Online Appendix for "The Cyclical Component of Labor Market Polarization and Jobless Recoveries in the US"

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This online appendix provides a number of detailed derivations and robustness analyses. Appendix A provides details on the Bayesian setup and estimation. Appendix B discusses details on data construction, model selection, and illustrates sampler convergence for key model parameters. Appendix C provides an analytical derivation of the occupation-specific trend component and graphically illustrates an occupation-specific decomposition into trend and cyclical components. Finally, in Appendix D we generalize the model to factor-specific state variables and break dates. Based on several generalized specifications, we illustrate that the conclusions presented in the main text are robust to these alternative specifications.

Appendix A. Bayesian Setup and Estimation

Appendix A.1. Parametrization of the transition distribution

Normalizing the transition to state 1 as the reference state, i.e. $\gamma_{j1,\cdot} = 0$, $j = 1, 2$, the explicit parametrization of (5) is:

$$\xi_t = \begin{bmatrix} \frac{1}{1+\sum_{s=\{2,4\}} \exp\left(X_t'\gamma_{1s}\right)} & \frac{\exp\left(\gamma_{12,0}+\gamma_{12,1}x_t+\gamma_{12,2}t\right)}{1+\sum_{s=\{2,4\}} \exp\left(X_t'\gamma_{1s}\right)} & 0 & \frac{\exp\left(\gamma_{14,2}t\right)}{1+\sum_{s=\{2,4\}} \exp\left(X_t'\gamma_{1s}\right)} \\ \frac{1}{1+\sum_{s=\{2,3\}} \exp\left(X_t'\gamma_{2s}\right)} & \frac{\exp\left(\gamma_{22,0}+\gamma_{22,1}x_t+\gamma_{22,2}t\right)}{1+\sum_{s=\{2,3\}} \exp\left(X_t'\gamma_{2s}\right)} & \frac{\exp\left(\gamma_{23,2}t\right)}{1+\sum_{s=\{2,3\}} \exp\left(X_t'\gamma_{2s}\right)} & 0 \\ 0 & 0 & \frac{\exp\left(\gamma_{33,0}+\gamma_{33,1}x_t\right)}{\sum_{s=3}^4 \exp\left(\gamma_{3s,0}+\gamma_{3s,1}x_t\right)} & \frac{\exp\left(\gamma_{34,0}+\gamma_{34,1}x_t\right)}{\sum_{s=3}^4 \exp\left(\gamma_{3s,0}+\gamma_{3s,1}x_t\right)} \\ 0 & 0 & \frac{\exp\left(\gamma_{43,0}+\gamma_{43,1}x_t\right)}{\sum_{s=3}^4 \exp\left(\gamma_{4s,0}+\gamma_{1,4s}x_t\right)} & \frac{\exp\left(\gamma_{44,0}+\gamma_{44,1}x_t\right)}{\sum_{s=3}^4 \exp\left(\gamma_{4s,0}+\gamma_{4s,1}x_t\right)} \end{bmatrix} \tag{A.1}$$

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The vector $X_t' = (1, x_t, t)$ contains a constant, GDP growth (x_t) and a time trend t. GDP growth provides additional information for transitions into business cycle phases (recovery or recession), and time t introduces prior information on the break date. The parameters $\gamma_{jl,m}$, with $j, l = 1, \ldots, 4$, and $m = 0, 1, 2$, correspond to the state-dependent, state-specific effects of the variables in X_t. So, $\gamma_{jl,m}$ represents either the constant transition ($m = 0$) effect, the effect of GDP growth ($m = 1$) or the trend effect ($m = 2$) on the transition probability to switch from state j to state l. The denominators are written in a general form, but note that appropriate elements of γ_{14} and γ_{23} are restricted to zero.

Time enters the transition distribution of states 1 and 2, to include prior information on the break date around 1990. We normalize t to be zero in the third quarter of 1990, which corresponds to the peak of the 1980s expansion. The effect of time t should be decreasing for $\xi_{j2,t}$, $j = 1, 2$ and increasing for $\xi_{14,t}$ and $\xi_{23,t}$. Therefore, we expect to estimate $(\gamma_{12,2}, \gamma_{22,2}) \leq 0$ and $(\gamma_{14,2}, \gamma_{23,2}) > 0$. These expectations can be included as information into the prior distribution. In the empirical application, we are less informative and set $\pi(\gamma_{12,2}, \gamma_{22,2}) = N(0, 0.16 \cdot I_2)$ and $\pi(\gamma_{14,2}, \gamma_{23,2}) = N(1, 0.16 \cdot I_2)$, i.e. we do not truncate the distributions.

Normalizing t to zero in the third quarter of 1990 favors a break after the expansion of the 1980s into the early 1990s recession. We explicitly make this choice based on the stylized patterns in Figure 1. Our prime interest is to identify the existence, magnitude, and potential *effects* of a structural break around 1990, rather than the timing of the break itself. The current specification provides a convenient framework to conduct posterior inference on the structural component of employment dynamics before and after 1990. Nevertheless, the framework is general enough to conduct inference on the break date itself in future research.

Appendix A.2. State-space representation

To expose the setup in a concise way, we cast model (1)-(4) into a condensed state-space framework (see also Chan and Jeliazkov (2009)). First, we stack all filtered units in period t into the $N \times 1$ vector y_t^*:

$$\begin{aligned}\Psi(L)y_t = y_t^* &= \lambda f_t - \lambda \odot (\psi_{\cdot 1} \otimes \mathbf{1}_{1\times k}) f_{t-1} - \cdots - \lambda \odot \left(\psi_{\cdot q} \otimes \mathbf{1}_{1\times k}\right) f_{t-q} + \epsilon_t \qquad \text{(A.2)}\\ &\quad \epsilon_t \sim N(0, \Sigma_\epsilon),\ \Sigma_\epsilon \text{ diagonal}\\ f_t &= \mu_{S_t} + \Phi_1 f_{t-1} + \cdots + \Phi_p f_{t-p} + \eta_t, \quad \eta_t \sim N(0, I_k) \qquad \text{(A.3)}\end{aligned}$$

where $\odot$ and $\otimes$ represent the Hadamar and the Kronecker product, respectively. The $N \times 1$ vector $\psi_{\cdot j}$, $j = 1, \ldots, q$, stacks the coefficient at lag j of the idiosyncratic dynamics (see (4)) of all units. The $1 \times k$ row vector $\mathbf{1}_{1\times k}$ is filled with 1s. The $K \times K$ matrices Φ_j are diagonal and each row of the $N \times K$ matrix λ, λ_i, contains only one non-zero element, i.e. $\lambda_{ik} \neq 0$ if $\delta_i = k$ and $\lambda_{ik} = 0$ otherwise. We stack all observations to obtain the matrix representation:

$$\begin{aligned}\boldsymbol{y}^* &= \boldsymbol{\Lambda} \boldsymbol{f} + \boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim N\left(0, I_{T-q} \otimes \Sigma_\epsilon\right) \qquad \text{(A.4)}\\ \boldsymbol{\Phi} \boldsymbol{f} &= \boldsymbol{\mu} + \boldsymbol{\eta} \quad \boldsymbol{\eta} \sim N(0, \boldsymbol{\Omega}) \qquad \text{(A.5)}\end{aligned}$$

where $\boldsymbol{y}^* = \left({y^*_{q+1}}', \ldots, {y^*_T}'\right)'$ and $\boldsymbol{f} = \left(f'_{q+1-\max(p,q)}, \ldots, f'_{q+1}, \ldots, f'_T\right)'$ stacks all unobserved factors, including initial states. The matrices $\boldsymbol{\Lambda}$ and $\boldsymbol{\Phi}$ are, respectively, of dimension $(T-q)N \times (T+d)\,k$ and square $(T+d)k$, with $d = (p-q) I_{\{p>q\}}$. Typically, these matrices are sparse and band-diagonal:

$$\boldsymbol{\Lambda} = \left[\begin{array}{c|cccccc} & -\lambda \odot \left(\psi_{\cdot q} \otimes \mathbf{1}_{1\times k}\right) & \ldots & \lambda & 0\ldots & & 0\\ \mathbf{0}_{(T-q)N\times dk} & & \ddots & \ddots & & \ddots & \vdots\\ & 0\ldots & 0 & & -\lambda \odot \left(\psi_{\cdot q} \otimes \mathbf{1}_{1\times k}\right) & \ldots & \lambda \end{array}\right]$$

$$\boldsymbol{\Phi} = \left[\begin{array}{ccccccc} & I_p \otimes I_k & & 0 & \ldots & & \\ \hline -\Phi_p & \ldots & -\Phi_1 & I_k & 0 & \ldots & \\ & & & & \ddots & & \\ & \ldots & 0 & -\Phi_p & \ldots & -\Phi_1 & I_k \end{array}\right], \quad \boldsymbol{\Omega} = \begin{bmatrix} I_p \otimes \Sigma^0_\eta & 0 & \ldots \\ 0 & & \\ \vdots & I_{T+d-p} \otimes I_k & \end{bmatrix}$$

where Σ_η^0 represents the variance of the initial states (see below). The vector $\boldsymbol{\mu}$ includes the state-dependent intercept,

$$\boldsymbol{\mu} = \left[\mathbf{0}_{1\times\max(p,q)k}, \mu'_{S_{q+1}}, \ldots, \mu'_{S_T}\right]'$$

Appendix A.3. Likelihood and prior distributions

Given the representation in (A.4)-(A.5), the complete data likelihood has a normal distribution:

$$L(\boldsymbol{y}^*|\boldsymbol{f}, \mathbf{S}, \boldsymbol{\delta}, \theta) \sim N\left(\boldsymbol{\Lambda}\boldsymbol{f}, I_{T-q} \otimes \Sigma_\epsilon\right) \tag{A.6}$$

Conditional on the state indicator, from (A.5) we obtain following prior distribution for the unobserved factors:

$$\begin{aligned} \boldsymbol{f}|\mathbf{S}, \theta \quad &\sim \quad N\left(\mathrm{f}_0, F_0^{-1}\right) \\ &\mathrm{f}_0 = \boldsymbol{\Phi}^{-1}\boldsymbol{\mu}^*, \;\; F_0 = \boldsymbol{\Phi}'\boldsymbol{\Omega}^{-1}\boldsymbol{\Phi} \end{aligned} \tag{A.7}$$

In $\boldsymbol{\Omega}$, the variance of the initial states, Σ_η^0, may be chosen to be diffuse. Here, we will choose Σ_η^0 to be a multiple of the identity matrix, $\Sigma_\eta^0 = \kappa I_k$.

The prior for the unobserved state indicator factorizes into

$$\pi(\mathbf{S}|\boldsymbol{\xi}) = \prod_{t=q+1}^{T} \pi\left(S_t|S^{t-1}, \boldsymbol{\xi}_t\right)\pi\left(S_q\right)$$

where the initial state distribution $\pi\left(S_q\right)$ is assumed to be uniform across state 1 and 2, $P(S_q = s) = 0.5$, for $s = 1, 2$ and $P(S_q = s) = 0$ for $s = 3, 4$.

The prior for the classification indicator is assumed to be uniform discrete, $P(\delta_i = k) = 1/K$, $\forall i$.

To complete the model, we assume that the parameters are block-independent a priori, $\pi(\theta) = \pi(\boldsymbol{\lambda}|\boldsymbol{\delta})\pi(\boldsymbol{\psi})\pi(\boldsymbol{\phi})\pi(\boldsymbol{\mu})\pi(\boldsymbol{\sigma})\pi(\boldsymbol{\gamma})$, with standard distributions:

1. $\pi(\boldsymbol{\lambda}|\boldsymbol{\delta}) = \prod_{i=1}^N \pi(\lambda_{i\delta_i}) = \prod_{i=1}^N N(\mathrm{l}_0, \mathrm{L}_0)$
2. $\pi(\boldsymbol{\psi}) = \prod_{i=1}^N \pi(\psi_{i1}, \ldots, \psi_{iq}) = \prod_{i=1}^N N(q_0, Q_0) I_{\{Z(\psi_i)>1\}}$
   where $I_{\{\cdot\}}$ is the indicator function and $Z(\varphi) > 1$ means that the characteristic roots of the process $\varphi(L)$ lie outside the unit circle.

3. $\pi(\boldsymbol{\phi}) = \prod_{k=1}^{K} \pi(\phi_{k1}, \ldots, \phi_{kp}) = \prod_{k=1}^{K} N(p_0, P_0) I_{\{Z(\phi_k)>1\}}$
4. $\pi(\boldsymbol{\mu}) = \prod_{k=1}^{K} \pi(\mu_{k1}, \ldots, \mu_{k4}) = \prod_{k=1}^{K} N(m_0, M_0)$
5. $\pi(\boldsymbol{\sigma}) = \pi(\sigma_1^2, \ldots, \sigma_N^2) = \prod_{i=1}^{N} IG(\mathrm{e}_0, \mathrm{E}_0)$
6. $\pi(\boldsymbol{\gamma}) = \prod_{s=2}^{4} \pi(\boldsymbol{\gamma}_s) = \prod_{s=2}^{4} N(g_{0s}, G_{0s})$
   where $\boldsymbol{\gamma}_s = \left(\gamma'_{1s}, \ldots, \gamma'_{4s}\right)'$, $s = 2, \ldots, 4$, and g_{0s} and G_{0s} have appropriate dimensions.

Appendix A.4. Posterior Distributions

Combining the prior with the likelihood, we obtain the posterior for

1. the factors, $\pi\left(\boldsymbol{f}|\boldsymbol{y}^*, \mathbf{S}, \boldsymbol{\delta}, \theta\right) = N\left(\mathrm{f}, F^{-1}\right)$, with $F = F_0 + \boldsymbol{\Lambda}'\left(I_{T-q} \otimes \Sigma_\epsilon^{-1}\right)\boldsymbol{\Lambda}$ and $\mathrm{f} = F^{-1}\left(\boldsymbol{\Lambda}'\left(I_{T-q} \otimes \Sigma_\epsilon^{-1}\right)\boldsymbol{y}^* + F_0\right.$
   To avoid the full inversion of F we take the Cholesky decomposition, $F = LL'$, then $F^{-1} = L^{-1}L^{-1\prime}$. We obtain a draw $\boldsymbol{f}$ by setting $\boldsymbol{f} = \mathrm{f} + L^{-1}\boldsymbol{\nu}$, where $\boldsymbol{\nu}$ is a $(T + d)k$ vector of independent draws from the standard normal distribution.
2. the state indicator, $\pi\left(\mathbf{S}|\boldsymbol{f}, \boldsymbol{\xi}, \boldsymbol{\mu}, \boldsymbol{\phi}\right)$. To obtain a draw, we adapt the forward-filtering, backward-sampling procedure described in Chib (1996) to the time-varying Markov structure, see also Frühwirth-Schnatter (2010), Algorithm 11.1 and 11.2.
3. the classification indicator, $\pi\left(\boldsymbol{\delta}|\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{\psi}, \boldsymbol{\sigma}\right) = \prod_{i=1}^{N} \pi\left(\delta_i|\boldsymbol{y}_i, \boldsymbol{f}, \boldsymbol{\psi}_i, \sigma_i^2\right)$. To obtain a draw, we compute the posterior classification probabilities

$$
\begin{aligned}
P\left(\delta_i = k|\boldsymbol{y}_i, \boldsymbol{f}, \boldsymbol{\psi}_i, \sigma_i^2\right) \;&\propto\; L\left(\boldsymbol{y}_i|\boldsymbol{f}, \boldsymbol{\psi}_i, \sigma_i^2, \delta_i = k\right) P\left(\delta_i = k\right), \quad k = 1, \ldots, K \\
&\propto\; \left(\prod_{t=q+1}^{T} \left(\mathrm{L}_{i\delta_i}(f^*_{i\delta_i t})^2 + \sigma_i^2\right)\right)^{-1/2} \times \\
&\quad \exp\left\{-\frac{1}{2}\sum_{t=q+1}^{T} \frac{\left(y^*_{it} - \mathrm{l}_{i\delta_i} f^*_{i\delta_i t}\right)^2}{\mathrm{L}_{i\delta_i}(f^*_{i\delta_i t})^2 + \sigma_i^2}\right\} P\left(\delta_i = k\right) \qquad \text{(A.8)}
\end{aligned}
$$

   where y^*_{it} and $f^*_{i\delta_i t}$ represent the filtered values $y^*_{it} = y_{it} - \psi_{i1} y_{i,t-1} - \ldots \psi_{iq} y_{i,t-q}$ and $f^*_{i\delta_i t} = f_{\delta_i t} - \psi_{i1} f_{\delta_i, t-1} - \ldots \psi_{iq} f_{\delta_i, t-q}$, respectively, and $\mathrm{L}_{i\delta_i}$ and $\mathrm{l}_{i\delta_i}$ are the posterior moments of the factor loadings given below in (A.9). The indicator δ_i is set equal to

$$
k = \left(\sum_{l=1}^{K} I\left\{\left(\sum_{j=1}^{l} P(\delta_i = j|\cdot)\right) \leq U\right\}\right) + 1
$$

where $I\{\cdot\}$ is the indicator function, $P(\delta_i = j|\cdot)$ are the normalized posterior indicator probabilities obtained from (A.8) and $U \sim U(0,1)$ is drawn from the uniform distribution.

4. the parameters in the state transition distribution, $\pi(\boldsymbol{\gamma}|\mathbf{S},\mathbf{x},\boldsymbol{t})$. Conditional on two layers of data augmentation, the posterior turns out to be a normal distribution (see Frühwirth-Schnatter and Frühwirth (2010) and for additional details Kaufmann (2014)).

   - The first layer expresses the latent state utilities S^u_{st}, $\forall s \in \{2,\dots,4\}$, in difference to the maximum of all other *relevant* latent state utilities, and defines the binary observation $D_t^{(s)} = I\{S_t = s\}$. We obtain a linear, non-normal model:

     $$S^*_{st} := S^u_{st} - S^u_{-s,t} = c + \mathbf{X}_t'\boldsymbol{\gamma}_s + \upsilon_{st}, \quad \upsilon_{st} \text{ i.i.d. Logistic}$$

     where

     $$\begin{aligned} S^u_{st} &= \mathbf{X}_t'\boldsymbol{\gamma}_s + \nu^u_{st},\ \nu^u_{st} \text{ i.i.d. Type I Extreme Value} \\ S^u_{-s,t} &= \max_{j\in\mathcal{S}^*_{-s}} S^u_{jt} \end{aligned}$$

     with c being a constant, $\mathbf{X}_t' = \left(X_t'D_{t-1}^{(1)},\dots,X_t'D_{t-1}^{(4)}\right)$. The elements of $\boldsymbol{\gamma}_s$ are restricted appropriately to obtain the specification in (*A*.1). The *relevant* other latent utilities are those corresponding to states to which the transition probability is not restricted to zero in (A.1), see table A.1.

   - In the second layer, we approximate the Logistic distribution by a mixture of normals with M components, $\boldsymbol{R}_s = \left(R_{s,q+1},\dots,R_{sT}\right)$, $\forall s = 2,\dots,4$. Conditional on $\boldsymbol{S}^*_s = (S^*_{s,q+1},\dots,S^*_{sT})$ and $\boldsymbol{R}_s$, we obtain the normal posterior (see Kaufmann (2014) for additional details on the moments):

     $$\boldsymbol{\gamma}_s|\mathbf{S},\mathbf{X} \sim N\left(g_s\left(\boldsymbol{S}^*_s,\boldsymbol{R}_s\right), G_s\left(\boldsymbol{R}_s\right)\right)$$

5. the remaining parameters, which can be sampled out of standard distributions:

Table A.1: Relevant states in $\mathcal{S}^*_{-s}$ for $S_t = s$ given S_{t-1}

$S_t =$	2		3			4		
$S_{t-1}=$	1	2	2	3	4	1	3	4
$\mathcal{S}^*_{-s} =$	{1,4}	{1,3}	{1,2}	{4}	{4}	{1,2}	{3}	{3}

(a) $\pi(\boldsymbol{\lambda}|\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{\delta}, \boldsymbol{\sigma}, \boldsymbol{\psi}) = \prod_{i=1}^{N} N(\mathrm{l}_{i\delta_i}, \mathrm{L}_{i\delta_i})$, where

$$\mathrm{L}_{i\delta_i} = \left(\sigma_i^{-2} \sum_{t=q+1}^{T} {f^*_{i\delta_i t}}^2 + \mathrm{L}_0^{-1}\right)^{-1}, \quad \mathrm{l}_{i\delta_i} = \mathrm{L}_{i\delta_i}\left(\sigma_i^{-2} \sum_{t=q+1}^{T} y^*_{it} f^*_{i\delta_i t} + \mathrm{L}_0^{-1}\mathrm{l}_0\right) \tag{A.9}$$

(b) $\pi(\boldsymbol{\psi}|\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{\delta}, \boldsymbol{\sigma}, \boldsymbol{\lambda}) = \prod_{i=1}^{N} N(q_i, Q_i) I_{\{Z(\psi_i)>1\}}$, with

$$Q_i = \left(\sigma_i^{-2}\varepsilon'_{i,-1}\varepsilon_{i,-1} + Q_0^{-1}\right)^{-1}, \quad q_i = Q_i\left(\sigma_i^{-2}\varepsilon'_{i,-1}\varepsilon_i + Q_0^{-1}q_0\right) I_{\{Z(\psi_i)>1\}}$$

and where ε_i and $\varepsilon_{i,-1}$ are, respectively, the appropriately designed left- and right-hand side matrices of the regression model:

$$\varepsilon_{it} = \psi_1\varepsilon_{i,t-1} + \cdots + \psi_q\varepsilon_{i,t-q} + \epsilon_{it}, \ \epsilon_{it} \sim N(0, \sigma_i^2)$$

(c) $\pi(\boldsymbol{\phi}, \boldsymbol{\mu}|\boldsymbol{f}, \mathbf{S}) = \prod_{k=1}^{K} N(p_k, P_k) I_{\{Z(\phi_k)>1\}} I_{\{\mu_{k1}<\mu_{k2}, \mu_{k3}<\mu_{k4}\}}$, with

$$P_k = \left([f_{k,-1}\ D]'\,[f_{k,-1}\ D] + diag\,(P_0, M_0)^{-1}\right)^{-1} \tag{A.10}$$

$$p_k = P_k\left([f_{k,-1}\ D]'\, f_k + diag\,(P_0, M_0)^{-1}\, vec\,(p_0, m_0)\right) \tag{A.11}$$

and where f_k, $f_{k,-1}$, D are respectively, the appropriate matrices of the regression model:

$$f_{kt} = \phi_1 f_{k,t-1} + \cdots + \phi_p f_{k,t-1} + \mu_1 D_t^{(1)} + \cdots + \mu_4 D_t^{(4)} + \nu_t, \nu_t \sim N(0, 1)$$

(d) $\pi(\boldsymbol{\sigma}|\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{\delta}, \boldsymbol{\psi}, \boldsymbol{\lambda}) = \prod_{i=1}^{N} IG(\mathrm{e}_i, \mathrm{E}_i)$ where

$$\mathrm{e}_i = \mathrm{e}_0 + 0.5(T - q), \quad \mathrm{E}_i = \mathrm{E}_0 + 0.5 \sum_{t=q+1}^{T} \epsilon_{it}^2$$

Appendix B. Data, Model Selection, and Sampler Convergence

Appendix B.1. Adjusting for Administrative Changes in Occupatoin Classifications

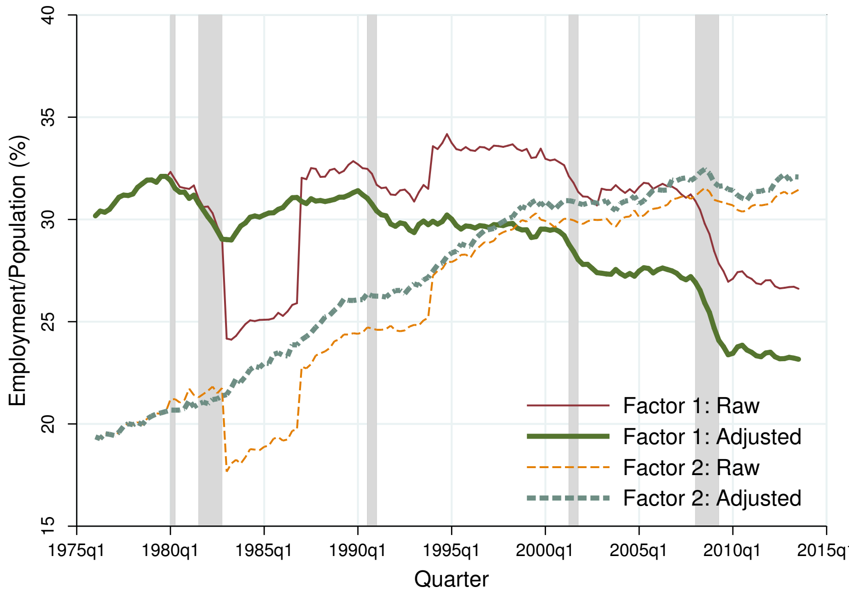
One of the biggest challenges in working with the detailed CPS data are the frequent changes in the DOL's system for classifying occupations. Even Dorn's (2009) consistent panel features many jumps in the level of employment since various occupations "jump" from one group to another, new occupations are introduced, or old ones disappear. These jumps are not readily visible in long run comparisons (e.g. across decades) but they become immediately apparent at higher frequencies. To avoid this problem, Foote and Ryan (2012), who also study the cyclicality of labor market polarization, decide to use industry-skill cells as a proxy for jobs/tasks instead of occupations specified by the DOL.

However, since the level jumps are due to purely administrative changes, they always happen in a single month. Therefore, one way to accommodate the level jumps, is to use growth rates instead of levels and "average out" the jumps for the occupations in which administrative changes happen. That is, we replace the growth rate at the jump with a linear interpolation. Figure B.1 shows the levels implied by our adjusted growth rate series. It is obvious that any adjustment procedure introduces some measurement error, but Figure 1 illustrates that the dynamic patterns in the level of routine and non-routine jobs implied by these adjusted growth rates is virtually the same as in the level series employed by Jaimovich and Siu (2018). In fact, our approach to adjust in growth rates is very similar in spirit to the "flows approach" of Cortes, Jaimovich, Nekarda, and Siu (2014).

Ultimately, it should be clear that all four approaches, broad aggregation as in Jaimovich and Siu (2018), forming industry-skill cells as in Foote and Ryan (2012), the "flows approach" by Cortes et al. (2014), and our adjustment in growth rates, are an imperfect solution and introduce some form of measurement error. However, given the nature of administrative changes in the DOL's definition of occupations, these are the best options available.[1]

[1]We obtain the same qualitative results when we estimate our model with 9 occupation groups assembled as in Jaimovich and Siu (2018).

Figure B.1: Employment Trends Based on Growth Rates



Notes: The figure illustrates the cumulative growth of employment/population in each occupation assigned to factors 1 and 2 in model (1), which are tabulated in Table 2. The imputed level series start with the level of employment/population in 1976q1 and illustrate the variation in growth rates used in our estimation procedure. The series labeled "raw" are are based on the unadjusted growth rates in the occupation level series while those labeled "adjusted" are based on a growth rate series in which the administrative "jumps" were interpolated based on the median January growth (all administrative jumps happen in January). Data for this graph are directly constructed from the monthly basic CPS files for the consistent panel of occupations compiled by Dorn (2009).

Appendix B.2. Model Selection

We obtain the most precise factor assignment when we set $K = 2$ and since the ultimate goal of this study is to analyze aggregate labor market dynamics, we choose the specification for which the variance share explained by cluster specific variation is largest. In particular, Table B.1 lists this statistic for alternative AR lag lengths, p and q, and shows that a specification with $p = q = 2$ performs best, on average, according to this metric. While this is our preferred specification, the "second best" alternative, $q = 3$ and $p = 2$, does not change our main results.

Table B.1: Model Selection

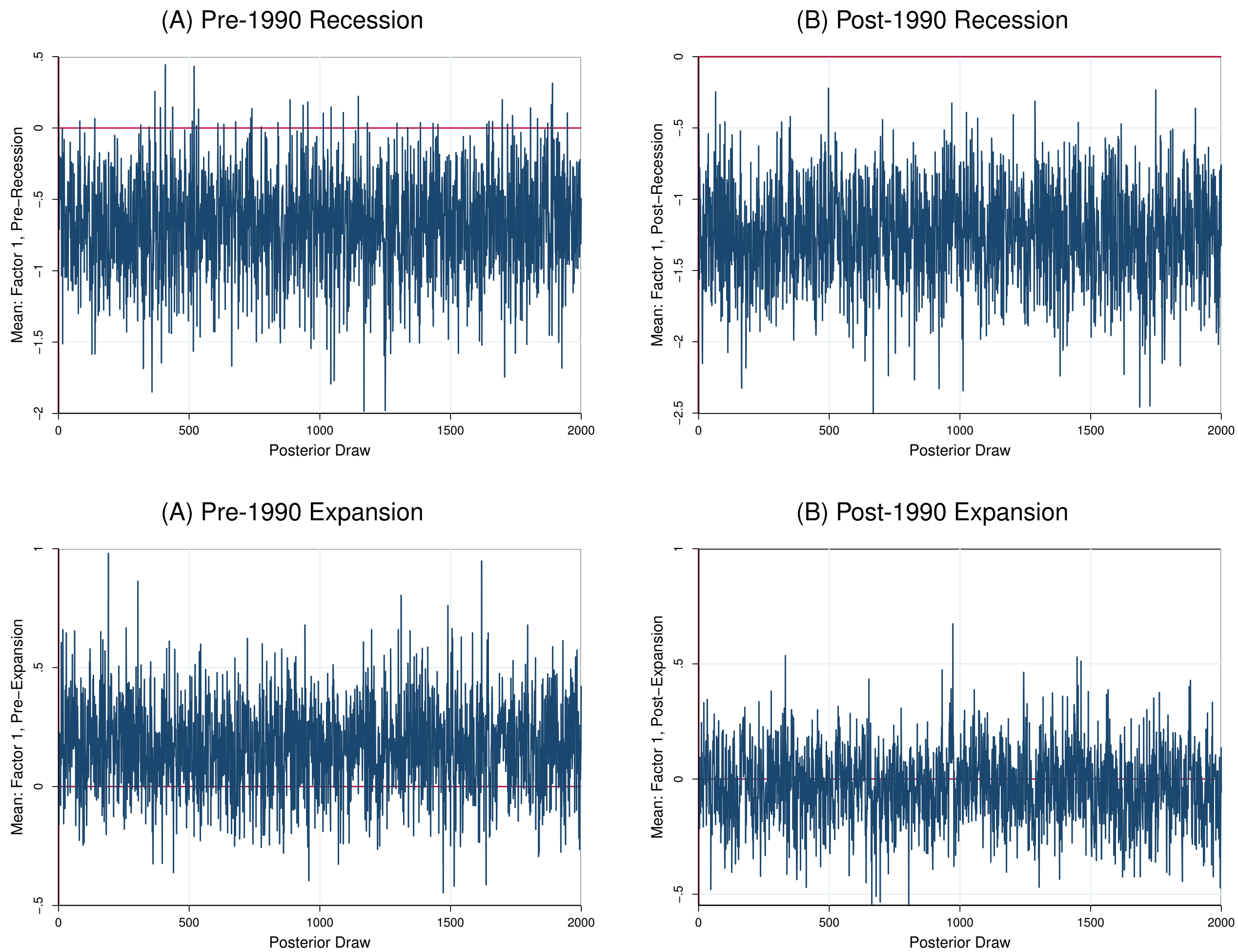
		$Var(\hat{Y}_k)/Var(Y_k)$		
q	p	Cluster 1	Cluster 2	Avg.
1	1	0.345	0.353	0.349
1	2	0.286	0.216	0.251
2	1	0.138	0.138	0.138
2	2	**0.607**	0.588	**0.597**
2	3	0.306	0.213	0.260
3	2	0.484	**0.620**	0.552
3	3	0.223	0.199	0.211

Notes: The table reports the fraction of the variation in aggregate employment/population that is explained by common cluster dynamics, conditional on the median factor assignment. Maxima are highlighted.

Appendix B.3. Sampler Convergence

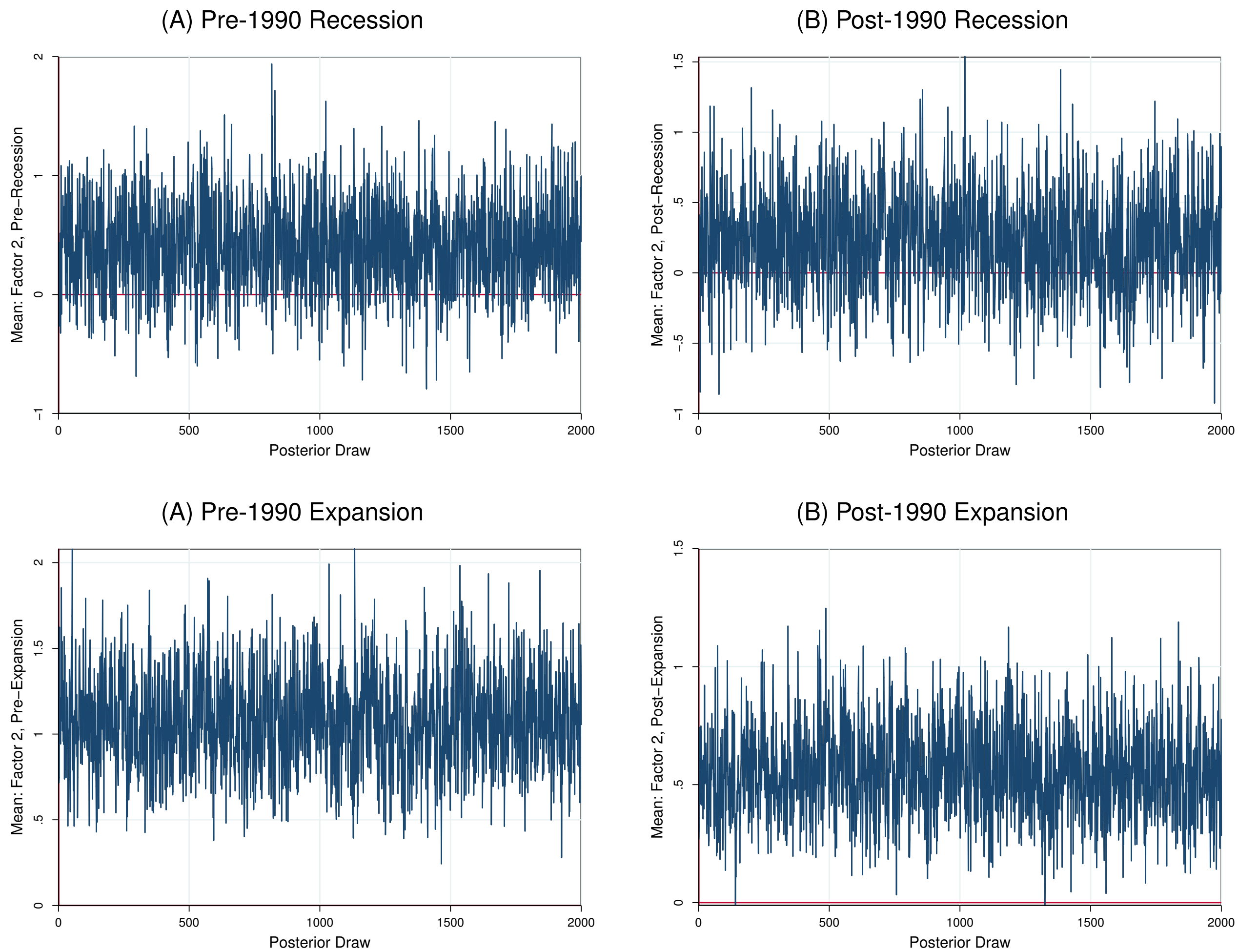
In total, we draw 500,000 times out of the posterior distribution and discard the first 100,000 as burn-in. To remove autocorrelation across draws, we retain every fourth of the remaining 100,000 draws. Figures B.2 and B.3 illustrate the first 2000 of these draws for the factor specific drifts μ_{kS_t}. These figures clearly illustrate convergence of the sampler. All other model parameters show similar patterns but omit these graphs for space considerations.

Figure B.2: State Dependent Mean of Factor 1



Notes: The graphs illustrate the first 2000 draws of the retained sample of posterior draws for μ_{kS_t}.

Figure B.3: State Dependent Mean of Factor 2



Notes: The graphs illustrate the first 2000 draws of the retained sample of posterior draws for μ_{kS_t}.

Appendix C. Deriving the Occupation-Specific Trend Component

We start out from the model defined for growth rates $y_{it} = (\tilde{y}_{it} - \tilde{y}_{i,t-1})/\tilde{y}_{i,t-1}$:

$$\begin{aligned}
y_{it} &= \sum_{k=1}^{K} \lambda_{ik} f_{kt} + \varepsilon_{it} && \text{(C.1)}\\
&= \lambda_{i\delta_i} f_{\delta_i t} + \varepsilon_{it} && \text{(C.2)}\\
\phi_k(L) f_{kt} &= \mu_{kS_t} + \nu_{kt},\ \nu_{kt} \sim N(0,1) && \text{(C.3)}\\
\psi_i(L)\varepsilon_{it} &= \epsilon_{it},\ \epsilon_{it} \sim N\left(0, \sigma_i^2\right) && \text{(C.4)}
\end{aligned}$$

with occupation-specific factor indicator $\delta_i = \{1, \dots, K\}$, factor-specific $AR(p)$ processes, $\phi_k(L) = 1 - \phi_{k1}L - \cdots - \phi_{kp}L^p$, $k = 1, \dots, K$, and occupation-specific (idiosyncratic) $AR(q)$ processes $\psi_i(L) = 1 - \psi_{i1}L - \cdots - \psi_{iq}L^q$, $i = 1, \dots, N$ (in the application $p = q = 2$).

Conditional on the state indicator S^T, we derive the Wold representation of (C.1) (with $\phi_k(L)^{-1} = C_k(L)$ and $\psi_i(L)^{-1} = B_i(L)$):

$$\begin{aligned}
y_{it} &= \lambda_{i\delta_i} f_{\delta_i t} + \varepsilon_{it} && \text{(C.5)}\\
&= \lambda_{i\delta_i}\left[\iota \sum_{j=0}^{t-1} \Phi_{\delta_i}^{j} \boldsymbol{\mu}_{\delta_i S_{t-j}} + \left[C_{\delta_i}(1) + (1-L)\, C_{\delta_i}^{*}(L)\right] \nu_{\delta_i t}\right] + \\
&\quad \left[B_i(1) + (1-L)\, B_i^{*}(L)\right]\epsilon_{it} && \text{(C.6)}
\end{aligned}$$

where $\iota = (1, 0_{1\times p-1})$ is a selection vector and Φ_k and $\boldsymbol{\mu}_{k,S_t}$ are the system matrices of the $AR(p)$ companion form, i.e. for $p = 2$:

$$\Phi_k = \begin{bmatrix} \phi_{k1} & \phi_{k2} \\ 1 & 0 \end{bmatrix},\ \boldsymbol{\mu}_{k,S_t} = \begin{bmatrix} \mu_{kS_t} \\ 0 \end{bmatrix}$$

For the decomposition of $C_k(L)$ and $B_k(L)$ we exploit the fact that a process $W(L) = W_0 + W_1 L + \cdots + W_p L^p$, $W_0 = I$, can be represented as $W(L) = [W(1) + (1-L)\, W^*(L)]$, with $W(1) = W_0 + \cdots + W_p$ and $W^*(L)$ being of order $p-1$ with $W_j^* = -\sum_{i=j+1}^{p} W_i$, $j = 0, \dots, p-1$.[2]

[2]The inversion of a univariate $AR(p)$ process, $\phi(L)x_t = \left(1 - \cdots - \phi_p L^p\right) x_t = \upsilon_t$, yields an infinite MA process, $x_t = C(L)\upsilon_t = \sum_{j=0}^{\infty} C_j L^j \upsilon_{t-j}$. In this case, the decomposition into a "deterministic" part $C(1)$ and a "stochastic" part

Because the eigenvalues of Φ_k are smaller than 1, the term $\sum_{j=0}^{t-1} \Phi_{\delta_i}^{j} \boldsymbol{\mu}_{\delta_i S_{t-j}}$ is well approximated by $C_k(1)\boldsymbol{\mu}_{\delta_i S_t}$. Substituting and gathering terms yields

$$\begin{aligned} y_{it} &= \underbrace{\lambda_{i\delta_i}\left[\iota C_{\delta_i}(1)\left(\boldsymbol{\mu}_{\delta_i S_t} + \nu_{\delta_i t}\right)\right]}_{\tau_t^c} + \underbrace{B_i(1)\epsilon_{it}}_{\tau_t^i} + \\ &\quad \underbrace{\lambda_{i\delta_i}\,(1-L)\,C_{\delta_i}^{*}\,(L)\,\nu_{\delta_i t} + (1-L)\,B_i^{*}\,(L)\,\epsilon_{it}}_{\tau_t^{cycl}} \end{aligned} \tag{C.7}$$

Here, $C_{\delta_i}(1) = (1 - \phi_{\delta_i 1} - \phi_{\delta_i 2})^{-1}$ and $B_i(1) = (1 - \psi_{i1} - \psi_{i2})^{-1}$ represent the long-run effect of shocks on the level variables, and $\iota C_{\delta_i}(1)\boldsymbol{\mu}_{\delta_i S_t}$ can be interpreted as the period-state-specific unconditional mean growth rate. The terms on the first line in (C.7) may thus be interpreted as the trend growth rates stemming from the common trend and the idiosyncratic permanent component, τ_t^c and τ_t^i, respectively. The terms on the second line, would represent the stationary stochastic component of the growth rate, $\tau_t^{cycl} = y_{it} - \tau_t^c - \tau_t^i$, in other words the growth component in deviation from trend growth.

For the level $\tilde{y}_{it}$ we obtain:

$$\tilde{y}_{it} = \left(1 + \tau_t^c + \tau_t^i + \tau_t^{cycl}\right)\tilde{y}_{i,t-1} \tag{C.8}$$

$$= \left(1 + \tau_t^c\right)\tilde{y}_{i,t-1} + \tau_t^i \tilde{y}_{i,t-1} + \tau_t^{cycl}\tilde{y}_{i,t-1} \tag{C.9}$$

with $\tau_t^{cycl}\tilde{y}_{i,t-1} = \tilde{y}_{it} - \left(1 + \tau_t^c + \tau_t^i\right)\tilde{y}_{i,t-1}$. The first and second terms represent the trend levels contributed from, respectively, the common trend and the idiosyncratic permanent component, while the third term captures the stationary stochastic component in deviation from the trend level.

The following figures provide a graphical decomposition of the level series into these components. To draw the graphs, we evaluate (C.7)-(C.9) for each draw and take the average. Additionally, conditional on the posterior mean classification probability $\bar{\delta}_i = \max_k \left\{\sum_{m=1}^{M} \delta_i^{(m)} = k\right\}$ we show graphs of aggregated group-specific employment share levels and corresponding trend levels. Table C.2 displays the variance shares of the common trend and permanent idiosyncratic components in growth rates, pre-, post-break and over the whole observation period, and the average variance

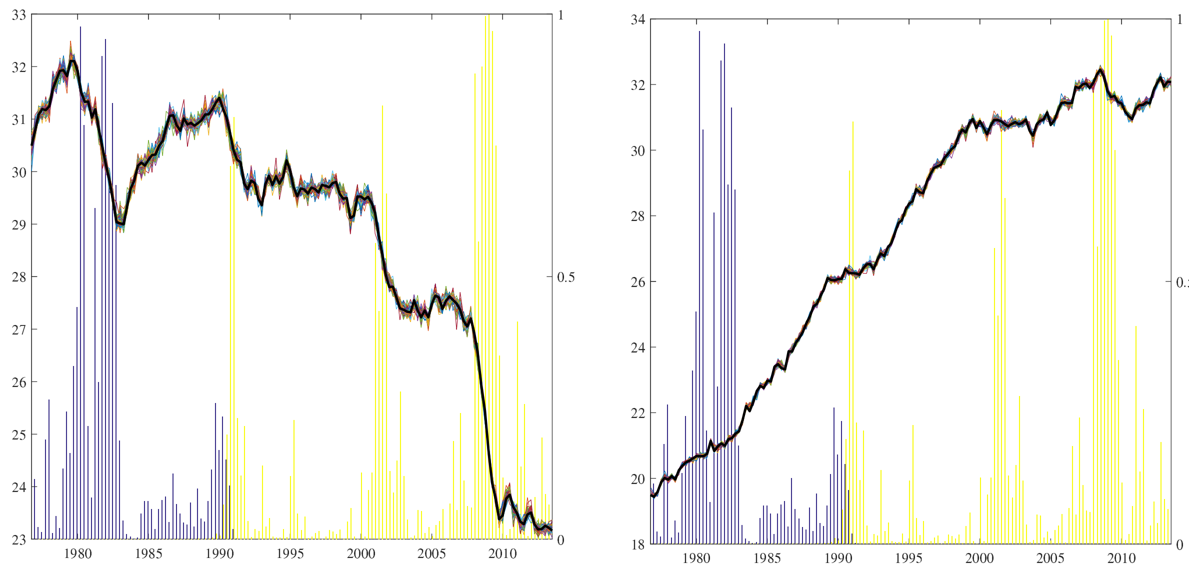
$(1-L)C^{*}(L)$, $C(L) = C(1) + (1-L)C^{*}(L)$, yields $C(1) = \left(1 - \phi_1 - \cdots - \phi_p\right)^{-1}$, which is easily computed.

share accounted for by the common component as well.

Table C.2: Common state indicator, break date at 1990Q3. Variance share in growth rates accounted for by trend growth of permanent ($\tau^c = Var(\tau^c_t)/Var(y_t)$) and idiosyncratic ($\tau^i = Var(\tau^i_t)/Var(y_t)$) component, by common component overall ($cc = Var(\lambda_{i\delta_i} f_{\delta_i t})/Var(y_t)$)

Occupations	$\bar{\lambda}_{i\delta_i}$	τ^c	τ^i	τ^c	τ^i	τ^c	τ^i	cc
		Pre 1990Q3		Post 1990Q3		Overall		
Cluster 1 (Routine occupations)								
F.1 Machine Operators, Assemblers, Inspectors	1.09	0.45	0.86	0.34	0.78	0.37	0.79	0.30
E.2 Construction Trades	0.88	0.28	0.89	0.19	0.69	0.22	0.74	0.17
E.4 Precision Production	0.84	0.26	0.56	0.19	0.47	0.21	0.49	0.17
F.2 Transportation and Material Moving	0.70	0.29	0.42	0.36	0.41	0.34	0.42	0.27
E.1 Mechanics and Repairers	0.63	0.13	0.38	0.14	0.36	0.14	0.37	0.11
B.2 Sales	0.46	0.17	0.54	0.18	0.42	0.17	0.46	0.14
B.3 Administrative Support	0.15	0.07	1.09	0.10	1.09	0.08	1.07	0.07
C.1 Housekeeping and Cleaning	-0.01	0.01	0.42	0.01	0.35	0.01	0.37	0.01
Cluster 2 (Non-routine occupations)								
A.2 Management Related	0.80	0.13	0.46	0.15	0.46	0.15	0.46	0.14
C.37 Misc. Personal Care and Service	0.60	0.02	0.42	0.02	0.45	0.02	0.43	0.02
A.1 Executive, Administrative, Managerial	0.57	0.18	0.68	0.14	0.64	0.16	0.64	0.16
C.36 Child Care Workers	0.42	0.02	0.50	0.02	0.53	0.02	0.52	0.02
E.3 Extractive	0.42	0.02	0.54	0.01	0.52	0.01	0.53	0.01
A.3 Professional Specialty	0.39	0.06	0.47	0.21	0.65	0.11	0.52	0.10
C.32 Healthcare Support	0.33	0.03	0.38	0.03	0.37	0.03	0.38	0.03
B.1 Technicians and Related Support	0.22	0.02	0.73	0.03	0.78	0.03	0.76	0.02
C.33 Building, Grounds Cleaning, Maintenance	0.21	0.01	0.42	0.01	0.45	0.01	0.44	0.01
C.34 Personal Appearance	0.13	0.01	0.34	0.01	0.31	0.01	0.32	0.01
C.31 Food Preparation and Service	0.12	0.01	0.45	0.01	0.42	0.01	0.43	0.01
C.2 Protective Service	0.08	0.01	0.33	0.02	0.33	0.02	0.33	0.01
C.35 Recreation and Hospitality	-0.04	0.00	0.35	0.01	0.41	0.01	0.37	0.00

Figure C.4: Cluster-specific occupation level (black) along with common trend and idiosyncratic permanent components and mean posterior probabilities of state 1 and 3..



Routine occupations

Non-routine occupations.

Figure C.5: Series-specific decomposition into the common trend component (left: level (red) and trend (blue)), the idiosyncratic permanent component (middle) and stationary stochastic component (right).

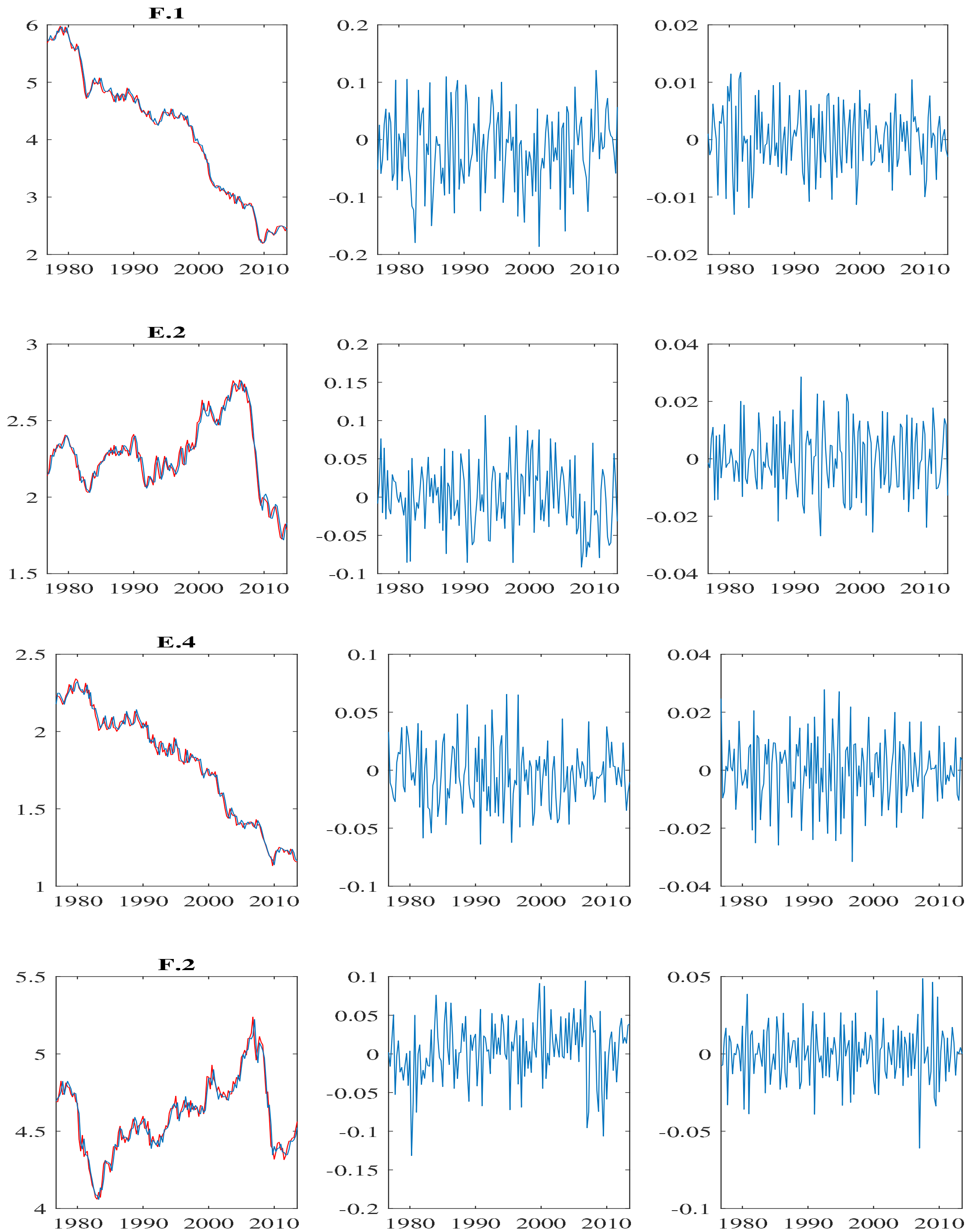


Figure C.6: Series-specific decomposition into the common trend component (left: level (red) and trend (blue)), the idiosyncratic permanent component (middle) and stationary stochastic component (right).

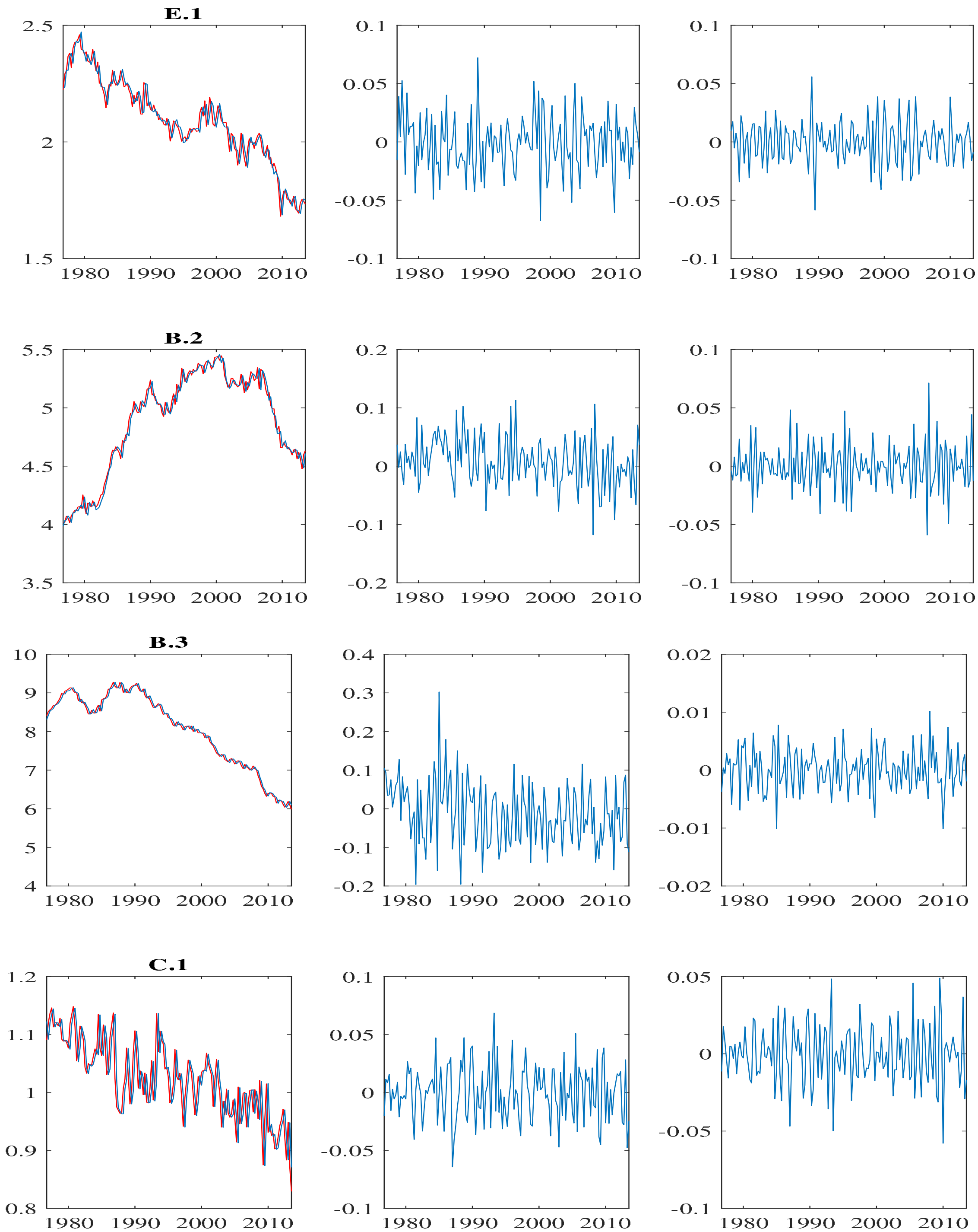


Figure C.7: Series-specific decomposition into the common trend component (left: level (red) and trend (blue)), the idiosyncratic permanent component (middle) and stationary stochastic component (right).

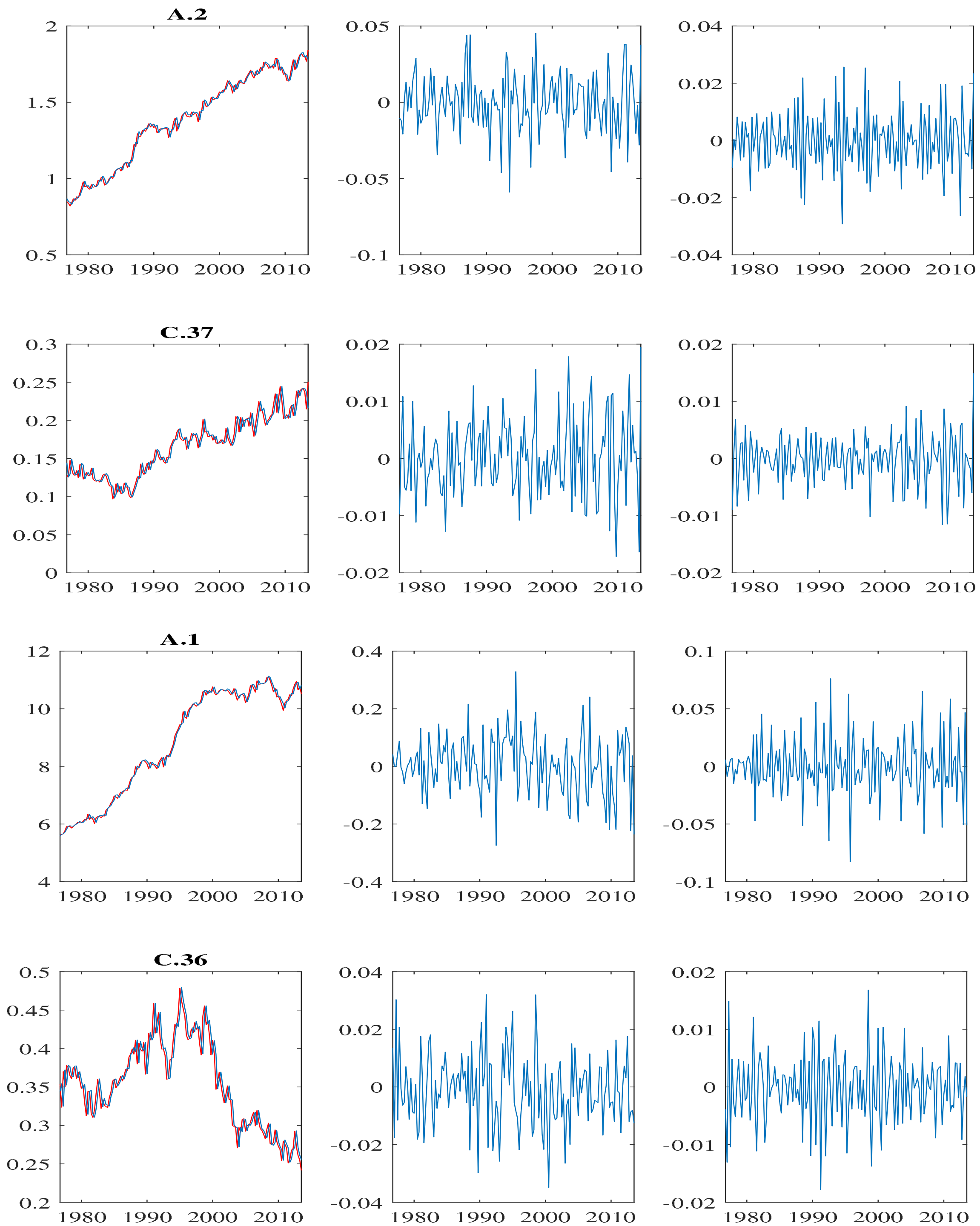


Figure C.8: Series-specific decomposition into the common trend component (left: level (red) and trend (blue)), the idiosyncratic permanent component (middle) and stationary stochastic component (right).

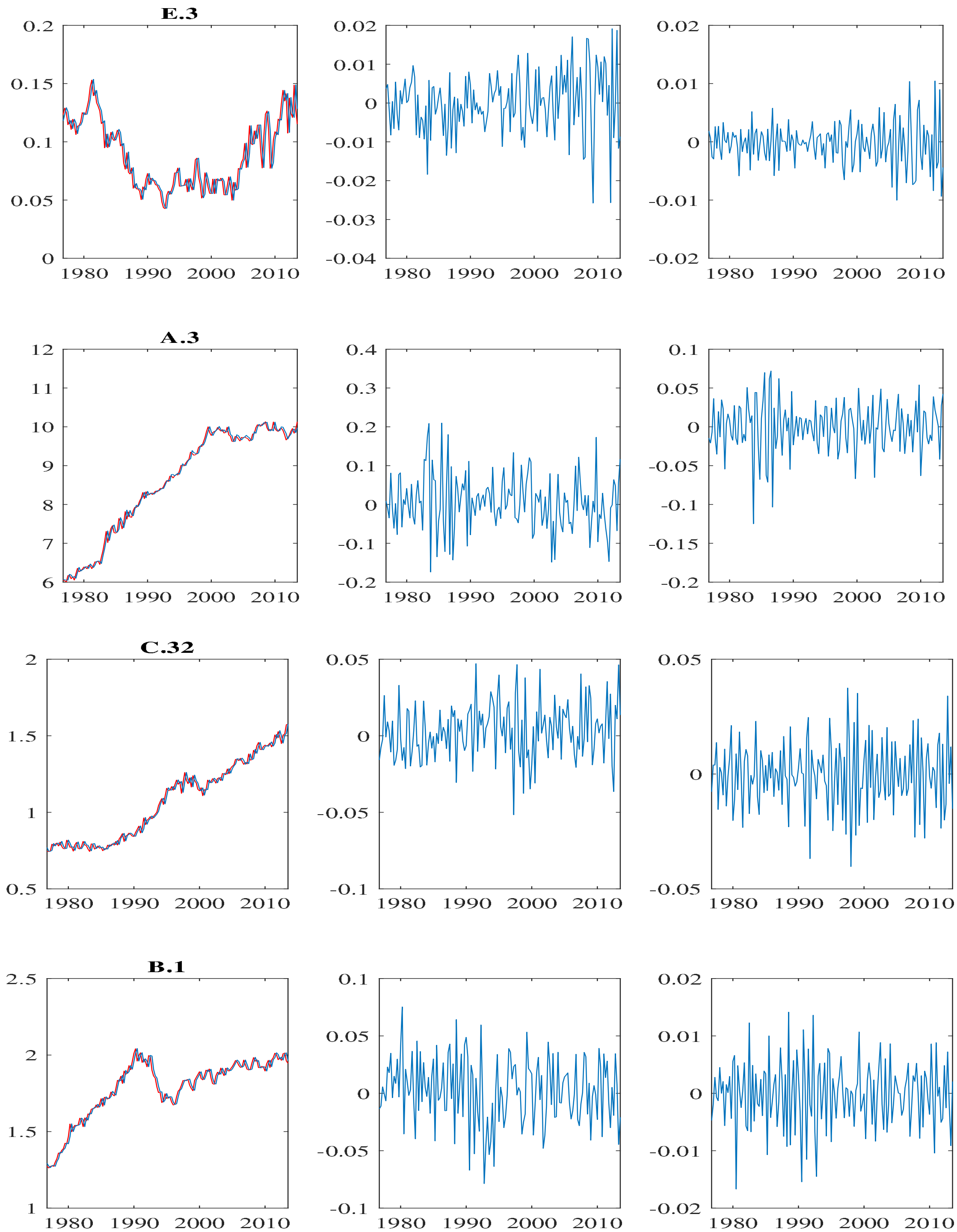


Figure C.9: Series-specific decomposition into the common trend component (left: level (red) and trend (blue)), the idiosyncratic permanent component (middle) and stationary stochastic component (right).

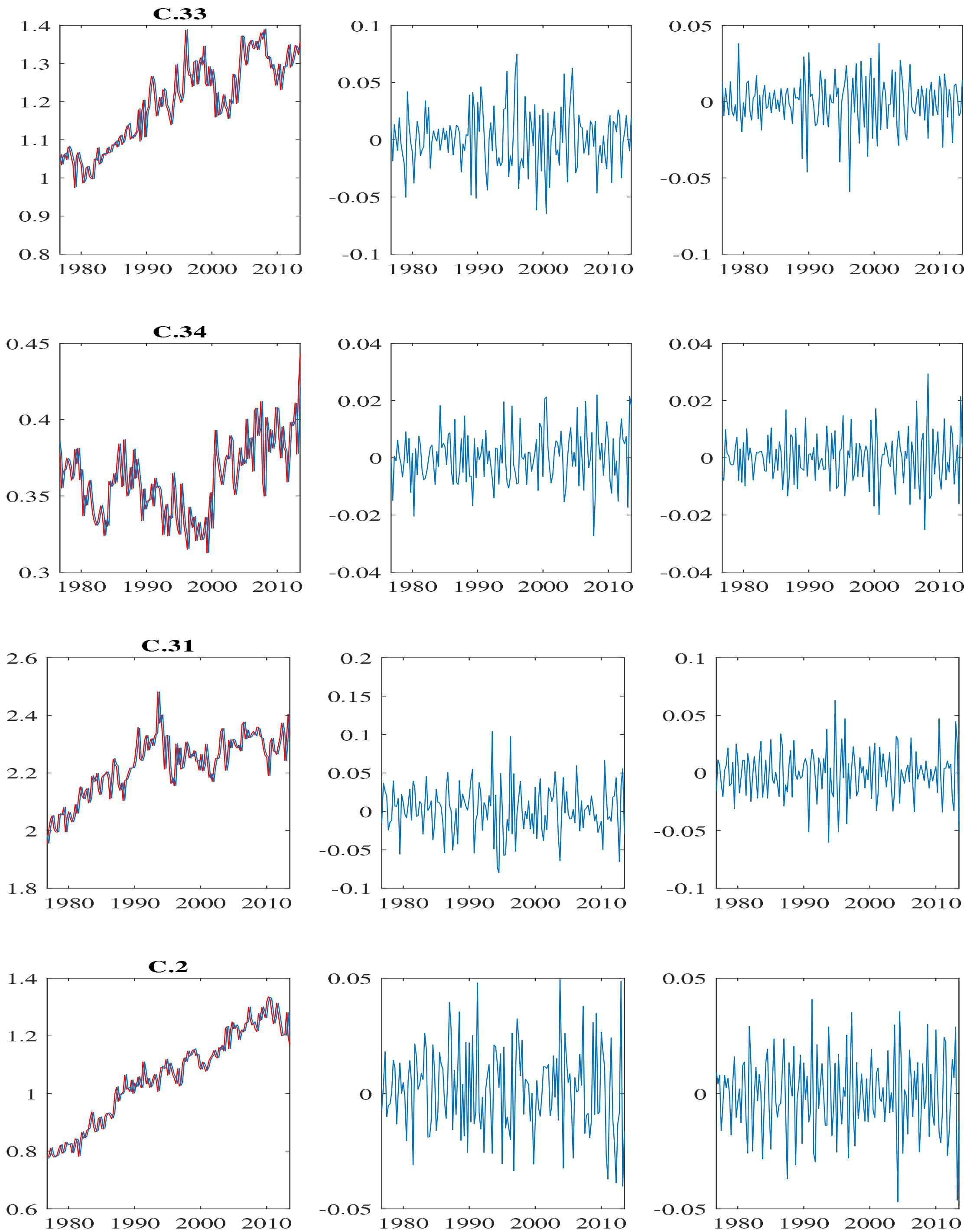
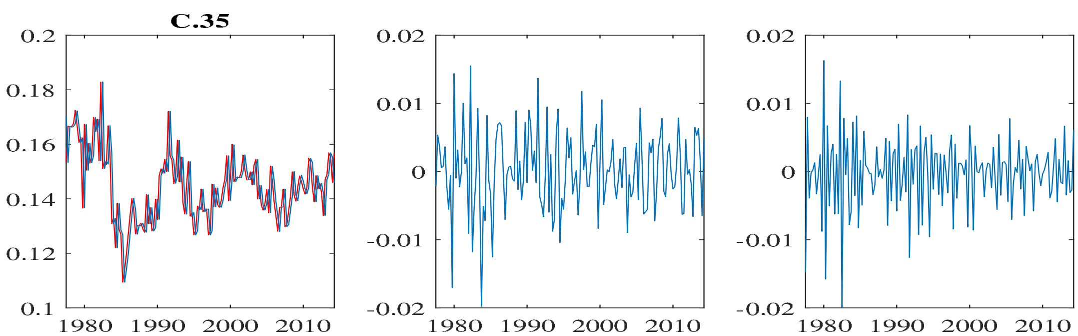


Figure C.10: Series-specific decomposition into the common trend component (left: level (red) and trend (blue)), the idiosyncratic permanent component (middle) and stationary stochastic component (right).



Appendix D. Robustness to Alternative Specifications in a Generalized Model

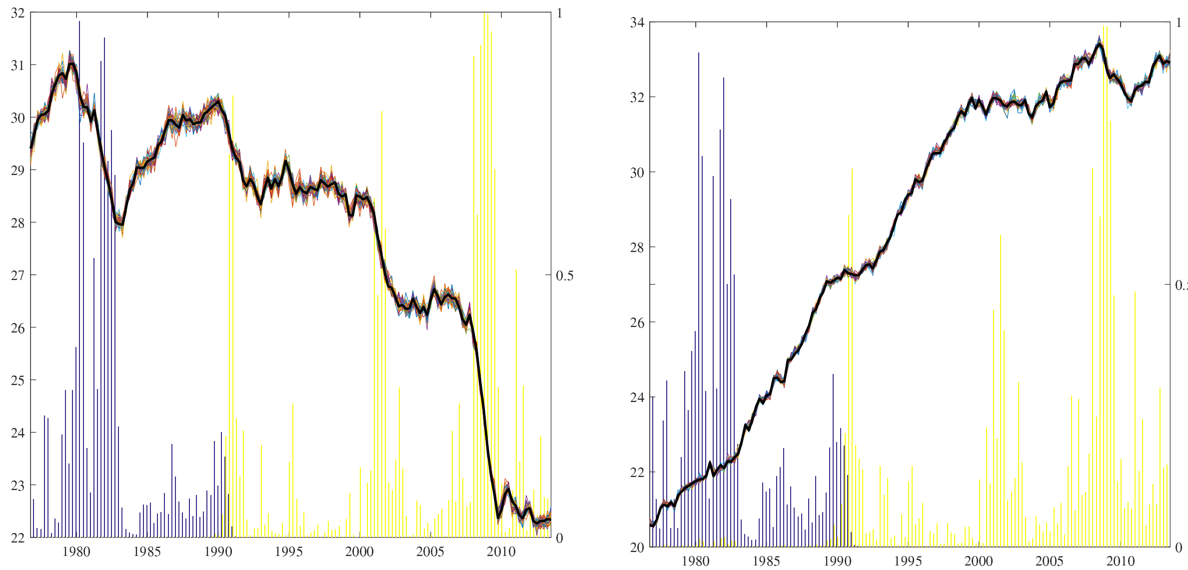
To investigate the robustness of our main results, we generalize the model to allow for cluster-specific state variables with independent breaks, and estimate specifications that allow for up to four clusters. This generalization allows us to test for the sensitivity with respect to the assumptions of synchronized business cycle dynamics and break dates. For example, a model with three factors, in which we impose a synchronized break date for two factors (e.g., in 1990q3) and a third factor with a different break date (e.g. 1983q3), would allow for the possibility that some occupations are better represented by a factor with a break in 1983q3, rather than in 1990q3, as postulated in our baseline estimation. In general, we find that our main conclusions are robust to such alternative specifications.

To save space, we report two specifications as illustrative examples: one specification with two clusters and cluster-specific state indicators; and one with four clusters that allows for three alternative break dates. The main inference remains largely the same: first, we find that "routine" occupations tend to sort into clusters that contract more strongly post-break, and "non-routine" occupations are generally assigned to clusters that grow throughout the entire sample, but less strongly post-break. Second, we find that occupation specific employment dynamics experienced a structural break around 1990. Thus, the main insights from the 2-cluster model are robust to these extensions.

Appendix D.1. 2 Clusters and Cluster-Specific State Variables

This section reports estimates from a model with a synchronized break at 1990Q3 but otherwise independent, cluster-specific state variables. The estimates are virtually identical to the ones reported in the baseline specification.

Figure D.11: Cluster-specific state indicators, break date at 1990Q3. Cluster-specific occupation level (black) along with common trend and idiosyncratic permanent components and mean posterior probabilities of state 1 and 3.



Routine occupations

Non-routine occupations.

Table D.3: Mean posterior state-specific growth rates, break date at 1990Q3

Cluster	Pre 1990Q3		Post 1990Q3	
	State 1	State 2	State 1	State 2
1	-0.72	0.16	-1.22	-0.03
2	0.38	1.08	0.21	0.55

Table D.4: Cluster-specific state indicator, break date at 1990Q3. Cluster analysis

Occupations	$P(\delta_i = 1\|y)$	$P(\delta_i = 2\|y)$	$\bar{\lambda}_{i\delta_i}$	median($\lambda_{i\delta_i}$)	+/- one stand.dev.	
Cluster 1 (Routine occupations)						
F.1 Machine Operators, Assemblers, Inspectors	1.00	0.01	1.10	1.10	0.79	1.40
E.2 Construction Trades	0.99	0.01	0.86	0.87	0.58	1.15
E.4 Precision Production	1.00	0.00	0.83	0.84	0.60	1.06
F.2 Transportation and Material Moving	1.00	0.00	0.69	0.69	0.53	0.86
E.1 Mechanics and Repairers	1.00	0.00	0.62	0.62	0.46	0.79
B.2 Sales	0.96	0.04	0.45	0.45	0.33	0.56
B.3 Administrative Support	0.70	0.30	0.13	0.14	-0.09	0.35
Cluster 2 (Non-routine occupations)						
A.2 Management Related	0.00	1.00	0.80	0.80	0.60	1.01
C.37 Misc. Personal Care and Service	0.18	0.82	0.59	0.63	0.01	1.16
A.1 Executive, Administrative, Managerial	0.00	1.00	0.58	0.57	0.39	0.78
C.36 Child Care Workers	0.30	0.70	0.44	0.43	-0.05	0.93
A.3 Professional Specialty	0.01	0.99	0.39	0.39	0.27	0.51
E.3 Extractive	0.45	0.55	0.37	0.39	-0.71	1.45
C.32 Healthcare Support	0.15	0.85	0.32	0.37	-0.01	0.64
B.1 Technicians and Related Support	0.25	0.75	0.21	0.22	0.02	0.40
C.33 Building, Grounds Cleaning, Maintenance	0.27	0.73	0.20	0.21	-0.05	0.46
C.34 Personal Appearance	0.44	0.56	0.14	0.14	-0.16	0.44
C.31 Food Preparation and Service	0.50	0.50	0.11	0.11	-0.05	0.28
C.2 Protective Service	0.39	0.61	0.06	0.15	-0.28	0.41
C.1 Housekeeping and Cleaning	0.48	0.52	-0.01	-0.02	-0.34	0.32
C.35 Recreation and Hospitality	0.44	0.56	-0.05	-0.06	-0.50	0.39

Table D.5: Cluster-specific state indicator, break date at 1990Q3. Variance share in growth rates accounted for by trend growth of permanent ($\tau^c = Var(\tau_t^c)/Var(y_t)$) and idiosyncratic ($\tau^i = Var(\tau_t^i)/Var(y_t)$) component, by common component overall ($cc = Var(\lambda_{i\delta_i} f_{\delta_i t})/Var(y_t)$).

Occupations	$\bar{\lambda}_{i\delta_i}$	τ^c	τ^i	τ^c	τ^i	τ^c	τ^i	cc
		Pre 1990Q3		Post 1990Q3		Overall		
Cluster 1 (Routine occupations)								
F.1 Machine Operators, Assemblers, Inspectors	1.10	0.20	0.62	0.18	0.62	0.39	0.79	0.31
E.2 Construction Trades	0.86	0.11	0.77	0.09	0.61	0.21	0.75	0.17
E.4 Precision Production	0.83	0.11	0.48	0.10	0.41	0.21	0.48	0.17
F.2 Transportation and Material Moving	0.69	0.13	0.34	0.19	0.33	0.34	0.43	0.27
E.1 Mechanics and Repairers	0.62	0.05	0.35	0.08	0.33	0.14	0.37	0.11
B.2 Sales	0.45	0.07	0.48	0.08	0.37	0.17	0.46	0.13
B.3 Administrative Support	0.13	0.01	1.02	0.02	1.00	0.08	1.11	0.06
Cluster 2 (Non-routine occupations)								
A.2 Management Related	0.80	0.04	0.41	0.04	0.39	0.15	0.47	0.14
C.37 Misc. Personal Care and Service	0.59	0.00	0.40	0.00	0.43	0.02	0.43	0.02
A.1 Executive, Administrative, Managerial	0.58	0.05	0.55	0.04	0.53	0.17	0.63	0.17
C.36 Child Care Workers	0.44	0.00	0.47	0.00	0.50	0.02	0.51	0.02
A.3 Professional Specialty	0.39	0.02	0.45	0.05	0.56	0.11	0.53	0.10
E.3 Extractive	0.37	0.00	0.52	0.00	0.51	0.01	0.53	0.01
C.32 Healthcare Support	0.32	0.00	0.36	0.00	0.35	0.03	0.38	0.03
B.1 Technicians and Related Support	0.21	0.00	0.69	0.00	0.74	0.03	0.76	0.02
C.33 Building, Grounds Cleaning, Maintenance	0.20	0.00	0.40	0.00	0.43	0.01	0.44	0.01
C.34 Personal Appearance	0.14	0.00	0.33	0.00	0.30	0.01	0.32	0.01
C.31 Food Preparation and Service	0.11	0.00	0.43	0.00	0.41	0.01	0.43	0.01
C.2 Protective Service	0.06	0.00	0.31	0.00	0.32	0.02	0.33	0.01
C.1 Housekeeping and Cleaning	-0.01	0.00	0.41	0.00	0.34	0.01	0.37	0.01
C.35 Recreation and Hospitality	-0.05	0.00	0.34	0.00	0.40	0.01	0.37	0.00

Appendix D.2. 4 Clusters and Cluster-Specific State Variables (One Break at 1983q3, Two at 1990q3, One at 2007q4)

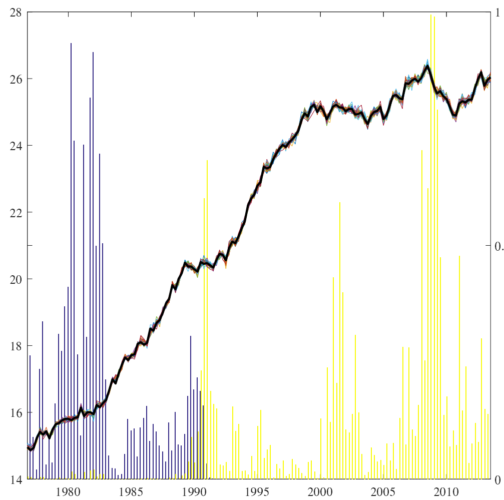
This section reports the result form a model with four clusters. For two clusters we impose a break in 1990q3, for one cluster we impose the break in 1983q3, and for one cluster we impose a break in 2007q4. These break dates are chosen based on visual inspection of Figure 1 in the main text. We have experimented with various alternative break dates and our main insights remain unchanged.

In this model, cluster 1 groups "non-routine" occupations, and the estimated pre- and post-break factor-specific growth rates are virtually identical to those estimated for "non-routine" occupations in the 2-factor specification. The common feature of this occupation group is that it experiences employment growth in both expansions and recessions, and it experiences a break at 1990q3.

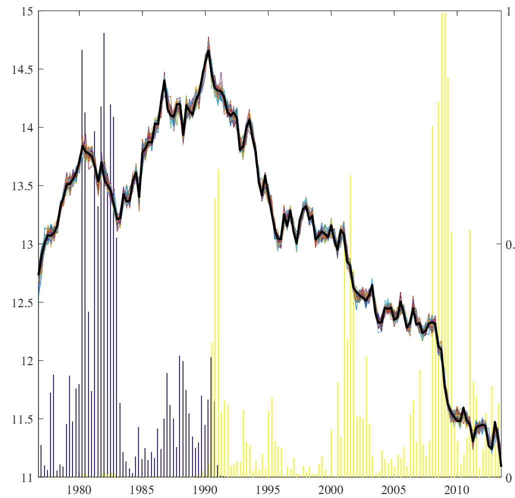
Clusters 2-4 now pick up occupations that were mostly associated with "routine" occupations in the 2-factor model. The common feature of these three factors are strong contractions during recessions. Moreover, cluster 2, with a break in 1990q3, shows significantly different factor specific growth rates pre- and post-break and the estimated growth rates are largely in line with the cluster grouping "routine" occupations in the 2-factor model. Table D.7 reveals that this cluster is comprised mostly of administrative and clerical jobs, often referred to as "routine cognitive" occupations in the polarization literature, which suggests that these occupations are particularly important for the observed break in dynamics around 1990. This observation is in line with findings by Cortes, Jaimovich, and Siu (2017), who find that "routine cognitive" occupations experience the most substantial changes around 1990. In contrast, pre- and post-break factor specific growth rates for factors 3 and 4 do not differ significantly, suggesting that occupation-specific employment dynamics likely did not experience meaningful structural breaks at 1983Q3 and 2007Q4. We find very similar results for additional specifications with alternative break dates.

In sum, the main insights of the 2-factor model are largely preserved across a variety of alternative specifications within this generalized model: first, "non-routine" occupations tend to sort into a cluster that experiences positive employment growth, both in recessions and expansions; second, "routine" occupations tend to sort into clusters that contract during recessions; third, there is a significant break around 1990, with the feature that the cluster comprising mostly of "non-routine" occupations tends to grow less strongly in both recessions and recoveries, while the cluster with a break around 1990 grouping mostly "routine" occupations tends to contract more strongly during recessions, and recover more slowly during expansions.

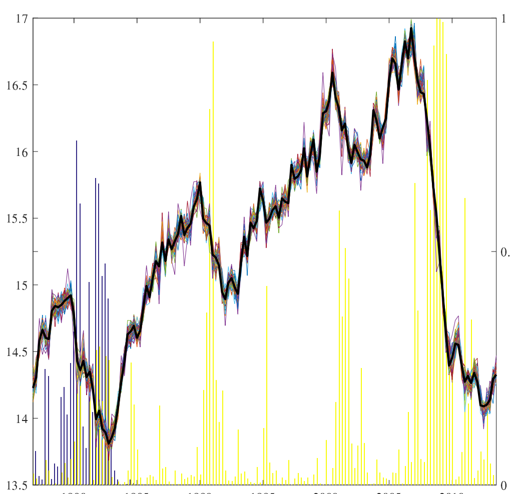
Figure D.12: Cluster-specific state indicators, break date at 1983Q3, two at 1990Q3 and at 2007Q4 (in brackets). Cluster-specific occupation level (black) along with common trend and idiosyncratic permanent components and mean posterior probabilities of state 1 and 3.



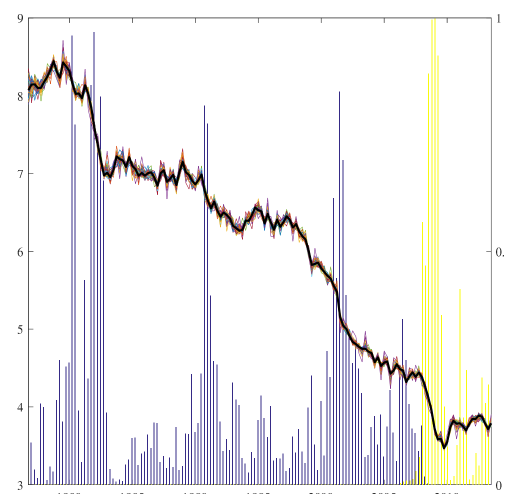
Cluster 1 (1990Q3)



Cluster 2 (1990Q3)



Cluster 3 (1983Q3)



Cluster 4 (2007Q4)

Table D.6: Mean posterior state-specific growth rates, break date at 1983Q3, two at 1990Q3 and at 2007Q4

Cluster	Break date	Pre break		Post break	
		State 1	State 2	State 1	State 2
1	1990Q3	0.38	1.01	0.22	0.53
2	1990Q3	-0.55	0.31	-1.08	-0.46
3	1983Q3	-0.78	-0.01	-1.17	0.24
4	2007Q4	-0.81	-0.24	-1.13	0.05

Table D.7: Cluster-specific state indicator, break date at 1983Q3, two at 1990Q3 and at 2007Q4 (in brackets). Cluster analysis

Occupations	$P(\delta_i = j \mid y)$				$\bar{\lambda}_{i\delta_i}$	median($\lambda_{i\delta_i}$)	+/- one stand.dev.	
	$j = 1$	$j = 2$	$j = 3$	$j = 4$				
Cluster 1 (1990Q3)								
A.2 Management Related	0.87	0.00	0.00	0.12	0.58	0.73	0.04	1.12
A.1 Executive, Administrative, Managerial	0.94	0.00	0.00	0.06	0.56	0.57	0.19	0.93
C.36 Child Care Workers	0.44	0.17	0.19	0.20	0.36	0.33	-0.24	0.97
A.3 Professional Specialty	0.85	0.00	0.00	0.14	0.30	0.39	-0.01	0.60
C.37 Misc. Personal Care and Service	0.50	0.17	0.14	0.20	0.19	0.24	-0.51	0.89
C.32 Healthcare Support	0.63	0.14	0.08	0.16	0.15	0.27	-0.27	0.57
E.3 Extractive	0.27	0.23	0.25	0.25	0.08	0.13	-0.99	1.15
C.33 Building, Grounds Cleaning, Maintenance	0.39	0.26	0.17	0.17	0.07	0.10	-0.27	0.40
Cluster 2 (1990Q3)								
B.3 Administrative Support	0.06	0.90	0.01	0.03	0.60	0.71	0.23	0.97
B.1 Technicians and Related Support	0.39	0.40	0.09	0.12	0.19	0.23	-0.06	0.44
C.31 Food Preparation and Service	0.17	0.49	0.23	0.11	0.18	0.20	-0.03	0.40
C.1 Housekeeping and Cleaning	0.24	0.31	0.25	0.20	0.10	0.10	-0.24	0.43
Cluster 3 (1983Q3)								
F.2 Transportation and Material Moving	0.00	0.00	1.00	0.00	0.95	0.96	0.80	1.10
E.2 Construction Trades	0.00	0.01	0.98	0.00	0.88	0.87	0.60	1.15
E.1 Mechanics and Repairers	0.00	0.08	0.77	0.15	0.53	0.53	0.37	0.69
B.2 Sales	0.08	0.01	0.88	0.03	0.39	0.39	0.27	0.52
C.34 Personal Appearance	0.21	0.23	0.42	0.14	0.14	0.15	-0.27	0.55
C.2 Protective Service	0.28	0.11	0.32	0.29	-0.16	-0.22	-0.50	0.18
Cluster 4 (2007Q4)								
F.1 Machine Operators, Assemblers, Inspectors	0.00	0.12	0.03	0.85	1.82	1.87	1.54	2.10
E.4 Precision Production	0.00	0.14	0.02	0.84	0.82	0.81	0.62	1.01
C.35 Recreation and Hospitality	0.28	0.25	0.19	0.28	-0.11	-0.09	-0.57	0.36

Table D.8: Cluster-specific state indicator, break date at 1983Q3, two at 1990Q3 and at 2007Q4 (in brackets). Variance share in growth rates accounted for by trend growth of permanent ($\tau^c = Var(\tau_t^c)/Var(y_t)$) and idiosyncratic ($\tau^i = Var(\tau_t^i)/Var(y_t)$) component, by common component overall ($cc = Var(\lambda_{i\delta_i} f_{\delta_i t})/Var(y_t)$).

Occupations	$\bar{\lambda}_{i\delta_i}$	τ^c	τ^i	τ^c	τ^i	τ^c	τ^i	cc
		Pre break		Post break		Overall		
Cluster 1 (1990Q3)								
A.2 Management Related	0.58	0.04	0.42	0.03	0.41	0.14	0.48	0.14
A.1 Executive, Administrative, Managerial	0.56	0.06	0.50	0.04	0.48	0.20	0.61	0.20
C.36 Child Care Workers	0.36	0.00	0.47	0.00	0.50	0.02	0.52	0.02
A.3 Professional Specialty	0.30	0.02	0.42	0.05	0.52	0.12	0.50	0.12
C.37 Misc. Personal Care and Service	0.19	0.00	0.41	0.00	0.43	0.02	0.44	0.01
C.32 Healthcare Support	0.15	0.00	0.36	0.00	0.35	0.03	0.38	0.03
E.3 Extractive	0.08	0.00	0.52	0.00	0.51	0.01	0.53	0.01
C.33 Building, Grounds Cleaning, Maintenance	0.07	0.00	0.40	0.00	0.44	0.01	0.44	0.01
Cluster 2 (1990Q3)								
B.3 Administrative Support	0.60	0.28	0.14	0.27	0.15	0.57	0.33	0.57
B.1 Technicians and Related Support	0.19	0.00	0.70	0.00	0.75	0.03	0.77	0.03
C.31 Food Preparation and Service	0.18	0.01	0.43	0.00	0.40	0.02	0.43	0.02
C.1 Housekeeping and Cleaning	0.10	0.00	0.40	0.00	0.34	0.01	0.37	0.01
Cluster 3 (1983Q3)								
F.2 Transportation and Material Moving	0.95	0.35	0.10	0.38	0.10	0.63	0.20	0.55
E.2 Construction Trades	0.88	0.18	0.67	0.11	0.59	0.22	0.70	0.19
E.1 Mechanics and Repairers	0.53	0.06	0.40	0.04	0.35	0.11	0.39	0.09
B.2 Sales	0.39	0.09	0.42	0.06	0.40	0.14	0.46	0.11
C.34 Personal Appearance	0.14	0.00	0.36	0.00	0.30	0.01	0.32	0.01
C.2 Protective Service	-0.16	0.00	0.30	0.00	0.32	0.02	0.33	0.02
Cluster 4 (2007Q4)								
F.1 Machine Operators, Assemblers, Inspectors	1.82	0.68	0.04	0.71	0.03	0.92	0.19	0.81
E.4 Precision Production	0.82	0.10	0.42	0.25	0.30	0.18	0.43	0.16
C.35 Recreation and Hospitality	-0.11	0.00	0.36	0.00	0.43	0.01	0.37	0.01

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