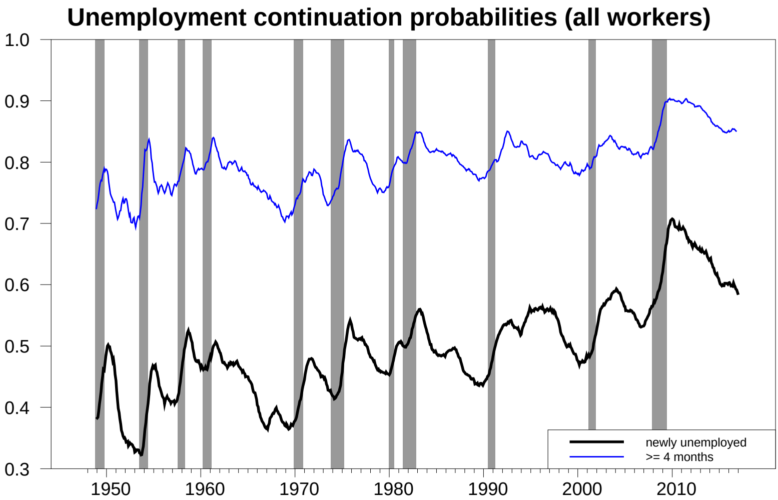
Heterogeneity and Unemployment Dynamics (Hie Joo Ahn and James D. Hamilton)

- Theme: Cannot understand unemployment dynamics using representative worker model
- New inflows of individuals who have unusual difficulty finding jobs is key characteristic of economic recessions

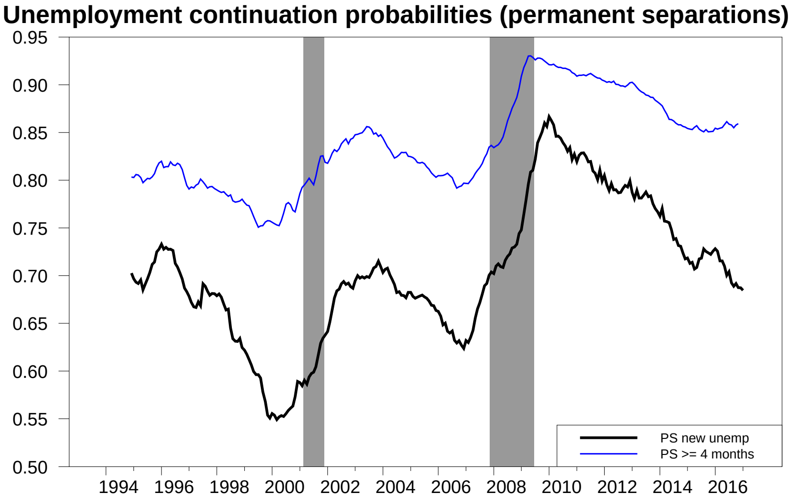
Key fact: very different unemployment continuation probabilities

- If someone has been unemployed for only one month, there is a very good chance they will not be unemployed next month
- If someone has been unemployed for 4 months or more, they are extremely likely to still be unemployed next month

It is better to be an average newly unemployed in Great Recession than someone who has been unemployed for more than 4 months in the very best times



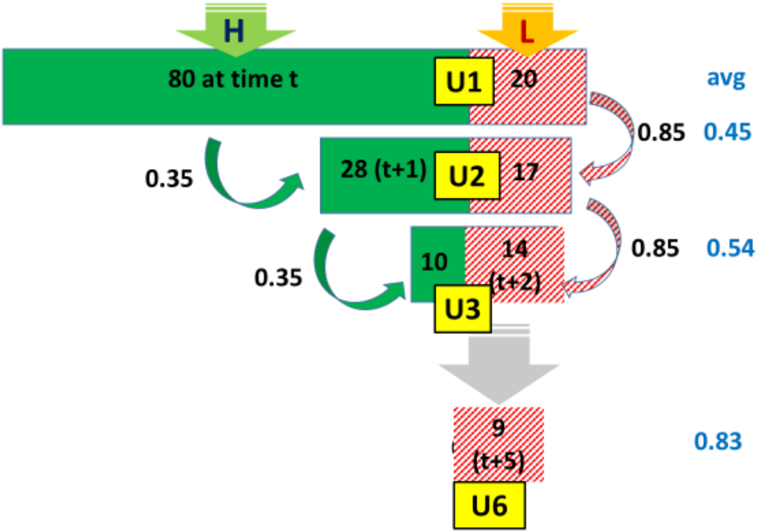
Differences in continuation probabilities between newly unemployed and long-term unemployed still dramatic when condition on any observable characteristic



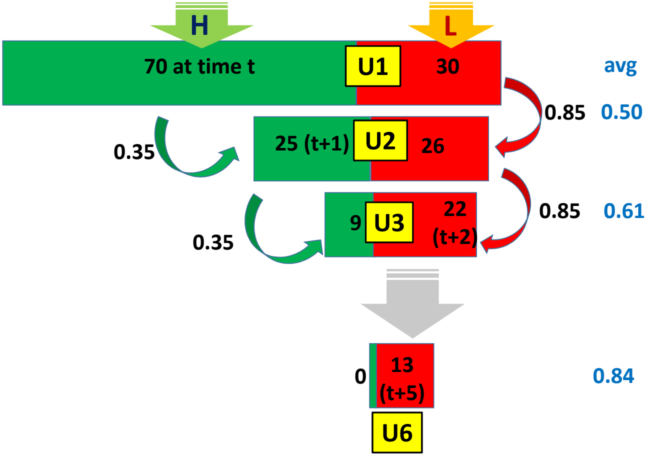
Possible explanations

- **Genuine duration dependence:** The process of being unemployed changed the person (lost human capital, discrimination by employers)
- **Dynamic sorting (unobserved heterogeneity):** Some people had lower probability of exiting unemployment to begin with and those are the only ones left after 6 months

Illustration of dynamic sorting



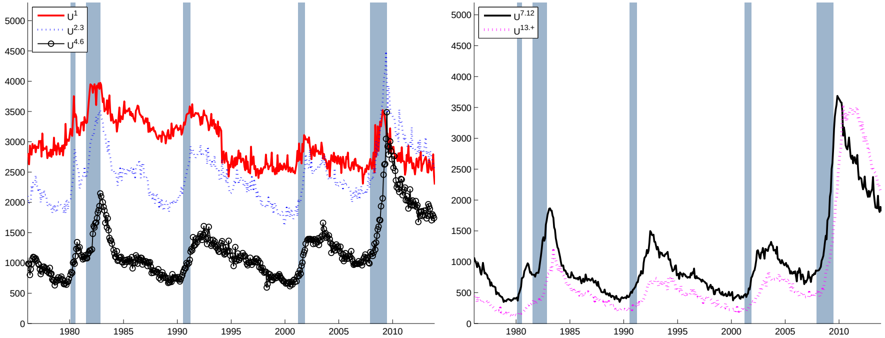
What happens when fraction of type L increases?



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 - 2013:M12

Unemployment counts by duration



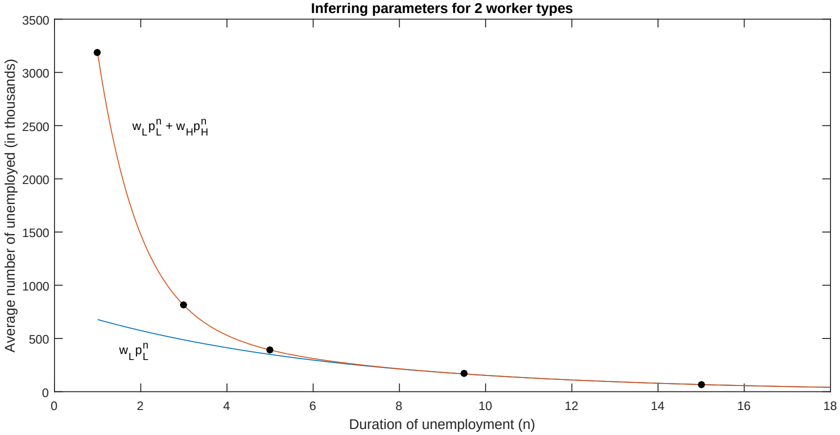
Intuition for identification

What can we learn from historical average $\bar{y} = T^{-1}\sum_{t=1}^{T} y_t$?

- Suppose 2 unobserved types and all parameters are constant over time.
- Unemployed person of type L has probability p_L of still being unemployed next month.
- Type H has probability p_H of still being unemployed next month.
- On average there are w_L and w_H newly unemployed individuals of each type each month.

$\bar{U}^1 = w_L + w_H$
$\bar{U}^{n+1} = w_L p_L^n + w_H p_H^n$

Given observation of $\bar{U}^n$ for four different n we can infer average values of (w_L, w_H, p_L, p_H)



Sample calculations

For example, to fit historical averages $\bar{U}^1$, $\bar{U}^{2.3}$, $\bar{U}^{4.6}$, $\bar{U}^{7.12}$ we would use

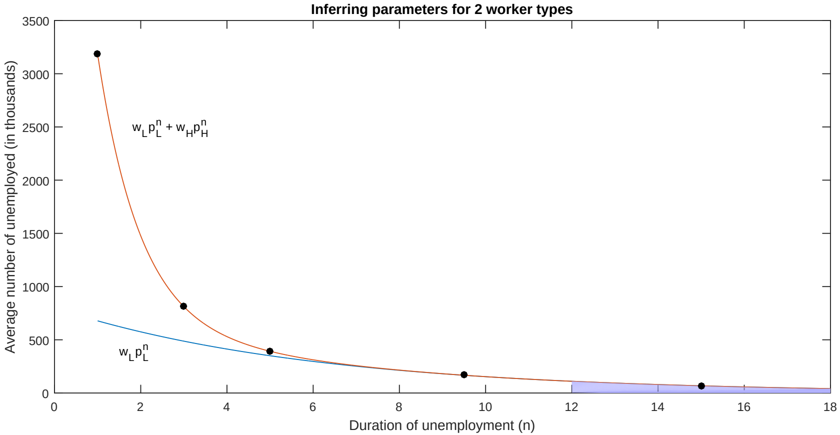
$$w_H = 2.53 \text{ million}$$

$$w_L = 0.68 \text{ million}$$

$$p_L = 0.85$$

$$p_H = 0.36$$

For these data, the unused 5th observation is predicted almost perfectly



predicted value for $\bar{U}^{13.+} = \sum_{n=13}^{48}(w_L p_L^n + w_H p_H^n) = 614,000$
observed value for $\bar{U}^{13.+} = 636,000$

Model with both heterogeneity and genuine duration dependence

Katz and Meyer (1990) (proportional hazards with positive hazard function)

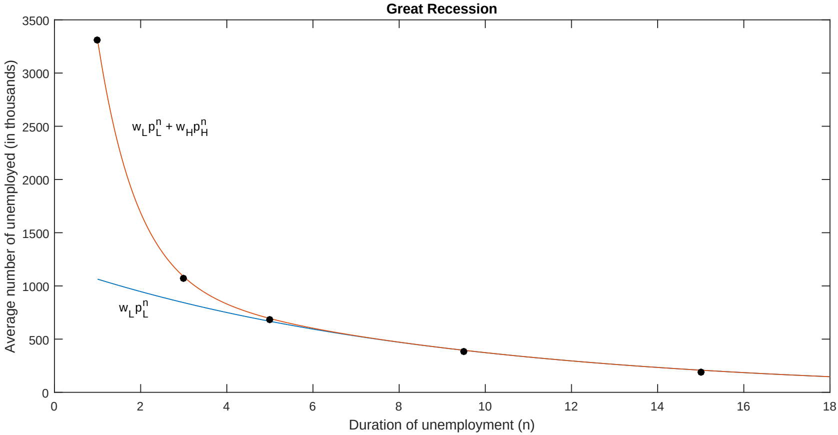
$$p_i(\tau) = exp\{-exp[x_i + d_\tau]\}$$

$$U^{k+1} = \sum_{i=L,H} w_i p_i(1) p_i(2) \cdots p_i(k).$$

If could represent d_τ with a single parameter, e.g. $d_\tau = \delta(\tau - 1)$, we could choose values for the 5 parameters $x_L, x_H, w_L, w_H, \delta$ to exactly match the observed values of the five averages $\bar{U}^1$, $\bar{U}^{2.3}$, $\bar{U}^{4.6}\bar{U}^{7.12}$, $\bar{U}^{13.+}$.

Inferred role of GDD is small ($\delta = -0.003$)

Fit of model without GDD to averages since 2007



Similar to earlier value for p_L

Significantly bigger value for w_L

$\Rightarrow$ inflows of new type L workers were key in Great Recession.

Allowing for more general genuine duration dependence

Alternatively, if we wanted to use the two subsamples together and assumed a time-invariant function for genuine duration dependence, could estimate for a two-parameter representation of d_τ.

- 10 observations (value of five averages across two subsamples)
- 10 unknowns (values of w_L, w_H, x_L, x_H for two subsamples plus two parameters for function d_τ)
- Using full time-series sample can estimate a totally general function for time-invariant GDD or even allow simple time-variation $d_{t,\tau}$

Strategy for using full panel y_t, $t =$1976:M1-2013:M12

(1) Assume driving variables evolve smoothly over time

- $w_{Lt} = w_{L,t-1} + \epsilon^w_{Lt}$
- $w_{Ht} = w_{H,t-1} + \epsilon^w_{Ht}$
- $x_{Lt} = x_{L,t-1} + \epsilon^x_{Lt}$
- $x_{Ht} = x_{H,t-1} + \epsilon^x_{Ht}$

Strategy for using full panel y_t, $t =$1976:M1-2013:M12

(2) Observed variables depend on history of shocks plus measurement error

- $U_t^{2.3} = \sum_{i=H,L} \left[w_{i,t-1} P_{i,t}(1) + w_{i,t-2} P_{i,t}(2) \right] + r_t^{2.3}$
- $P_{i,t}(j) = p_{i,t-j+1}(1) p_{i,t-j+2}(2) \cdots p_{i,t}(j)$
- $p_{i,t}(\tau) = \exp[-\exp(x_{i,t} + d_{t,\tau})]$

Strategy for using full panel y_t, $t =$1976:M1-2013:M12

(3) Write as nonlinear state-space model

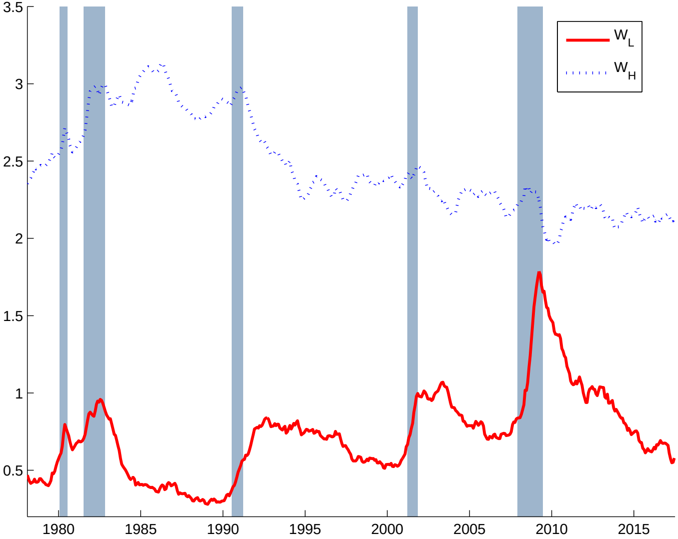
- state vector: current and 47 lags of $(w_L, w_H, x_L, x_H)'$
- observation vector: 5 elements of $y_t = (U_t^1, U_t^{2.3}, U_t^{4.6}, U_t^{7.12}, U_t^{13.+})'$
- with one more observation than needed for the 4 shocks, can allow for completely different duration dependence for all τ if it is constant over time $(d_{t,\tau} = d_\tau)$
- can also allow for simple time variation in $d_{t,\tau}$, e.g., two different functions depending on extension of unemployment insurance

Summary of procedure

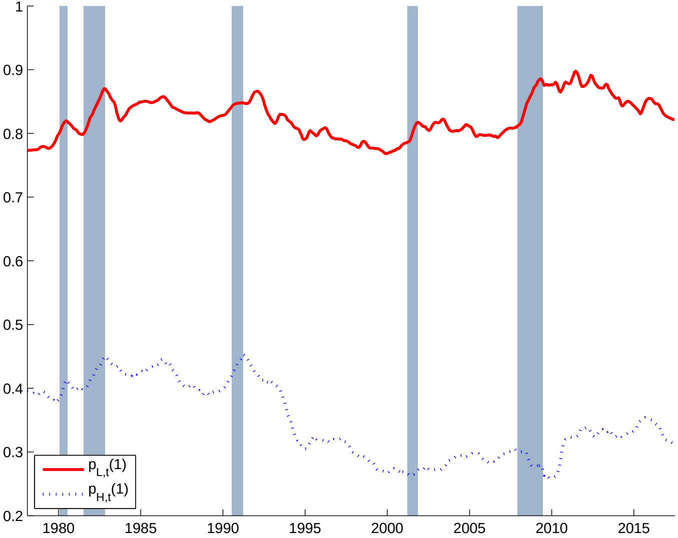
With nonlinear state-space model:

- can calculate likelihood function of observed data $y_1, ..., y_T$
- can maximize likelihood function with respect to population parameters
  - variances of 4 shocks to (w_L, w_H, x_L, x_H)
  - variances of 5 measurement errors
  - parameters that characterize the function $d_{t,\tau}$
- can form optimal inference based on the data $y_1, ..., y_T$ about unobserved variables (w_L, w_H, x_L, x_H)

Estimated number of newly unemployed workers of each type for each month

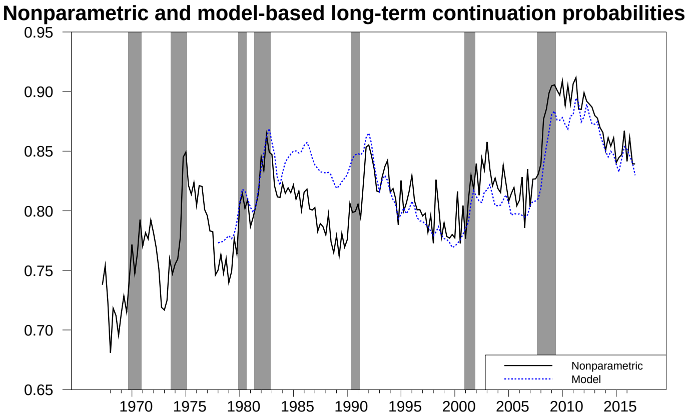


Estimated probability that a newly unemployed worker of each type will still be unemployed the following month



Could we corroborate this nonparametrically?

- Let $u_t^{4.+}$ be number of people unemployed 4 months or longer in month t
- According to model, most of these are type L
- $u_{t+3}^{4.6} =$ new inflows into the $4+$ category between $t+1$ and $t+3$
- $u_{t+3}^{4.+} = p_t^{4.+} u_t^{4.+} + u_{t+3}^{4.6}$
- $p_t^{4.+}$ is the 3-month continuation probability for the $4.+$ group
- How much does cube root of $p_t^{4.+}$ differ from model's type L continuation probability?

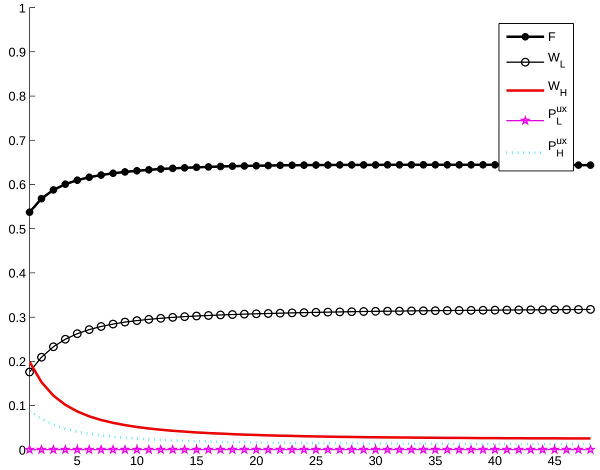


Nonparametric and model-based long-term continuation probabilities
0.95
0.90
0.85
0.80
0.75
0.70
0.65
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015
Nonparametric
Model

Benefits of having fully specified dynamic statistical model

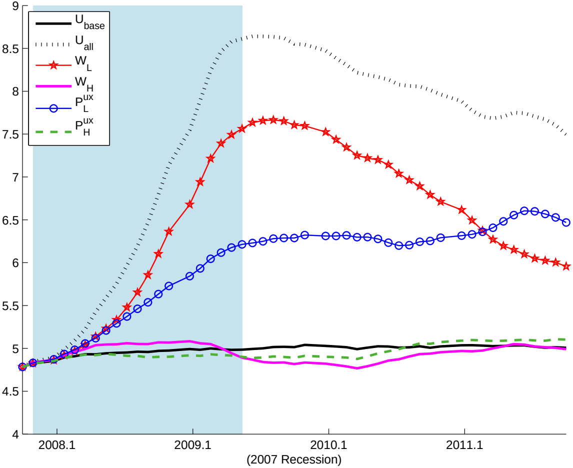
- We have a model-implied **s-month-ahead forecast** of total unemployment U_{t+s} based on observation of $y_t, y_{t-1}, ..., y_1$ for any horizon s
- **Variance decomposition:** We can break down the mean-squared error of this forecast into parts coming from each of the 4 structural shocks
- **Historical decomposition:** We can break down the actual historical forecast error for any t and s into contributions coming from each of the 4 structural shocks

Variance decomposition: new inflows of type L workers are most important



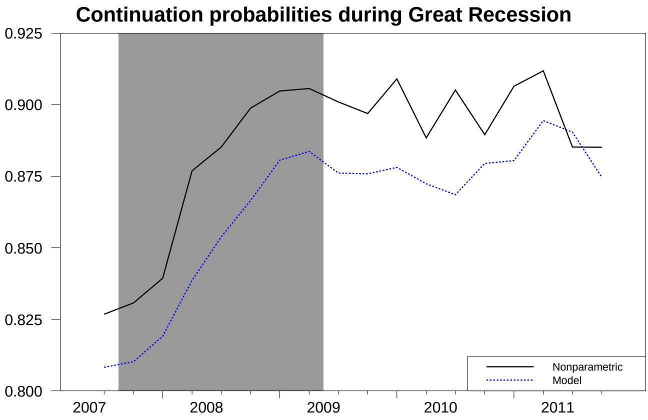
Fraction of s-month-ahead MSE in forecasting total unemployment that comes from each shock plotted as a function of s

Historical decomposition of Great Recession: new inflows w_L most important



Contribution of each of the 4 shocks to total unemployment during and after the Great Recession

Nonparametric confirmation of interpretation of Great Recession



Nonparametric confirmation of importance of inflows

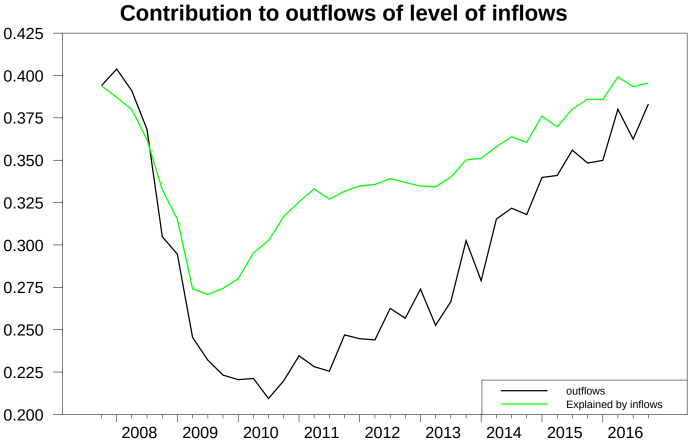
labor force L_t
inflow rate $x_t \simeq U_t^1 / L_t$
outflow rate $f_1 = 1 - p_t$
$u_{t+1} = p_t u_t + u_{t+1}^1$

$$\Delta f_t = c_f + \phi_{ff,1} \Delta f_{t-1} + \cdots + \phi_{ff,8} \Delta f_{t-8} + \phi_{fx,1} \Delta x_{t-1} + \cdots + \phi_{fx,8} \Delta x_{t-8} + \varepsilon_{ft}$$

$$\Delta x_t = c_x + \phi_{xf,1} \Delta f_{t-1} + \cdots + \phi_{xf,8} \Delta f_{t-8} + \phi_{xx,1} \Delta x_{t-1} + \cdots + \phi_{xx,8} \Delta x_{t-8} + \varepsilon_{xt}.$$

Variance decomposition: inflows account for 59% of the error forecasting outflows 3 years ahead

Historical decomposition of outflows in bivariate VAR

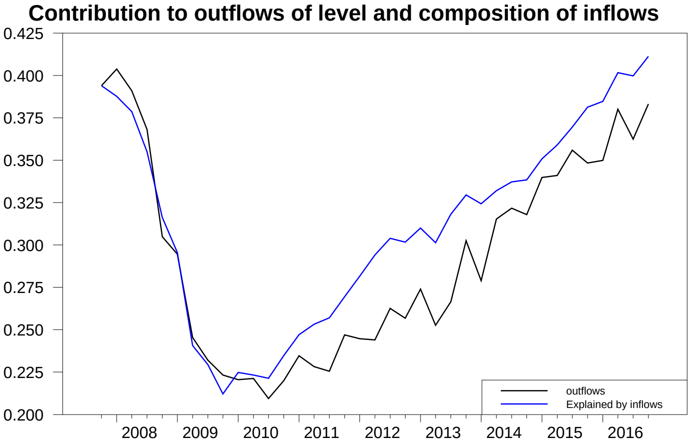


Nonparametric confirmation of importance of composition of inflows

Add to VAR initial claims for unemployment insurance as percent of labor force.

Now explain 76% of variance of outflows at 3-year horizon from shocks to level and composition of inflows.

Historical decomposition of outflows in 3-variable VAR

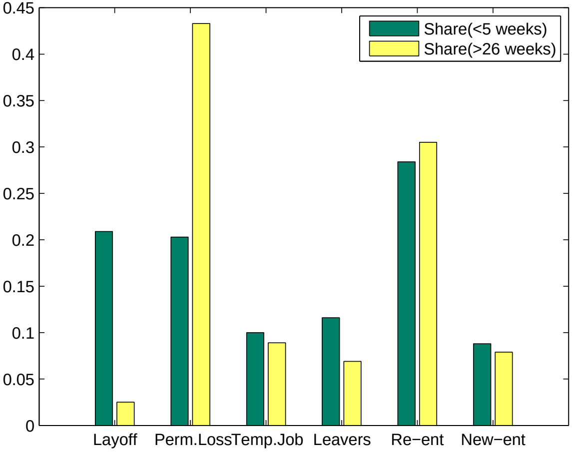


Who are the type L workers?

So far we argued that type L can be identified ex post by fact they're unemployed for long periods.

Can we predict who will be type L based on observable characteristics when they first enter unemployment?

1994-2013 average shares of unemployment by reason



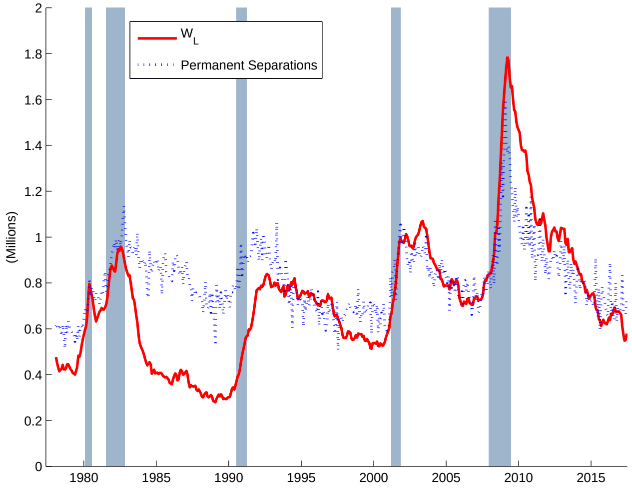
- Green: share in newly unemployed
- Yellow: share in long-term unemployed

Where did the increase in U_t^1 during the Great Recession come from?

March 2008 - March 2009:

- the number of newly unemployed U_t^1 increased by 642,000
- the number of newly unemployed who indicated that permanent separation was the reason increased by 454,000
- $452/642 = 72\%$ of the increase came from permanent separations

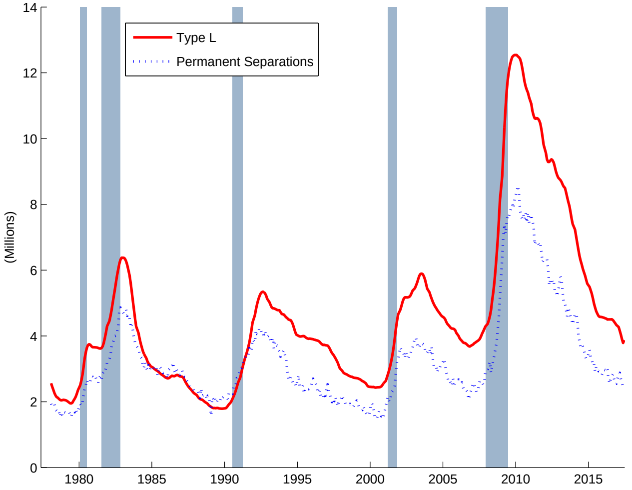
Total number of unemployed type L workers (red) and number of all unemployed workers who gave permanent separation as reason (dashed blue)



Model-based evidence on role of permanent separation

- Ahn (2014) estimated models like this one separately for individuals with same observed characteristic j
- e.g., estimated just using individuals who all gave permanent separation as reason
- identified type L and type H individuals as separate components of the observed total U_{jt}

Ahn's estimates of the number of type *L* individuals giving each separate reason for unemployment



Robustness checks

Broad conclusions of the paper are robust with respect to:

- alternative treatments of 1994 redesign
- just use post 1994 data
- allow GDD to vary with eligibility for unemployment insurance
- allow structural shocks to be contemporaneously correlated
- conceptually view transitions as occurring weekly instead of monthly

Conclusion

Unobserved heterogeneity is crucial for interpreting aggregate unemployment dynamics.

Once this is taken into account, changes in **composition of inflows** are key driver of recessions.

Involuntary permanent separations are seen to be the most important factor.