Online Appendix: The Role of Observed and Unobserved Heterogeneity in the Duration of Unemployment

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1 Data

This section discusses the data construction and various issues regarding the unemployment duration data in the Current Population Survey (CPS).

1.1 Data construction

The CPS microdata are used for the construction of numbers unemployed with duration less than 5 weeks, between 5 and 14 weeks, between 15 and 26 weeks, between 27 and 52 weeks and longer than 52 weeks by each individual characteristic. The microdata are publicly available at the NBER website (http://www.nber.org/data/cps_basic.html). Since the CPS is a probability sample, each individual is assigned a unique weight that is used to produce the aggregate data series.

The category for demographic characteristics that I consider is as follows: (1) Men/Age 16-24/High school graduates and less than high school, (2) Men/Age 16-24/ Some college,

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associate degree and college graduates, (3) Men/Age 25-44/ High school graduates and less than high school, (4) Men/Age 25-44/ Some college and associate degree (5) Men/Age 25-44/College graduates, (6) Men/Age 45 and over/High school graduates and less than high school, (7) Men/Age 45 and over/ Some college or higher, (8) Women/Age 16-24/High school graduates and less than high school, (9) Women/Age 16-24/Some college, associate degree and college graduates, (10) Women/Age 25-44/High school graduates and less than high school, (11) Women/ Age 25-44/Some college and associate degree (12) Women/Age 25-44/College graduates, (13) Women/Age 45 and over/High school graduates and less than high school, (14) Women/Age 45 and over/Some college, associate degree and college graduates. These demographic classification is consistently available throughout the sample period from 1976.

Besides, I consider five categories for reason for unemployment: (1) temporary layoff, (2) permanent separations (including other separation and temporary job ended), (3) job leavers, (4) re-entrants and, (5) new entrants to the labor force. Permanent separations include permanent job losers and persons who completed temporary jobs. The separate series, permanent job losers and persons who completed temporary jobs, are publicly available from 1994, but their sum (permanent separations) is available back to 1976.

In addition, I consider the industry and occupation information of unemployed workers. There have been several changes in the industry classification since 1976. I consider eight groups for industry: (1) agriculture, forestry, fishing, farming and mining, (2) construction, (3) manufacturing, (4) wholesale and retail trade, (5) transportation, utilities and information, (6) Finance, (7) Service, (8) Public administration. This level of disaggregation of industry is consistently available from 1976. I consider four categories for occupation: (1) routine-manual, (2) routine-congnitive, (3) nonroutine-manual, and (4) nonroutine-congitive following Jaimovich and Siu (2020). The four occupation groupings are consistently available from 1983.

1.2 The CPS redesign

It is well known that the CPS redesign in 1994 understates the size of individuals unemployed for 1 month and could have subsequently affected the size of longer duration groups after 1994. I do not take into account the possible effect of CPS redesign on the distribution of unemployment duration for two reasons. First, the goal of this paper is to explain changes in the observed distribution of unemployment duration and the observed share of long-term unemployment. Although the data are observed with possible measurement errors, correcting the measurement errors is beyond the scope of this paper. Second, the main interest of this paper is not about the relative importance of inflows and outflows in the unemployment dynamics, in which the correction of short-term unemployment for the CPS redesign could be important as mentioned by Shimer (2012).

Due mainly to the CPS redesign, type H inflows of new entrants to the labor force step down in 1994. The CPS redesign in 1994 broadened the range of individuals who are classified as reentrants to the labor force and narrowed the range of new entrants to the labor force. Before the change, only individuals who had worked full time were considered to be reentrants when they enter the labor force. Those who had a part-time job or had a job lasting less than two weeks were classified as new entrants. After 1994, individuals having any type of previous work experience and returning to the labor force are classified as reentrants to the labor force, and those having no previous work experience are classified as new entrants to the labor force. These changes raised the proportion of reentrants to the labor force but lowered that of new entrants in the unemployment pool. Polivka and Miller (1998) provide adjustment factors for the unemployment rates of the two groups that are methodologically consistent, but do not provide factors for their distribution of unemployment duration. Therefore, I do not adjust the duration distribution of new entrants and reentrants to the labor force after 1994. Even if I increase type H inflows with the adjustment factor, the inflows do not exhibit any particular trend.

1.3 Measurement issues in the duration data

Note that the data of unemployment duration are observed with reporting errors such as the digit preference as documented in Ahn and Hamilton (Forthcoming). The model considered in this paper is limited to control such measurement errors. In spite of this caveat, I use the data as they are, because the goal of this analysis is to understand the changing distribution of reported unemployment duration in the CPS. In addition, the duration data have been frequently used in the studies on unemployment dynamics (e.g., Shimer (2012)).

Alternatively, one might consider using the labor-flows data by the duration of unemployment. With such data, we can further investigate the role of unobserved heterogeneity in transitions from unemployment to employment and those from unemployment to nonparticipation. In principle, the data can be constructed from the CPS micro data. However, due to the frequent inconsistency between the reported duration of unemployment and the reported labor force status of previous and subsequent months, identifying the role of unobserved heterogeneity and GDD based on the labor-flows data is challenging. For example, there are quite a few individuals who report being unemployed for longer than six months in month $t-2$, out of the labor force in month $t-1$, and unemployed for longer than six months in month t. Another example is that workers report having a job in month $t-1$ but being unemployed for longer than six months in month t. These observations make the unemployment hazards implied by the labor flows inconsistent with those implied by the distribution of unemployment duration as discussed by Kudlyak and Lange (2017) and Ahn and Hamilton (Forthcoming). These measurement issues hamper one to credibly analyze how much unobserved worker heterogeneity contributes to changes in the distribution of unemployment duration. Acknowledging the limitation of this paper's approach, a more comprehensive model that identifies the labor flows of workers with unobserved types as well as the reporting errors will be ideal.

1.4 Transitions from temporary layoffs to permanent separation

There are unemployed individuals who indicate temporary layoffs as their reason for unemployment but change their answers to permanent separation in the subsequent months. The model does not take these transitions into account. According to the CPS micro data, about 10% of those who indicate temporary layoffs as their reason for unemployment change their answers to permanent job loss in the next month. In terms of the size, these individuals take less than 5% of permanent job losers. They are distributed relatively evenly across duration categories among workers on temporary layoffs (10% of those unemployed for 1, 2-3, and 4-6 months, and 14% of those unemployed for longer than 6 months). Treating these individuals as permanent job losers raises the inflows of permanent job losers, but does not materially change the distribution of unemployment duration among permanent job losers. Likewise, removing these individuals from workers on temporary layoffs does not meaningfully change the distribution of unemployment duration in the group, either. To examine how much these response changes would bias the result, I estimate the model with the data adjusted for the response switches. Among permanent job losers, both inflows become larger by 7%, but the fraction of type H and L workers in the inflows as well as their unemployment-continuation probabilities do not change significantly. Among workers on temporary layoffs, the fraction of type L workers is now a little over 10%, slightly lower than the original estimate, but the unemployment-continuation probabilities are similar to the estimates before the adjustment. It is mainly because the adjustment does not significantly change both groups' distribution of unemployment duration from which the fraction type H and L workers in the inflows as well as their unemployment-continuation probabilities are identified. To conclude, taking response switches into account does not change the key results. It rather strengthens the conclusion, because the fraction of permanent job losers out of total type L workers becomes larger.

2 Estimation algorithm

The nonlinear state space model used in this paper can be summarized as

$$
\begin{aligned}
x_{jt} &= Fx_{j,t-1} + \epsilon_{jt} \\
y_{jt} &= h(x_{jt}) + r_{jt}
\end{aligned}
$$

for $x_{jt} = (\xi'_{jt}, \xi'_{j,t-1}, ..., \xi'_{j,t-47})'$, $E(\epsilon_{jt}\epsilon'_{jt}) = \Sigma_j$ and $E(r_{jt}r'_{jt}) = R_j$. The nonlinear function $h(.)$ as well as elements of the variance matrices R_j and Σ_j depend on the parameter vector

$\theta_j = (\delta^E_{j1}, \delta^E_{j2}, \delta^E_{j3}, \delta^R_{j1}, \delta^R_{j2}, \delta^R_{j3}, R^1_j, R^{2.3}_j, R^{4.6}_j, R^{7.12}_j, R^{13.+}_j, \sigma^{Lw}_j, \sigma^{Hw}_j, \sigma^{Lx}_j, \sigma^{Hx}_j)'$. The extended Kalman filter is an iterative algorithm to calculate a forecast $\hat{x}_{j,t+1|t}$ of the state vector conditioned on knowledge of θ_j and observation of $Y_{jt} = (y'_{jt}, y'_{j,t-1}, ..., y'_{j1})'$ with $P_{j,t+1|t}$ the mean squared error of this forecast. With these we can approximate the distribution of y_{jt} conditioned on $Y_{j,t-1}$ as $N(h(\hat{x}_{jt|t-1}), H'_{jt}P_{jt|t-1}H_{jt} + R_j)$ for $H_{jt} = \partial h(x_{jt})/\partial x'_{jt}|_{x_{jt}=\hat{x}_{jt|t-1}}$ from which the likelihood function associated with that θ_j can be calculated and maximized numerically. The forecast of the state vector can be updated using

$$\hat{x}_{j,t+1|t} = F\hat{x}_{jt|t-1} + FK_{jt}(y_{jt} - h(\hat{x}_{jt|t-1}))$$

$$K_{jt} = P_{jt|t-1}H_{jt}(H'_{jt}P_{jt|t-1}H_{jt} + R_j)^{-1}$$

$$P_{j,t+1|t} = F(P_{jt|t-1} - K_{jt}H'_{jt}P_{jt|t-1})F' + Q_j.$$

A similar recursion can be used to form an inference about x_{jt} using the full sample of available data, $\hat{x}_{jt|T} = E(x_{jt}|y_{jT}, ..., y_{j1})$.

For the initial value for the extended Kalman filter, we calculated the values that would be implied if pre-sample values had been realizations from an initial steady state, estimating the (4×1) vector $\bar{\xi}_{j0}$ from the average values for $\bar{U}^1_j, \bar{U}^{2.3}_j, \bar{U}^{4.6}_j, \bar{U}^{7.12}_j$ and $\bar{U}^{13.+}_j$ over January 1976 - December 1979 using the method described in section 1.1 of Ahn and Hamilton

(2020) given the GDD parameter estimated from the average values for $\bar{U}_j^1, \bar{U}_j^{2.3}, \bar{U}_j^{4.6}, \bar{U}_j^{7.12}$ and $\bar{U}_j^{13.+}$ over the sample period. Our initial guess was then $\hat{x}_{j1|0} = \iota_{48} \otimes \bar{\xi}_{j0}$ where ι_{48} denotes a (48×1) vector of ones. Diagonal elements of $P_{j1|0}$ determine how much the presample values of ξ_{jl} are allowed to differ from this initial guess $\hat{\xi}_{jl|0}$. For this we set $E(\xi_{jl} - \hat{\xi}_{jl|0})(\xi_{jl} - \hat{\xi}_{jl|0})' = c_0 I_4 + (1-l)c_1 I_4$ with $c_1 = 0.1$ and $c_0 = 1$ or 10.[1] The value for c_0 is quite large relative to the range of $\xi_{jt|T}$ over the complete observed sample, ensuring that the particular value we specified for $\hat{x}_{j1|0}$ has little influence. For $k < l$ we specify the covariance[2] $E(\xi_{jl} - \bar{\xi}_{j0})(\xi_{jk} - \bar{\xi}_{j0})' = E(\xi_{jk} - \bar{\xi}_{j0})(\xi_{jl} - \bar{\xi}_{j0})'$. The small value for c_1 forces presample ξ_{jl} to be close to ξ_{jk} when l is close to k, again consistent with the observed month-to-month variation in $\hat{\xi}_{jt|T}$.

We calculated standard errors for the estimate $\hat{\theta}$ as in equation (3.13) in Hamilton (1994):

$$E(\hat{\theta} - \theta)(\hat{\theta} - \theta)' \simeq V = K_1^{-1} K_2 K_1^{-1}$$

$$K_1 = \left. \frac{\partial \ell(\theta)}{\partial \theta \partial \theta'} \right|_{\theta = \hat{\theta}}$$

$$K_2 =_{t=1}^{T} \left\{ \left[\left. \frac{\partial \ln f(y_t | Y_{t-1}; \theta)}{\partial \theta} \right|_{\theta=\hat{\theta}} \right] \left[\left. \frac{\partial \ln f(y_t | Y_{t-1}; \theta)}{\partial \theta} \right|_{\theta=\hat{\theta}} \right]' \right\}.$$

The standard errors used for the smoothed estimates incorporate both filter and parameter uncertainty. The matrix $P_{t|T}$ summarizes uncertainty we would have about x_t even if we knew the true value of the parameters in θ. Given that we also have to estimate θ, the true uncertainty is greater than that represented by $P_{t|T}$. Following Ansley and Kohn (1986)

[1] I use 10 for temporary layoffs and permanent separation, and 1 for groups with other reasons for unemployment.

[2] In other words,

$$P_{1|0} = \begin{bmatrix} c_0 I_4 & c_0 I_4 & c_0 I_4 & \cdots & c_0 I_4 \\ c_0 I_4 & c_0 I_4 + c_1 I_4 & c_0 I_4 + c_1 I_4 & \cdots & c_0 I_4 + c_1 I_4 \\ c_0 I_4 & c_0 I_4 + c_1 I_4 & c_0 I_4 + 2c_1 I_4 & \cdots & c_0 I_4 + 2c_1 I_4 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ c_0 I_4 & c_0 I_4 + c_1 I_4 & c_0 I_4 + 2c_1 I_4 & \cdots & c_0 I_4 + 47 c_1 I_4 \end{bmatrix}.$$

we calculate the total variance as

$$P_{t|T}\Big|_{\theta=\hat{\theta}} + Z_t V Z_t'$$

$$\underset{(4\times 12)}{Z_t} = \left.\frac{\partial \hat{x}_{t|T}}{\partial \theta'}\right|_{\theta=\hat{\theta}}.$$

The values of $\{Z_t\}_{t=1}^T$ can be found by numerical differentiation, e.g., replace $\hat{\theta}$ with $\hat{\theta}+\delta e_i$ for δ being a small number and e_i the ith column of I_{15} and then redo the iteration to calculate $\hat{x}_{t|T}(\hat{\theta}+\delta e_i)$. The ith column of Z_t is then $\delta^{-1}[\hat{x}_{t|T}(\hat{\theta}+\delta e_i) - \hat{x}_{t|T}|(\hat{\theta})]$.

3 Normalized inflows by reason for unemployment

To examine how much changes in the population affect the estimated inflows by reason for unemployment, I report the inflows divided by the civilian noninstitutional population in Figure 1. The variation in the inflows normalized by population is not different from that in original estimates.[3]

4 Other empirical results

This section documents the estimates by demographic characteristic, which were contained in the previous version of this paper. The sample period is 1976-2013.

The smoothed estimates for the continuation probabilities of type H and L individuals within each group j are plotted in Figure 2. There are three distinct features. First, substantial unobserved heterogeneity exists in the continuation probabilities within every group in normal and recessionary periods. Average type L continuation probabilities are between 0.74 and 0.95 as reported in Tables 2 and 3. Average type H continuation probabilities are between 0.34 and 0.48. Second, the continuation probabilities of type H and L workers go up during recessions. Notably, the continuation probabilities of both types reach their highest

[3]This analysis is suggested by a referee.

levels during the Great Recession and remain elevated three years into the recovery in most of the groups. In addition, despite sharing the common cyclicality, the dynamics of continuation probabilities are different between types and across groups. For example, among men aged 25 to 44 with a high school education or less, type H probability recovers close to the pre-recession level, but their type L probability stays elevated three years after the Great Recession is over. Meanwhile, both type H and L continuation probabilities of women in the same age and education group remain elevated during the post-recession period.

Figure 3 plots smoothed estimates for the inflows of type H and L individuals in each group. As documented in Tables 2 and 3, type L individuals make up a small portion of inflows and represent, on average, 4 to 36 percent of the newly unemployed across all groups. Despite the small share of inflows, type L newly unemployed individuals are an important factor in determining the size of long-term unemployment, as they have higher unemployment continuation probabilities. In addition, type L inflows exhibit stronger counter-cyclicality than type H inflows do. Therefore, the share of type L workers among the newly unemployed of each group goes up during recessions. The Great Recession is distinguished from previous recessions in that the inflows of type L workers, as well as their share among newly unemployed individuals, reach their highest levels in most of the groups.

Looking at the individual groups in more detail, the share and the cyclical fluctuations of type L individuals in the inflows differ substantially by demographic characteristic. The type L share of the inflows is higher among older and more highly educated individuals. Particularly, type L inflows show stronger counter-cyclicality among workers aged 25 to 44 who have some college education or an associate degree than other groups. Meanwhile, the type L share is lower and type L inflows exhibit more subdued counter-cyclical fluctuations among younger and less-educated workers (aged 16 to 24 with a high school diploma or less education). However, the average numbers of type L newly unemployed people in both groups are not so much different, as the number of newly unemployed individuals aged 16 to 24 with lower education is much larger in the first place.

It is notable that both the type L share of inflows and their continuation probabilities rise dramatically during the Great Recession in most of the categories. This explains why we observe the sharp increase in the average duration of unemployment and the share of long-term unemployment in every corner of the economy, as discussed in previous studies (Hall (2014); Kroft et al. (2016); and Krueger et al. (2014)). Unlike the conclusions of Kroft et al. (2016) and Krueger et al. (2014) that compositional variations in the unemployment of worker heterogeneity played a limited role in the rise of long-term unemployment during the Great Recession, the empirical results suggest that the changes in the composition of type L workers in the disaggregate unemployment was crucial to the rise of long-term unemployment during the Great Recession and its recovery phase.

Unobserved heterogeneity is also important in the low-frequency dynamics of unemployment. Abraham and Shimer (2001) claim that the population aging and the increased job-attachment of women explain the upward trend in average duration of unemployment accompanied by the secular decrease in the incidence of unemployment. The empirical results of this paper suggest that these secular changes are also closely related to unobserved heterogeneity. Among workers aged 16 to 24 who have a high-school education or less, the type H inflows decrease throughout the sample period, while the type L inflows remain around the same level. Meanwhile, both type H and L newly unemployed individuals aged 45 and over show upward trends. This suggests that the aging of the population is associated with the low-frequency dynamics of unemployment mainly through the secular decrease in the number of newly unemployed individuals who are type H among young and less-educated workers. In addition, it is notable that there is an upward trend in the type H continuation probabilities among women aged 16 to 44 whose education level is lower than college graduation. This might reflect that type H workers of this group are likely to be those female workers whose labor force attachment has increased over time. They might have become to stay unemployed longer to look for a job instead of leaving the labor force to, for instance, take care of their children, which also has contributed to the rising trend in the average duration of unemployment. In sum, the secular changes in the type H inflows of young and less-educated workers and the type H continuation probabilities of women aged lower than 45 who are not college graduates suggest that structural development in the labor market, such as demographic changes and increased labor force attachment of women, have asymmetric effects on workers with unobserved types, and this is an important source of the upward trend in the average duration of unemployment as well as the downward trend in the inflows to unemployment in the U.S. labor market.

The estimated continuation probabilities and inflows of type H and L workers by industry are documented in Figures 4 and 5. Those estimates by occupation are shown in Figure 6 and 7. The composition of type L inflows by detailed demographic characteristics is documented in Figure 8, and that by other observable characteristic is summarized in Figure 9.

5 Variance decomposition

In this section, I introduce the variance decomposition for the dynamic accounting identity developed by Ahn and Hamilton (2020) to the estimates of group j. Similarly to the variance decomposition of linear VAR, this method measures how much each shock contributes to the mean-squared error (MSE) of an s-period-ahead forecast of a magnitude of interest. As a byproduct, we can also identify which observable characteristic is most closely associated with type L attribute. Uncertainty surrounding the type L inflow is the most crucial factor accounting for the variance of unemployment among those whose observable characteristic is most closely associated with type L, while type H inflow are the main component explaining the variance of other groups.

The state space model for the dynamic accounting identity of unemployment can be used to forecast the unemployment of group j s-period-ahead at t. Let $y_{j,t+s}$ be the the vector $[U^{1}_{j,t+s}, U^{2.3}_{j,t+s}, U^{4.6}_{j,t+s}, U^{7.12}_{j,t+s}, U^{13.+}_{j,t+s}]'$, and $\hat{y}_{j,t+s|t}$ be the forecast of $y_{j,t+s}$ made at t. If we linearize the measurement equation, the forecast error can be written as

$$y_{j,t+s} - \hat{y}_{j,t+s|t} = \sum_{l=1}^{s} [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})]\varepsilon_{j,t+l},$$

where $\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})$ is a (5×4) matrix of coefficients that are functions of $\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s}$. The MSE matrix that captures the s-period-ahead forecast of $y_{j,t+s}$ is

$$\begin{aligned} & E(y_{j,t+s} - \hat{y}_{j,t+s|t})(y_{j,t+s} - \hat{y}_{j,t+s|t})' \\ = & \sum_{l=1}^{s} [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})]\Sigma_j [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})]' \\ = & \sum_{l=1}^{s} \sum_{m=1}^{4} \Sigma_j^m [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})e_m][\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})e_m]' \end{aligned}$$

for e_m, column m of the (4×4) identity matrix, and Σ_j^m, the row m, column m element of Σ_j. Thus, the contribution of innovations of type L workers' inflows (the first element of $\varepsilon_{jt} = (\varepsilon_{jt}^{Lw}, \varepsilon_{jt}^{Hw}, \varepsilon_{jt}^{Lx}, \varepsilon_{jt}^{Hx})')$ to the MSE of the s-period-ahead linear forecast error of group j's unemployment, $\iota_5' y_{jt}$, is given by

$$\iota_5' \sum_{l=1}^{s} \Sigma_j^1 [\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})e_1][\Psi_{sl}(\xi_{jt}, \xi_{j,t-1}, ..., \xi_{j,t-47+s})e_1]' \iota_5 \qquad (1)$$

where ι_5 denotes a (5×1) vector of ones. Equation (1) is evaluated at the smoothed inferences $\{\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T}\}$, and then takes the average value across all dates t in the sample. This gives us an estimate of the contribution of the type L workers' inflows to unemployment fluctuations of group j over a horizon of s months:

$$q_{s,1}^j = T^{-1} \sum_{t=1}^{T} \iota_5' \sum_{l=1}^{s} \Sigma_j^1 [\Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T})e_1][\Psi_{sl}(\hat{\xi}_{jt|T}, \hat{\xi}_{j,t-1|T}, ..., \hat{\xi}_{j,t-47+s|T})e_1]' \iota_5.$$

Consequently, the ratio of the first factor's contribution to the MSE of predicting unemployment of group j at horizon s, $v^j_{s,1}$ is measured from

$$v^j_{s,1} = q^j_{s,1} / (\sum_{m=1}^{4} q^j_{s,m}).^4$$

Finally, the ratio of the ith factor's contribution of the MSE of predicting aggregate unemployment at horizon s is calculated from

$$v_{s,i} = \frac{\sum\limits_{j=1}^{J} q^j_{s,i}}{\sum\limits_{j=1}^{J}\sum\limits_{m=1}^{4} q^j_{s,m}} = \sum_{j=1}^{J} \left(\frac{\sum\limits_{m=1}^{4} q^j_{s,m}}{\sum\limits_{j=1}^{J}\sum\limits_{m=1}^{4} q^j_{s,m}} \right) v^j_{s,i} \tag{2}$$

Figures 9-12 report the variance decomposition. Figure 9 shows the contribution of each factor to the MSE in predicting unemployment as a function of the forecasting horizon by gender, age, and education. How much uncertainty about future inflows and continuation probabilities of type H and L workers matters in forecasting unemployment s-period ahead differs significantly based on the observable characteristics of unemployed individuals. For most demographic groups, type L inflows are found to be the most important factor in cyclical unemployment dynamics. In particular, type L inflows are the major driver of the cyclical variation in unemployment among men whose education level is higher than high school graduation and women younger than 45. Meanwhile, type L continuation probabilities are the crucial factor among women aged 45 and over, and men aged 45 and over who are high-school graduates or have a lower level of education. In addition, type H inflows and continuation probabilities explain most of unemployment fluctuations throughout different frequencies in the group of women aged 16-24.

Figure 10 show the variance decomposition by reason for unemployment. The observed category that exhibits the largest difference is reason for unemployment. Type L inflow is the

[4] The contribution of GDD to the variance of unemployment is not separately considered for two reasons. First, the change in GDD is assumed to be deterministic in the model. Second, the consequence of changes in GDD to the unemployment dynamics in the disaggregate level is negligible as shown in the historical decompositions demonstrated in the next section.

major driver of the unemployment dynamics of permanent job losers, while type H workers are crucial in the unemployment dynamics of workers on temporary layoffs, job leavers, and new entrants to the labor force. This finding again confirms the finding that type L attribute is closely associated with permanent job loss.

Looking at this in more detail, type L inflows are the most important source of uncertainty in forecasting the unemployment of permanent job losers. When a forecaster predicts the unemployment of this group one- to- two- years ahead, which is business-cycle frequency in a spectral decomposition, more than 60 percent of MSE is associated with the uncertainty of type L inflows.[5] Meanwhile, the uncertainty of type L continuation probability is the most critical factor in predicting the unemployment of reentrants to the labor force for all forecasting horizons. Type L inflows and continuation probability together account for more than 80 percent of the MSE associated with two-year-ahead forecasts of unemployment of permanent job losers and reentrants to the labor force.

Meanwhile, type H inflows are the most important factor in predicting unemployment for workers on temporary layoffs, job leavers, and new entrants to the labor force throughout the forecasting horizons, while the type L contribution is small. Uncertainty about type H inflows explains more than 70 percent of the MSE in predicting unemployment of these groups three months ahead, and more than 50 percent of the MSE associated with two-year-ahead forecasts.[6] Type H inflows and continuation probability together account for between 60 and 70 percent of the MSE in predicting the unemployment of these groups in the business-cycle frequency.

It is notable that among workers who experienced involuntary separation, the unemployment dynamics of workers on temporary layoff are quite different from those of permanent

[5]The error of forecasting unemployment between one- and- two- years ahead comes critically from the uncertainty around when the next recession will begin or the current recession ends. The MSE associated with two-year-ahead forecasts is closely related to what some researchers refer to as the "business cycle frequency."

[6]The importance of type H inflows in the unemployment dynamics of job leavers suggests that type H inflows in this group could be associated with churning of which the crucial component is quits (Lazear and Spletzer (2012)).

job losers. This result implies that whether a job loser gets recalled or not could be an important source of heterogeneity in the unemployment dynamics, as claimed by Fujita and Moscarini (2017). In addition, there is a substantial difference between those who enter the labor force for the first time and those who left the labor force and come back. Reentrants to the labor force could be those who had difficulty getting a job, possibly because of permanent job loss, and then left the labor force out of discouragement. Type L continuation probabilities are important in their dynamics, since they could have inherited type L characteristics associated with the circumstance of job loss before they left the labor force.

As shown by figures 11 and 12, the difference across groups with observed characteristics is not as prominent when we disaggregate the data by industry and occupation.

6 Distribution of completed duration spells

In this section, I analyze how much of the differences across newly unemployed individuals in any given month in how long it will take before they complete their unemployment spell can be explained on the basis of their observed characteristics and unobserved types. Since we have the full information on the number of newly unemployed individuals with the two unobserved types in group of observable characteristic j and their paths of unemployment continuation probabilities over time, we can use simulations to recover the distribution of completed-duration spells of those who become newly unemployed in month t, and compute how much observed and unobserved heterogeneity accounts for the variance of distribution.

Let n_{mt} be the completed duration spell of individual who becomes unemployed in month t. If we let $Var(n_{mt})$ be the unconditional variance of completed-duration spells of individual m who becomes newly unemployed in month t, $Var(n_{mt})$ is decomposed into the following:

$$Var(n_{mt}) = \underbrace{Var[E(n_{mt}|O_m = j)]}_{\substack{\text{heterogeneity} \\ \textit{between} \\ \text{observed characteristics}}} + \underbrace{E[Var(n_{mt}|O_m = j)]}_{\substack{\text{heterogeneity} \\ \textit{within} \\ \text{observed characteristic.}}}. \tag{3}$$

The first term in the right-hand side is the dispersion explained by the difference among observed groups, and the second term captures the average dispersion within each group. The $Var(n_{mt}|O_m = j)$ can be further decomposed into

$$Var(n_{mt}|O_m = j) = \underbrace{Var[E(n_{mt}|O_m = j, Q_m = s)|O_m = j]}_{\substack{\text{heterogeneity} \\ \textit{between} \\ \text{unobserved types}}} + \underbrace{E[Var(n_{mt}|O_m = j, Q_m = s)|O_m = j]}_{\substack{\text{heterogeneity} \\ \textit{within} \\ \text{unobserved type}}}. \tag{4}$$

The first term in equation (4) captures the dispersion of average completed-duration spells explained by the difference between two unobserved types, and the second term is the average dispersion within each type.

By plugging equation (4) into equation (3), we have the full decomposition of the distribution of completed duration spells as follows:

$$\begin{aligned} Var(n_{mt}) \quad = \quad & \underbrace{Var[E(n_{mt}|O_m = j)]}_{\substack{\text{heterogeneity} \\ \textit{between} \\ \text{observed characteristics}}} + \underbrace{E[Var\{E(n_{mt}|O_m = j, Q_m = s)|O_m = j\}]}_{\substack{\text{heterogeneity} \\ \textit{between} \\ \text{unobserved types}}} \\ & + \underbrace{E[E\{Var(n_{mt}|O_m = j, Q_m = s)|O_m = j\}]}_{\text{idiosyncrasy}}. \end{aligned} \tag{5}$$

The first component in equation (5) is the variance that is accounted for by the difference in completed duration spells across individuals with different observed characteristics. The second term is the amount explained by differences in the average completed-duration spells of type H and L workers. The last term is the remaining MSE, resulting from idiosyncratic differences across individuals that are not captured by either observed characteristics or unobserved types.

Figure 13 displays the result of this decomposition for every month between 1980:M01 and 2013:M12. Whether an individual is type H or L explains around 40 percent of variance of completed duration spells on average. By contrast, observed characteristics of unemployed individuals only account for less than 10 percent on average. The contribution of unobserved types to the cross-sectional dispersion of completed-duration spells increases to above 50 percent in the year 2011, when the long-term unemployment reached the post-WWII era's record-high level. The overall result suggests that differences in observable characteristics of unemployed individuals play little role in accounting for the cross-sectional dispersion of completed-duration spells, and that the two unobserved types that are crucial in the dynamics of disaggregate unemployment are much more important in the distribution of completed unemployment duration.

7 Implication to the natural rate of unemployment

The empirical results suggest that unobserved worker types are important in accounting for changes in the distribution of unemployment duration. What is the policy implication? Could expansionary fiscal and monetary policy have helped to lower the long-term unemployment crisis during the Great Recession?

The answer to this question hinges on whether stronger labor demand can lower the unemployment of type L workers who tend to stay unemployed longer. An expansionary policy that can raise aggregate demand might help these workers return to work. Meanwhile, strong labor demand and an expansionary policy may not be able to alter workers' characteristics and do not reverse structural evolution in the labor market such as skill-biased technological changes. This implies that type L unemployment might be associated with structural unemployment. In this case, an expansionary policy might have limitations in bringing down the long-term unemployment, as the share of type L unemployment stays at an elevated level.

To examine which hypothesis is more likely, I insert $\frac{U_t^L}{N_t}$, the share within the labor force of total type L unemployment—the sum of type L unemployment of each observed group—to a Phillips curve specification similar to Coibion and Gorodnichenko (2015), as follows,

$$\pi_t - \pi_t^* = c + \sum_{j=1}^{8} \beta_j(\pi_{t-j} - \pi_{t-j}^*) + \delta_1(u_t - u_t^*) + \delta_2 \frac{U_t^L}{N_t} + e_t. \tag{6}$$

In this specification, the gap between CPI inflation (π_t,) and the 12-month-ahead inflation expectations from the Michigan survey (π_t^*) is explained by the gap between the unemployment rate (u_t) and the CBO estimate of the natural rate of unemployment (hereafter, NRU, u_t^*), the fraction of type L unemployment within the labor force ($\frac{U_t^L}{N_t}$), along with the lags of the inflation gap. The notation e_t is the residual. If the type L unemployment rate is more likely to be structural unemployment, δ_2 will be positive with statistical significance.[7]

The first column of Table 7 documents the coefficient estimates of equation (6). The coefficient δ_2 is positive, but δ_1 is negative. In addition, both are statistically significant supporting the hypothesis that the type L unemployment rate has information about structural unemployment not well captured by the CBO's estimate of NRU. I replace the Michigan survey's inflation expectation with the four-quarter moving average of inflation up to t (in column 2) following Coibion and Gorodnichenko (2015), and use the personal consumption expenditure price index (PCEPI) as an alternative measure of π_t (in columns 3 and 4), which produces results qualitatively the same as the result of the baseline specification (in column 1). In addition, I replace π_t with the wage inflation, including the four-quarter growth rates of average hourly earnings and average weekly earnings. As the expectation of wage inflation is not available, I use the four-quarter moving average of each wage inflation measure as a proxy. The model with wage inflation also yields results similar to those of the model with CPI and PCEPI inflation.[8]

[7] If it captures cyclical unemployment more, then δ_1 and δ_2 will be negative, but imprecisely estimated due to multicolinearity between $u_t - u_t^*$ and $\frac{U_t^L}{N_t}$ (Kiley (2015)). If multicolinearity exists between two variables, and the two variables enter the equation jointly, the coefficients will not be statistically significant but the joint hypothesis that these two coefficients are zero will be rejected. Meanwhile, both coefficients will be statistically significant and different from zero, if each variable enters the equation separately.

[8] I also used compensation per hour as an alternative wage measure. Though δ_2 is not statistically significant, it is still positive.

I also replace $\frac{U_t^L}{N_t}$ with a fraction of permanently separated type L unemployment out of the labor force, $\frac{U_{PS,t}^L}{N_t}$.

$$\pi_t - \pi_t^* = c + \sum_{j=1}^{8} \beta_j(\pi_{t-j} - \pi_{t-j}^*) + \delta_1(u_t - u_t^*) + \delta_2 \frac{U_{PS,t}^L}{N_t} + e_t \tag{7}$$

As shown in Table 8, the coefficient on $\frac{U_{PS,t}^L}{N_t}$ is statistically significant and is larger than that on $\frac{U_t^L}{N_t}$ in equation (6) across specifications with different measures of inflation and inflation expectations.[9] This result suggests that type L permanent job losers likely represent structural unemployment, and thus a demand-boosting policy might have limitations in mitigating the joblessness of these workers.

[9]Table 7 is analogous to Table 8.

Figures and Tables

Normalized inflows by reason for unemployment

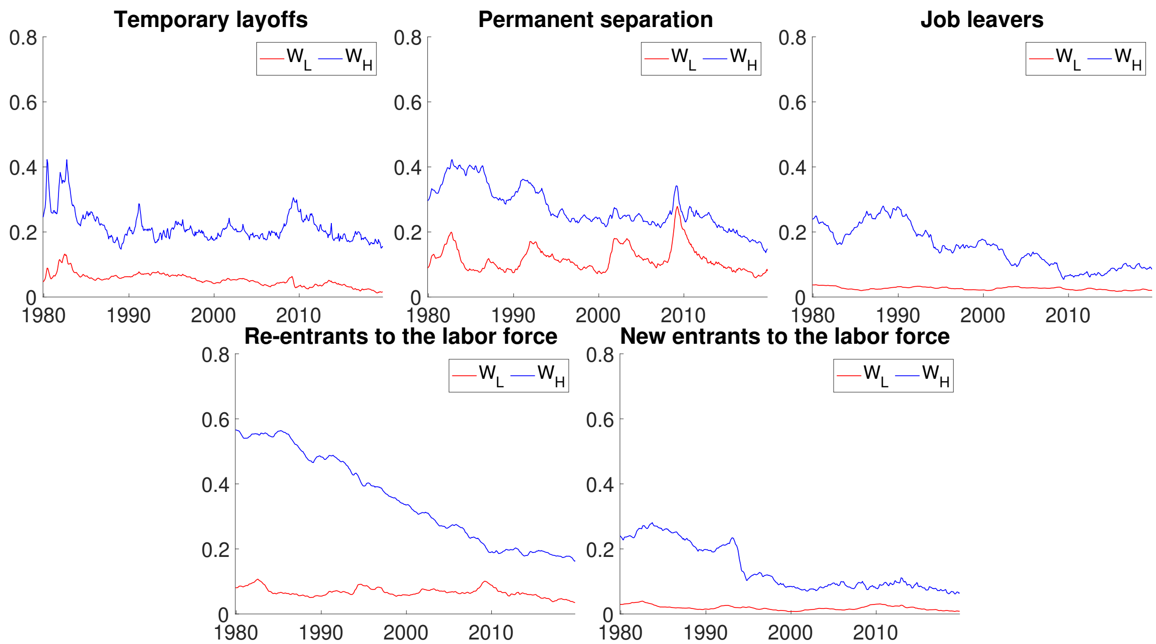

Figure 1: Fraction of inflows of each group and each type out of the civilian non-institutional population (%)

Gender/age/education

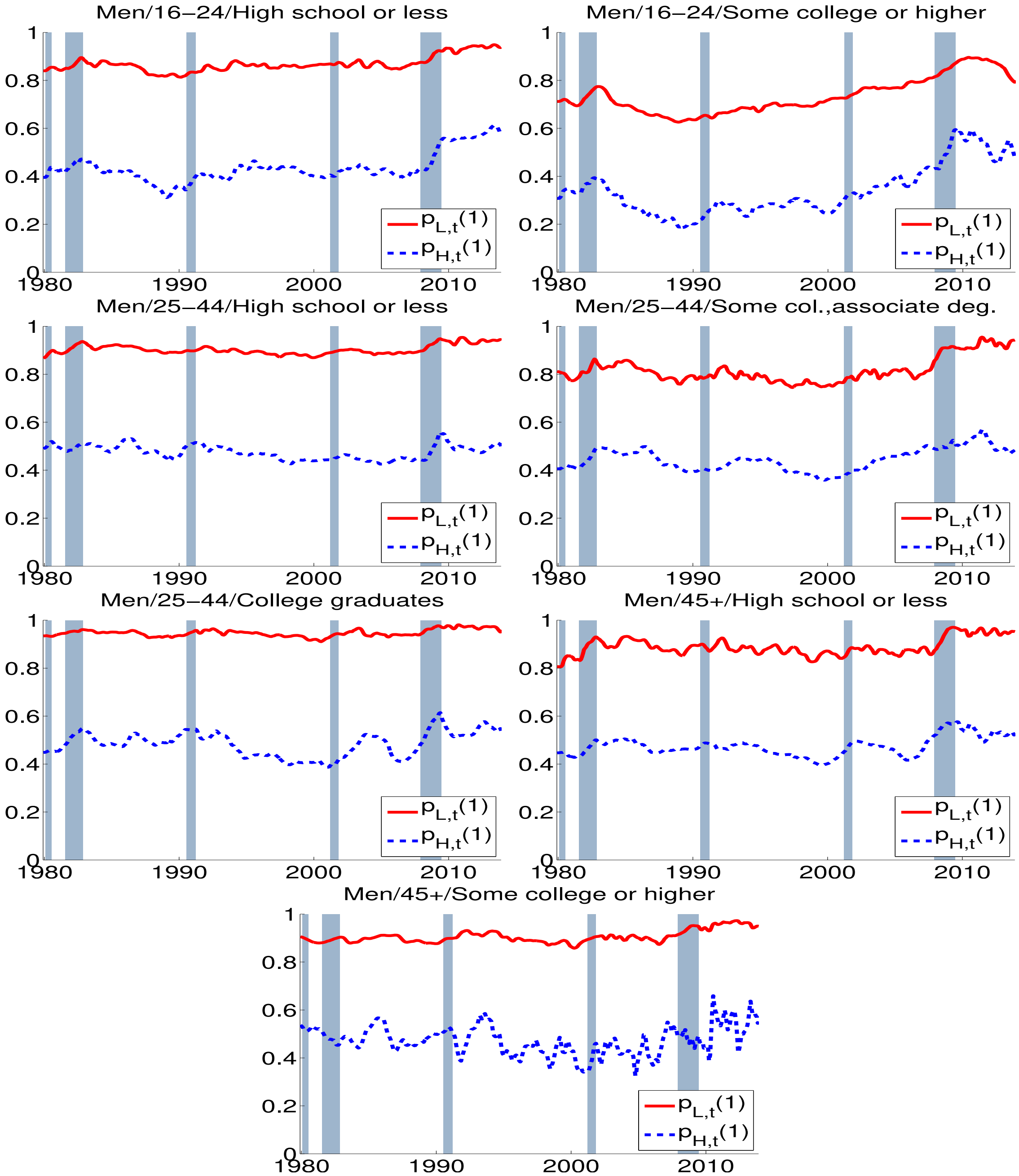

Figure 2. Probability that a newly unemployed worker of each type will still be unemployed the following month ($\widehat{p}^{z}_{jt|T}$ for $z = L, H$) by gender, age and education. Shaded areas denote NBER recessions.

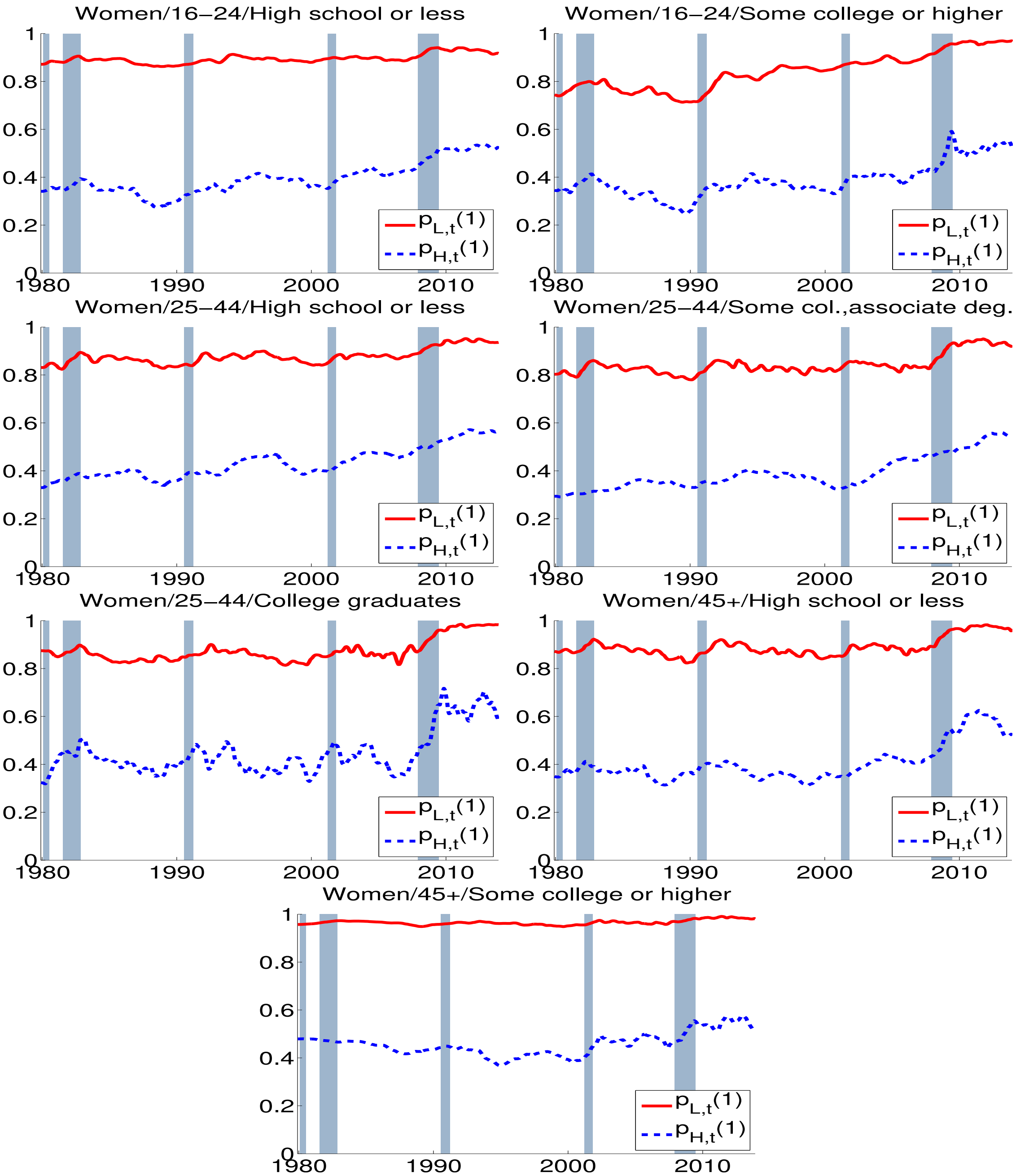

Figure 2. Probability that a newly unemployed worker of each type will still be unemployed the following month ($\widehat{p}^{z}_{jt|T}$ for $z = L, H$) by gender, age and education (continued). Shaded areas denote NBER recessions.

Gender-age-education

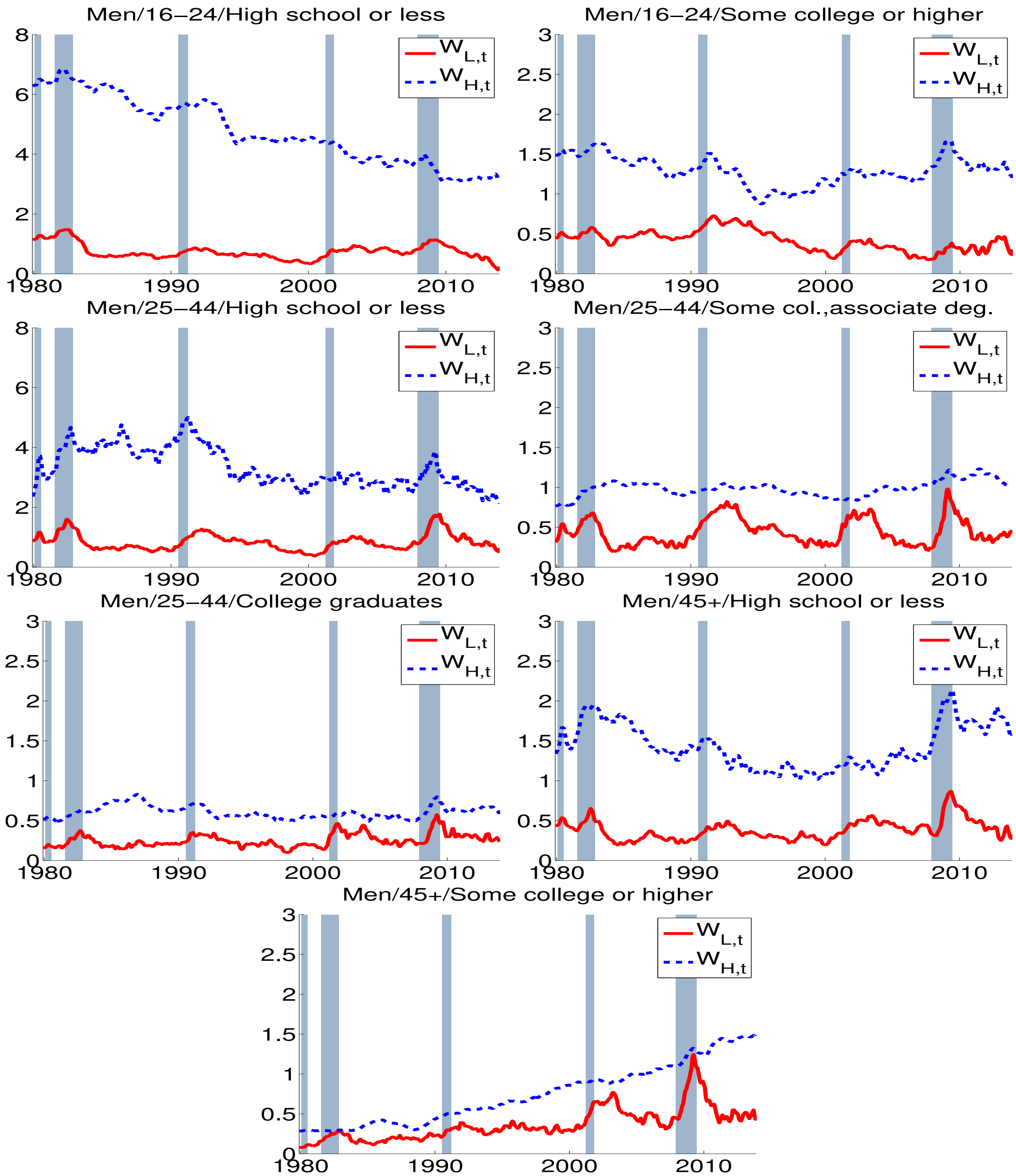

Figure 3. Number of newly unemployed workers of each type ($\widehat{w}^z_{jt|T}$ for $z = L,H$) by gender, age and education. Units are in hundred thousands. Shaded areas denote NBER recessions.

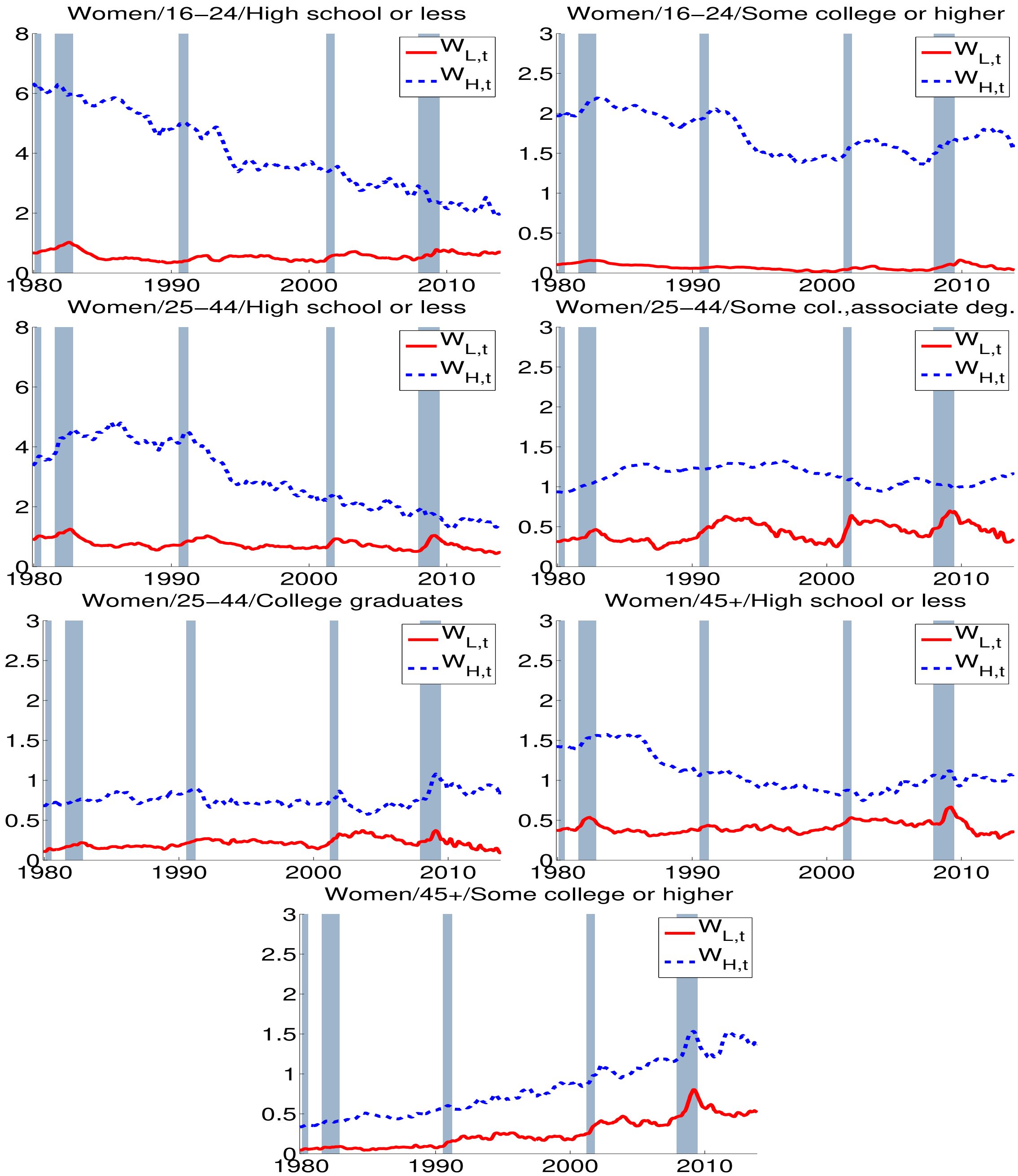

Figure 3. Number of newly unemployed workers of each type ($\widehat{w}^z_{jt|T}$ for $z = L,H$) by gender, age and education (continued). Units are in hundred thousands. Shaded areas denote NBER recessions.

Industry

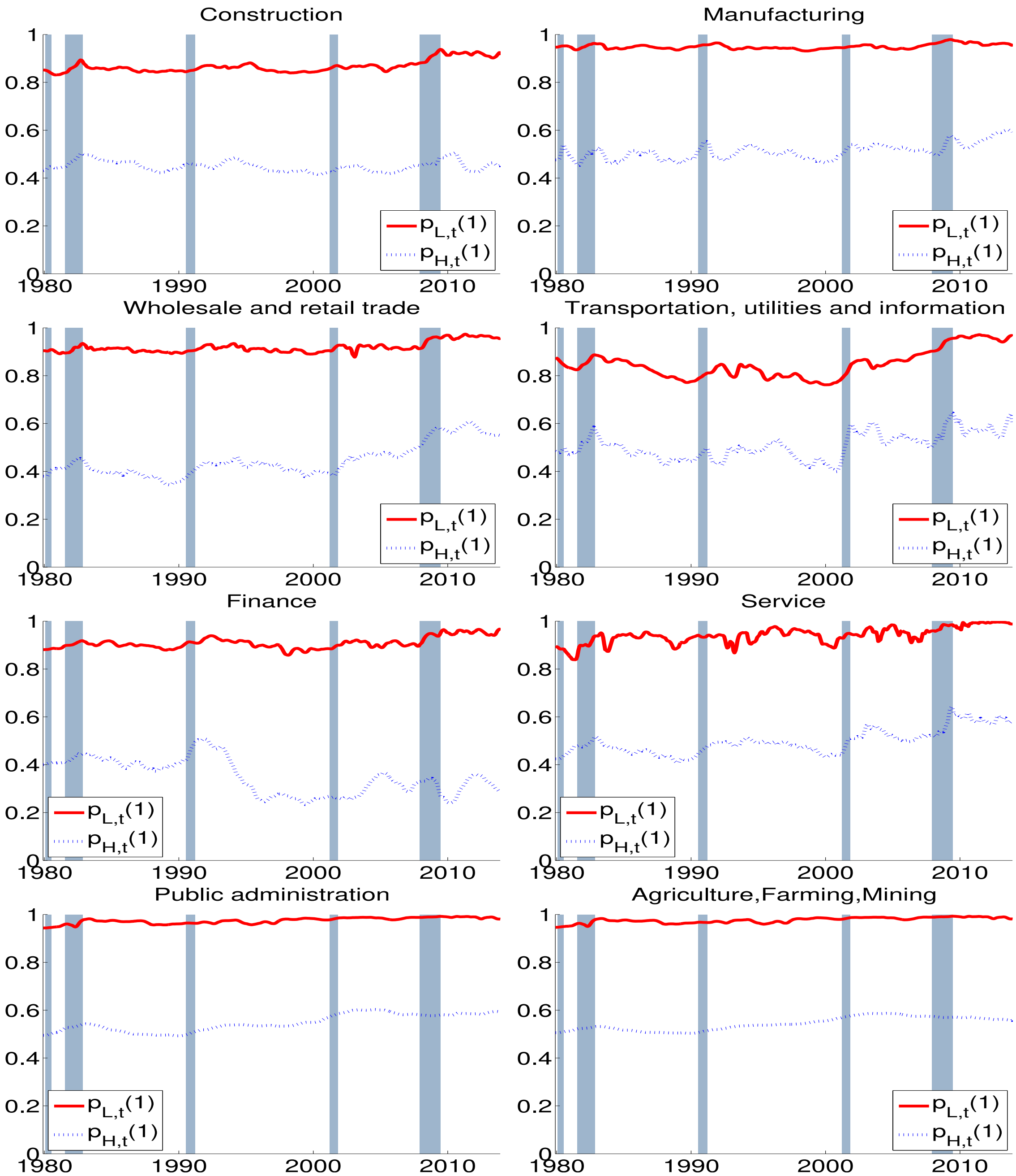

Figure 4. Probability that a newly unemployed worker of each type will still be unemployed the following month ($\widehat{p}^{z}_{jt|T}$ for $z = L, H$) by industry. Shaded areas denote NBER recessions.

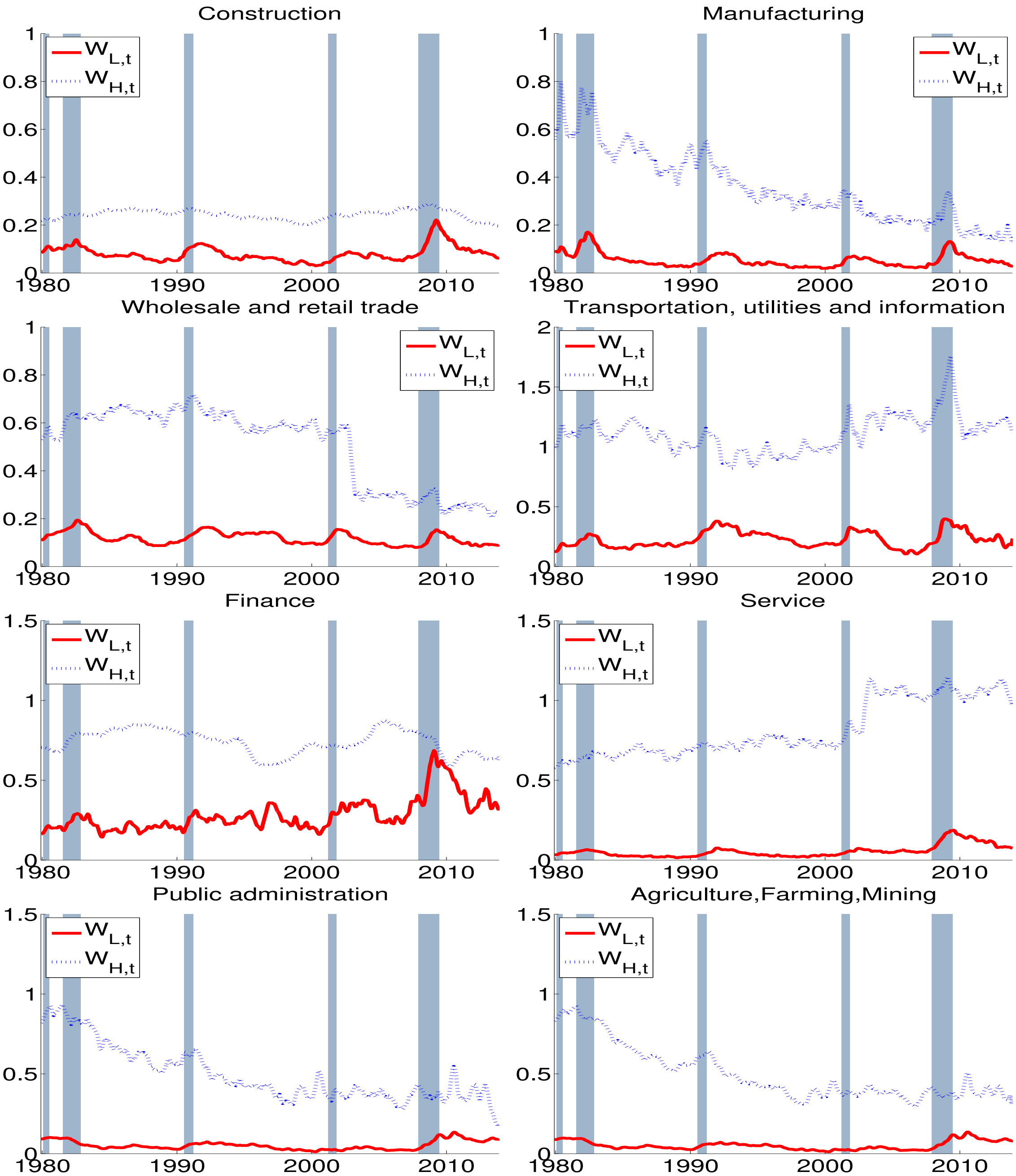

Figure 5. Number of newly unemployed workers of each type ($\widehat{w}^z_{jt|T}$ for $z = L,H$) by industry. Units are in hundred thousands. Shaded areas denote NBER recessions.

Occupation

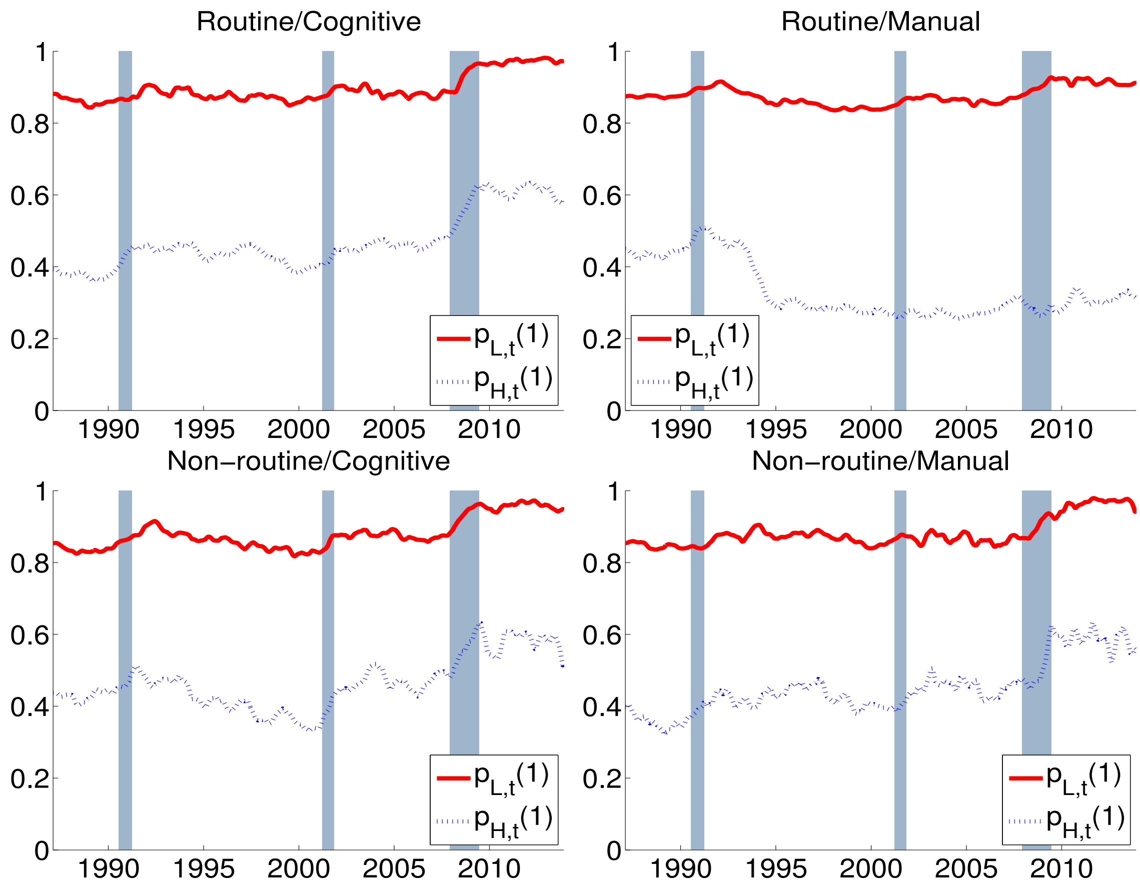

Figure 6. Probability that a newly unemployed worker of each type will still be unemployed the following month ($\widehat{p}^{z}_{jt|T}$ for $z = L, H$) by occupation. Shaded areas denote NBER recessions.

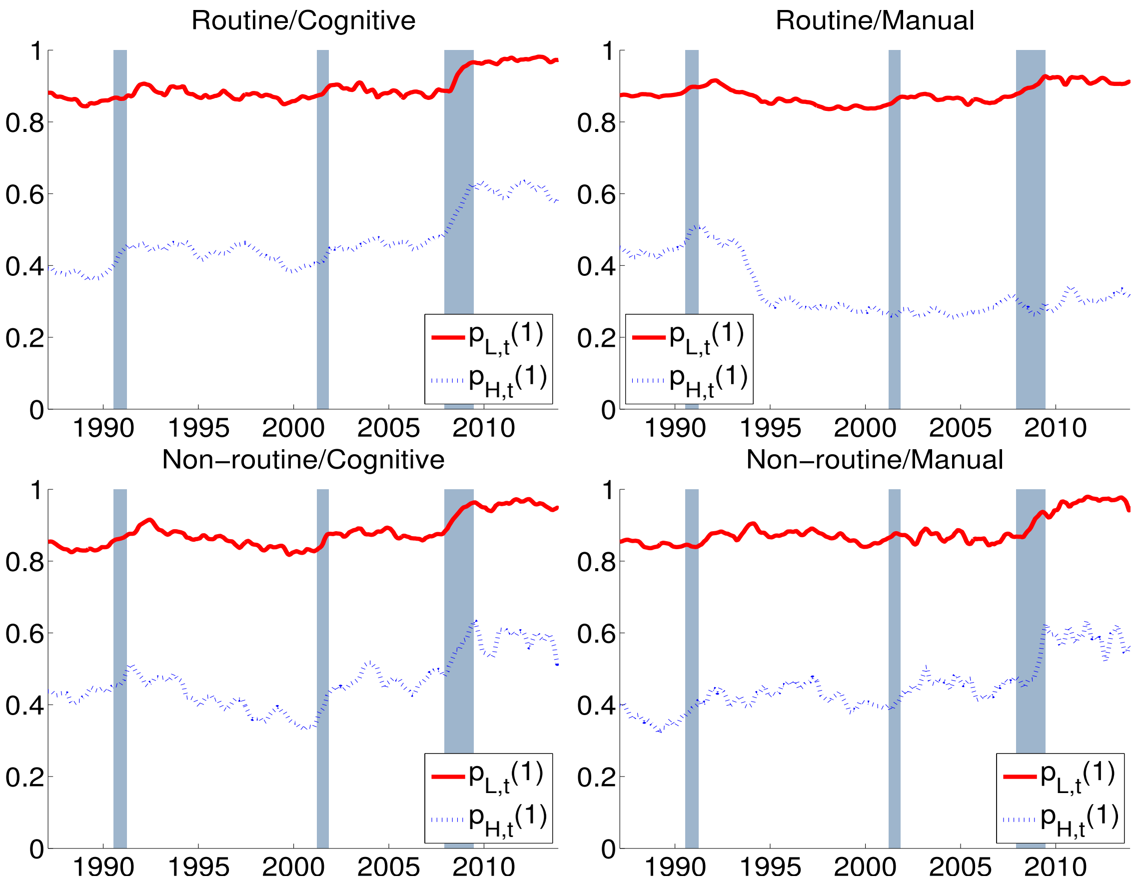

Figure 7. Number of newly unemployed workers of each type ($\widehat{w}^{z}_{jt|T}$ for $z = L,H$) by occupation. Units are in hundred thousands. Shaded areas denote NBER recessions.

Decomposition of type L unemployment

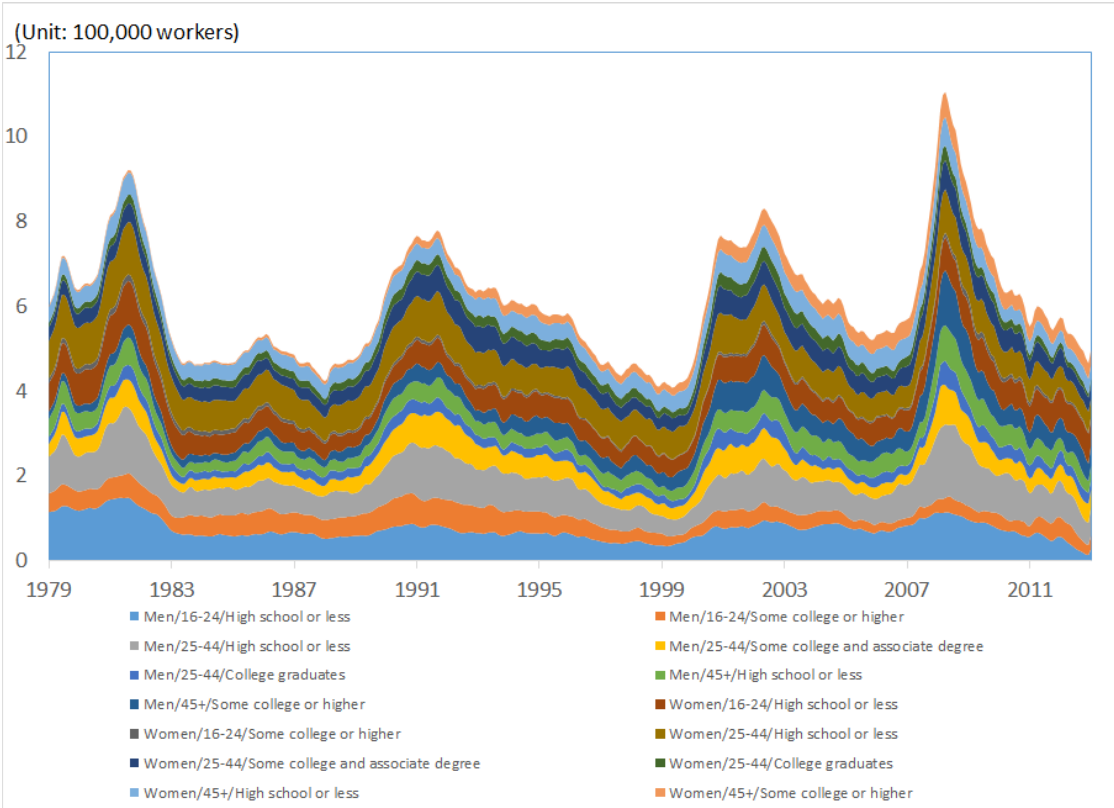

Figure 8. Composition of total type L inflows by gender, age and education

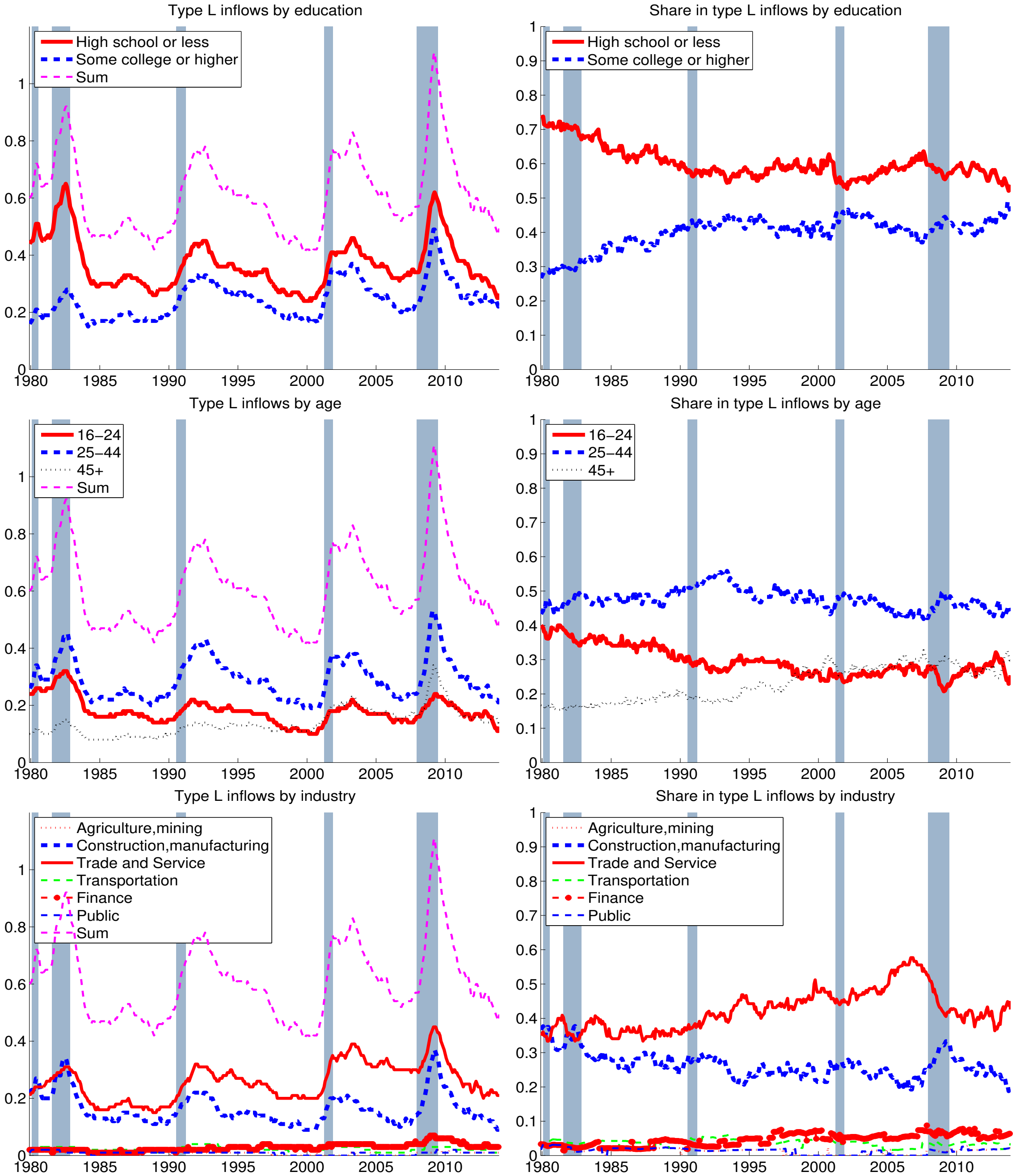

Figure 9. Size and share of type L individuals of each group by education, age, industry, and occupation. Units for the inflows are in millions. Shaded areas denote NBER recessions.

Notes to Figure 9. Type L inflows by industry and occupation does not exactly add up to the total type L inflows, because type L individuals who do not have previous work experience are not considered. However, the difference is small and does not change the result qualitatively.

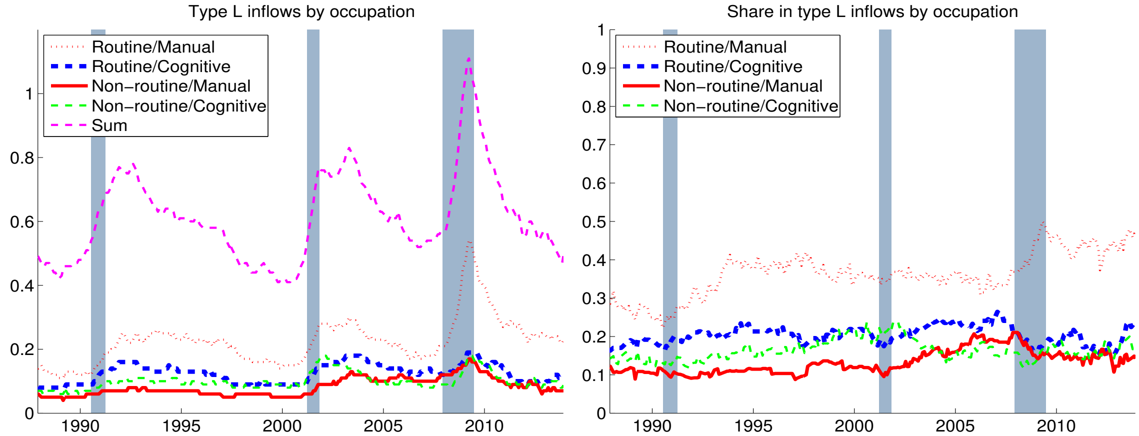

Figure 9. Size and share of type L individuals of each group by education, age, industry, and occupation (continued). Units for the inflows are in millions. Shaded areas denote NBER recessions.

Notes to Figure 9. Type L inflows by industry and occupation does not exactly add up to the total type L inflows, because type L individuals who do not have previous work experience are not considered. However, the difference is small and does not change the result qualitatively.

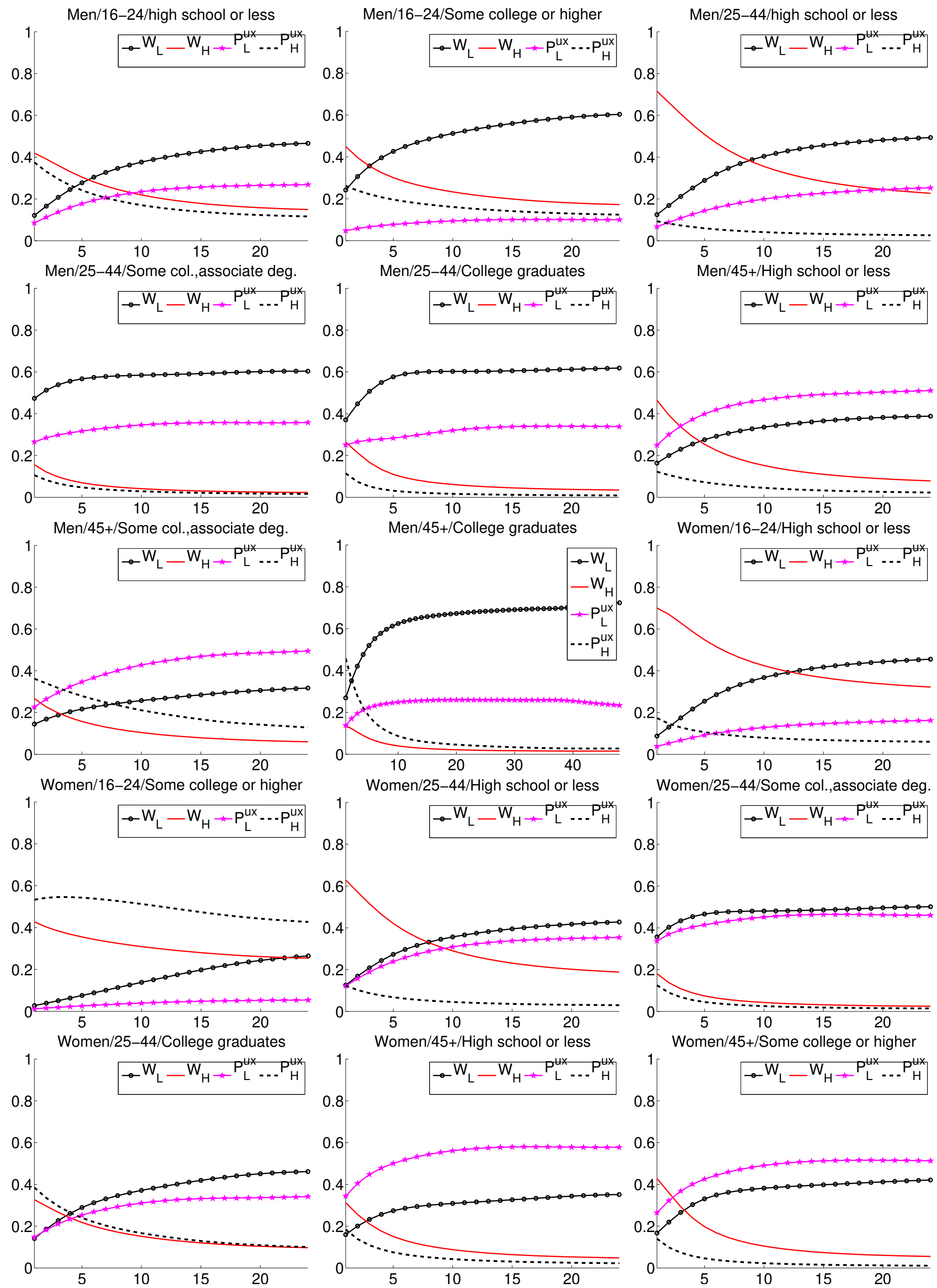

Figure 9. Fraction of variance of error in forecasting total unemployment at different horizons attributable to separate factors by gender, age and education.

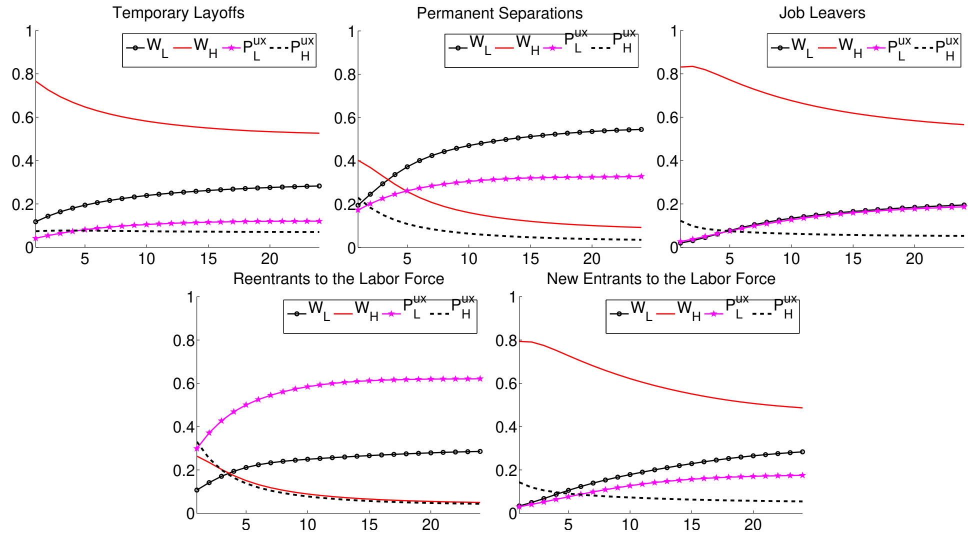

Figure 10. Fraction of variance of error in forecasting total unemployment at different horizons attributable to separate factors by reason for unemployment.

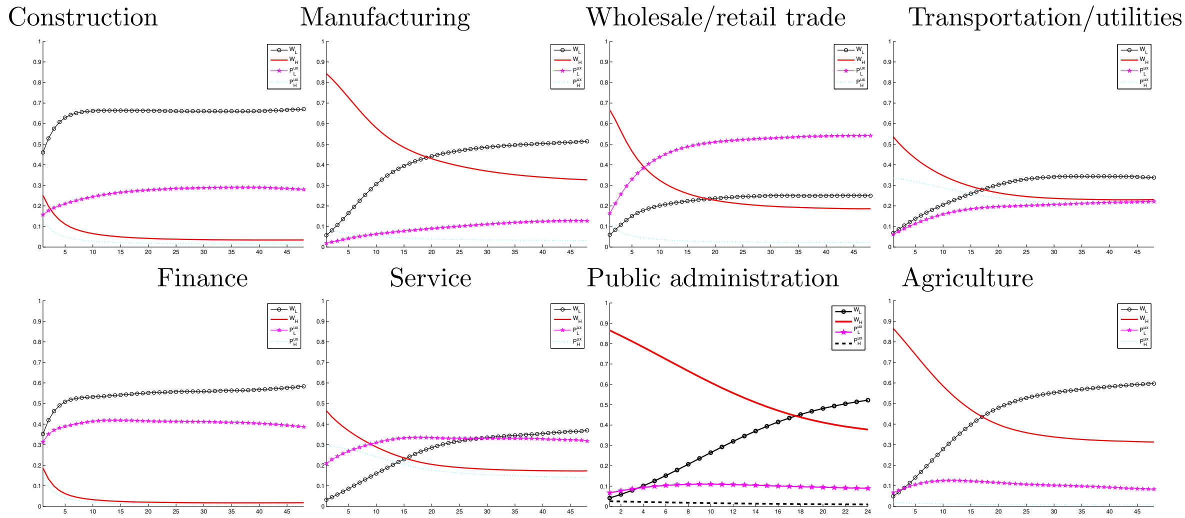

Figure 11. Fraction of variance of error in forecasting total unemployment at different horizons attributable to separate factors by industry. Note to Figure 11. The transportation/utilities sector includes information, and the agriculture sector includes farming and mining.

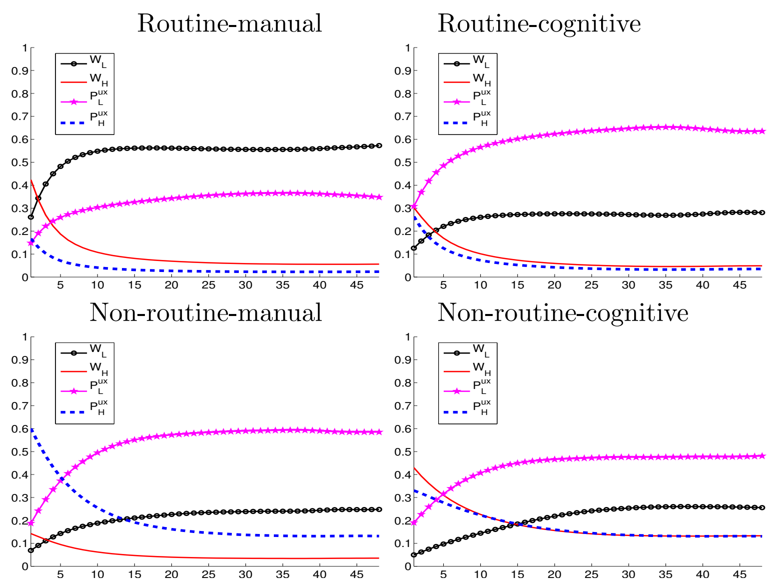

Figure 12. Fraction of variance of error in forecasting total unemployment at different horizons attributable to separate factors by occupation.

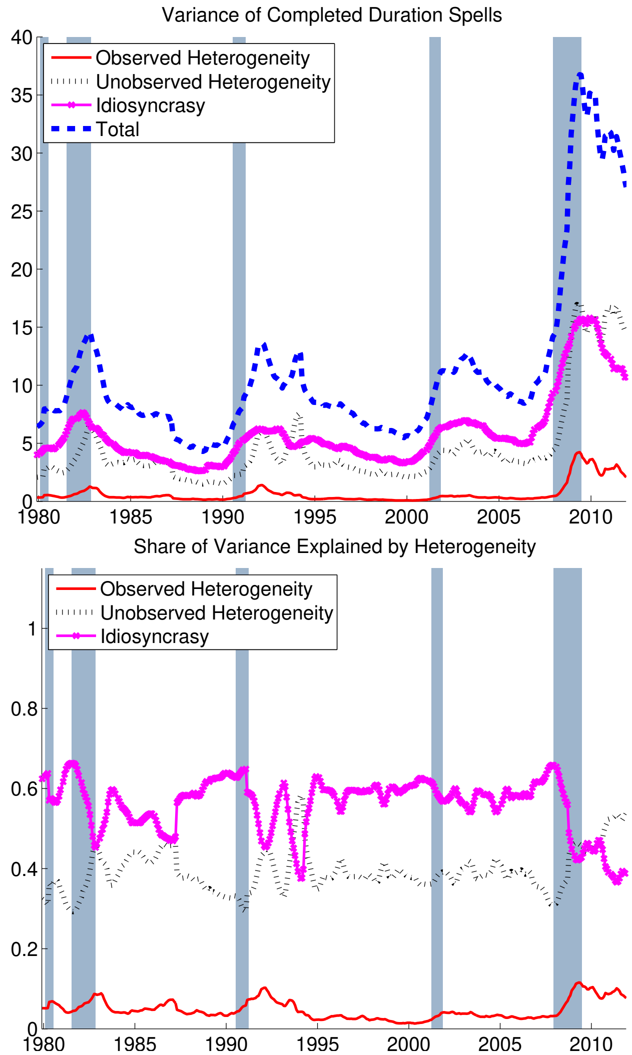

Figure 13. Amount of variance of the completed duration spells of unemployment across individuals accounted for by observed and unobserved heterogeneity. Upper panel: Level. Lower panel: Share out of total variance.

Tables

Table 1: Parameter estimates

	σ^w_{jL}	σ^w_{jH}	σ^x_{jL}	σ^x_{jH}	R^1_j	$R^{2.3}_j$	$R^{4.6}_j$	$R^{7.12}_j$	$R^{13.+}_j$
TL	0.011	0.032***	0.080**	0.049***	0.040***	0.033***	0.019***	0.013***	0.017***
	(0.007)	(0.006)	(0.040)	(0.010)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
PS	0.018***	0.023***	0.068***	0.050***	0.051***	0.046***	0.041***	0.038***	0.028***
	(0.002)	(0.005)	(0.010)	(0.010)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
JL	0.003***	0.014***	0.049***	0.036***	0.028***	0.020***	0.016***	0.014***	0.011***
	(0.001)	(0.002)	(0.010)	(0.006)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
RE	0.007***	0.011***	0.088***	0.032***	0.050***	0.039***	0.027***	0.028***	0.024***
	(0.001)	(0.002)	(0.031)	(0.008)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
NE	0.003***	0.013***	0.066***	0.029***	0.032***	0.022***	0.015***	0.015***	0.013***
	(0.001)	(0.002)	(0.015)	(0.007)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)

	δ^E_1	δ^E_2	δ^E_3	δ^R_1	δ^R_2	δ^R_3
TL	-0.050*	-0.028	-0.040	-0.081***	0.021	-0.072
	(0.029)	(0.089)	(0.030)	(0.012)	(0.074)	(0.053)
PS	0.407***	-0.211***	0.153***	0.311***	-0.089*	0.122***
	(0.055)	(0.037)	(0.049)	(0.048)	(0.045)	(0.054)
JL	0.211***	-0.086***	0.023	0.165***	-0.047	-0.032
	(0.047)	(0.044)	(0.047)	(0.043)	(0.037)	(0.044)
RE	0.198**	-0.189***	0.176***	0.184***	-0.165***	0.176***
	(0.096)	(0.037)	(0.052)	(0.079)	(0.036)	(0.064)
NE	0.258***	-0.157***	0.186*	0.228***	-0.114**	0.137*
	(0.063)	(0.054)	(0.096)	(0.058)	(0.054)	(0.082)

Note: TL, PS, JL, RE, and NE stand for temporary layoffs, permanent separations, job leavers, reentrants to the labor force, and new entrants to the labor force, respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. White (1982) quasi-maximum-likelihood standard errors are in parentheses.

Table 2. Average type L share and continuation probability (Men, 1980:M1-2013:M12)

Education	High school			College			
				Some/graduate	Some	Graduate	Some/graduate
Age	16-24	25-44	45+	16-24	25-44	25-44	45+
Type L share in inflows	0.13	0.20	0.21	0.24	0.31	0.36	0.26
Type L continuation prob.	0.87	0.90	0.89	0.74	0.82	0.88	0.95
Type H continuation prob.	0.44	0.48	0.47	0.34	0.44	0.45	0.48
Share in total L inflows	0.12	0.14	0.06	0.07	0.07	0.07	0.04
Share in total inflows	0.17	0.13	0.06	0.05	0.05	0.04	0.03

Table 3. Average type L share and continuation probability (Women, (1980:M1-2013:M12)

Education	High school			College			
				Some/graduate	Some	Graduate	Some/graduate
Age	16-24	25-44	45+	16-24	25-44	25-44	45+
Type L share in inflows	0.12	0.20	0.26	0.04	0.26	0.20	0.22
Type L continuation prob.	0.90	0.88	0.89	0.84	0.84	0.95	0.87
Type H continuation prob.	0.39	0.43	0.41	0.39	0.39	0.47	0.45
Share in L inflows	0.09	0.12	0.07	0.01	0.07	0.04	0.03
Share in total inflows	0.14	0.11	0.05	0.06	0.05	0.04	0.03

Table 4. Key characteristic of type L inflows (1980:M1-2013:M12)

Key characteristic	Fraction in w_L	Fraction in $w_L + w_H$
Men	57%	52%
Age 25-44	48%	42%
High school or less	60%	66%

Table 5. Average type L share and continuation probability by industry (1980:M1-2013:M12)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Type L share in inflows	0.15	0.26	0.18	0.19	0.17	0.26	0.16	0.15
Type L continuation prob.	0.91	0.87	0.91	0.91	0.83	0.87	0.86	0.92
Type H continuation prob.	0.52	0.44	0.49	0.45	0.51	0.35	0.46	0.53
Share in L inflows	0.01	0.14	0.12	0.19	0.04	0.05	0.23	0.01

Notes to Table 5. Only those who report their previous industry are taken into account in computing the share of each group in the total type L inflows. Newly unemployed individuals who does not have previous industry are not considered. (1) Agriculture, forestry, fishing, farming and mining, (2) Construction, (3) Manufacturing, (4) Wholesale and retail trade, (5) Transportation, (6) Finance, (7) Service, (8) Public Administration. The shares in L inflows does not add up to 1, since unemployed individuals who do not have previous work experience are not considered.

Table 6. Average type L share and continuation probability by occupation (1988:M1-2013:M12)

	(1)	(2)	(3)	(4)
Type L share in inflows	0.22	0.19	0.15	0.26
Type L continuation prob.	0.88	0.90	0.88	0.90
Type H continuation prob.	0.33	0.47	0.45	0.53
Share in L inflows	0.37	0.20	0.13	0.16

Notes to Table 6. Only those who report their previous occupation are taken into account in computing the share of each group in the total type L inflows. Newly unemployed individuals who does not have previous occupations are not considered. (1) Routine/manual occupation, (2) Routine/cognitive occupation, (3) Non-routine/manual occupation, (4) Non-routine/cognitive occupation. The shares in L inflows does not add up to 1, since unemployed individuals who do not have previous work experience are not considered.

Table 7. Parameter estimates of Phillips correlation with type L unemployment rate

	(1)	(2)	(3)	(4)	(5)	(6)
$u_t - u_t^*$	-0.494**	-0.401**	-0.447**	-0.311**	-0.155**	-0.314**
	(0.148)	(0.097)	(0.156)	(0.087)	(0.042)	(0.076)
U_t^L/N_t	0.393**	0.327**	0.380**	0.264**	0.102*	0.263**
	(0.154)	(0.101)	(0.158)	(0.083)	(0.040)	(0.076)
π_{t-1}^{gap}	0.898**	0.974**	0.815**	0.958**	1.024**	0.921**
	(0.088)	(0.087)	(0.098)	(0.100)	(0.090)	(0.090)
π_{t-2}^{gap}	0.019	-0.426**	0.004	-0.462**	-0.153	-0.312**
	(0.118)	(0.124)	(0.126)	(0.136)	(0.126)	(0.119)
π_{t-3}^{gap}	0.105	0.266**	0.064	0.153	-0.101	-0.053
	(0.116)	(0.128)	(0.123)	(0.141)	(0.120)	(0.110)
π_{t-4}^{gap}	-0.359**	-0.761**	-0.304**	-0.729**	-0.518**	-0.515**
	(0.116)	(0.114)	(0.122)	(0.127)	(0.109)	(0.094)
π_{t-5}^{gap}	0.176	0.678**	0.154	0.631**	0.553**	0.444**
	(0.116)	(0.115)	(0.123)	(0.129)	(0.112)	(0.096)
π_{t-6}^{gap}	0.207*	-0.192	0.169	-0.147	-0.181	-0.209**
	(0.116)	(0.128)	(0.124)	(0.142)	(0.121)	(0.102)
π_{t-7}^{gap}	-0.150	0.027	-0.071	-0.144	0.026	-0.012
	(0.118)	(0.124)	(0.123)	(0.135)	(0.121)	(0.101)
π_{t-8}^{gap}	-0.021	-0.170**	0.004	-0.078	-0.040	-0.071
	(0.084)	(0.081)	(0.091)	(0.092)	(0.080)	(0.075)
constant	-0.897	-0.678**	-1.020**	-0.595**	-0.193	-0.555**
	(0.345)	(0.223)	(0.394)	(0.186)	(0.087)	(0.166)
Adjusted R^2	0.868	0.770	0.815	0.754	0.814	0.750
Sample period	1980-2013	1980-2013	1980-2013	1985-2013	1980-2013	1980-2013

Notes to Table 7. Each column reports the coefficient estimates based on the combination of following data: (1) CPI and Michigan survey; (2) CPI and moving average; (3) PCEPI and Michigan survey; (4) PCEPI and moving averages; (5) Average hourly earnings and moving averages; (6) Average weekly earnings and moving averages. Standard errors of coefficient estimates are in parentheses.

Table 8. Parameter estimates of Phillips correlation with type L unemployment rate

	(1)	(2)	(3)	(4)	(5)	(6)
$u_t - u_t^*$	-0.479**	-0.378**	-0.573**	-0.340**	-0.124**	-0.265**
	(0.140)	(0.090)	(0.160)	(0.088)	(0.039)	(0.072)
$U_{PS,t}^L/N_t$	0.611**	0.499**	0.821**	0.492**	0.113*	0.263**
	(0.235)	(0.152)	(0.259)	(0.138)	(0.061)	(0.076)
π_{t-1}^{gap}	0.896	0.976**	0.780**	0.944**	1.040**	0.921**
	(0.089)	(0.087)	(0.097)	(0.100)	(0.090)	(0.090)
π_{t-2}^{gap}	0.011**	-0.431**	0.014	-0.457**	-0.150	-0.307**
	(0.118)	(0.123)	(0.123)	(0.135)	(0.127)	(0.119)
π_{t-3}^{gap}	0.112**	0.268**	0.076	0.152	-0.114	-0.066
	(0.116)	(0.128)	(0.121)	(0.140)	(0.121)	(0.110)
π_{t-4}^{gap}	-0.354	-0.759**	-0.265**	-0.716**	-0.520**	-0.515**
	(0.116)	(0.114)	(0.120)	(0.126)	(0.110)	(0.094)
π_{t-5}^{gap}	0.176**	0.678**	0.155	0.621**	0.569**	0.456**
	(0.115)	(0.115)	(0.121)	(0.128)	(0.113)	(0.096)
π_{t-6}^{gap}	0.205	-0.196	0.168	-0.142	-0.184	-0.217**
	(0.116)	(0.128)	(0.121)	(0.141)	(0.123)	(0.102)
π_{t-7}^{gap}	-0.147**	0.036	-0.065	-0.130	0.015	-0.010
	(0.118)	(0.124)	(0.121)	(0.134)	(0.122)	(0.101)
π_{t-8}^{gap}	-0.018**	-0.172**	-0.007	-0.073	-0.035	-0.062
	(0.084)	(0.081)	(0.089)	(0.091)	(0.081)	(0.075)
constant	-0.615	-0.440**	-0.991**	-0.469**	-0.081	-0.361**
	(0.239)	(0.153)	(0.269)	(0.138)	(0.060)	(0.114)
Adjusted R^2	0.868	0.752	0.822	0.758	0.809	0.750
Sample period	1980-2013	1980-2013	1980-2013	1985-2013	1980-2013	1980-2013

Notes to Table 8. Each column reports the coefficient estimates based on the combination of following data: (1) CPI and Michigan survey; (2) CPI and moving average; (3) PCEPI and Michigan survey; (4) PCEPI and moving averages; (5) Average hourly earnings and moving averages; (6) Average weekly earnings and moving averages. Standard errors of coefficient estimates are in parentheses.

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