industries' production streams. Our model has a similar hierarchical structure to Kose et al. (2003) but with endogenously-determined clusters as in Francis et al. (2017). In addition to these features, each industry has a stochastic trend, an aggregate recession regime that affects all industries, a connected or clustered component representing the comovement across industries, and an idiosyncratic autoregressive component.

The previous literature has focused on two types of shocks: aggregate shocks as affecting all industries simultaneously and idiosyncratic shocks that are specific to industries (Foerster et al., 2011; Atalay, 2017). Here, we consider an intermediate layer of comovement analogous to the two-digit NAICS sectoral level (Garin et al., 2018; Li & Martin, 2019) but with endogenously defined groupings. While the sectoral characterization assumes that demand shocks create comovement within a sector or that supply chains are intra-sectoral, our model nests that definition by having a national business cycle and idiosyncratic industry shocks, similar to the previous literature, and allowing for industries to cluster endogenously. This allows for industries to be related to other industries within their own sector, but also allows for inter-sectoral supply chains or demand shocks of complementary goods. This is akin to Lee (2010), who found that the synchronization of international business cycles is due to intra-industry rather than inter-industry trade flows, and Acemoglu et al. (2012), who found that sector-specific shocks can propagate to other sectors and lead to aggregate fluctuations.

Similar to Camacho & Leiva-Leon (2019), who use industry employment data, we find that industries cluster into a few groups that are often similar to industrial subsectors but are sometimes different. A number of industries experience significant periods of secular decline, albeit with different timings. Apart from the aggregate business cycle phases, industries cluster together. Some of these clusters reflect supply chains that are isolated within the sector (motor vehicles); others are final good industries with similar demand elements (agricultural products). We find that for most industries the aggregate regime accounts for most of the cyclical variance, similar to Foerster et al. (2011), Garin et al. (2018), and Li & Martin (2019). However there are industries that behave similarly to the findings of Atalay (2017) where the "sectoral" or cluster grouping accounts for a larger portion of the variance.

The balance of the paper is laid out in the following order: Section 2 presents the clustered factor model with aggregate Markov-switching. Section 3 outlines the estimation technique via the Gibbs sampler. Section 4 describes the disaggregated industrial production data and industry-specific characteristics and discusses the results. Section 5 concludes the paper.

2. Model

In many applications investigating cross-series cyclical correlation [e.g., Francis et al. (2017) and González-Astudillo (2019)] the panels consist of countries or states and the models are estimated with data transformed into growth rates. Unlike the diversified economies in other studies, some of the industries in our sample may experience secular declines over part or all of the sample. Because these periods of secular decline could be misinterpreted as recessions, we estimate the model in levels. Each industry's industrial production (IP) time series has the following components: (i) a trend; (ii) a national cycle that moves all or most industries at once; (iii) a "connected" component—where "connected" industries are endogenously determined—that moves industries together *outside* of the national cycle; and (iv) an idiosyncratic cycle that accounts for possible AR dynamics outside of the industrial clusters.

The unobserved components (UC) framework simultaneously estimates the trend and cycle. Let Y_{nt} denote the log level of industrial production for industry $n = 1, ..., N$ in month $t = 1, ..., T$ that has two unobserved components, a trend and a cycle. The cyclical component is further decomposed into two parts:

$$Y_{nt} = \tau_{nt} + \tilde{z}_{nt} + v_{nt}, \tag{1}$$

where τ_{nt} represents a permanent trend. The transitory cycle is composed of two terms: $\tilde{z}_{nt}$ represents the connected component and v_{nt} represents the idiosyncratic component. The connected component is correlated across industries and embodies both national and industrial cluster components, while the idiosyncratic component allows for possible industry specific cycles. We assume that shocks to the cycle and trend components are uncorrelated. Additionally, we must make assumptions about the form of each of these components, which we will expand on below.

While there are a variety of methods to detrend data [see Canova (1998) and McElroy & Wildi (2020) for an overview], because the timing of secular declines varies across industries, linear or deterministic trends may not be flexible enough. An alternative to UC is using the Hodrick-Prescott (HP) filter to pre-filter the data. However, the HP-filter can introduce spurious cycles into the data (Cogley & Nason, 1995) and the conditions that would make the HP-filter optimal are rare (Hamilton, 2018). Therefore, we model each industry trend as a random walk with possibly time-varying drift:

$$\tau_{nt} = \delta_{nt} + \tau_{n,t-1} + e_{nt}, \tag{2}$$

where e_{nt} are normally-distributed permanent innovations, $e_{nt} \sim N(0, \sigma^2_{en})$. We assume that the shocks to trend e_{nt} are independent across time [i.e., $E(e_{nt}e_{ns}) = 0 \ \forall t \neq s$ and $\forall n$] and across industries [i.e., $E(e_{mt}e_{nt}) = 0 \ \forall m \neq n$]. To capture industries in secular decline, the sign of the drift parameter, δ_{nt}, is unrestricted. In the baseline model, we assume the drift term is constant, $\delta_{nt} = \delta_n$.

The connected component, $\tilde{z}_{nt}$, from (1) allows for both national business cycle movements and a common component across clustered industries. Using the language of Francis et al. (2017), we model the common connected component as a "cluster factor": Industries that belong to the same cluster are attached to the same cluster factor, subject to an industry-specific factor loading.

Formally, define a cluster indicator, γ_{nk}, where $\gamma_{nk} = 1$ if industry n belongs to cluster $k \in \{1, ..., K\}$ and $\gamma_{nk} = 0$ otherwise. Here, $K << N$ represents the total number of clusters. Each industry n belongs to a single cluster, so that $\sum_k \gamma_{nk} = 1$. Then, we can write the connected component, $\tilde{z}_{nt}$, as:

$$\tilde{z}_{nt} = \alpha_n \sum_{k=1}^{K} \gamma_{nk} [\mu_{k0} + \mu_k S_t + \phi_k(L) z_{kt-1} + u_{kt}],$$

where z_{kt} is the time-t value of the kth cluster factor and $\alpha_n > 0$ is industry n's factor loading. We assume that z_{kt} consists of an AR(p_z) process with a regime-switching intercept that depends on an aggregate, discrete state variable, $S_t \in \{0, 1\}$. The drift term in the trend equation (2) requires the normalization of μ_{k0}. We impose $\mu_{k0} = 0$ and $\mu_k < 0$, so $S_t = 1$ captures an aggregate downturn and $S_t = 0$ captures an aggregate expansion [see also Kim & Nelson (1999)]. S_t follows a first-order Markov-process with constant transition probabilities $\pi_{ji} = \Pr[S_t = j | S_{t-1} = i]$, which are compiled in a transition matrix Π. The roots of $\phi_k(L) = \phi_{k1}L + ... + \phi_{kp_z}L^{p_z}$ lie strictly outside of the unit circle and $E(u^2_{kt}) = \sigma^2_{uk}$. The innovations to the cluster factors are assumed to be uncorrelated across clusters and we normalize $\sigma^2_{uk} = 1 \ \forall \ k = 1, .., K$ to identify the scale of each z. We assume no correlation between components [i.e., $E(e_{mt}u_{nt}) = 0 \ \forall m, n$]; this assumption can be relaxed (Morley et al., 2003) but can result in a volatile trend and a cycle that is mostly noise.

The idiosyncratic component, v_{nt}, from (1) captures the residual industry-specific dynamics and follows an AR(p_v):

$$v_{nt} = \rho_n(L)v_{nt-1} + \eta_{nt},$$

where the roots of $\rho_n(L) = \rho_{n1}L + ... + \rho_{np_v}L^{p_v}$ lie strictly outside of the unit circle, $E(\eta_{nt}^2) = \sigma_{\eta n}^2$, and $E[\eta_{nt}\eta_{mt}] = 0$ for $n \neq m$ and for all t. The latter restriction assumes that any correlation across the cycles are attributable only to the connected component.

Our model has the flavor of Friedman's plucking model [see Friedman (1964, 1993) and Dupraz et al. (2021)], where expansions are periods when the economy is near trend and recessions are periods when the cycle is "plucked" downward from trend. While the timing of the national downturns are common across the industries, how these downturns affect each industry is idiosyncratic, determined by their common cluster parameter, μ_k, and the industry-specific factor loadings, α_n.

3. Estimation

We estimate the model using the Gibbs sampler [see Gelfand & Smith (1990); Casella & George (1992); Carter & Kohn (1994)]. This Markov Chain Monte Carlo technique separates the latent variables and parameters into blocks to be drawn from their conditional posterior distributions, given the data and other latent variables and parameters.

Collect the cross-sectional components as $Y_t = [Y_{1t}, ..., Y_{Nt}]'$, $\tau_t = [\tau_{1t}, ..., \tau_{Nt}]'$ and $v_t = [\nu_{1t}, ..., \nu_{Nt}]$. Collect the cross-cluster components as $z_t = [z_{1t}, ..., z_{Kt}]'$. Define Γ as the $(N \times K)$ matrix of cluster memberships with representative element $\gamma_{nk} \in \{0, 1\}$ as given above. Then, collect the time series of the trend components, $\tau_T = [\tau_1, ..., \tau_T]$; the cluster factors, $\mathbf{z}_T = [z_1, ..., z_T]$; the idiosyncratic cycle components, $\mathbf{v}_T = [v_1, ..., v_T]$; and the aggregate regime series, $\mathbf{S}_T = [S_1, ..., S_T]$.

Let Ψ represent the full set of parameters that includes the drift parameters, δ; the trend innovation variances, $\Sigma_e = diag\left[\sigma_{e1}^2, ..., \sigma_{eN}^2\right]$; the common recession magnitudes, μ; the regime process transition matrix, Π; the cluster membership indicators, Γ; the factor loadings, α; the cluster AR coefficients, Φ; the idiosyncratic AR parameters, ρ; and the idiosyncratic variances, $\Sigma_\eta = diag\left[\sigma_{\eta 1}^2, ..., \sigma_{\eta N}^2\right]$. Recall that we normalized the cluster factor variances, $\Sigma_u = diag\left[\sigma_{u1}^2, ..., \sigma_{uK}^2\right] =$

I_K. In what follows, Ψ_{-x} represents the full set of parameters excluding x.

The joint posterior distribution is formed from 5,000 iterations of the sampler after an initial burn-in of 5,000 iterations.

3.1. Priors

The drift parameter, the recession depth, and all AR coefficients have normal prior distributions. All innovation variances have inverse gamma priors. The transition probabilities for the aggregate regime process are assumed to have a Dirichlet prior distribution.

The composition of each cluster is determined endogenously by the similarity in the movements in the Y_{nt}s across industries. We can incorporate additional information by assuming a multinomial logistic prior for the cluster membership indicator, γ_{nk}. Suppose there exists a vector, x_{nk}, of variables that may influence whether a series n belongs to cluster k. We assess the prior probability that series n belongs to cluster k as:

$$\Pr\left[\gamma_{nk}=1|x_{nk}\right]=\begin{cases}\exp\left(x_{nk}^{'}\beta_k\right)/\left[1+\sum\exp\left(x_{nk}^{'}\beta_k\right)\right] & k=2,...,K\\ 1/\left[1+\sum\exp\left(x_{nk}^{'}\beta_k\right)\right] & k=1\end{cases}, \tag{3}$$

for $n=1,...,N$ and where we have normalized $\beta_1=0$. Note also that the vector, x_{nk}, need not be composed of the same variables for each cluster k but that the covariates in each x_{nk} must be time-invariant and industry specific (i.e., not functions of the composition of the clusters or computed relative to another industry $m \neq n$). That is, we cannot include in x_{nk} variables such as the value of inputs flowing from one industry to another nor the value of inputs flowing from one industry to all other industries in a cluster. As in Hamilton & Owyang (2012) and Francis et al. (2017), we think of the prior hyperparameters, β_k's, as population parameters signifying the clusters' relationships.

Table 1 shows the prior distributions for the model parameters.

3.2. Draw $\boldsymbol{\tau}_T, \boldsymbol{z}_T, \boldsymbol{v}_T|\Psi, \boldsymbol{S}_T, \mathbf{Y}_T$

The latent variables are drawn using the smoothing sampler of Durbin & Koopman (2002) with the correction outlined by Jarociński (2015). To implement the smoothed sampler, we must cast

Table 1: **Prior Distributions for Estimation**

Parameter	Prior Distribution	Hyperparameter
$\boldsymbol{\pi}_i$	$D(\bar{\pi}_{1i}, \bar{\pi}_{2i})$	$\bar{\pi}_{ji} = 1$ for $j = 1, 2$ and $i = 1, 2$
μ_k	$N(m_0, M_0)$	$m_0 = -2,\ M_0 = 1$
$\boldsymbol{\phi}_k$	$N(f_0, F_0)$	$f_0 = [0.9, 0]',\ F_0 = (0.1)^2 \times \mathbf{I}_2$
α_n	$N(a_0, A_0)$	$a_0 = 1,\ A_0 = 1$
$\boldsymbol{\beta}_k$	$N(b_0, B_0)$	$b_0 = \mathbf{0}_3,\ B_0 = \text{diag}(0.5, 3, 3)$
δ_n	$N(d_0, D_0)$	$d_0 = 1,\ D_0 = 1$
σ_{en}	$IG\left(\frac{\bar{\upsilon}_{en}}{2}, \frac{\bar{\zeta}_{en}}{2}\right)$	$\bar{\upsilon}_{en} = 6,\ \bar{\zeta}_{en} = 4$
$\boldsymbol{\rho}_n$	$N(r_0, R_0)$	$r_0 = [0.9, 0]',\ P_0 = (0.1)^2 \times \mathbf{I}_2$
$\sigma_{\eta n}$	$IG\left(\frac{\bar{\upsilon}_{\eta n}}{2}, \frac{\bar{\zeta}_{\eta n}}{2}\right)$	$\bar{\upsilon}_{\eta n} = 6,\ \bar{\zeta}_{\eta n} = 4$

the model in its state space form. The measurement equation is

$$Y_t = H\xi_t,$$

where $H = \left[I_N, I_N, \tilde{\Gamma}, \mathbf{0}_{N\times N(p_v-1)}, \mathbf{0}_{N\times K(p_z-1)}\right]$, $\tilde{\Gamma} = \alpha\odot\Gamma$, and the state vector is $\xi_t = [\tau_t', v_t', z_t', v_{t-1}', ...,$ $v_{t-p_v+1}', z_{t-1}', ..., z_{t-p_z+1}']'$. The state equation is

$$\xi_t = \Lambda_t + \Theta\xi_{t-1} + \omega_t,$$

where $\Lambda_t = [\mathbf{0}_{N\times 1}', \mathbf{0}_{N\times 1}', S_t\mu', \mathbf{0}_{N(p_v-1)\times 1}', \mathbf{0}_{K(p_z-1)\times 1}']'$,

$$\Theta = \begin{bmatrix} I_N & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \Delta_1 & \mathbf{0} & \Delta_2 \cdots \Delta_{p_v} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \Omega_1 & \mathbf{0} & \Omega_2 \cdots \Omega_{p_z} \\ \mathbf{0} & I_N & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & I_{N(p_v-2)} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & I_K & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & I_{K(p_z-2)} \end{bmatrix},$$

$\Delta_p = diag(\rho_{1p}, ..., \rho_{Np})$, $\Omega_p = diag(\phi_{1p}, ..., \phi_{Kp})$ and $\omega_t = [e_t', \eta_t', u_t', \mathbf{0}'_{N(p_v-1)\times 1}, \mathbf{0}'_{K(p_z-1)\times 1}]'$.

The sampler requires a distribution for the initial state vector $\xi_0 \sim N(\xi_{0|0}, P_{0|0})$ [see Durbin & Koopman (2012)]. The initial mean and variance-covariance terms for the stationary series in ξ_0 (v and z) are set to the unconditional mean and variance-covariance terms [see Hamilton (1994, p. 378)]. Because the trend, τ, is nonstationary, the initial values are set using a diffuse prior, where the trend element in $\xi_{0|0}$ is set to the initial observation Y_0 and the corresponding diagonal elements of $P_{0|0}$ to 10^7.

3.3. Draw $\boldsymbol{S}_T, \Pi | \Psi_{-\Pi}, \boldsymbol{\tau}_T, \boldsymbol{z}_T, \boldsymbol{v}_T, \mathbf{Y}_T$

The draws for the cluster factor dynamics are standard steps for an AR process with Markov-switching (Kim & Nelson, 1999). Conditional on $\boldsymbol{z}_T$, μ, and Π, the state vector $\mathbf{S}_T$ can be drawn using the filter outlined by Hamilton (1989). We initialize the filter with the steady-state probabilities implied by Π: $p(S_0 = 0) = \frac{1-\pi_{11}}{2-\pi_{00}-\pi_{11}}$ and $p(S_0 = 1) = \frac{1-\pi_{00}}{2-\pi_{00}-\pi_{11}}$. The filter is run forward for $t = 1, ..., T$ to obtain

$$p(S_t|z_t, ..., z_1) = \frac{f(z_t|S_t, z_{t-1}, ..., z_1)p(S_t|z_{t-1}, ..., z_1)}{f(z_t|z_{t-1}, ..., z_1)},$$

where

$$f(z_t|S_t, z_{t-1}, ..., z_1) \propto \exp\left\{-0.5\sum_{t=1}^{T}[z_t - \mu S_t \Phi(L) z_{t-1}]'[z_t - \mu S_t - \Phi(L) z_{t-1}]\right\},$$

$$p(S_t|z_{t-1}, ..., z_1) = \sum_{i=0}^{1} p(S_t|S_{t-1} = i)p(S_{t-1} = i|z_{t-1}, ..., z_1)$$

and

$$f(z_t|z_{t-1}, ..., z_1) = \sum_{j=0}^{1} f(z_t|S_t = j, z_{t-1}, ..., z_1)p(S_t = j|z_{t-1}, ..., z_1).$$

We then draw the terminal state S_T from $p(S_T|z_T, ..., z_1)$, which is provided by the last iteration of the forward filter. The remaining states, $S_{T-1}, ..., S_1$, are drawn recursively:

$$p(S_t|S_{t+1} = j) \propto p(S_{t+1} = j|S_t)p(S_t|z_t, ..., z_1),$$

using a backward smoother (Chib, 1996).

Each of the columns $\pi_i = [\pi_{1i}, \pi_{2i}]'$ of the transition matrix Π are drawn from their conditional posterior distribution given by

$$\pi_i \sim D(\bar{\pi}_{1i} + N_{1i}, \bar{\pi}_{2i} + N_{2i}),$$

where N_{ji} is the number of transitions from state i to state j in $\boldsymbol{S}_T$ and the prior is the Dirichlet distribution $\boldsymbol{\pi}_i \sim D(\bar{\pi}_{1i}, \bar{\pi}_{2i})$.

3.4. Draw $\mu, \Phi|\Psi_{-\mu,\Phi}, \boldsymbol{\tau}_T, \boldsymbol{z}_T, \boldsymbol{v}_T, \boldsymbol{S}_T, \mathbf{Y}_T$

Drawing the parameters governing the cluster dynamics is straightforward, conditional on knowing the state vector, S_T, and cluster factors, $\boldsymbol{z}_T$. We first draw μ_k for each cluster, then the AR parameters, $\Phi_k = [\phi_{k1}, ..., \phi_{kp_z}]'$. Let $\mu_k \sim N(m_0, M_0)$ be the prior distribution for the "plucking" parameter. We can then draw μ_k from its posterior distribution using a rejection sampler to ensure the identification is satisfied:

$$\mu_k \sim N(m_1, M_1),$$

where

$$m_1 = M_1(M_0^{-1}m_0 + X_\mu' Y_{\mu k}),$$

$$M_1 = (M_0^{-1} + X_\mu' X_\mu),$$

$X_\mu = [S_{p_z+1}, ..., S_T]'$ and

$$Y_{\mu,k} = \begin{bmatrix} z_{k,p_z+1} - \sum_p \phi_{kp} z_{k,p_z+1-p} \\ \vdots \\ z_{k,T} - \sum_p \phi_{kp} z_{k,T-p} \end{bmatrix}.$$

Given the prior $\Phi_k \sim N(f_0, F_0)$, we draw the cluster AR parameters using a rejection sampler to ensure stationarity from

$$\Phi_k \sim N(f_1, F_1),$$

where

$$f_1 = F_1(F_0^{-1} f_0 + X'_{\Phi k} Y_{\Phi k}),$$

$$F_1 = (F_0^{-1} + X'_{\Phi k} X_{\Phi k}),$$

$$X_{\Phi k} = \begin{bmatrix} z_{k,p_z} & \cdots & z_{k,1} \\ \vdots & & \vdots \\ z_{k,T-1} & \cdots & z_{k,T-p_z} \end{bmatrix}$$

and $Y_{\Phi k} = [z_{k,p_z+1} - \mu_k S_{p_z+1}, ..., z_{k,T} - \mu_k S_T]'$.

3.5. *Draw* $\Gamma, \alpha, \beta | \Psi_{-\alpha,\beta,\Gamma}, \boldsymbol{\tau}_T, \boldsymbol{z}_T, \boldsymbol{v}_T, \boldsymbol{S}_T, \mathbf{Y}_T, \mathbf{x}$

The cluster membership indicators in Γ could be drawn industry-by-industry from each respective conditional posterior distribution as in Frühwirth-Schnatter (2006, Ch. 3). However, we found this method mixed poorly due to the restriction that clusters are non-empty. Therefore, we opted to draw the membership indicators for each cluster γ_k using a Metropolis-within-Gibbs step. At each Gibbs iteration, we propose a new cluster membership matrix Γ^* that differs from the previous iteration's draw, $\Gamma^{[i-1]}$, by a single industry n. That is, with equal probability, we either add or take away an industry from cluster k to get Γ^*. If $\gamma_k^{[i-1]}$ is already at the minimum cluster size, a random industry is added to cluster k. The proposal is then accepted with probability

$$A = \min \left[1, \frac{p(\Gamma^* | \beta, \mathbf{x})}{p(\Gamma^{[i-1]} | \beta, \mathbf{x})} \frac{f(\boldsymbol{Y} | \Gamma^*)}{f(\boldsymbol{Y} | \Gamma^{[i-1]})} \frac{q(\Gamma^{[i-1]} | \Gamma^*)}{q(\Gamma^* | \Gamma^{[i-1]})} \right],$$

where $p(\Gamma|\beta, \mathbf{x})$ is the prior given by (3),

$$f(\boldsymbol{Y}|\Gamma) \propto \exp\left\{-0.5\sum_{t=1}^{T}(\Delta Y_t - \delta - \Delta v_t - \alpha \otimes \Gamma z_t)'\Sigma_e^{-1}(\Delta Y_t - \delta - \Delta v_t - \alpha \otimes \Gamma z_t)\right\}$$

and $q\left(\Gamma^{[i]}|\Gamma^{[i-1]}\right)$ is the proposal distribution. Because the proposal distribution is symmetric, the last term in the acceptance probability is equal 1.

After proposing the cluster membership indicators in Γ, the draw for α is straightforward and can be carried out industry-by-industry. Assuming a prior distribution of $\alpha_n \sim N(a_0, A_0)$, each factor loading is drawn using a rejection sampler from its posterior distribution given by

$$\alpha_n \sim N(a_1, A_1),$$

where

$$a_1 = A_1(A_0^{-1}a_0 + X'_{\alpha n}Y_{\alpha n}),$$

$$A_1 = (A_0^{-1} + X'_{\alpha n}X_{\alpha n}),$$

$X_{\alpha n} = [\frac{\sum_k \gamma_{nk}\Delta z_{k1}}{\sigma_{en}}, ..., \frac{\sum_k \gamma_{nk}\Delta z_{kT}}{\sigma_{en}}]'$ and $Y_{\alpha n} = [\frac{\Delta Y_{n1} - \delta_n - \Delta v_{n1}}{\sigma_{en}}, ..., \frac{\Delta Y_{nT} - \delta_n - \Delta v_{nT}}{\sigma_{en}}]'$.

Given the cluster membership indicators in Γ, the draw of the prior hyperparameters β follows from the data augmentation technique presented in Section 3.2 of Frühwirth-Schnatter & Frühwirth (2010). To identify the parameters in the multinomial logistic, we set $\beta_1 = 0$ implying Cluster 1 is the baseline category. Thus, β_k for $k = 2, ..., K$ can be interpreted as the change in the log-odds ratio relative to Cluster 1.

3.6. Draw $\delta, \Sigma_{\boldsymbol{e}}|\Psi_{-\delta,\Sigma_{\boldsymbol{e}}}, \boldsymbol{\tau}_T, \boldsymbol{z}_T, \boldsymbol{v}_T, \boldsymbol{S}_T, \mathbf{Y}_T$

We draw the drift parameters, δ_n, and the variance terms in $\boldsymbol{\Sigma_e}$ industry-by-industry. Given the prior $\delta_n \sim N(d_0, D_0)$, the posterior distribution is then:

$$\delta_n \sim N(d_1, D_1),$$

where

$$D_1 = (D_0^{-1} + X'_{\delta n} X_{\delta n}),$$

$$d_1 = D_1(D_0^{-1} d_0 + X'_{\delta n} Y_{\delta n}),$$

$X_{\delta n} = \sigma_{en}^{-1} \mathbf{1}_{T-1}$ and $Y_{\delta n} = [\frac{\Delta\tau_{n2}}{\sigma_{en}}, ..., \frac{\Delta\tau_{nT}}{\sigma_{en}}]'$. To allow for secular declines in certain industries, we place no restrictions on the sign of δ_n.

Given the prior, $\sigma_{en}^2 \sim IG(\frac{\bar{\upsilon}_{en}}{2}, \frac{\bar{\zeta}_{en}}{2})$, we draw σ_{en}^2 from its posterior distribution given by

$$\sigma_{en}^2 \sim IG(\frac{\upsilon_{en}}{2}, \frac{\zeta_{en}}{2}),$$

where $\upsilon_{en} = \bar{\upsilon}_{en} + T - 1$ and $\zeta_{en} = \bar{\zeta}_{en} + \sum_{t=2}^{T} (\Delta\tau_{nt} - \delta_n)^2$.

3.7. Draw $\rho, \Sigma_\eta | \Psi_{-\rho,\Sigma_\eta}, \boldsymbol{\tau}_T, \boldsymbol{z}_T, \boldsymbol{v}_T, \boldsymbol{S}_T, \mathbf{Y}_T$

Given the prior, $\rho_n \sim N(r_0, R_0)$, we draw ρ_n using a rejection sampler to ensure stationarity from its posterior distribution:

$$\rho_n \sim N(r_1, R_1),$$

where

$$R_1 = (R_0^{-1} + X'_{\rho n} X_{\rho n}),$$

$$r_1 = R_1(R_0^{-1} r_0 + X'_{\rho n} Y_{\rho n}),$$

$$X_{\rho n} = \begin{bmatrix} \frac{v_{n,p_v}}{\sigma_{\eta n}} & \cdots & \frac{v_{n,1}}{\sigma_{\eta n}} \\ \vdots & & \vdots \\ \frac{v_{n,T-1}}{\sigma_{\eta n}} & \cdots & \frac{v_{n,T-p_v}}{\sigma_{\eta n}} \end{bmatrix}$$

and $Y_{\rho n} = \left[\frac{v_{n,p_v+1}}{\sigma_{\eta n}}, ..., \frac{v_{n,T}}{\sigma_{\eta n}}\right]'$. We implement a rejection sampler to ensure all of the roots for any draw $\rho_n(L)$ lie outside the unit circle, and thus v_n remains stationary.

Let $\sigma_{\eta n}^2 \sim IG(\frac{\bar{\upsilon}_{\eta n}}{2}, \frac{\bar{\zeta}_{\eta n}}{2})$ be the prior for $\sigma_{\eta n}$. The posterior distribution is then given by

$$\sigma_{\eta n}^2 \sim IG(\frac{\upsilon_{\eta n}}{2}, \frac{\zeta_{\eta n}}{2}),$$

where $\upsilon_{\eta n} = \bar{\upsilon}_{\eta n} + T - p_v$ and $\zeta_{\eta n} = \bar{\zeta}_{\eta n} + \sum_{t=p_v+1}^{T} \left(v_{nt} - \rho_n(L)v_{nt-1}\right)^2$.

3.8. Choosing the Number of Clusters, Minimum Cluster Size, and Lag Length

We treat the number of clusters, K, and the lag lengths, p_z and p_ν, as model selection issues. Additionally, if left unrestricted, the proposal density for the cluster membership draw of the sampler could create empty clusters. While we could set the minimum size of a cluster, $\underline{n}_K$, equal to 1, we also do not want to create degenerate clusters (i.e., clusters with only a single member). Because choosing any minimum cluster size greater than 1 might be arbitrary, we will also treat this parameter as a model selection issue.

In principle, we could search over all combinations of these four parameters, given a limited support for each. This would require estimating a very large set of models. Many of the papers in the unobserved components literature set the number of lags equal to 2—the minimum number of lags required for the model to be identified [see, for example, Harvey (1985), Clark (1987), Harvey & Jaeger (1993), Morley et al. (2003), and González-Astudillo (2019)]. In the interest of computational feasibility, we conduct the model selection exercise hierarchically: We first set $p_z = p_\nu = 2$ and optimize the number of clusters and the minimum cluster size. Then, based on these values, we determine the optimal number of lags.

As shown by Kass & Raftery (1995), Bayesian Information Criterion (BIC) provides an asymptotic approximation of the marginal likelihood and is relatively easy to compute. We compare the BIC across models for $K \in \{2, ..., 10\}$ and $\underline{n}_K \in \{2, ..., 10\}$. Alternative criterion, including Akaike Information Criterion (AIC) and Deviance Information Criterion (DIC), corroborate our findings of the optimal cluster size [see Spiegelhalter et al. (2002)]. Then, given the choice of K and $\underline{n}_K$, we choose p_z and p_ν from $p_z \in \{2, ..., 8\}$ and $p_\nu \in \{2, ..., 6\}$.

4. Empirical Application

4.1. Data

To estimate our model, we require two different sets of data. First, we require a set of business cycle indicators. Second, we require a set of cross-sectional covariates to populate the prior on cluster membership.

4.1.1. Business Cycle Indicator

While the growth rate of real gross domestic product (GDP) is often used to represent business cycle fluctuations, the NBER Business Cycle Dating Committee also considers other variables such as employment and industrial production (IP). Industry-level GDP is available only at a quarterly frequency back to 2005. Employment can be problematic for identifying turning points. Following the three recessions of 1990-91, 2001, and the Great Recession, employment recovered slower than output [see, for example, Jaimovich & Siu (2020)]. These "jobless" recoveries can skew the timings of the turning points if labor market variables alone are used. In light of these issues, we use monthly, seasonally-adjusted, industry-level IP. These data are available from the Board of Governors of the Federal Reserve System.

Monthly industry-level IP is disaggregated to the four-digit NAICS industry level. During the early-1990s, the standard industry classification changed from the SIC to the NAICS. The two industry classification systems differ in both the number of industries and how they are classified. Broad industrial sectors (one-digit) remain essentially unchanged but the three-digit industries cannot be easily merged. While the SIC classification provides a longer sample (back to 1948), the NAICS contains industries (e.g., information technologies) that have recently risen in importance. Our sample includes 82 industries covering the time period 1972:01 to 2019:12. These industries are listed in the first column of Tables 2 and 3; their NAICS industry designation is listed in the second column.

4.1.2. Covariate Data for the Prior

The cluster membership indicators determine which industries comove. The prior on each indicator is logistic, parameterized by covariates that may influence cluster composition. We require a set of industry-specific characteristics that are time-invariant and can measure the links between industries. Industry comovement could result from sector-specific shocks that affect industries within a single NAICS designation or from shocks that affect industries across sectors through supply chain dependencies. To answer the question posed in the introduction, our covariate data

Table 2: **Parameter Estimates**. This table shows median posterior estimates of each industry's trend drift δ_n; magnitude of average aggregate recession $\alpha_n \gamma_{nk} \mu_k$; and the variance decomposition of the cycle component c_{nt} into the aggregate regime S_t and cluster-specific shock u_{kt}.

Industry Name	NAICS	δ_n	$\alpha_n \gamma_{nk} \mu_k$	VDC_S	VDC_u
Veneer, Plywood, and Engineered Wood Pro...	3212	0.09	-1.33	0.36	0.17
Other Wood Product	3219	0.05	-1.89	0.6	0.11
Clay Product and Refractory	3271	-0.09	-1.04	0.56	0.1
Glass and Glass Product	3272	0.04	-1.32	0.72	0.13
Cement and Concrete Product	3273	0.05	-1.77	0.63	0.11
Lime and Gypsum Product	3274	0.07	-1.35	0.47	0.08
Other Nonmetallic Mineral Product	3279	0.11	-1.89	0.59	0.11
Iron and Steel Products	3311	-0.03	-3.81	0.67	0.12
Alumina and Aluminum Production and Proc...	3313	0.01	-2.28	0.48	0.09
Nonferrous Metal	3314	-0.04	-1.59	0.55	0.1
Foundries	3315	-0.05	-2.6	0.83	0.15
Hardware	3325	-0.08	-1.91	0.79	0.14
Machine Shops, Turned Product, and Screw...	3327	0.18	-2.3	0.8	0.14
Other Fabricated Metal Product	3329	0.04	-1.73	0.81	0.14
Agriculture, Construction, and Mining Ma...	3331	0.05	-2.19	0.54	0.1
Industrial Machinery	3332	0.02	-1.73	0.51	0.09
Commercial and Service Industry Machiner...	3333	0.19	-0.48	0.48	0.41
Ventilation, Heating, Air-Conditioning, ...	3334	0.04	-2.43	0.64	0.11
Metalworking Machinery	3335	0	-1.89	0.65	0.12
Engine, Turbine, and Power Transmission ...	3336	0.02	-2.14	0.76	0.13
Computer and Peripheral Equipment	3341	1.43	-0.42	0.32	0.29
Communications Equipment	3342	0.74	-1.28	0.6	0.11
Audio and Video Equipment	3343	-0.02	-0.54	0.05	0.05
Semiconductor and Other Electronic Compo...	3344	1.43	-1.96	0.69	0.12
Navigational, Measuring, Electromedical,...	3345	0.37	-1.05	0.64	0.11
Electric Lighting Equipment	3351	-0.02	-1.91	0.7	0.12
Household Appliance	3352	0.04	-2.37	0.52	0.24
Electrical Equipment	3353	-0.02	-1.79	0.79	0.14
Other Electrical Equipment and Component...	3359	0.12	-2.34	0.83	0.15
Motor Vehicle	3361	0.21	-12.79	0.64	0.34
Motor Vehicle Body and Trailer	3362	0.07	-2.87	0.52	0.27
Motor Vehicle Parts	3363	0.18	-5.16	0.58	0.3
Aerospace Product and Parts	3364	0.12	-0.39	0.03	0.27
Ship and Boat Building	3366	0.05	-0.73	0.2	0.04
Office and Other Furniture	3372	0.1	-1.44	0.79	0.14
Logging	1133	0.02	-0.97	0.17	0.08
Sawmills and Wood Preservation	3211	0.06	-1.77	0.43	0.2
Forging and Stamping	3321	0.07	-2.37	0.82	0.15
Cutlery and Handtool	3322	-0.09	-1.59	0.78	0.14
Architectural and Structural Metals	3323	0.08	-1.67	0.79	0.14

are chose to determine whether comovement results from connectedness in an industry's supply chain that extends within or across the two-digit sector.

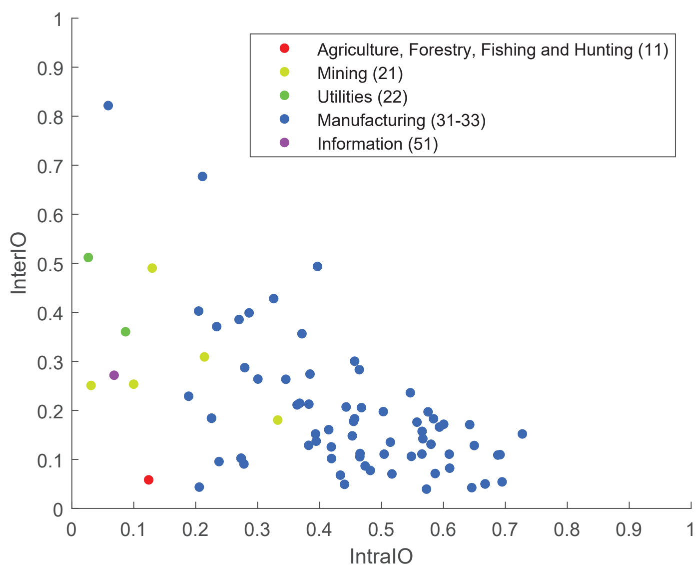
We compute two measures of connectedness within a supply chain: the dollar value of commodities flowing to other industries either within or across its two-digit NAICS code. We employ the

Table 3: **Parameter Estimates (continued)**. This table shows median posterior estimates of each industry's trend drift δ_n; magnitude of average aggregate recession $\alpha_n \gamma_{nk} \mu_k$; and the variance decomposition of the cycle component c_{nt} into the aggregate regime S_t and cluster-specific shock u_{kt}.

Industry Name	NAICS	δ_n	$\alpha_n \gamma_{nk} \mu_k$	VDC_S	VDC_u
Spring and Wire Product	3326	0	-2.18	0.83	0.15
Coating, Engraving, Heat Treating, and A...	3328	0.21	-2.12	0.82	0.15
Railroad Rolling Stock	3365	-0.05	-0.8	0.53	0.44
Other Transportation Equipment	3369	0.23	-0.91	0.34	0.11
Household and Institutional Furniture an...	3371	0.02	-1.79	0.65	0.3
Medical Equipment and Supplies	3391	0.32	-0.87	0.63	0.11
Animal Food	3111	0.25	-0.07	0.07	0.52
Grain and Oilseed Milling	3112	0.15	-0.04	0.02	0.19
Sugar and Confectionery Product	3113	0.08	-0.94	0.3	0.05
Fruit and Vegetable Preserving and Speci...	3114	0.08	-0.07	0	0.04
Dairy Product	3115	0.09	-0.02	0.01	0.1
Animal Slaughtering and Processing	3116	0.19	-0.03	0.03	0.22
Other Food	3119	0.21	-0.06	0	0.02
Beverage	3121	0.15	-0.28	0.14	0.04
Tobacco	3122	-0.18	-0.54	0.12	0.02
Fabric Mills	3132	-0.11	-1.45	0.62	0.29
Textile and Fabric Finishing and Fabric ...	3133	-0.17	-2	0.64	0.29
Textile Furnishings Mills	3141	-0.08	-1.84	0.61	0.28
Other Textile Product Mills	3149	0.01	-1.57	0.51	0.24
Apparel	315	-0.38	-1.41	0.79	0.14
Leather and Allied Product	316	-0.31	-1.35	0.72	0.13
Pulp, Paper, and Paperboard Mills	3221	0.01	-1.36	0.55	0.25
Converted Paper Product	3222	0.04	-1.32	0.62	0.29
Printing and Related Support Activities	323	0.06	-0.95	0.81	0.14
Petroleum and Coal Products	324	0.07	-0.68	0.32	0.15
Basic Chemical	3251	0.07	-1.71	0.55	0.1
Resin, Synthetic Rubber, and Artificial ...	3252	0.09	-3.2	0.61	0.28
Pesticide, Fertilizer, and Other Agricul...	3253	0.13	-0.68	0.31	0.12
Pharmaceutical and Medicine	3254	0.22	-0.02	0	0.02
Paint, Coating, and Adhesive	3255	0.08	-1.2	0.63	0.11
Soap, Cleaning Compound, and Toilet Prep...	3256	0.13	-0.92	0.49	0.09
Plastics Product	3261	0.25	-2.02	0.77	0.14
Rubber Product	3262	0.01	-1.84	0.61	0.11
Newspaper, Periodical, Book, and Directo...	5111	-0.11	-0.68	0.72	0.13
Bakeries and Tortilla	3118	0.03	-0.35	0.32	0.15
Oil and Gas Extraction	211	0.09	-0.27	0.07	0.67
Metal Ore Mining	2122	0.07	-1.93	0.36	0.06
Nonmetallic Mineral Mining and Quarrying...	2123	0.05	-1.71	0.73	0.13
Support Activities for Mining	213	-0.09	-0.02	0	0.01
Electric Power Generation, Transmission,...	2211	0.18	-0.31	-0.04	0.81
Natural Gas Distribution	2212	0.01	-0.65	-0.02	0.46
Coal Mining	2121	0.01	-0.03	0	0

"make"-"use" tables from the Bureau of Labor Statistics to create an input-output matrix similar to Caunedo (2020). The "make" table captures what commodity each industry makes or produces; the "use" table shows the components that each industry uses for production. Specifically, the "make" table collects w_{nct}, the dollar value of commodity c produced by industry n, into a $N \times C$ output matrix W_t for year t. The "use" table collects u_{cnt}, the dollar value of commodity c used as an input by industry n, into a similar $C \times N$ input matrix U_t for year t. The input-output matrix, then, is $IO_t = [W_t \oslash (J_N W_t)]\, U_t$, where J_N is a $N \times N$ matrix of ones and $\oslash$ represents Hadamard division. Therefore, each entry of the $N \times N$ matrix, IO_t, shows how the output in each industry is used as an input by each other industry in a given year. We normalize the input-output matrix by the total dollar flow into a given industry to obtain each industry's relative intermediate importance: $\tilde{IO}_t = IO_t \oslash (J_N IO_t)$. The "make"-"use" tables are available annually for 205 industries from 1997 to 2019. We restrict our sample to match the 82 industries available for IP.

Figure 1: **Connectedness Measures**. This scatterplot shows the two measures of industry connectedness as constructed from the input-output matrices. *Intra-IO* measures the percentage of total output of a given industry that is used as an input to industries within its sector (i.e., industries which have the same two digit NAICS code). *Inter-IO* measures the percentage of total output of a given industry that is used as an input to industries outside its sector.



We measure within- or intra-industry connectedness (*intra-IO*) as the sum of the proportions of a given industry's output used as an input into other industries with the same two-digit NAICS code. Conversely, our measure of across- or inter-industry connectedness (*inter-IO*) is the sum of the proportions of a given industry's output used as an input into industries outside its two-digit

NAICS code. Because the covariates entering the multinomial logistic prior must be time-invariant, we take the average of each connectedness measure across all of the years for which data is available. Figure 1 shows a scatterplot of the average connectedness measures for each industry color-coded by 2-digit NAICS sector. As one might expect, the two covariates are negatively but not perfectly correlated, as some output from each sector used as final goods is in neither *inter-IO* nor *intra-IO*.

4.2. Main Results

Using the method outlined in Section 3, the optimal number of clusters is determined to be $K = 7$ with the minimum cluster size restricted to $\underline{n}_k = 4$. Given these values, the optimal lag length for the cluster cycles is $p_z = 6$ while the optimal number of lags for the idiosyncratic component is $p_v = 3$. In the following subsections, we present the results based on this model specification; the subsequent section shows a few representative industries.

4.2.1. Industry Trends

The industry-level trends differentiate our models from Foerster et al. (2011), Garin et al. (2018), and Li & Martin (2019), and we can identify secularly declining industries. Of particular interest are industries that experience both increasing and decreasing trends over the period. These periods could affect the identification of the aggregate regimes, and issues surrounding them might not be resolved by differencing as in Francis et al. (2017).

The second columns of Tables 2 and 3 show the NAICS four-digit industry code and the third columns show the estimated drift parameter. Eighteen of the 82 industries have negative mean drift. Three of these industries—tobacco, newspapers, and railroad rolling stock (consisting of train cars, etc.)—are not surprising: Demand for these products has been declining for various reasons. Iron and steel and their related sectors; apparel; and leather may have declining trends because of foreign competition. Other textile subsectors have small, positive drift parameters. On the other hand, some high tech industries—computer peripherals, semiconductors, and communications—have steep upward trends suggested by large, positive drift parameters.

As alluded to above, not all of these industries experience a secular decline over the entire subsample. For example, newspapers and apparel—both of which we will discuss in more detail below—increase or are constant for the initial part of the sample but then decline over the last 20-25 years. In these cases (and others), neither a linear trend nor differencing (or, equivalently, computing growth rates) would remove the time-varying trend and allow us to identify the cyclical features. The downward trend in a portion of the time sample could be identified by the filter as recession periods. The UC framework's time-varying trends is robust to these partial-sample downward trends.

4.2.2. Aggregate Recessions

In our model, comovement is influenced by two components: the aggregate recession indicator, S_t, and the common cluster cycle, z_{kt}. The aggregate recession indicator drives comovement across all industries, while the cluster cycle drives comovement between a subset of industries. Industry-level IP identifies troughs with more precision than it does peaks, which has been noted by Chang & Hwang (2015). Industries appear to recover simultaneously but fall into recession at different times. This result motivates our approach of using both an aggregate regime and cluster cycles that allow groups of industries to experience business cycle fluctuations outside the aggregate cycle.

Figure 2: **Aggregate Recession**. This figure shows the mean probability of recession for the entire panel of industries (i.e., $S_t = 1$). The gray bars reflect official NBER U.S. recession dates.

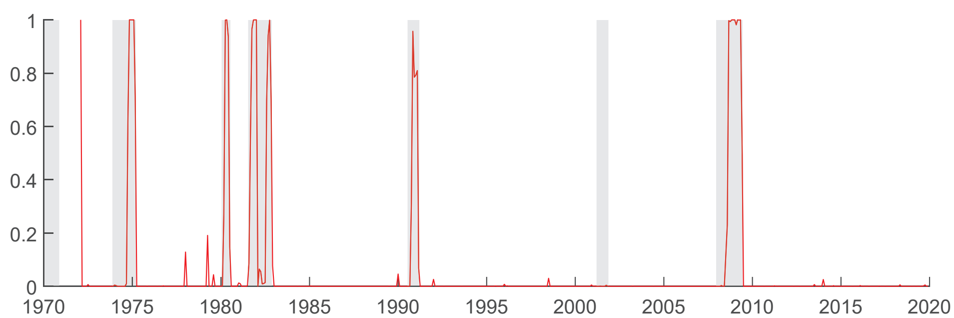
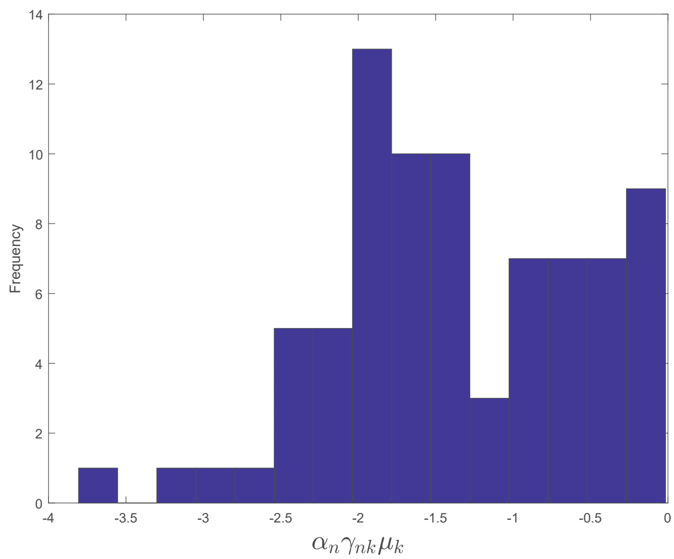


Figure 2 plots the posterior regime probabilities for S_t, along with the NBER recessions shaded in grey. With the exception of the 1990-91 and 2001 events, the aggregate regime variable indicates a recession with posterior probability 1 for all of the NBER recessions in the sample period. The 1990-91 event is identified at an 80-percent posterior probability threshold. Omission of the 2001 event is consistent with Chauvet & Piger (2008) and results from our use of the latest vintage of data. Positive data revisions subsequent to the NBER announcement of the 2001 turning points made identification of the recession less likely. The aggregate regime variable has only one false positive at the beginning of the sample, which may be a product of the initialization of the sampler and/or the poor end-of-sample properties of the filter. The dataset does not include the recession starting in 1969.

Figure 3: **Recession Depth**. This histogram shows the posterior median for each industry's recession depth $\alpha_n \gamma_{nk} \mu_k$. We omit motor vehicles from the histogram due to its extreme value (-13.03).



Our model also identifies the industry-level depth of recession, $\alpha_n \gamma_{nk} \mu_k$. The fourth columns of Tables 2 and 3 show the mean depth of the recessions for the cross-section of industries. Figure 3 plots a histogram of the depth of recessions for the various industries. In general, raw materials sectors experience some of the largest declines in IP (over 4 percentage points for some industries) during recessions. Other durable goods industries—e.g., household appliances, motor vehicles, and motor vehicle related industries—also experience large declines during recessions, possibly because consumers delay these purchases during tough times. Conversely, inelastic demand products such as food and food products (except sugar and confectionery products, which may be more elastic), pharmaceuticals and medicine, and energy-related industries experience the mildest recessions.

4.2.3. Cluster Composition

While the aggregate regime affects all industries, comovement across subsets of industries is determined by membership in a cluster. While two industries in the same cluster can have different trends and idiosyncratic cycles, they share a common cluster factor, z_{kt}.

Tables 4 and 5 show the posterior probabilities for the cluster membership indicator, γ_{nk}. While most industries are assigned to one cluster with high probability, a few industries' cluster memberships are not as well identified. For example, pesticide and fertilizer is assigned to Cluster 3 with 52% posterior probability and not assigned to any other cluster with more than 25% posterior probability. Beverages are assigned to Cluster 1 with 56% posterior probability but are also assigned to Cluster 6 with greater than 40% posterior probability. Typically, membership ambiguity arises because an industry has cyclical properties similar to more than one factor, making the likelihood of being assigned to multiple clusters about equal. Alternatively, an industry may be acyclical or not well represented by any cluster factor. While our model does not allow single-member clusters, industries not well represented by any of the K cluster factors will draw loadings close to zero and have most of their variance explained by their idiosyncratic components.

Table 4: **Cluster Membership**. This table displays the posterior probability of cluster membership for each industry. These probabilities are computed as the average of the draws of γ_{nk} across all Gibbs iterations.

		Cluster (k)						
Industry Name	NAICS	1	2	3	4	5	6	7
Veneer, Plywood, and Engineered Wood Pro...	3212	1	0	0	0	0	0	0
Other Wood Product	3219	0	0	0	0	0	1	0
Clay Product and Refractory	3271	0	0	0	0	0	1	0
Glass and Glass Product	3272	0	0	0	0	0	1	0
Cement and Concrete Product	3273	0	0	0	0	0	1	0
Lime and Gypsum Product	3274	0	0	0	0	0	1	0
Other Nonmetallic Mineral Product	3279	0	0	0	0	0	1	0
Iron and Steel Products	3311	0	0	0	0	0	1	0
Alumina and Aluminum Production and Proc...	3313	0	0	0	0	0	1	0
Nonferrous Metal	3314	0	0	0	0	0	1	0
Foundries	3315	0	0	0	0	0	1	0
Hardware	3325	0	0	0	0	0	1	0
Machine Shops, Turned Product, and Screw...	3327	0	0	0	0	0	1	0
Other Fabricated Metal Product	3329	0	0	0	0	0	1	0
Agriculture, Construction, and Mining Ma...	3331	0	0	0	0	0	1	0
Industrial Machinery	3332	0	0	0	0	0	1	0
Commercial and Service Industry Machiner...	3333	0	0	0	0	1	0	0
Ventilation, Heating, Air-Conditioning, ...	3334	0	0	0	0	0	1	0
Metalworking Machinery	3335	0	0	0	0	0	1	0
Engine, Turbine, and Power Transmission ...	3336	0	0	0	0	0	1	0
Computer and Peripheral Equipment	3341	0	0	0	0	1	0	0
Communications Equipment	3342	0	0	0	0	0	1	0
Audio and Video Equipment	3343	0	0	0	0	1	0	0
Semiconductor and Other Electronic Compo...	3344	0	0	0	0	0	1	0
Navigational, Measuring, Electromedical,...	3345	0	0	0	0	0	1	0
Electric Lighting Equipment	3351	0	0	0	0	0	1	0
Household Appliance	3352	1	0	0	0	0	0	0
Electrical Equipment	3353	0	0	0	0	0	1	0
Other Electrical Equipment and Component...	3359	0	0	0	0	0	1	0
Motor Vehicle	3361	0	0	1	0	0	0	0
Motor Vehicle Body and Trailer	3362	0	0	1	0	0	0	0
Motor Vehicle Parts	3363	0	0	1	0	0	0	0
Aerospace Product and Parts	3364	0	1	0	0	0	0	0
Ship and Boat Building	3366	0	0	0	0	0	1	0
Office and Other Furniture	3372	0	0	0	0	0	1	0
Logging	1133	1	0	0	0	0	0	0
Sawmills and Wood Preservation	3211	1	0	0	0	0	0	0
Forging and Stamping	3321	0	0	0	0	0	1	0
Cutlery and Handtool	3322	0	0	0	0	0	1	0
Architectural and Structural Metals	3323	0	0	0	0	0	1	0

Table 5: **Cluster Membership (continued)**. This table displays the posterior probability of cluster membership for each industry. These probabilities are computed as the average of the draws of γ_{nk} across all Gibbs iterations.

		Cluster (k)						
Industry Name	NAICS	1	2	3	4	5	6	7
Spring and Wire Product	3326	0	0	0	0	0	1	0
Coating, Engraving, Heat Treating, and A...	3328	0	0	0	0	0	1	0
Railroad Rolling Stock	3365	0	0	0	0	1	0	0
Other Transportation Equipment	3369	0.16	0	0.49	0	0	0.34	0
Household and Institutional Furniture an...	3371	1	0	0	0	0	0	0
Medical Equipment and Supplies	3391	0	0	0	0	0	1	0
Animal Food	3111	0	0	0	0	0	0	1
Grain and Oilseed Milling	3112	0	0	0	0	0	0	1
Sugar and Confectionery Product	3113	0	0	0	0	0	1	0
Fruit and Vegetable Preserving and Speci...	3114	0.01	0.97	0	0	0	0.03	0
Dairy Product	3115	0	0	0	0	0	0	1
Animal Slaughtering and Processing	3116	0	0	0	0	0	0	1
Other Food	3119	0.04	0	0	0.52	0.01	0.43	0
Beverage	3121	0.56	0	0	0	0	0.44	0
Tobacco	3122	0.02	0.22	0	0	0	0.75	0
Fabric Mills	3132	1	0	0	0	0	0	0
Textile and Fabric Finishing and Fabric ...	3133	1	0	0	0	0	0	0
Textile Furnishings Mills	3141	1	0	0	0	0	0	0
Other Textile Product Mills	3149	1	0	0	0	0	0	0
Apparel	315	0	0	0	0	0	1	0
Leather and Allied Product	316	0	0	0	0	0	1	0
Pulp, Paper, and Paperboard Mills	3221	1	0	0	0	0	0	0
Converted Paper Product	3222	1	0	0	0	0	0	0
Printing and Related Support Activities	323	0	0	0	0	0	1	0
Petroleum and Coal Products	324	0.93	0	0	0	0	0.07	0
Basic Chemical	3251	0	0	0	0	0	1	0
Resin, Synthetic Rubber, and Artificial ...	3252	1	0	0	0	0	0	0
Pesticide, Fertilizer, and Other Agricul...	3253	0.24	0	0.52	0	0	0.23	0
Pharmaceutical and Medicine	3254	0.03	0.08	0	0.48	0.01	0.4	0
Paint, Coating, and Adhesive	3255	0	0	0	0	0	1	0
Soap, Cleaning Compound, and Toilet Prep...	3256	0	0	0	0	0	1	0
Plastics Product	3261	0	0	0	0	0	1	0
Rubber Product	3262	0	0	0	0	0	1	0
Newspaper, Periodical, Book, and Directo...	5111	0	0	0	0	0	1	0
Bakeries and Tortilla	3118	1	0	0	0	0	0	0
Oil and Gas Extraction	211	0	1	0	0	0	0	0
Metal Ore Mining	2122	0	0	0	0	0	1	0
Nonmetallic Mineral Mining and Quarrying...	2123	0	0	0	0	0	1	0
Support Activities for Mining	213	0.04	0.04	0	0.79	0	0.07	0.06
Electric Power Generation, Transmission,...	2211	0	0	0	1	0	0	0
Natural Gas Distribution	2212	0	0	0	1	0	0	0
Coal Mining	2121	0	0.72	0	0.21	0.02	0.06	0

Each of the $K = 7$ clusters has a different number of members. Cluster 6 is the largest, while the other clusters are smaller—close or equal to the minimum cluster size, $\underline{n}_k = 4$. Thus, the majority of the manufacturing economy has a common cycle. Figure 4 shows the seven cluster cycles. The sixth panel is the cluster cycle associated with the largest group of industries. Unsurprisingly, this factor declines during NBER recessions and—for the most part—rises during expansions. This cyclical pattern is not entirely attributable to the aggregate regime, which does not tend to switch at the beginning of NBER recessions. It does, however, suggest that the majority of industries follow the NBER cycle.

Other clusters have common cycles that differ from the NBER cycle. Many of these also fall—to varying degrees—during NBER recessions. However, some (e.g., a collection of energy sectors assigned to Cluster 2) experience fluctuations different from the aggregate but common to the group. Cluster 4 appears acyclical.

4.2.4. Marginal Effects

The preceding section reviewed how the industries cluster; here, we investigate what factors influence cluster membership. Determining which factors might influence cluster membership can help us answer if industry comovement is influenced by similarity in their supply chain characteristics. The prior is logistic, populated by the cluster covariates, $\mathbf{x}_{nk}$, and the prior hyperparameters, β_k, that are estimated jointly with the model parameters. We evaluate how changing an element of $\mathbf{x}_{nk}$ affects the prior probability of cluster membership by computing marginal effects. Marginal effects are the changes in the cluster membership prior probabilities produced by changes in the specified element of $\mathbf{x}_{nk}$ from one standard deviation below its mean to one standard deviation above its mean. In this calculation, all other elements of $\mathbf{x}_{nk}$ are fixed at their respective means.

Table 6 shows the marginal effects. The two cluster covariates evaluate the effects of differences in an industry's supply chain. An increase in *intra-IO* increases the percentage of that industry's production network that lies *within* its two-digit sector. An increase in *inter-IO*, on the other hand, increases the percentage of the industry's production network that lies *outside* its two-digit sector. Industries that have high *intra-IO (inter-IO)* have more vertical (horizontal) supply chains.

Figure 4: **Cluster Cycles**. This figure shows the median posterior draw of the factor z_{kt} for each cluster k. The gray bars reflect official NBER U.S. recession dates.

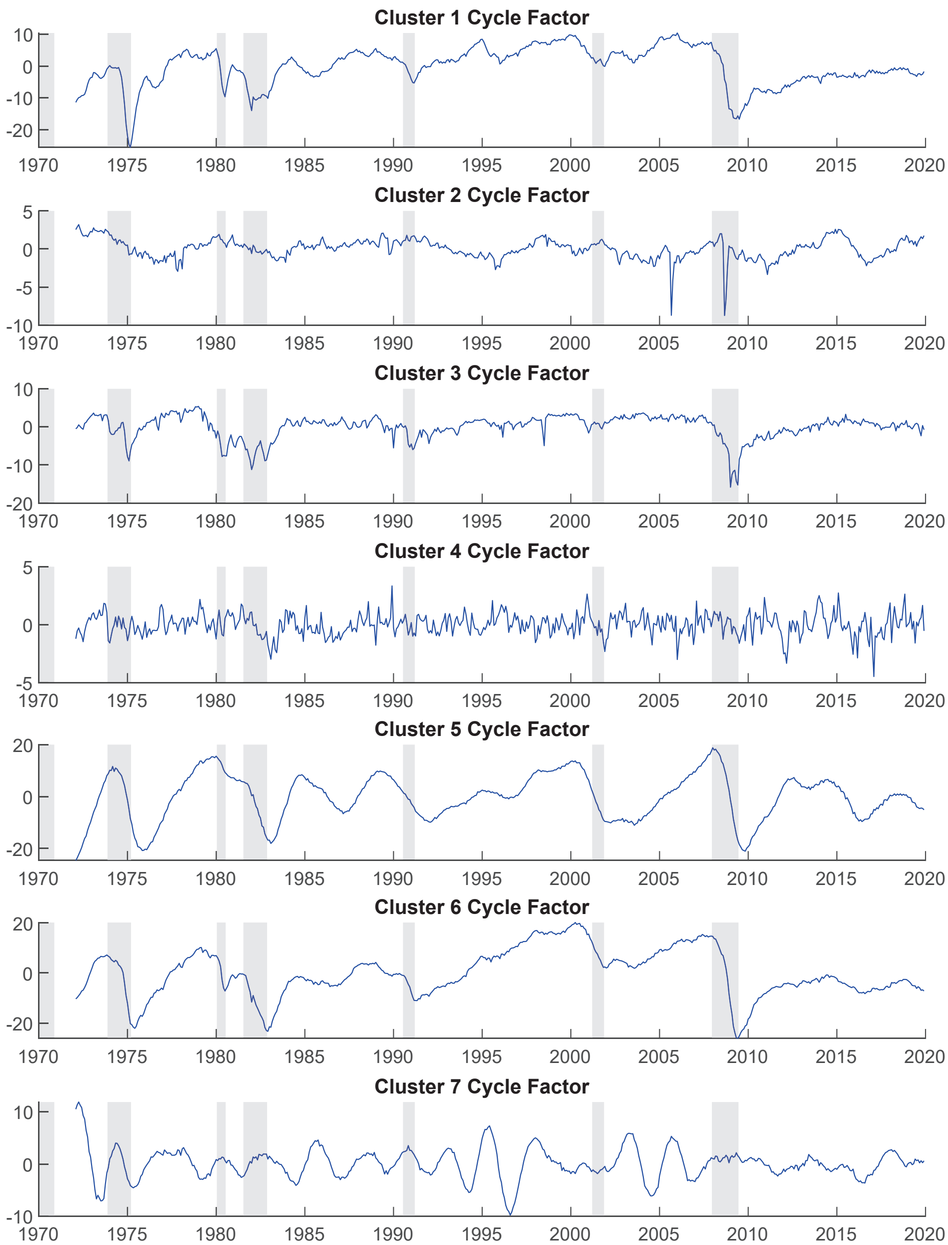


Table 6: **Marginal Effects of the Connectedness Measures**. This table shows the marginal effects of each connectedness measure on the prior probability of cluster membership. The marginal effects are computed as the difference in prior probability when the covariate is one standard deviation above its mean minus the prior probability when the covariate is one standard deviation below its mean. The numbers indicate the posterior median and bold indicates the 68% highest posterior density interval does not include 0.

	Intra-IO	Inter-IO
Cluster 1	-0.06	**0.11**
Cluster 2	-0.02	-0.02
Cluster 3	**0.40**	**0.20**
Cluster 4	**-0.31**	0.02
Cluster 5	**0.13**	-0.02
Cluster 6	0.05	0.06
Cluster 7	**-0.21**	**-0.32**

An increase in *intra-IO* raises the prior probability of belonging to Cluster 3, which consists of industries in the production network for motor vehicles. This result is consistent with Acemoglu et al. (2012) and Carvalho (2014), who use the 2008 automotive bailout to illustrate the interconnectedness stemming from an overlap of suppliers and dealers. They find that any failure up or down the supply chain can lead to severe production lags for another company and drive comovements within the production network.

Increases in inter-IO raise the prior probability of belong to Cluster 1, which is mostly composed of wood, paper, and textile industries that have widespread horizontal production networks. Cluster 7 is comprised of agricultural final goods; thus, shifting their supply chains to more within-sector or more outside-sector both lower the probability of belonging to these clusters.

Overall, we find that industries often cluster based on similarities in their supply chain characteristics—industries with vertical supply chains tend to cluster with other industries with similar vertical supply chains. However, the results are mixed—some industry comovement is not explained by supply chain similarities, leaving opportunities for future research.

4.2.5. Variance Decompositions

To determine whether aggregate, "sectoral", or industry shocks are relatively more important, we compute the percentage of the variance of the cycle component, c_{nt}, attributed to the aggregate regime, S_t, the shock to the cluster factor, u_{kt}, and shock to the idiosyncratic component, η_{nt}. We calculate the implied variance decomposition based on the model parameters [see Kose et al. (2003), Jackson et al. (2016)] and treat the binary variable, S_t, as a shock. The final two columns of Tables 2 and 3 show the percentage of the total variance of c_{nt} attributed to S_t and u_{kt}; the remainder is attributed to the idiosyncratic component.

As one might surmise, the aggregate regime accounts for the majority of the cycle variance for most of the industries in the largest industry group, Cluster 6. This result is again consistent with previous studies that argue for the importance of the national shock relative to sectoral shocks. For most of the industries in our sample, this hypothesis is true. For most of the industries allocated to the other groups, the cluster factor explains a relatively larger portion of the variance of the cyclical component. The exceptions are the members in Cluster 2, which are acyclical industries. Because the clusters are generally smaller than a two-digit NAICS sector, the relative importance of the cluster factor suggests that, when properly defined, "sectoral" shocks can better explain industry fluctuations. Industries driven mostly by their idiosyncratic components are often the same as those assigned with nonzero probability to more than one cluster.

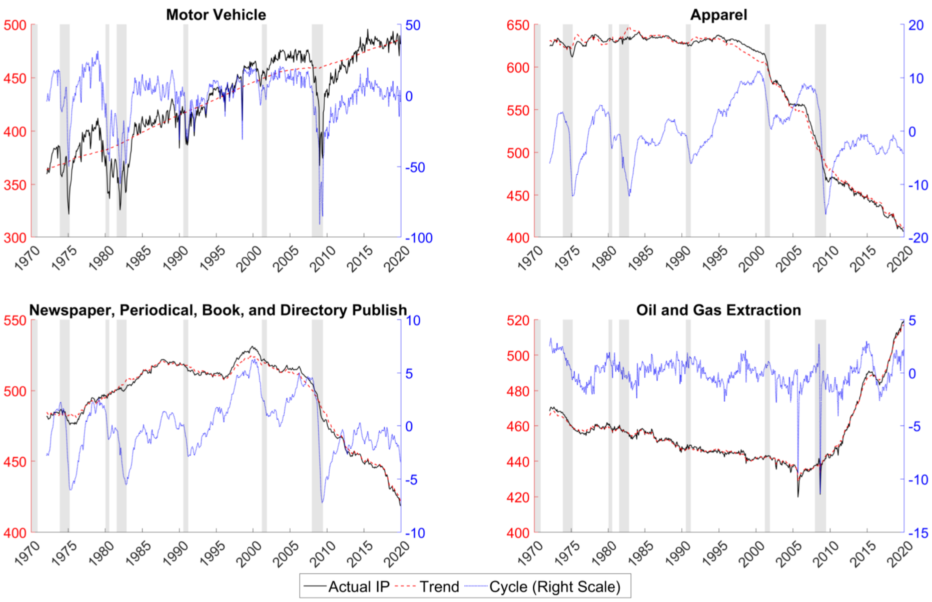
4.3. Industry Examples

Our model combines clustering and aggregate regime components that can summarize a large panel of data with enough flexibility to differentiate individual idiosyncratic series. Here, we consider a few of the industries that have particularly interesting historical time series. Figure 5 shows the decompositions of four industries with various features in their trends and cycles.

The top-left panel shows the trend and cycle for the motor vehicle industry. This industry exhibits textbook characteristics of the plucking model: The trend drifts upward, and the cycle shows dramatic declines during NBER recessions.

The top-right panel shows apparel, an industry we mentioned in the discussion above. Apparel has a flat trend from the beginning of the sample through the mid-1990s, when it began a secular decline. The timing of the decline is subsequent to the ratification of NAFTA in 1993 and just predates the normalization of trade relations with China in 2000. Apparel is highly cyclical, consistent

Figure 5: **Industry Examples of Trend-Cycle Decomposition**. This figure shows actual IP as well as the median posterior estimate for the trend component, τ_{nt}, and cycle component, c_{nt}, for four select industries. The gray bars reflect official NBER U.S. recession dates.



with clothing being a good that consumers delay purchasing until the economy recovers.

The bottom-left panel shows another industry we mentioned above: newspapers, periodicals, books, and directory publishing. The industry has an upward trend from the beginning of the sample until the late 1980s; the trend flattens out until around 1998 and then begins a secular decline. The year 1998 is important for the newspaper industry as it marks the first time a significant news story (the Bill Clinton/Monica Lewinsky scandal) broke first over the internet.

The bottom-right panel shows the trend and cycle for oil and gas extraction. While there are cyclical features, the two most dramatic movements for the industry occur during large declines in oil prices in September 2005 and September 2008. In September 2005 there was a peak in oil prices followed by a decline over the next two months. This peak falls between a peaceful transition of power in Saudi Arabia (August) and their inclusion in the World Trade Organization (November). The decline in September 2008 lies between a precipitous decline of oil prices during the Great Recession, which saw a peak of \$133.88 per barrel in June and a trough of \$39.09 per barrel in

February 2009.

Oil and gas extraction also displays unique features in its trend. At the beginning of the sample, the industry experiences a slight secular decline; around 2006, when production from shale oil reserves increased dramatically, the trend in oil and gas extraction reversed course, rising for the balance of the sample.

5. Conclusion

One focus of the analysis of industrial business cycles has been the relative importance of aggregate, sectoral, and industry-specific shocks. A confounding problem that has gone somewhat unstudied is how to define sectors, the level of aggregation below the nation but above individual NAICS four-digit industries. Past studies considered two-digit industries with the idea that comovement is driven by either demand shocks across common sector goods or supply shocks in production networks contained within the sector.

We use a model that allows us to relax such restrictions by defining clusters of comoving industries based on their business cycle characteristics. We can then determine whether the comoving industries are related by their supply chain characteristics—either common intra- or inter-sectoral production networks. Moreover, constructing sectors based on business cycle fluctuations rather than on NAICS classifications emphasizes the role of sector-specific shocks in business cycle fluctuations.

We find that some industries cluster based on common supply chain characteristics. In particular, a group of motor vehicle production industries that share a production network tend to comove. On the other hand, a group of final goods agricultural industries that do not have prevalent intra- or inter-sectoral production networks comove. Finally, a large group of industries that belong to multiple sectors also comove. This last group may be consistent with stylized facts established previously in the literature that argue that aggregate shocks have become relatively more important than sectoral shocks (Foerster et al., 2011; Garin et al., 2018; Li & Martin, 2019). This latter result may suggest that, when the sectors are properly defined, subnational industry shocks are still relatively important (Atalay, 2017).

Our paper motivates a number of potential avenues for future research. First, one could allow the regime switching process to follow time-varying transition probabilities, as outlined by Kaufmann (2015), Francis et al. (2019), and Psaradakis & Sola (2021), to investigate the effect of certain policies or shocks. For example, time-varying transition probabilities could capture the degree to which the stance of monetary policy influences the aggregate regime. Second, previous studies such as Kim & Piger (2002), Dueker (2006), Billio et al. (2016), and Liu & Song (2021) find that more than two regimes are necessary to capture the different phases of the business cycle – usually recession, low-growth, and high-growth states. This extension could be particularly useful for capturing extreme downturns, such as the recent recession associated with the COVID-19 pandemic. Lastly, the regime switching dynamics could be made more general from the aggregate process presented in our model. The Markov-switching dynamic panel models of Kaufmann (2010), Billio et al. (2016), Casarin et al. (2018), and Agudze et al. (2021) offer a prospective framework that could capture industry-specific cycle synchronization while still controlling for stochastic trends when added to our unobserved components model.

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Acemoglu, D., Carvalho, V. M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, *80*, 1977–2016. doi:10.3982/ECTA9623.

Agudze, K. M., Billio, M., Casarin, R., & Ravazzolo, F. (2021). Markov switching panel with network interaction effects. *Journal of Econometrics*, . doi:10.1016/j.jeconom.2021.04.004.

Atalay, E. (2017). How important are sectoral shocks? *American Economic Journal: Macroeconomics*, *9*, 254–80. doi:10.1257/mac.20160353.

Billio, M., Casarin, R., Ravazzolo, F., & Van Dijk, H. K. (2016). Interconnections between eurozone and US booms and busts using a Bayesian panel Markov-switching VAR model. *Journal of Applied Econometrics*, *31*, 1352–1370. doi:10.1002/jae.2501.

Camacho, M., & Leiva-Leon, D. (2019). The propagation of industrial business cycles. *Macroeconomic Dynamics*, *23*, 144–177. doi:10.1017/s1365100516001140.

Canova, F. (1998). Detrending and business cycle facts. *Journal of Monetary Economics*, *41*, 475–512. doi:10.1016/S0304-3932(98)00006-3.

Carlino, G. A., & DeFina, R. H. (2004). How strong is co-movement in employment over the business cycle? evidence from state/sector data. *Journal of Urban Economics*, *55*, 298–315. doi:10.1016/S0094-1190(03)00084-6.

Carter, C. K., & Kohn, R. (1994). On gibbs sampling for state space models. *Biometrika*, *81*, 541–553. doi:10.1093/biomet/81.3.541.

Carvalho, V. M. (2014). From micro to macro via production networks. *Journal of Economic Perspectives*, *28*, 23–48. doi:10.1257/jep.28.4.23.

Casarin, R., Foroni, C., Marcellino, M., Ravazzolo, F. et al. (2018). Uncertainty through the lenses of a mixed-frequency Bayesian panel Markov-switching model. *Annals of Applied Statistics*, *12*, 2559–2586. doi:10.1214/18-aoas1168.

Casella, G., & George, E. I. (1992). Explaining the gibbs sampler. *The American Statistician*, *46*, 167–174. doi:10.2307/2685208.

Caunedo, J. (2020). Aggregate fluctuations and the industry structure of the us economy. *European Economic Review*, *129*, 1–22. doi:10.1016/j.euroecorev.2020.103567.

Chang, Y., & Hwang, S. (2015). Asymmetric phase shifts in US industrial production cycles. *Review of Economics and Statistics*, *97*, 116–133. doi:10.1162/REST_a_00436.

Chauvet, M., & Piger, J. (2008). A comparison of the real-time performance of business cycle dating methods. *Journal of Business & Economic Statistics*, *26*, 42–49. doi:10.1198/073500107000000296.

Chib, S. (1996). Calculating posterior distributions and modal estimates in markov mixture models. *Journal of Econometrics*, *75*, 79–97. doi:10.1016/0304-4076(95)01770-4.

Christiano, L. J., & Fitzgerald, T. J. (1998). The business cycle: it's still a puzzle. *Economic Perspectives - Federal Reserve Bank of Chicago*, *22*, 56–83.

Clark, P. K. (1987). The cyclical component of U.S. economic activity. *The Quarterly Journal of Economics*, *102*, 797–814. doi:10.2307/1884282.

Cogley, T., & Nason, J. M. (1995). Effects of the Hodrick-Prescott filter on trend and difference stationary time series implications for business cycle research. *Journal of Economic Dynamics and Control*, *19*, 253–278. doi:10.1016/0165-1889(93)00781-X.

Comin, D., & Philippon, T. (2005). The rise in firm-level volatility: Causes and consequences. *NBER Macroeconomics Annual*, *20*, 167–201. doi:10.1086/ma.20.3585419.

Cooper, R., & Haltiwanger, J. (1990). Inventories and the propagation of sectoral shocks. *The American Economic Review*, *80*, 170–190.

Dueker, M. J. (2006). Using cyclical regimes of output growth to predict jobless recoveries. *Federal Reserve Bank of St. Louis Review*, *88*, 145–53. doi:10.20955/r.88.145-154.

Dupraz, S., Nakamura, E., & Steinsson, J. (2021). *A plucking model of business cycles*. Technical Report Working Paper No. 26351 National Bureau of Economic Research. doi:10.3386/w26351.

Durbin, J., & Koopman, S. J. (2002). A simple and efficient simulation smoother for state space time series analysis. *Biometrika*, *89*, 603–616. doi:10.1093/biomet/89.3.603.

Durbin, J., & Koopman, S. J. (2012). *Time Series Analysis by State Space Methods*. Oxford University Press. doi:10.1093/acprof:oso/9780199641178.001.0001.

Foerster, A. T., Sarte, P.-D. G., & Watson, M. W. (2011). Sectoral versus aggregate shocks: A structural factor analysis of industrial production. *Journal of Political Economy*, *119*, 1–38. doi:10.1086/659311.

Francis, N., Owyang, M. T., & Savascin, O. (2017). An endogenously clustered factor approach to international business cycles. *Journal of Applied Econometrics*, *32*, 1261–1276. doi:10.1002/jae.2577.

Francis, N., Owyang, M. T., & Soques, D. (2019). Business cycles across space and time. *FRB St. Louis Working Paper*, . doi:10.20955/wp.2019.010.

Friedman, M. (1964). Monetary Studies of the National Bureau. *The National Bureau Enters its 45th Year*, *44*, 7–25.

Friedman, M. (1993). The plucking model of business fluctuations revisited. *Economic Inquiry*, *31*, 171–177. doi:10.1111/j.1465-7295.1993.tb00874.x.

Frühwirth-Schnatter, S. (2006). *Finite Mixture and Markov Switching Models*. New York: Springer Science & Business Media. doi:10.1007/978-0-387-35768-3.

Frühwirth-Schnatter, S., & Frühwirth, R. (2010). Data augmentation and MCMC for binary and multinomial logit models. In T. Kneib, & G. Tutz (Eds.), *Statistical Modelling and Regression Structures* (pp. 111–132). Physica-Verlag HD. doi:10.1007/978-3-7908-2413-1_7.

Garin, J., Pries, M. J., & Sims, E. R. (2018). The relative importance of aggregate and sectoral shocks and the changing nature of economic fluctuations. *American Economic Journal: Macroeconomics*, *10*, 119–48. doi:10.1257/mac.20140089.

Gelfand, A. E., & Smith, A. F. M. (1990). Sampling-based approaches to calculating marginal densities. *Journal of the American Statistical Association*, *85*, 398–409. doi:10.1080/01621459.1990.10476213.

González-Astudillo, M. (2019). Estimating the US output gap with state-level data. *Journal of Applied Econometrics*, *34*, 795–810. doi:10.1002/jae.2705.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, *57*, 357–384. doi:10.2307/1912559.

Hamilton, J. D. (1994). *Time Series Analysis*. Princeton, NJ: Princeton University Press. doi:10.2307/j.ctv14jx6sm.

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. *Review of Economics and Statistics*, *100*, 831–843. doi:10.1162/rest_a_00706.

Hamilton, J. D., & Owyang, M. T. (2012). The propagation of regional recessions. *Review of Economics and Statistics*, *94*, 935–947. doi:10.1162/REST_a_00197.

Harvey, A. C. (1985). Trends and cycles in macroeconomic time series. *Journal of Business & Economic Statistics*, *3*, 216–227. doi:10.2307/1391592.

Harvey, A. C., & Jaeger, A. (1993). Detrending, stylized facts and the business cycle. *Journal of Applied Econometrics*, *8*, 231–247. doi:10.1002/jae.3950080302.

Hornstein, A. (2000). The business cycle and industry comovement. *Federal Reserve Bank of Richmond Economic Quarterly*, *86*, 27–48.

Jackson, L. E., Kose, M. A., Otrok, C., & Owyang, M. T. (2016). Specification and estimation of Bayesian dynamic factor models: A Monte Carlo analysis with an application to global house price comovement. In E. Hillebrand, & S. J. Koopman (Eds.), *Dynamic Factor Models - Advances in Econometrics* (pp. 361–400). Emerald Group Publishing Limited volume 35. doi:10.1108/s0731-905320150000035009.

Jaimovich, N., & Siu, H. E. (2020). Job polarization and jobless recoveries. *Review of Economics and Statistics*, *102*, 129–147. doi:10.1162/rest_a_00875.

Jarociński, M. (2015). A note on implementing the Durbin and Koopman simulation smoother. *Computational Statistics & Data Analysis*, *91*, 1–3. doi:10.1016/j.csda.2015.05.001.

Kass, R. E., & Raftery, A. E. (1995). Bayes factors. *Journal of the American Statistical Association*, *90*, 773–795. doi:10.1080/01621459.1995.10476572.

Kaufmann, S. (2010). Dating and forecasting turning points by Bayesian clustering with dynamic structure: A suggestion with an application to Austrian data. *Journal of Applied Econometrics*, *25*, 309–344. doi:10.1002/jae.1076.

Kaufmann, S. (2015). K-state switching models with time-varying transition distributions–does loan growth signal stronger effects of variables on inflation? *Journal of Econometrics*, *187*, 82–94. doi:10.1016/j.jeconom.2015.02.001.

Kim, C.-J., & Nelson, C. R. (1999). *State-Space Models with Regime Switching*. Cambridge, MA: The MIT Press.

Kim, C.-J., & Piger, J. (2002). Common stochastic trends, common cycles, and asymmetry in economic fluctuations. *Journal of Monetary Economics*, *49*, 1189–1211. doi:10.1016/s0304-3932(02)00146-0.

Kim, K., & Kim, Y. S. (2006). How important is the intermediate input channel in explaining sectoral employment comovement over the business cycle? *Review of Economic Dynamics*, *9*, 659–682. doi:10.1016/j.red.2006.06.002.

Kose, M. A., Otrok, C., & Whiteman, C. H. (2003). International business cycles: World, region, and country-specific factors. *American Economic Review*, *93*, 1216–1239. doi:10.1257/000282803769206278.

Lee, J. (2010). Trade integration and business cycle comovement: Evidence from the US. *The International Trade Journal*, *24*, 361–388. doi:10.1080/08853908.2010.513640.

Leiva-Leon, D. (2017). Measuring business cycles intra-synchronization in US: A regime-switching interdependence framework. *Oxford Bulletin of Economics and Statistics*, *79*, 513–545. doi:10.1111/obes.12157.

Li, N., & Martin, V. L. (2019). Real sectoral spillovers: A dynamic factor analysis of the Great Recession. *Journal of Monetary Economics*, *107*, 77–95. doi:10.1016/j.jmoneco.2018.10.002.

Liu, H., & Song, X. (2021). Bayesian analysis of hidden markov structural equation models with an unknown number of hidden states. *Econometrics and Statistics*, *18*, 29–43. URL: https://www.sciencedirect.com/science/article/pii/S2452306220300356. doi:https://doi.org/10.1016/j.ecosta.2020.03.003.

McElroy, T. S., & Wildi, M. (2020). The multivariate linear prediction problem: Model-based and direct filtering solutions. *Econometrics and Statistics*, *14*, 112–130. URL: https://www.sciencedirect.com/science/article/pii/S2452306220300034. doi:https://doi.org/10.1016/j.ecosta.2019.12.004.

Morley, J. C., Nelson, C. R., & Zivot, E. (2003). Why are the Beveridge-Nelson and unobserved-components decompositions of GDP so different? *Review of Economics and Statistics*, *85*, 235–243. doi:10.1162/003465303765299765.

Murphy, K. M., Shleifer, A., & Vishny, R. W. (1989). Industrialization and the big push. *Journal of Political Economy*, *97*, 1003–1026.

Owyang, M. T., Piger, J., & Wall, H. J. (2005). Business cycle phases in U.S. states. *Review of Economics and Statistics*, *87*, 604–616. doi:10.20955/wp.2003.011.

Owyang, M. T., Piger, J. M., Wall, H. J., & Wheeler, C. H. (2008). The economic performance of cities: A Markov-switching approach. *Journal of Urban Economics*, *64*, 538–550. doi:10.1016/j.jue.2008.05.006.

Psaradakis, Z., & Sola, M. (2021). Markov-switching models with state-dependent time-varying transition probabilities. *Econometrics and Statistics*, . URL: https://www.sciencedirect.com/

science/article/pii/S2452306221000575. doi:https://doi.org/10.1016/j.ecosta.2021.04.007.

Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & Van Der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *64*, 583–639. doi:10.1111/1467-9868.00353.