

# Duration structure of unemployment hazards and the trend unemployment rate

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# New method to estimate the trend unemployment rate

Develop a new method to estimate the trend unemployment rate taking into account the **time-varying duration profile of unemployment hazards**

- characterized by three time-varying factors—level, slope and curvature → **Duration structure of unemployment hazards**

## **Duration-structure trend unemployment rate (DS-TUR)**

- The unemployment rate composed of the trend components of time-varying parameters constituting the duration structure of unemployment hazards and the trend inflows to unemployment
- The identification of trend unemployment rate is achieved not only from the trends in labor-force flows but also from the low-frequency changes in the distribution of unemployment duration.

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## **Duration-structure trend unemployment rate (DS-TUR)**

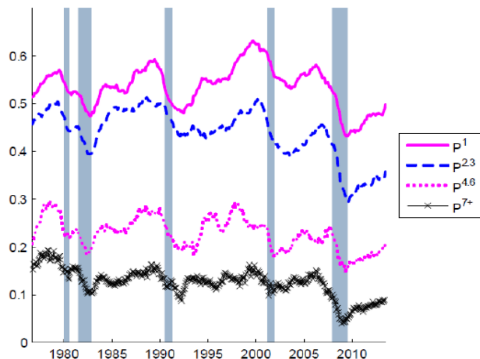
- The unemployment rate composed of the trend components of time-varying parameters constituting the duration structure of unemployment hazards and the trend inflows to unemployment
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## Key findings

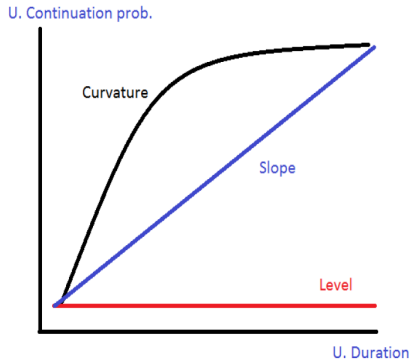
1. The *DS-TUR* exhibits a secular decline between 1980 and 2000, a slow uptrend during the 2000s, and a decline between 2011 and 2019.
  - The slow uptrend during the 2000s reflects the secular rise in long-term unemployment.
2. Without mismatch or the extension of UI benefits considered, the *DS-TUR* exhibits a rise and fall during 2007-2011.
3. The short-term component has trended down since 1980, while the long-term component shows an uptrend between 2000-2011 → falling frictional unemployment, rising structural unemployment.
4. The short-term unemployment-rate gap has a strong Phillips correlation with the PCE inflation.

# Model: Duration structure of unemployment hazards

## Unemployment-exit probability



## Duration profile of U-continuation probability



**Laguerre function** is used to model the nonlinear duration profile of unemployment continuation probabilities.

# Model: Duration structure of unemployment hazards

## 1. Term structure of interest rates

$$f(\tau) = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix}' \begin{bmatrix} 1 \\ e^{\tau/\lambda} \\ (\tau/\lambda)e^{\tau/\lambda} \end{bmatrix} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix}' \begin{bmatrix} f_0 \\ f_1 \\ f_2 \end{bmatrix}$$

## 2. Duration structure of unemployment hazards

$$\begin{aligned} x_t(\tau) &= \underbrace{\beta_{0t}}_{\text{Level}} + \underbrace{\beta_{1t}e^{-(12-\tau)/\lambda_t}}_{\text{Slope}} + \underbrace{\beta_{2t}((12-\tau)/\lambda_t)e^{-(12-\tau)/\lambda_t}}_{\text{Curvature}}, \text{ for } \tau < 12 \\ &= \underbrace{\beta_{0t}}_{\text{Level}} + \underbrace{\beta_{1t}}_{\text{Slope}}, \text{ for } \tau \geq 12 \end{aligned}$$

Assumption: an individual's unemployment exit-probability does not change once unemployed longer than one year (Kroft, Lange, and Notowidigdo, 2013).

## Data used in the analysis

$U_t^1$  = number of people newly unemployed in month  $t$  (S.A.)

$U_t^{2.3}$  = number of people unemployed for 2-3 months

$U_t^{4.6}$  = 4-6 months

$U_t^{7.12}$  = 7-12 months

$U_t^{13.+}$  = more than 1 year

$y_t = (U_t^1, U_t^{2.3}, U_t^{4.6}, U_t^{7.12}, U_t^{13.+})'$  for  $t = 1976:M1 - 2019:M12$



# Dynamic accounting identity: Ahn and Hamilton (2020)

$$U^1 = w.$$

$$p(\tau) = \exp[-\exp(x(\tau))] \quad \text{for } \tau = 1, 2, 3, \dots,$$

probability to stay unemployed next month of those unemployed for  $\tau$  month

$$P(k) = p(1)p(2)\dots p(k),$$

probability to stay unemployed for  $k$  consecutive months

$$U^{2.3} = [wP(1) + wP(2)], \quad U^{4.6} = \sum_{k=3}^5 [wP(k)]$$

$$U^{7.12} = \sum_{k=6}^{11} [wP(k)], \quad U^{13.+} = \sum_{k=12}^{47} [wP(k)]$$

We have five unknown parameters,  $w$ ,  $\beta_0$ ,  $\beta_1$ ,  $\beta_2$ , and  $\lambda$ , which allows us to fit the five data points,  $U^1$ ,  $U^{2.3}$ ,  $U^{4.6}$ ,  $U^{7.12}$ ,  $U^{13.+}$ , exactly.

## State Space Model: Measurement equation

$$U_t^1 = w_t + r_t^1$$

$$U_t^{2.3} = [w_{t-1}P_t(1) + w_{t-2}P_t(2)] + r_t^{2.3}$$

$$U_t^{4.6} = \sum_{k=3}^5 [w_{t-k}P_t(k)] + r_t^{4.6}$$

$$U_t^{7.12} = \sum_{k=6}^{11} [w_{t-k}P_t(k)] + r_t^{7.12}$$

$$U_t^{13.+} = \sum_{k=12}^{47} [w_{t-k}P_t(k)] + r_t^{13.+}$$

## State Space Model: Measurement equation

$$P_t(j) = p_{t-j+1}(1)p_{t-j+2}(2)\dots p_t(j).$$

$$r_t \sim N(0, R)$$

$$\underbrace{R}_{5 \times 5} = \begin{bmatrix} R_1^2 & 0 & 0 & 0 & 0 \\ 0 & R_{2.3}^2 & 0 & 0 & 0 \\ 0 & 0 & R_{4.6}^2 & 0 & 0 \\ 0 & 0 & 0 & R_{7.12}^2 & 0 \\ 0 & 0 & 0 & 0 & R_{13.+}^2 \end{bmatrix}.$$

## State Space model: State equation

Assume driving variables evolve smoothly over time

- $w_t = w_{t-1} + \epsilon_t^w$
- $\lambda_t = \lambda_{H,t-1} + \epsilon_t^\lambda$
- $\beta_{0t} = \beta_{0,t-1} + \epsilon_t^{\beta_0}$
- $\beta_{1t} = \beta_{1,t-1} + \epsilon_t^{\beta_1}$
- $\beta_{2t} = \beta_{2,t-1} + \epsilon_t^{\beta_2}$

## State Space model: State equation

Let  $\xi_t$  be the vector  $(w_t, \lambda_t, \beta_{0t}, \beta_{1t}, \beta_{2t})'$  and  $\varepsilon_t = (\varepsilon_t^w, \varepsilon_t^\lambda, \varepsilon_t^{\beta_0}, \varepsilon_t^{\beta_1}, \varepsilon_t^{\beta_2})'$ .

$$\underbrace{\xi_t}_{5 \times 1} = \xi_{t-1} + \underbrace{\varepsilon_t}_{5 \times 1}$$

$$\underbrace{\varepsilon_t}_{5 \times 1} \sim N(\underbrace{0}_{5 \times 1}, \underbrace{\Sigma}_{5 \times 5})$$

$$\underbrace{\Sigma}_{5 \times 5} = \begin{bmatrix} (\sigma^w)^2 & 0 & 0 & 0 & 0 \\ 0 & (\sigma^\lambda)^2 & 0 & 0 & 0 \\ 0 & 0 & (\sigma^{\beta_0})^2 & 0 & 0 \\ 0 & 0 & 0 & (\sigma^{\beta_1})^2 & 0 \\ 0 & 0 & 0 & 0 & (\sigma^{\beta_2})^2 \end{bmatrix}.$$

# State Space Model

$$\underbrace{\begin{bmatrix} \xi_t \\ \xi_{t-1} \\ \xi_{t-2} \\ \vdots \\ \xi_{t-46} \\ \xi_{t-47} \end{bmatrix}}_{240 \times 1} = \underbrace{\begin{bmatrix} \underbrace{I}_{5 \times 5} & \underbrace{0}_{5 \times 5} & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & I & 0 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \dots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & I & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & I & 0 \end{bmatrix}}_{240 \times 240} \underbrace{\begin{bmatrix} \xi_{t-1} \\ \xi_{t-2} \\ \xi_{t-3} \\ \vdots \\ \xi_{t-46} \\ \xi_{t-47} \end{bmatrix}}_{240 \times 1} + \underbrace{\begin{bmatrix} \underbrace{\varepsilon_t}_{5 \times 1} \\ \underbrace{0}_{5 \times 1} \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}}_{240 \times 1} .$$

Nonlinear state space model  $\rightarrow$  Extended Kalman filter

## Estimates: level, slope and curvature

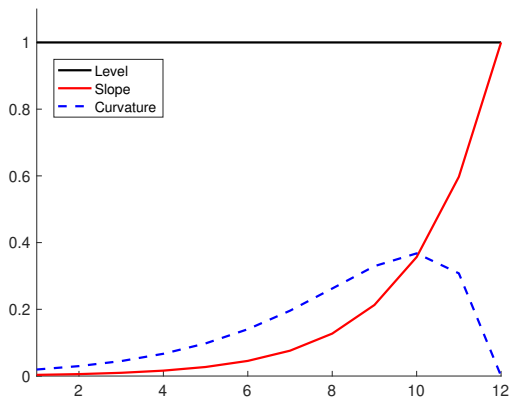
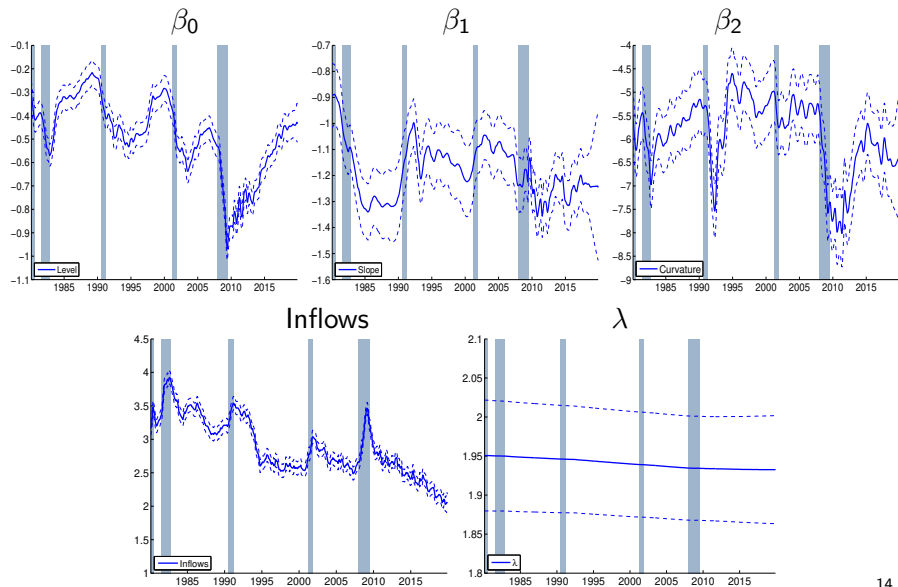


Figure: Estimates of level, slope and curvature with the value of  $\lambda_t = 1.94$

# Estimates: factor loadings, inflows, and $\lambda$





# Monthly unemployment-continuation probabilities

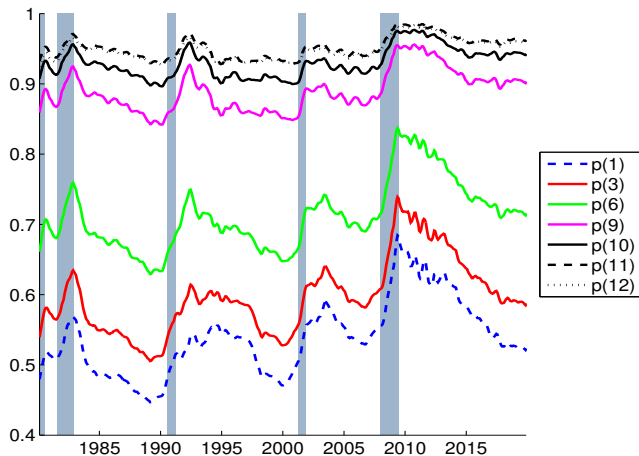


Figure: The model-implied monthly unemployment continuation probabilities by duration of unemployment

# Duration-structure trend unemployment rate (DS-TUR)

**Definition of DS-TUR** The unemployment rate consisted only of the trend components of  $(\hat{w}_{t|T}, \hat{\beta}_{0,t|T}, \hat{\beta}_{1,t|T}, \hat{\beta}_{2,t|T})'$  and the level of  $\hat{\lambda}_{t|T}$ .

- 1 Extract the trend components of the four parameters, and feed the trends back into the accounting identity model to recover the trend unemployment
- 2 Divide the trend unemployment by the trend labor force

$$DS-TUR_t = 100 \times \frac{\mathbf{1}' h(\hat{\psi}_{t|T}, \hat{\psi}_{t-1|T}, \dots, \hat{\psi}_{t-47|T}, \hat{\lambda}_{t|T}, \hat{\lambda}_{t-1|T}, \dots, \hat{\lambda}_{t-47|T})}{\hat{\psi}_{t|T}^{LF}}$$

where

$$\hat{\psi}_{t|T} = [\hat{\psi}_{t|T}^w, \hat{\psi}_{t|T}^{\beta 0}, \hat{\psi}_{t|T}^{\beta 1}, \hat{\psi}_{t|T}^{\beta 2}]'$$

$\mathbf{1}$ : a  $(5 \times 1)$  vector of ones

$h(\cdot)$ : the measurement equations without measurement errors.

# Trend-cycle decomposition

Estimate the standard model for trend-cycle decomposition (specified in a quarterly frequency) with a Bayesian method (Chan et al.(2019))

Assume that  $\hat{w}_{q|T}$  follows an  $I(2)$  process. The trend component  $\psi_q^w$  has a time-varying growth rate,  $\mu_q^w$ :

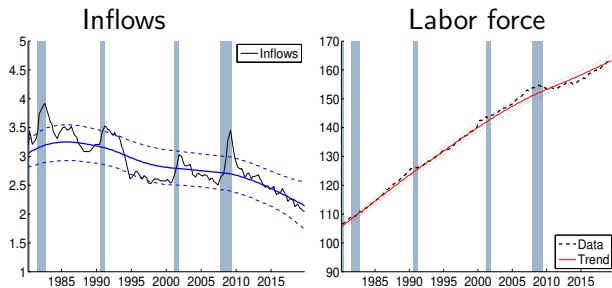
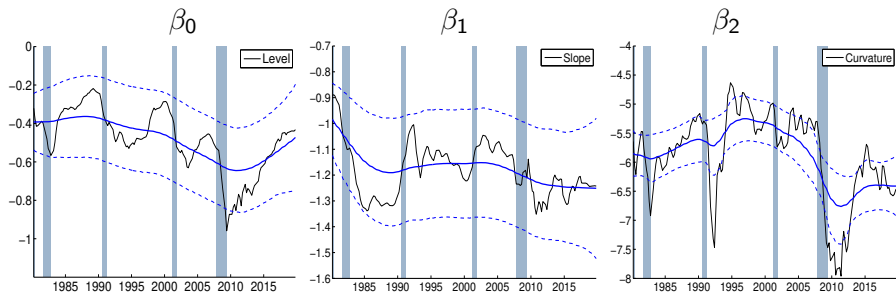
$$\hat{w}_{q|T} = \underbrace{\psi_q^w}_{\text{trend}} + \underbrace{c_q^w}_{\text{cycle}}$$

$$\begin{aligned} \text{Trend} \quad \psi_q^w &= \mu_q^w + \psi_{q-1}^w \\ \mu_q^w &= \mu_{q-1}^w + \epsilon_{\psi q}^w, \quad \epsilon_{\psi q}^w \sim N(0, (\sigma_\psi^w)^2) \\ \Rightarrow \Delta \psi_q^w &= \Delta \psi_{q-1}^w + \epsilon_{\psi q}^w. \end{aligned}$$

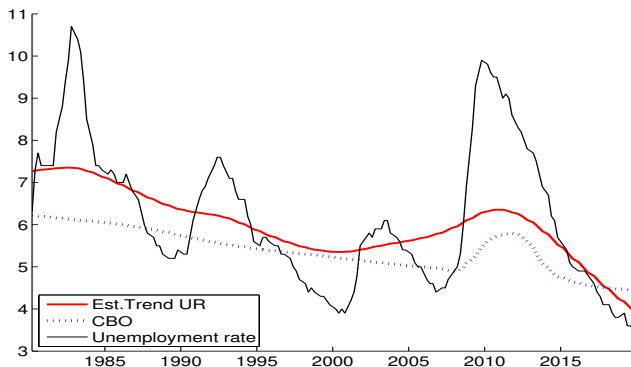
$$\text{Cycle} \quad c_q^w = \phi_1^w c_{q-1}^w + \phi_2^w c_{q-2}^w + \epsilon_{cq}^w, \quad \epsilon_{cq}^w \sim N(0, (\sigma_c^w)^2)$$

The same model is used to estimate the trends of other parameters.

# Trend estimates



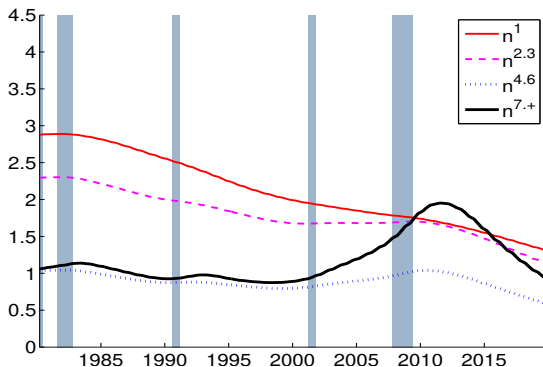
# DS-TUR (1980-2019)



The low-frequency variation in the distribution of unemployment duration is used to identify the trend unemployment rate.

- The persistent effects of structural changes in the labor markets (e.g., mismatch and extended UI benefits) are captured by the long-term trend unemployment.

# Duration components of DS-TUR



Decline in short-term U. since 1980s → decreased frictional unemployment  
Increase in long-term U. during 2000s → increased structural unemployment

# Implications for the Phillips curve

Consider a simple Phillips curve model

$$\pi_q = c_0 + c_1 gap_q + c_2 \pi_{q-1} + c_3 \pi_{q-2} + c_4 \pi_q^e + c_5 \pi_{q-1}^e + e_q$$

where  $\pi_q^e$  denotes the average 1-year-ahead inflation expectations from the Michigan survey in quarter  $q$ .

Alternatively, also replace  $gap_q$  with  $gap_q^j$  for  $j = 1, 2, 3, 4, 6, 7, +$ , where

$$gap_q^j = ru_q^j - DS-TUR_q^j$$

## Key results

- The short-term unemployment rate gap has a strong Phillips correlation with PCE inflation, while the Phillips correlation with the aggregate gap is small.
- Replacing the unemployment-rate gaps with the unemployment rates by the duration, none of the Phillips correlation coefficients are statistically significant.

# Implications for the Phillips curve

Table: Estimation results (2000:Q1-2019:Q4)

	$gap_q$	$gap_q^1$	$gap_q^{2.3}$	$gap_q^{1.3}$	$gap_q^{1.6}$	$gap_q^{7.+}$	$gap_q^{CBO}$
$c_0$	-0.30	-0.22	-0.31	-0.28	-0.25	-0.28	-0.33
S.E.	(0.33)	(0.32)	(0.32)	(0.31)	(0.32)	(0.33)	(0.33)
Gap	<b>-0.070*</b>	<b>-1.32**</b>	<b>-0.60**</b>	<b>-0.46**</b>	<b>-0.24**</b>	<b>-0.071</b>	<b>-0.071*</b>
S.E.	(0.037)	(0.46)	(0.20)	(0.15)	(0.088)	(0.059)	(0.037)
$\pi_{q-1}$	0.99**	0.92**	0.90**	0.89**	0.91**	1.026**	0.98**
1 S.E.	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	(0.11)
$\pi_{q-2}$	-0.37**	-0.29**	-0.32**	-0.31**	-0.33**	-0.38**	-0.37**
S.E.	(0.090)	(0.091)	(0.089)	(0.088)	(0.089)	(0.092)	(0.091)
$\pi_q^e$	0.63**	0.54**	0.61**	0.58**	0.60**	0.64**	0.64**
S.E.	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
$\pi_{q-1}^e$	-0.28**	-0.23*	-0.23**	-0.22**	-0.25**	-0.31**	-0.27**
S.E.	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)	(0.14)
Adj. R <sup>2</sup>	0.77	0.78	0.78	0.79	0.78	0.77	0.77



# Implications for the Phillips curve

Table: Estimation results (2000:Q1-2019:Q4)

	$ru_q$	$ru_q^1$	$ru_q^{2.3}$	$ru_q^{1.3}$	$ru_q^{1.6}$	$ru_q^{7.+}$
$c_0$	-0.087	-0.24	0.075	0.058	0.056	-0.25
S.E.	(0.34)	(0.51)	(0.38)	(0.43)	(0.30)	(0.33)
UR	<b>-0.048</b>	<b>0.0042</b>	<b>-0.26</b>	<b>-0.10</b>	<b>-0.086</b>	<b>-0.076</b>
S.E.	(0.030)	(0.23)	(0.20)	(0.16)	(0.063)	(0.050)
$\pi_{q-1}$	1.00**	1.049**	0.99**	1.021**	1.00**	1.010**
S.E.	(0.11)	(0.19)	(0.11)	(0.11)	(0.11)	(0.10)
$\pi_{q-2}$	-0.36**	-0.37**	-0.34**	-0.35**	-0.35**	-0.38**
S.E.	(0.090)	(0.094)	(0.092)	(0.093)	(0.092)	(0.091)
$\pi_q^e$	0.64**	0.62**	0.63**	0.62**	0.63**	0.65**
S.E.	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
$\pi_{q-1}^e$	-0.29**	-0.34**	-0.29**	-0.32**	-0.31**	-0.29**
S.E.	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Adj. R <sup>2</sup>	0.76	0.76	0.77	0.76	0.76	0.77

# Conclusion

This paper

- 1 introduces the duration structure of unemployment hazards
- 2 develops a novel method to estimate the trend unemployment rate

Main takeaways:

- 1 The identification of trend unemployment rate is achieved not only from the trends in labor-force flows but also from the low-frequency changes in the distribution of unemployment duration.
- 2 Secular decline in short-term trend unemployment rate → decline in frictional unemployment rate; Secular rise in long-term trend unemployment rate → rise in structural unemployment rate.
- 3 The short-term unemployment-rate gap has a strong Phillips correlation with PCE inflation.