A Congestion Theory of Unemployment Fluctuations

Yusuf Mercan
U Melbourne

Benjamin Schoefer
UC Berkeley

Petr Sedláček
U Oxford & CEPR

November, 2020
Motivation

Propose a congestion theory of unemployment fluctuations

◦ rationalizes why job creation is so unattractive in recessions

◦ provides a unified explanation for a range of other patterns:
  ◦ countercyclical labor wedge
  ◦ countercyclical earnings losses from job displacement and labor market entry
  ◦ relative insensitivity of labor markets to policy changes

Theory rests on two empirical facts

1. in recessions, more unemployed find jobs

2. limited capacity to absorb increases in unemployment (even with unchanged productivity)

⇒ Countercyclical congestion
Outline

1. Empirical evidence
   - countercyclical shifts towards recently unemployed workers
   - congestion in hiring

2. Model structure
   - congestion mechanism
   - standard DMP model

3. Business cycle performance
   - volatility and comovement of labor market variables
   - congestion unemployment

4. Three additional macroeconomic applications
   - labor wedge, earnings losses, sensitivity to policy changes
1. Empirical Evidence

Recently unemployed workers and congestion
1. Share of recently unemployed in workforce
1. Share of recently unemployed in workforce

Use CPS data (1976-2019): # of weeks workers spent in unemployment in previous year

Regression coefficient = .493
Flow origins of employment distribution shifts

Unemployment-to-employment (UE) flows are strongly countercyclical
  - see e.g. Burda, Wyplosz (1992), Fujita, Ramey (2009), Elsby et al. (2013)
Flow origins of employment distribution shifts

Unemployment-to-employment (UE) flows are strongly countercyclical

- see e.g. Burda, Wyplosz (1992), Fujita, Ramey (2009), Elsby et al. (2013)

![Graph showing UE flows and unemployment rate](image-url)
Why are UE flows countercyclical?

Use steady state expressions for unemployment, \( u = \delta / (\delta + f) \), and UE flows \( UE = f \cdot u \),

- \( \delta \): separation probability, \( f \): job finding probability

\[
\frac{dUE}{UE} = \frac{df}{f} + \frac{du}{u} \rightarrow \frac{dUE/UE}{du/u} = \frac{1}{(1 - u)\left[-1 + \frac{d\delta/\delta}{df/f}\right]} + 1,
\]

Relative cyclicity of \( \delta \) and \( f \) is key:

- if \( \frac{d\delta/\delta}{df/f} = 0 \), then \( \frac{dUE/UE}{du/u} = -\frac{u}{1-u} \rightarrow \text{UE flows are procyclical} \)

- if \( \frac{d\delta/\delta}{df/f} < -\frac{u}{1-u} \), then \( \frac{dUE/UE}{du/u} > 0 \rightarrow \text{UE flows are countercyclical} \)
Cyclicality of job finding and separation probabilities

![Graph showing cyclicality of job finding and separation probabilities over time with log deviation from trend on the y-axis and years from 1980 to 2020 on the x-axis. The graph includes lines for job finding rate (f) and separation rate (δ).]

[see more] [see OECD]
Cyclicality of job finding and separation probabilities

[Diagram showing the cyclicality of job finding and separation probabilities over the years 1980 to 2020. The figures illustrate the log deviation from trend for both job finding rate (f) and separation rate (δ). There are also comparisons between actual values and constant separations, with the latter showing smoother trends.]

[See more information on the OECD website for further details.]
2. Limited capacity to absorb increases in unemployment

We define congestion (in hiring)

◦ Limited capacity to absorb “pure” increases in unemployment
  ◦ i.e. increases in unemployment that leave fundamentals (productivity) unchanged

Intuition from “standard” search model

◦ hiring depends on fundamentals (productivity), but “size” of market is irrelevant
◦ rise in unemployed, with unchanged productivity, (immediately) hired away

Dynamics after “pure” increase in unemployment (consider $\uparrow EU$):

◦ $u' = u - f(\bar{\theta})u + \uparrow EU$: no congestion ($\upsilon$ move 1-to-1 with $u$, i.e. $\theta = \upsilon/u$ fixed)
◦ $u' = u - \bar{UE} + \uparrow EU$: full congestion (economy absorbs only $\bar{UE}$ at a time, i.e. $UE$ fixed)
Response of labor markets to “pure” unemployment increase

\[ \theta = \frac{\nu}{u} \text{ (and implicitly } f) \]

\[ UE = f \cdot u \]
Response of labor markets to “pure” unemployment increase

Estimate VAR: \( y_t = [\ln ALP_t, \ln \delta_t, \ln \theta_t] \)

- \( ALP = \) average labor productivity, \( \delta = \) EU probability, \( \theta = \) labor market tightness
- Cholesky identification: response to \( \delta \) keeps \( ALP \) fixed upon impact
Response of labor markets to “pure” unemployment increases

Our results suggest that labor markets

- cannot easily absorb rise in unemployment even with productivity unchanged

Similar results found at the firm- and local labor market level

- Doran, Gelber, Isen (2020): U.S. visa lotteries to measure exogenous new hires
  - → (more than) fully crowd out additional hiring in that job position

  - → unaffected plants in local labor markets do not expand own hiring

- Mercan, Schoefer (2020): review of 15 studies
  - → limited short-run spillovers to unaffected firms in local labor markets
Three Levels of Evidence for Congestion

1. Firm-level hiring

2. Local labor market shocks

3. Aggregate time series
Figure 1. Effect of H-1B Visas on Total Firm Employment, by Employer Size

Notes: The figure shows the coefficient and 95 percent confidence interval on chance lottery wins from median regressions in which the dependent variable is the total number of employees in a firm, pooling together Quarters 1-4 of the first fiscal year that an employee can work at the firm in the regression, among employers of the indicated size or smaller in Year-1 (where the maximum employer size in each case is shown on the x-axis). The horizontal line at +1 on the y-axis corresponds to the case where hiring an extra H-1B visa worker leaves other employment unchanged (so that total employment would increase by exactly one). The horizontal line at 0 on the y-axis corresponds to the case where hiring an extra H-1B visa worker crowds out other workers one-for-one (so that total employment would increase by zero). We show the coefficient for employers of each size ranging from 0-10 to 0-500, with the upper bound of the size range in increments of 10. Note that the samples overlap across different regressions; for example, firms with 10 or fewer employees are included in the samples in all 50 regressions shown. We use the baseline employment specification, in which we control for lagged employment and expected lottery wins.
Data: Local Labor Markets (Gathmann, Helm, Schoenberg 2020)

Figure 1. Annual employment changes in the event firm before and after a mass layoff. The figure displays the timing of employment changes (in logs) in the event plant. The upper panel shows that during mass layoff years total employment in the average district decreases by about 20% (0.33 log-points). The lower panel traces out the effects of mass layoffs on local employment up to 10 years (as opposed to 4 years in the baseline specification) after the event. Since we have to drop events occurring after 1998, the sample reduces to 55 (as opposed to 62) events and their control districts.

Table 1. Annual employment changes in the mass layoff firm, weighted by employment in the same broad industry (column (4)) are affected by a mass layoff in a neighboring district. The negative spillover effects of mass layoffs therefore appear to be spatially concentrated in firms located in the same district as the mass layoff firm.

We do not find an employment decline before the event—in contrast to some earlier studies (Eliason and Storrie 2006; Pannel and Hammer 2008; Schwerdt 2011). The table further reveals that workers who get displaced in a mass layoff are slightly less educated than displaced workers who remain with the event plant. Prior to the mass layoff, displaced workers also earn lower wages and exhibit a lower worker fixed effect than their coworkers in the same firm.

What types of shocks trigger such large reductions in firm size? Panel A of Figure 4. Long-run effects of mass layoffs on local employment. The figure plots, based on a variant of equation (9), the long-run effects of mass layoffs. Panel (a) plots the long-run effects of mass layoffs on overall local employment (light gray line) and on local employment excluding the event firm (black line). Regressions are estimated at the 2-digit industry and trace out the effects of mass layoffs on local employment up to 10 years (as opposed to 4 years in the baseline specification) after the event. Since we have to drop events occurring after 1998, the sample reduces to 55 (as opposed to 62) events and their control districts.

In the third, our definition of a mass layoff event rules out equally large shocks in preceding years. Displacement studies analyze quarterly data). Second, we study mass layoffs and not plant closures; and different results. First, we include all layoffs that occur up to a year fixed effects, event period fixed effects and 2-digit industry.

Figure 2. Regional and Spillover Effects in the Long-Run

Downloaded from https://academic.oup.com/jeea/article/18/1/427/5247011 by guest on 30 September 2020
Data: Impulse Responses to an Expansion in the Unemployment Pool

(Mercan and Schoefer 2020)
2. Model

Main Idea
Main idea

Use standard Diamond-Mortensen-Pissarides (DMP) model, but
  ◦ incorporate diminishing returns to cohorts of new hires

Within this framework
  ◦ times of increased UE flows, i.e. recessions (empirical fact 1)
  → diminishing marginal product of new hires → discouraged job creation (empirical fact 2)

We micro-found the above by assuming
  ◦ imperfect substitution between workers with different type of labor market experience
    ◦ akin to e.g. Katz, Murphy (1992), Card, Lemieux (2000), Jeong et al. (2013)
    ◦ consistent with job ladders, skill/experience accumulation etc...
Main idea

Imperfect substitution between workers with different type of labor market experience

\[ Y = z \left( \sum_{k}^{K} \alpha_k n_k^{\sigma} \right)^{1/\sigma} \]

- \( z \): aggregate (total factor) productivity
- \( k \): particular type of labor market experience (e.g. job ladder, skill, ...)
- \( n_k \): # of workers of type \( k \)
- \( \alpha_k \): relative scale
- \( \sigma \): “elasticity of substitution”
  - \( \sigma = 1 \): “no congestion” (standard) model
  - \( \sigma < 1 \): model allowing for congestion
Main Idea

Relative supply of worker types matters for productivity:

\[ p_k = \frac{\partial Y}{\partial n_k} = \alpha_k n_k^{\sigma-1} \frac{Y}{\sum_{l=1}^{K} \alpha_l n_l^{\sigma}} \]

In recessions, when UE flows rise

- recently unemployed become relatively abundant in employment (empirical fact 1)
- \( \rightarrow \) diminishing marginal product of new hires \( \rightarrow \) discouraged job creation (empirical fact 2)

Countercyclical congestion reinterprets recessions: why does unemployment rise?

- rather than asking why firms hire so little
- we posit that the jobs to be filled by the unemployed are already crowded
2. Model

Details
Worker heterogeneity and congestion

Worker “types”

- $k \in \mathcal{K} = \{1, ..., K\}$: particular worker types
- in employment, workers move up one level each period, $k_{t+1} = k_t + 1$,
- in unemployment, workers move down $k_u(k)$ levels each period, $k_{t+1} = k_t - k_u(k_t)$,
  - $k_u(k) \in \{0, 1, ..., k - 1\}$ nests no-, full- and partial-downgrading [see more]
Worker heterogeneity and congestion

Worker “types”

- $k \in \mathcal{K} = \{1, ..., K\}$: particular worker types
- in employment, workers move up one level each period, $k_{t+1} = k_t + 1$,
- in unemployment, workers move down $k_u(k)$ levels each period, $k_{t+1} = k_t - k_u(k_t)$,
  - $k_u(k) \in \{0, 1, ..., k - 1\}$ nests no-, full- and partial-downgrading [see more]

Congestion

- final good produced combining intermediate goods ($n_k$): $Y = z \left( \sum_{k=1}^{K} \alpha_k n_k^\sigma \right)^{1/\sigma}$
- intermediate goods produced by “firms” using CRS technology
- competitive market prices of intermediate goods: $p_k = \frac{\partial Y}{\partial n_k} = \alpha_k n_k^{\sigma - 1} \frac{Y}{\sum_{i=1}^{K} \alpha_i n_i^\sigma}$

Everything that follows mirrors “standard” search model
Environment and timing

Environment

○ workers hired by intermediate-goods firms on frictional labor market
    ○ random search, matches occur according to $M(u, v)$, $f(\theta) = M/u$ and $q(\theta) = M/v$
    ○ jobs separate with stochastic probability $\delta$

○ final goods firm buys intermediate-inputs on perfectly competitive market

○ Nash bargaining and free entry of intermediate-goods firms

Timing

○ aggregate shocks $(z, \delta)$ materialize

○ separated workers join unemployment pool, active matches produce

○ employed upgrade, unemployed downgrade types and thereafter matching occurs
Worker and firm value functions

Value of employment and unemployment for k-type worker

\[ W_{k,t} = w_{k,t} + \beta \mathbb{E}_t \left[ (1 - \delta_{t+1}) (W_{k+1,t+1} - U_{k+1,t+1}) + U_{k+1,t+1} \right], \]

\[ U_{k,t} = b + \beta \mathbb{E}_t \left[ f(\theta_t)(1 - \delta_{t+1}) (W_{k-k_u(k),t+1} - U_{k-k_u(k),t+1}) + U_{k-k_u(k),t+1} \right] \]

- \( w_{k,t} \): wage of k-type worker, \( b \): flow value of unemployment

Value of a job filled with k-type worker and value of unfilled job

\[ J_{k,t} = p_{k,t} - w_{k,t} + \beta \mathbb{E}_t \left[ (1 - \delta_{t+1}) (J_{k+1,t+1} - V_{t+1}) + V_{t+1} \right], \]

\[ V_t = -\kappa + q(\theta_t)\beta \mathbb{E}_t \left[ (1 - \delta_{t+1}) \frac{u_{k,t}}{u_t} (J_{k-k_u(k),t+1} - V_{t+1}) + V_{t+1} \right] \]

- \( \kappa \): flow cost of having an open vacancy
Productivity and The Size of the Hiring Cohort: New Hires and Average, w/ and w/o Congestion

- $p_1$ (σ = 0.241)
- ALP (σ = 0.241)
- $p_1 = ALP$ (σ = 1)
Model mechanism and alternatives

Congestion occurs because recently unemployed become abundant in recessions

- fall in marginal product slows further hiring (despite free entry)
- depends on distribution of types in (un-)employment (and $\sigma$)

Alternative: what if not all new hires cause congestion?

- only $1 - x$ cause congestion:

$$Y = z \left[ (1 - x) \left( \sum_{k=1}^{K} \alpha_k^c (n_k^c)^\sigma \right)^{1/\sigma} + x \left( \sum_{k=1}^{K} \alpha_k^{nc} n_k^{nc} \right) \right]$$

$\rightarrow$ isomorphic to our baseline, subject to reparameterizing $\sigma$

Alternative: what if hiring slowed by increased costs?

- $\kappa (UE_t)' > 0$: gives similar amplification, but misses a range of other results
3. Business cycle performance

Sources of amplification and congestion unemployment
Parameterization

“Standard” features parametrized in “standard” fashion (Shimer, 2005)
- in particular, $b$ s.t. replacement rate of 40 percent (i.e. high fundamental surplus)

Worker heterogeneity
- $K = 160$: absorbing “max type” until separation
- $k_u(k) = k - 1$: full downgrading (but recall robustness w.r.t. no-congestion hires)
- $\alpha_k$: s.t. $p_k = p = 1$ for all $k$ (all types have same surplus)

Aggregate shocks
- $z$ and $\delta$: target volatility and persistence of $ALP$ and $UE/E$ in data
  - $UE/E$ crucial for congestion mechanism

Congestion parameter $\sigma$
- match limited capacity to absorb unemployed (IRF of $\theta$ w.r.t. $\delta$)
Parameterizing $\sigma$

- Data
- No-congestion ($\sigma = 1$)
- Congestion ($\sigma = 0.241$)
## Model performance: business cycle statistics

<table>
<thead>
<tr>
<th>ALP</th>
<th>f</th>
<th>δ</th>
<th>u</th>
<th>v</th>
<th>θ</th>
<th>UE/E</th>
<th>MPL</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>s.d.(x)</td>
<td>0.010</td>
<td>0.053</td>
<td>0.067</td>
<td>0.104</td>
<td>0.127</td>
<td>0.229</td>
<td>0.067</td>
</tr>
<tr>
<td>corr(u, x)</td>
<td>-0.11</td>
<td>-0.93</td>
<td>0.85</td>
<td>1</td>
<td>-0.94</td>
<td>-0.98</td>
<td>0.83</td>
</tr>
</tbody>
</table>

| baseline model ($\sigma = 0.241$) |     |     |     |     |     |      |     |
| s.d.(x) | 0.010 | 0.059 | 0.122 | 0.121 | 0.102 | 0.207 | 0.067 | 0.055 |
| corr(u, x) | -0.46 | -0.92 | 0.74 | 1 | -0.72 | -0.94 | 0.87 | -0.86 |

| standard model ($\sigma = 1$) without separation shocks |     |     |     |     |     |      |     |
| s.d.(x) | 0.010 | 0.005 | 0.000 | 0.004 | 0.014 | 0.016 | 0.003 | 0.010 |
| corr(u, x) | -0.65 | -0.65 | 0.00 | 1 | -0.49 | -0.65 | -0.27 | -0.65 |

| standard model ($\sigma = 1$) with separation shocks |     |     |     |     |     |      |     |
| s.d.(x) | 0.010 | 0.005 | 0.073 | 0.055 | 0.046 | 0.017 | 0.054 | 0.010 |
| corr(u, x) | -0.50 | -0.62 | 0.91 | 1 | 0.96 | -0.62 | 0.70 | -0.50 |
Model Performance: Beveridge Curve

Data

- No-congestion ($\sigma = 1$)
- Congestion ($\sigma = 0.241$)
Parametrizing $\sigma$: Congestion and Amplification

![Graph showing RMSE vs degree of congestion]

- Y-axis: RMSE$_\theta$, data vs model IRF (measure of congestion)
- X-axis: (Inverse) degree of congestion, $\sigma$
- Data (right axis)
- Volatility of u. (right axis)
- Our calibration

The graph illustrates the relationship between the degree of congestion and the RMSE, showing how the volatility changes with the degree of congestion.
Sources of amplification

Surplus relevant for hiring in “standard” model \((S)\) and in congestion model \((S_1)\)

\[
S_t = z_t - b + \beta E_t (1 - \delta_{t+1})(1 - f(\theta_t)\phi)S_{t+1}
\]

\[
S_{1,t} = p_{1,t} - b + \beta E_t [(1 - \delta_{t+1})(S_{2,t+1} - f(\theta_t)\phi S_{1,t+1})]
\]

Differences between standard and our congestion model

- flow productivity channel: \(sd(p_t) > sd(z)\)
- cohort channels: continuation values have different dynamics
  - continuing in employment entails upgrading to \(S_{2,t+1}\)
  - falling into unemployment entails downgrading to \(S_{1,t+1}\)
Sources of amplification: flow productivity channel

Use data on ALP and UE/E to construct $p_1$
Sources of Amplification: cohort channels

IRFs of employment distributions to a one-time positive $\delta$ shock
Sources of amplification: quantification

\[ S_{1,t} = p_{1,t} - b + \beta \mathbb{E}_t[(1 - \delta_{t+1})S_{2,t+1} - f(\theta_t)(1 - \delta_{t+1})\phi S_{1,t+1}] \]

\[ S_{1,t} = z_t - b + \beta \mathbb{E}_t\left[(1 - \delta_{t+1})(1 - f(\theta^{st}_t)\phi)S^{st}_{t+1}\right] + \left(S^*_t - S^{st}_t\right) \]

(i) No-congestion model surplus

(ii) Flow productivity channel

\[ + \beta \mathbb{E}_t\left[(1 - \delta_{t+1})(1 - f(\theta_t)\phi)\left(S_{2,t+1} - S^*_t\right)\right] \]

(ii) Present value channel (cohort effect of “upgrading”)

\[ + \beta \mathbb{E}_t\left[(1 - \delta_{t+1})f(\theta_t)\phi\left(S_{2,t+1} - S_{1,t+1}\right)\right] \]

(iii) Outside option channel (cohort effect of “downgrading”)

\[ S^{st}_t = z_t - b + \beta \mathbb{E}_t\left[(1 - \delta_{t+1})(1 - f(\theta^{st}_t)\phi)S^{st}_{t+1}\right] \text{ & } \theta^{st}_t: \text{ no-congestion model surplus} \text{ & } \theta \]

\[ S^*_{1,t} = p_{1,t} - b + \beta \mathbb{E}_t\left[(1 - \delta_{t+1})(1 - f(\theta_t)\phi)S^*_t\right] \text{ : match surplus with productivity of } p_{1,t} \]
Sources of Amplification: quantification

Variation in counterfactual labor market tightness ($\tilde{\theta}$) driven by

- (i) no-congestion model surplus
- (ii) flow productivity channel
- (iii) present value channel
- (iv) outside option channel

<table>
<thead>
<tr>
<th>Source</th>
<th>$sd(\tilde{\theta})$</th>
<th>$sd(\tilde{\theta})/sd(\theta_{baseline})$</th>
<th>$cov(\theta_{baseline},\tilde{\theta})/var(\theta_{baseline})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline: (i)+(ii)+(iii)+(iv)</td>
<td>0.21</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>No outside option channel: (i)+(ii)+(iii)</td>
<td>0.18</td>
<td>0.86</td>
<td>0.85</td>
</tr>
<tr>
<td>No cohort effects: (i)+(ii)</td>
<td>0.05</td>
<td>0.25</td>
<td>0.16</td>
</tr>
<tr>
<td>No-congestion model surplus: (i)</td>
<td>0.02</td>
<td>0.09</td>
<td>0.05</td>
</tr>
</tbody>
</table>
Congestion unemployment: historical decomposition

\[ p_1 \quad (\sigma = 0.241) \]

\[ ALP \quad (\sigma = 0.241) \]

\[ p_1 = ALP \quad (\sigma = 1) \]
Congestion unemployment: historical decomposition

Isolate unemployment fluctuations driven solely by congestion: congestion unemployment

\[ S_{k,t}^c = p_{k,t} \cdot \frac{Z}{Z_t} - b + \beta E_t (1 - \bar{\delta}) S_{k+1,t+1}^c - \beta E_t (1 - \bar{\delta}) f(\theta_t^c) \phi S_{1,t+1}^c \forall k. \]

○ \( S_k^c \): surplus variation only due to congestion

\[ \kappa = q(\theta_t^c) \beta E_t (1 - \bar{\delta}) S_{1,t}^c \]

○ \( \theta^c \): variation in labor market tightness only due to congestion

\[ u_{t+1}^c = (1 - f(\theta_t^c)) u_t^c + \bar{\delta} (1 - u_t^c) \]

○ \( u^c \): congestion unemployment
Use data on ALP and UE/E to estimate time-path of entire model (Kalman filter)
4. Additional applications

Congestion and Three Macroeconomic Regularities
Macroeconomic implications of congestion

1. Business cycle accounting: the labor wedge
   - countercyclical in the data and attributed to “household side”

2. Costs of entering labor market and of displacement
   - large and countercyclical in the data

3. Sensitivity to labor market policies
   - relatively low, hard to square with high labor market volatility
1. The Labor Wedge

The labor wedge is defined as $MPL_t(1 - \tau_t) = MRS_t$

- estimates in data show a countercyclical labor wedge
  - see e.g. Hall (1997), Chari, Kehoe, McGrattan (2007), Shimer (2009)
  - moreover, fluctuations in labor wedge assigned mainly to “household” (MRS) side
    - models should focus on how MRS deviates from real wage (see e.g. Karabarbounis, 2014)

Extend our baseline model to include capital ($\tilde{K}$): $Y = z\tilde{K}^a \left( \left[ \sum_{k=1}^{K} \alpha_k n_k^\sigma \right]^{1/\sigma} \right)^{1-a}$

- considering the (spot) productivity of new hires $p_1$ only

\[ p_1 \begin{array}{c} \text{allocative/new hires’ MPL} \\ \text{standard MPL} \end{array} = (1-a) \frac{Y}{N} \begin{array}{c} \text{allocative/new hires’ MPL} \\ \text{standard MPL} \end{array} = \frac{\alpha_1 s_1^{\sigma-1}}{\sum_{k=1}^{K} \alpha_k s_k^\sigma} = MRS \text{ labor wedge (congestion term)} \]
1. The Labor Wedge: Congestion as a Resolution?
2. Costs of displacement and labor market entry

Large, countercyclical, persistent losses from displacement (e.g. Davis, von Wachter, 2011)
  ○ driven by wage drops, employer “quality” (e.g. Schmieder et al, 2019)

Graduating in recessions entails large, persistent, losses (e.g. Schwandt, von Wachter, 2019)
  ○ driven by wage drops, employer “quality” (e.g. Schwandt, von Wachter, 2019)

Level of costs explained through various theories
  ○ displacement costs: falls off a job ladder (e.g. Jarosch, 2015, Jung, Kuhn, 2018)
  ○ graduation costs: skills mismatch (e.g. Liu et al., 2016)

Our model is perfectly equipped to analyze the cyclicality of these costs
  ○ not well understood in existing literature
2. Costs of displacement

Replicate Davis, von Wachter (2011): earnings losses in recessions relative to booms
2. Costs of labor market entry

Replicate Schwandt, von Wachter (2019): earnings losses of new hires and unemployment
2. Costs of displacement and labor market entry

Our model offers a unified explanation

- relatively large cohorts of new hires are abundant in employment
- $\rightarrow$ pushes down their wages (reflecting marginal products)
- $\rightarrow$ cohort effects make these initial conditions long-lasting

The above mechanism is broadly consistent with the available evidence

- earnings losses linked to persistent wage declines
- driven primarily by a shift towards jobs of “lower quality”
3. Sensitivity to Policies

Costain and Reiter (2008): search models have a hard time

- simultaneously matching labor market volatility
- and sensitivity of the labor market to policies
- estimate long-run elasticity of $u$ w.r.t. $b$ of $\epsilon_{u,b} \in (2, 3.5)$

In our model, labor market volatility not generated by low fundamental surplus

- instead, countercyclical congestion makes labor market variables volatile
- implied long-run elasticity of $u$ w.r.t. $b$ of $\epsilon_{u,b} \approx 2.6$
Conclusion
Conclusion

Two key empirical facts

- 1. employment shifts towards recently unemployed in downturns
- 2. unemployment increases not absorbed quickly, even with unchanged fundamentals

We propose a model consistent with the above facts

- worker types not perfect substitutes for each other
- abundant types see their marginal productivity fall discouraging their hiring
- congestion is a strong amplification mechanism

Our baseline model sheds new light on a range of macroeconomic questions

- a congestion theory of unemployment fluctuations
- countercyclical labor wedge
- countercyclical costs of displacement and labor market entry
- low sensitivity of labor market to policies
Thanks
UE flows: observed and counterfactual (constant separations)
Response of labor markets to “pure” unemployment increase

- Data
- No-congestion ($\sigma = 1$)
- Congestion ($\sigma = 0.241$)

log deviation from steady state vs. Quarters
Worker type and (un-)employment evolution

Laws of motion for (un-)employment

\[ u_{k-k_u(k),t} = (1 - f(\theta_{t-1}))u_{k,t-1} + \delta_t e_{k-k_u(k),t} \quad \text{for } k \in \mathcal{K} \]

\[ e_{k-k_u(k),t} = (1 - \delta_{t-1})e_{k-k_u(k)-1,t-1} + f(\theta_{t-1})u_{k,t-1} \quad \text{for } k \in \mathcal{K} \]
Iso-congestion model

![Graph showing Iso-congestion curve \( \sigma(x) \) (left axis), Congestion along \( \sigma(x) \), model-data RMSE_\theta (right axis), and SD(u) along \( \sigma(x) \) (right axis).]
### Full set of parameter values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Target/Source</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td><strong>No congestion</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta$ - Discount factor</td>
<td>0.99</td>
<td>Annual interest rate</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>$\mu$ - Matching elasticity</td>
<td>0.72</td>
<td>Shimer (2005)</td>
<td>0.72</td>
<td>0.72</td>
</tr>
<tr>
<td>$m$ - Matching efficiency</td>
<td>0.57</td>
<td>Job finding probability</td>
<td>0.57</td>
<td>0.57</td>
</tr>
<tr>
<td>$\eta$ - Bargaining power</td>
<td>0.72</td>
<td>Hosios condition</td>
<td>0.72</td>
<td>0.72</td>
</tr>
<tr>
<td>$b$ - Unemployment flow value</td>
<td>0.39</td>
<td>Avg. replacement rate</td>
<td>0.40</td>
<td>0.40</td>
</tr>
<tr>
<td>$\kappa$ - Vacancy posting cost</td>
<td>0.21</td>
<td>Normalization $\theta = 1$</td>
<td>-</td>
<td>1.00</td>
</tr>
<tr>
<td>$\overline{z}$ - Productivity shock, mean</td>
<td>1</td>
<td>Normalization</td>
<td>-</td>
<td>1.00</td>
</tr>
<tr>
<td>$\sigma_z$ - Productivity shock, st. dev.</td>
<td>0.008</td>
<td>St. dev. of ALP</td>
<td>0.010</td>
<td>0.010</td>
</tr>
<tr>
<td>$\rho_z$ - Productivity shock, persistence</td>
<td>0.956</td>
<td>Persistence of ALP</td>
<td>0.74</td>
<td>0.69</td>
</tr>
<tr>
<td>$\delta$ - Separation shock, mean</td>
<td>0.037</td>
<td>Unemployment rate</td>
<td>0.063</td>
<td>0.063</td>
</tr>
<tr>
<td>$\sigma_\delta$ - Separation shock, st. dev.</td>
<td>0.107</td>
<td>St. dev. of UE/E</td>
<td>0.067</td>
<td>0.067</td>
</tr>
<tr>
<td>$\rho_\delta$ - Separation shock, persistence</td>
<td>0.709</td>
<td>Persistence of UE/E</td>
<td>0.84</td>
<td>0.74</td>
</tr>
<tr>
<td>$\rho_{\delta, z}$ - Correlation of shocks to $z$ and $\delta$</td>
<td>$-0.505$</td>
<td>$\text{corr}(ALP, \delta)$</td>
<td>$-0.41$</td>
<td>$-0.41$</td>
</tr>
<tr>
<td>$\sigma$ - Elasticity of substitution b/w workers</td>
<td>0.241</td>
<td>Impulse response of $\theta$ to $\delta$, see IRF Figure</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_k$ - Relative productivities of worker types</td>
<td>see Appendix</td>
<td>$p_k = 1$ for all $k$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
# Model Performance: Full business cycle statistics

<table>
<thead>
<tr>
<th></th>
<th>ALP</th>
<th>$f$</th>
<th>$\delta$</th>
<th>$u$</th>
<th>$v$</th>
<th>$\theta$</th>
<th>$UE/E$</th>
<th>$p_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.010</td>
<td>0.053</td>
<td>0.067</td>
<td>0.104</td>
<td>0.127</td>
<td>0.229</td>
<td>0.067</td>
<td>NA</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>0.75</td>
<td>0.87</td>
<td>0.77</td>
<td>0.93</td>
<td>0.93</td>
<td>0.94</td>
<td>0.84</td>
<td>NA</td>
</tr>
<tr>
<td>Correlation matrix</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$f$</td>
<td>0.04</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta$</td>
<td>-0.41</td>
<td>-0.71</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$u$</td>
<td>-0.11</td>
<td>-0.93</td>
<td>0.85</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$v$</td>
<td>0.30</td>
<td>0.87</td>
<td>-0.87</td>
<td>-0.94</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.22</td>
<td>0.92</td>
<td>-0.87</td>
<td>-0.98</td>
<td>0.99</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$UE/E$</td>
<td>-0.17</td>
<td>-0.72</td>
<td>0.57</td>
<td>0.83</td>
<td>-0.72</td>
<td>-0.78</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

| **Panel B: Congestion Model** |     |     |          |     |     |           |        |       |
| Standard deviation  | 0.010 | 0.059 | 0.122 | 0.121 | 0.102 | 0.207 | 0.067 | 0.055 |
| Autocorrelation     | 0.69 | 0.90 | 0.53 | 0.84 | 0.86 | 0.90 | 0.74 | 0.75 |
| Correlation matrix  |     |     |          |     |     |           |        |       |
| $f$                | 0.44 |     |          |     |     |           |        |       |
| $\delta$           | -0.41 | -0.51 | 1     |     |     |           |        |       |
| $u$                | -0.46 | -0.92 | 0.74 | 1   |     |           |        |       |
| $v$                | 0.35 | 0.92 | -0.16 | -0.72 | 1   |     |        |      |
| $\theta$           | 0.34 | 1.00 | -0.51 | -0.94 | 0.91 | 1   |        |      |
| $UE/E$             | -0.44 | -0.93 | 0.39 | 0.87 | -0.88 | -0.94 | 1     |      |
| $p_1$              | 0.49 | 0.95 | -0.43 | -0.86 | 0.90 | 0.95 | -0.97 | 1     |
# Model Performance: Full business cycle statistics

<table>
<thead>
<tr>
<th></th>
<th>ALP</th>
<th>f</th>
<th>$\delta_{imp}$</th>
<th>u</th>
<th>v</th>
<th>$\theta$</th>
<th>$UE/E$</th>
<th>$p_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Congestion Model - Calibrating to $UE/E$</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.010</td>
<td>0.059</td>
<td>0.122</td>
<td>0.121</td>
<td>0.102</td>
<td>0.207</td>
<td>0.067</td>
<td>0.055</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>0.69</td>
<td>0.90</td>
<td>0.53</td>
<td>0.84</td>
<td>0.86</td>
<td>0.90</td>
<td>0.74</td>
<td>0.75</td>
</tr>
<tr>
<td>Correlation matrix</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>f</td>
<td>0.44</td>
<td>(1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta$</td>
<td>-0.41</td>
<td>-0.51</td>
<td>(1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>u</td>
<td>-0.46</td>
<td>-0.92</td>
<td>0.74</td>
<td>(1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>v</td>
<td>0.35</td>
<td>0.92</td>
<td>-0.16</td>
<td>-0.72</td>
<td>(1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.34</td>
<td>1.00</td>
<td>-0.51</td>
<td>-0.94</td>
<td>0.91</td>
<td>(1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$UE/E$</td>
<td>-0.44</td>
<td>-0.93</td>
<td>0.39</td>
<td>0.87</td>
<td>-0.88</td>
<td>-0.94</td>
<td>(1)</td>
<td></td>
</tr>
<tr>
<td>$p_1$</td>
<td>0.49</td>
<td>0.95</td>
<td>-0.43</td>
<td>-0.86</td>
<td>0.90</td>
<td>0.95</td>
<td>-0.97</td>
<td>(1)</td>
</tr>
</tbody>
</table>

| **Panel B: Congestion Model - Calibrating to $\delta$** |     |     |     |     |     |     |       |       |
| Standard deviation | 0.010 | 0.041 | 0.084 | 0.086 | 0.077 | 0.144 | 0.052 | 0.054 |
| Autocorrelation | 0.69 | 0.92 | 0.62 | 0.87 | 0.82 | 0.92 | 0.76 | 0.75 |
| Correlation matrix |     |     |     |     |     |     |       |       |
| f | 0.36 | \(1\) |     |     |     |     |       |       |
| $\delta$ | -0.41 | -0.43 | \(1\) |     |     |     |       |       |
| u | -0.42 | -0.88 | 0.77 | \(1\) |     |     |       |       |
| v | 0.20 | 0.88 | 0.04 | -0.56 | \(1\) |     |       |       |
| $\theta$ | 0.36 | 1.00 | -0.43 | -0.90 | 0.87 | \(1\) |       |       |
| $UE/E$ | -0.31 | -0.91 | 0.52 | 0.89 | -0.72 | -0.91 | \(1\) |       |
| $p_1$ | 0.47 | 0.92 | -0.55 | -0.88 | 0.73 | 0.91 | -0.97 | \(1\) |