Labor market heretogeneities and the matching function

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The aggregate matching function

An important tool and a standard assumption in macro-labor models is the existence of a matching function

$$m_t = m_{0t} U_t^{\sigma} V_t^{1-\sigma}$$

- Relates the flow of new hires to the stocks of vacancies and unemployment
- Convenient device that "partially captures a complex reality [...] with workers looking for the right job and firms looking for the right worker" (Blanchard and Diamond, 1989).
- Analogous to production function

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}$$

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$$jf_t = \frac{m_t}{U_t} = m_0 \theta_t^{1-\sigma}$$

- Implicit assumption:
  - no heterogeneities
  - *or* heterogeneities, to the extent that they matter for jf_t, are captured, in a reduced-form, by θ_t
  $\rightarrow$ "Matching function meant to capture "a trading technology between heterogeneous agents" (Pissarides 2000, p.4)

The aggregate matching function

$$jf_t = m_0 \theta_t^{1-\sigma}$$

- Is m_{0t}, or "matching efficiency", constant?

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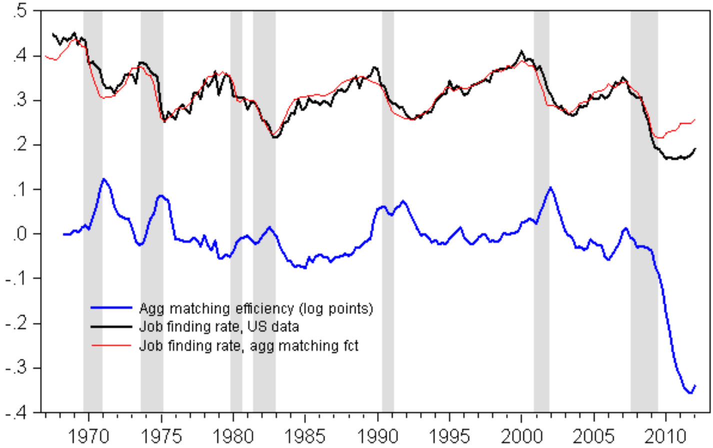
- Is m_{0t}, or "matching efficiency", constant?
- With CRS Cobb-Douglas matching function, regress

$$\ln jf_t = (1 - \sigma) \ln \theta_t + \ln m_0 + \varepsilon_t$$

$$\ln m_{0t} = \ln m_0 + \varepsilon_t$$

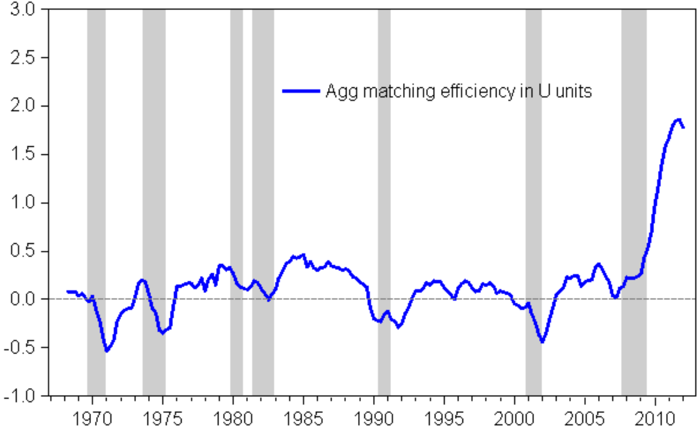
Matching efficiency, 1968-2012

The Solow residual of the matching function (4 qtrs MA)

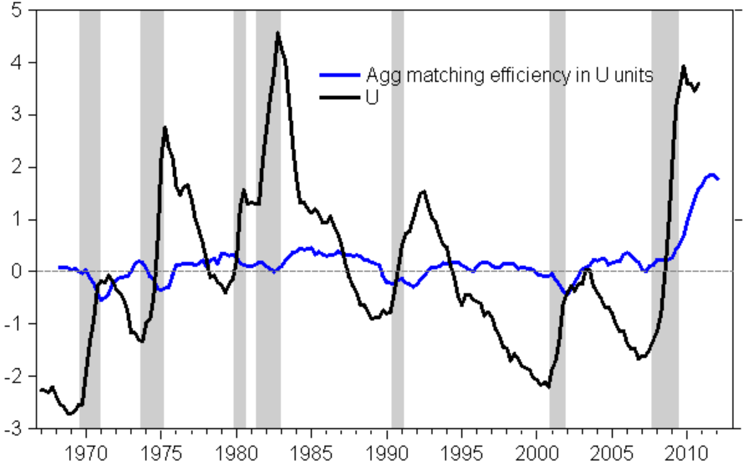


Residual in units of unemployment

Using steady-state unemployment (Barnichon and Figura 2011)



In units of unemployment



The residual of the matching function

- No trend
- Cyclical, lags the business cycle; declines in aftermaths of recessions and increases in later stages of expansions or during recessions
- Large decline with 2008-2009 recession adding $\simeq 1\frac{3}{4}$ ppt to U (and preventing it from declining)

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- Existence of labor market heterogeneities:
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  - Workers heterogeneity (observed and unobserved) $\longrightarrow$ *composition effect*

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  - Workers heterogeneity (observed and unobserved)
    $\longrightarrow$ *composition effect*
  - Heterogeneity in labor market conditions (tight markets coexist with slack markets)
    $\longrightarrow$ *dispersion effect*

This paper's interpretation (2)

- *Composition* of U pool is responsible for cyclicality until 2006
  - Fraction of job losers
  - Fraction of long-term U (mainly, unobserved characteristics)
- Since 2006, large increase in *dispersion* that reduced matching efficiency to record lows
  $\longrightarrow$ misallocation or mismatch?

Literature

- Agg. matching function literature Pissarides 1986, Blanchard and Diamond 1989, Bleakley and Fuhrer 1997, Petrongolo and Pissarides 2001
- Heterogeneity hypothesis on sources of fluctuations in JF Darby, Haltiwanger and Plant 1985, 1986, Baker 1992, Shimer 2007
  - heterogeneity does not matter
  - we revisit that conclusion by considering a larger spectrum of labor market heterogeneities
- Literature on mismatch Padoa Schioppa, 1991, Layard, Nickell and Jackman, 2005, Sahin, Song, Topa and Violante, 2011, Herz and van Rens 2011

Overview

1. A framework to study the effect of heterogeneities on "matching efficiency": composition and dispersion
2. Matching efficiency since 1976
   2.1 using micro CPS data 1976-2010
   2.2 building a new dataset with highly disaggregated data on U and V over 2006-2011
   $\longrightarrow$ necessary to capture dispersion in labor market conditions

Empirical Framework

Empirical framework

Main idea

- Aggregate job finding probability JF_t is an average over heterogenous workers j in heterogenous labor markets i

$$JF_t = \sum_{i,j} \frac{U_{ij,t}}{U_t} JF_{ij,t}.$$

Empirical framework

Modeling individual job finding probabilities

The job finding probability of individual of type j in labor market segment i (geographic location, industry group or occupation group)

$$JF_{ij,t}$$

- Individual type j defined by vector X_{jt} of K characteristics $\left\{x_{jt}^{k}\right\}$: sex, age, U reason, U duration (unobs. characteristics or hysteresis), search intensity

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- Labor market segment i has a matching technology and is characterized by labor market tightness $\theta_{it} = \frac{v_{it}}{u_{it}}$, and average matching efficiency m_i
- $$JF_{ij,t} = JF(X_{jt}, m_i, \theta_{it}, \theta_t)$$

Empirical framework

A decomposition of the determinants of average JF

$$JF_t = \sum_{i,j} \frac{U_{ij,t}}{U_t} JF(X_{jt}, m_i, \theta_{it}, \theta_t)$$

Second-order Taylor expansion $\theta_{it} \simeq \theta_t$ and $(X_{jt}, m_i) \simeq (\bar{X}, m_0)$

$$JF_t = \overline{JF}_t\left(\theta_t\right) + \sum_k JF_t^{U,k} + JF_t^m - MM_t\left(\frac{\theta_{it}}{\theta_t}\right) + \eta_t$$

The determinants of average JF

$$JF_t \simeq \underbrace{\overline{JF}_t\left(\theta_t\right)}_{1} + \sum_k JF_t^{U,k} + JF_t^m - MM_t\left(\frac{\theta_{it}}{\theta_t}\right)$$

1. First term: $\overline{JF}_t\left(\theta_t\right) = JF_{ij,t}(\bar{X}, \theta_t, \theta_t) = m_0 \theta_t^{1-\sigma}$

Average job finding rate absent heterogeneity
$\Rightarrow$ What an aggregate matching function would perfectly capture

The determinants of average JF

Composition effect

$$JF_t \simeq \overline{JF}_t\left(\theta_t\right) + \underbrace{\sum_k JF_t^{U,k}}_{\text{2a}} + JF_t^m - MM_t\left(\frac{\theta_{it}}{\theta_t}\right)$$

2a. Effect of composition

$$JF_t^{U,k} = \sum_j \frac{U_{j,t}}{U_t} \left.\frac{\partial JF}{\partial x_{jt}^k}\right|_{\theta_t,\bar{X}} \left(x_{jt}^k - \bar{x}^k\right)$$

If share of a group (e.g. job losers) with low JF_{ij} increases in recessions, then *average JF* will decline

The determinants of average JF

Composition effect

$$JF_t \simeq \overline{JF}_t(\theta_t) + \sum_k JF_t^{U,k} + \underbrace{JF_t^m}_{2b} - MM_t\left(\frac{\theta_{it}}{\theta_t}\right)$$

2b. Effect of composition

$$JF_t^m = \sum_i \frac{U_{i,t}}{U_t} \left.\frac{\partial JF}{\partial m_i}\right|_{\theta_t, \bar{X}} (m_i - m_o)$$

If more unemployed concentrated in segment with higher matching efficiency, average JF increases

The determinants of average JF

Dispersion effect

$$JF_t \simeq \overline{JF}_t(\theta_t) + \sum_k JF_t^{U,k} + JF_t^m - \underbrace{MM_t\left(\frac{\theta_{it}}{\theta_t}\right)}_{3}$$

3. Effect of dispersion

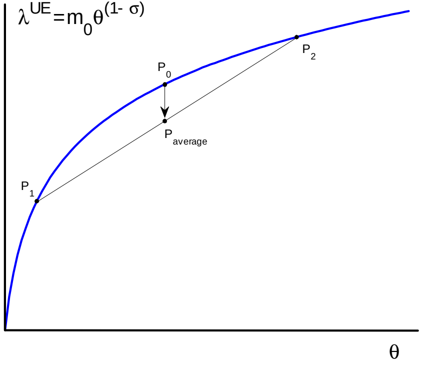
$$MM_t\left(\frac{\theta_{it}}{\theta_t}\right) = MM_0(\theta_t)\, Var\left(\frac{\theta_{it}}{\theta_t}\right)$$

If $JF_{ij}(X_{jt}, m_i, \theta_{it}, \theta_t)$ concave in θ_{it}, $MM_0(\theta_t) > 0$

$\Longrightarrow$ Dispersion in labor market tightness across segments will negatively affect *average* JF

Effect of dispersion on JF

- Two labor market segments: P_1 with θ_1 and P_2 with $\theta_2 \neq \theta_1$
- Job finding rate lower than if $P_1 = P_2 = P_{average}$



Dispersion ⇒ Lower average JF

Postulating a functional form for JF(ij)

Logistic functional form

$$\ln \frac{JF_{ij,t}}{1 - JF_{ij,t}} = \beta X_{jt} + \ln \frac{1 - e^{-m_i \theta_{it}^{(1-\sigma)\omega} \theta_t^{(1-\sigma)(1-\omega)}}}{e^{-m_i \theta_{it}^{(1-\sigma)\omega} \theta_t^{(1-\sigma)(1-\omega)}}} + \eta_{ij,t} \quad \text{with } \omega \in [0,1]$$

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- Absent heterogeneity, reduces to

$$JF_{ijt} = 1 - e^{m_0 \theta_t^{1-\sigma}} \quad \text{or} \quad jf_{ijt} = m_0 \theta_t^{1-\sigma}$$

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- With only labor market tightness heterogeneity, reduces to

$$jf_{ijt} = m_i \theta_{it}^{(1-\sigma)\omega} \theta_t^{(1-\sigma)(1-\omega)}$$

Postulating a functional form for JF(ij)

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- With only labor market tightness heterogeneity, reduces to

$$jf_{ijt} = m_i \theta_{it}^{(1-\sigma)\omega} \theta_t^{(1-\sigma)(1-\omega)}$$

- $\omega \in [0,1]$ captures impermeability of the local labor market
  - If $\omega = 1$, labor market segments impossible to cross, no impact of agg θ_t on jf_{ijt} (usual assumption in literature with heterogeneity)
  - If $\omega = 0$ there are no barriers between labor markets, a worker's job finding rate only depends on the aggregate θ_t.

A decomposition of aggregate matching efficiency

Some algebra gives

$$\ln m_{0t} - E_T \ln m_{0t} = h(\sigma, \theta_t) \left(\sum_k JF_t^{U,k} + JF_t^m \right) - \Delta mm_t + \zeta_t.$$

with

$$mm_t = g(\sigma, \omega) Var \left(\frac{\theta_{it}}{\theta_t} \right)$$

A decomposition of aggregate matching efficiency

$$\ln m_{0t} - E_T \ln m_{0t} \simeq \mathit{composition} - \mathit{dispersion}$$

The determinants of matching efficiency

1. CPS micro data 1976-2010
2. New dataset on labor market dispersion 2006-2011

Estimation

- Matched CPS micro data 1976-2010 (1.2 million obs)

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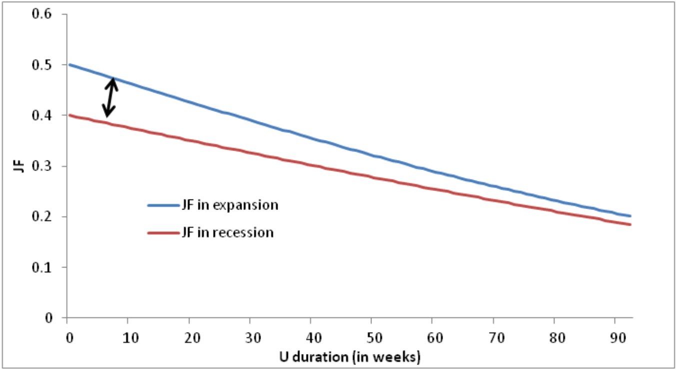
- Individual characteristics X_{jt}:
  - Observed: age, sex, (education, race)
  - Unobserved:
    - Reason for unemployment: quit, temp. or perm. layoff, LF entrant
    - U duration

$$JF_{ijt} = ... + dur_{jt}(\beta^{dur} + \gamma^{dur} dur_t)$$

$\rightarrow$ the slope can change as aggregate conditions change

The effect of duration on JF

Duration dependence is weaker in recessions



$\Longrightarrow$ Duration d captures mainly unobserved characteristics, not hysteresis

Estimation

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- Individual characteristics X_{jt}:
  - age, sex, (education, race)
  - reason for unemployment: quit, temp. or perm. layoff, LF entrant
  - U duration & U duration interacted with avg U duration
- Labor market segment state/industry and $\frac{\theta_{it}}{\theta_t}$ proxied by unemployment rate in state/industry $\frac{u_{it}}{u_t}$

Effect of extended UI on search intensity

- Can test the effect of extended U insurance (UI) on m_{0t} (through search intensity)

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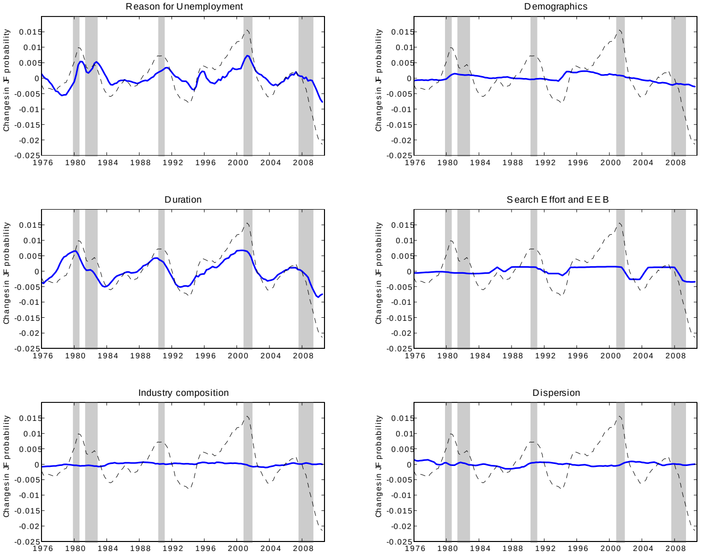
- Can test the effect of extended U insurance (UI) on m_{0t} (through search intensity)
- Add a dummy for period where extended UI is in effect
  Identification: (Kuang and Valletta, 2010)
  - Job losers eligible for UI benefits
  - Job leavers and new labor force entrants not eligible

Effect of composition

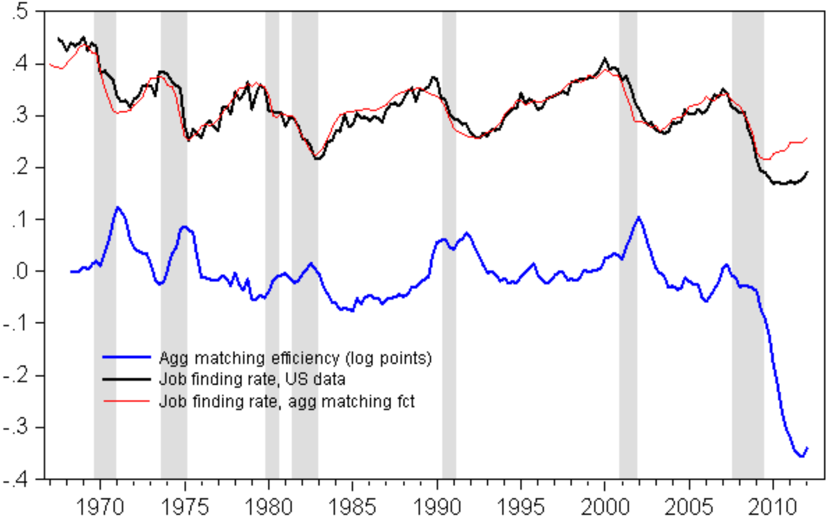


Effect of composition on JF

- 2 key factors:
  - Fraction of permanent layoffs (vs. temporary layoffs and quits)
  - Fraction of long-term unemployed
- Both of these characteristics are persistent in the U pool

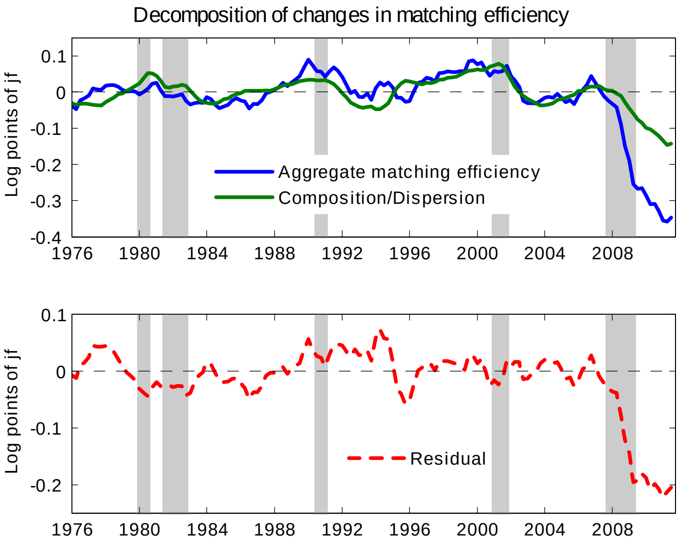
Composition and matching efficiency (4-qters MA)

Recall:



Composition and matching efficiency (4-qters MA)

Using richer framework:



Composition and matching efficiency

- Composition explains most of fluctuations in m_{0t} until 2006
- Fit particularly good after CPS redesign in 94
  - m_{ot} lags the cycle because fraction of long-term U and job losers are inertial
- 60% of decline in m_{0t} unexplained after 2006

A closer look at dispersion over 2006-2011

- Very difficult to measure the effect of dispersion:
  Need highly disaggregated data on $\theta_i = \frac{V_i}{U_i}$
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- We build a new dataset on θ_{it} with **unique** level of disaggregation over 2006-2010
- We observe $\theta_{it} = \frac{V_{it}}{U_{it}}$ over *564 labor markets* defined by occupation (6) and location (94)

A new dataset with V data by geography and occupation

Since November 2006, the Conference Board has published

- Number help-wanted online ads by state *and* occupation
- Number of ads by metropolitan statistical areas (MSA) *and* occupation

A new dataset with V data by geography and occupation

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- By splitting further across 6 occupation groups, largest unit (NYC/sales) represents only 1.5% of US U

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  e.g., a lot of hiring in construction occurs without formal posting of a vacancy
- Matching function efficiency m_i may differ across segments
- Treat informal hiring as a measurement error in vacancy

$$V_{it} = \alpha_i \widetilde{V}_{it}$$

with α_i the inverse of the share of formal hiring and $\widetilde{V}_{it}$ observed vacancy posting.

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  and from $\theta_t = \sum_i \frac{U_{it}}{U_t} \theta_{it}$,

$$\theta_t = \alpha_{0t} \tilde{\theta}_t \text{ and } \alpha_{0t} \equiv \sum_i \frac{V_{it}}{V_t} \alpha_i$$

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$$\theta_t = \alpha_{0t} \tilde{\theta}_t \text{ and } \alpha_{0t} \equiv \sum_i \frac{V_{it}}{V_t} \alpha_i$$

- Job finding rate in segment i

$$jf_{it} = m_0 \left(\alpha_i \tilde{\theta}_{it}\right)^{\omega(1-\sigma)} \left(\alpha_{0t} \tilde{\theta}_t\right)^{(1-\omega)(1-\sigma)} \tag{1}$$

Estimating the fraction of informal hiring (1)

- Effect of dispersion on m_{0t}

$$\Delta mm_t \simeq g(\omega, \sigma)\Delta Var\left(\frac{\alpha_i}{\alpha_{0t}}\frac{\tilde{\theta}_{it}}{\tilde{\theta}_t}\right)$$

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- Taking the log of (1) and differencing gives

$$\ln jf_{it} - \ln jf_{1t} = \omega(1-\sigma) \ln \frac{\alpha_i}{\alpha_1} + \omega(1-\sigma) \left(\ln \tilde{\theta}_{it} - \ln \tilde{\theta}_{1t} \right) + \xi_{it}$$

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- From estimates of $\frac{\alpha_i}{\alpha_1}$, we can obtain

$$\frac{\alpha_{0t}}{\alpha_1} = \sum_i \frac{V_{it}}{V_t}\frac{\alpha_i}{\alpha_1}$$

and get

$$\frac{\alpha_i}{\alpha_{0t}} = \frac{\alpha_i}{\alpha_1}\Big/\frac{\alpha_{0t}}{\alpha_1}.$$

Estimating the fraction of informal hiring (2)

- Panel with 564 segments and 4 time periods (2006-2007, 2008, 2009 and 2010)

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- Panel with 564 segments and 4 time periods (2006-2007, 2008, 2009 and 2010)
- Estimate

$$\omega(1-\sigma) = 0.22$$

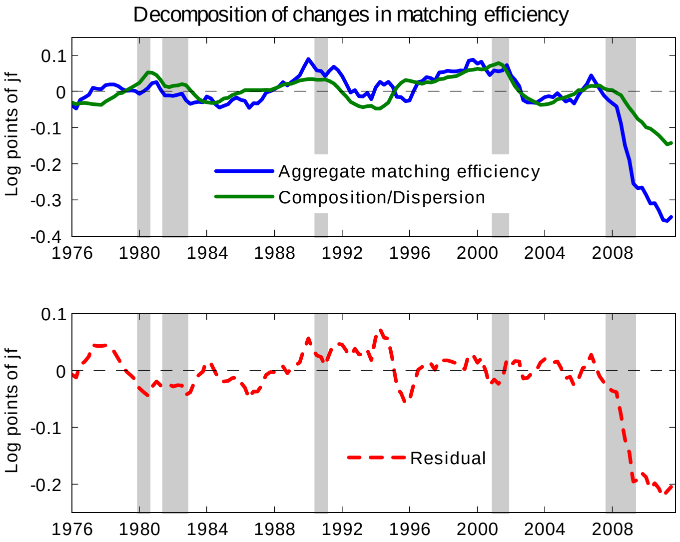
Using $1-\sigma = 0.33$, permeability coefficient

$$\omega \simeq 0.65$$

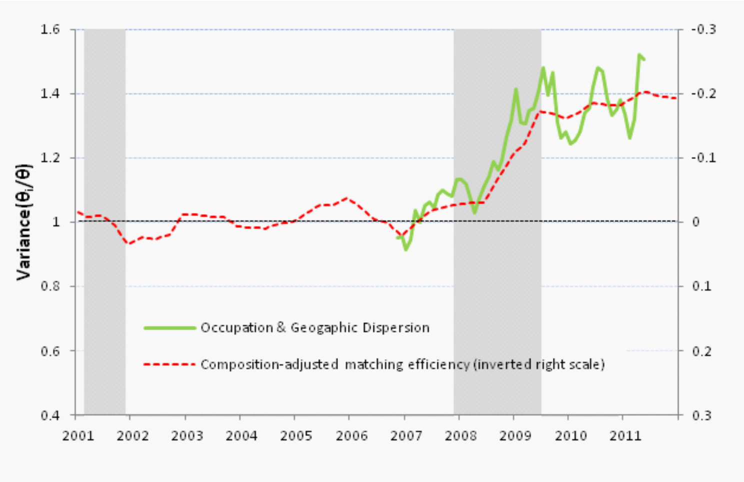
$\longrightarrow$ Even at a relatively high level of disaggregation, segments relatively impermeable

Composition and matching efficiency (4-qters MA)

Recall:



Dispersion over 2006-2011 and matching efficiency



⇒ The increase in dispersion coincides with decline in match efficiency!

Dispersion over 2006-2010 and matching efficiency

$$\Delta mm_t \simeq g(\omega,\sigma)\Delta Var\left(\frac{\alpha_i}{\alpha_{0t}}\frac{\tilde{\theta}_{it}}{\tilde{\theta}_t}\right)$$

Quantitatively, dispersion accounts for $\simeq$ 40% of decline in composition-adjusted matching efficiency

Dispersion at a higher level of disaggregation

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Dispersion at a higher level of disaggregation

- 564 labor market segments may still be too low to capture magnitude of increase in dispersion $\Delta Var\left(\frac{\theta_{it}}{\theta_t}\right)$
- Denote θ_i labor market tightness over elementary labor market unit
- We only observe segment j with n units
  $\Rightarrow$ measure only $\bar{\theta}_j$, the average of θ_i over many units

Dispersion at a higher level of disaggregation

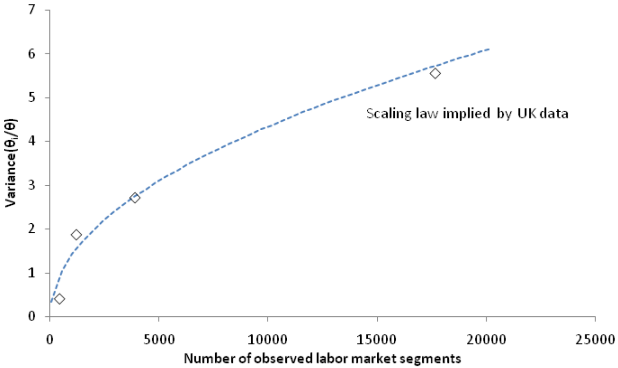
- 564 labor market segments may still be too low to capture magnitude of increase in dispersion $\Delta Var\left(\frac{\theta_{it}}{\theta_t}\right)$
- Denote θ_i labor market tightness over elementary labor market unit
- We only observe segment j with n units
  $\Rightarrow$ measure only $\bar{\theta}_j$, the average of θ_i over many units
- A simple model shows that true dispersion

$$Var\left(\frac{\theta_i}{\theta}\right) = f(n) Var_n\left(\frac{\bar{\theta}_j}{\theta}\right)$$

with $f(.) > 1$, $f'(.) > 0$ and f concave.

Dispersion at a higher level of disaggregation

- Empirically, can use UK data to estimate the scaling law $f(n)$
- UK public employment office collects vacancies at low levels to very high levels (20,000 segments)
- Estimate power law $f(n) = n^a$, $a < 1$



Dispersion at a higher level of disaggregation

- Construct an estimator of true $Var\left(\frac{\theta_i}{\theta}\right)$

$$\widehat{Var}_n\left(\frac{\theta_i}{\theta}\right) \equiv f(n) Var_n\left(\frac{\bar{\theta}_j}{\theta}\right)$$

Dispersion at a higher level of disaggregation

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- Assuming 81 occupations and 232 geographic units in US, we get that $f(n) \simeq 6$
  $\longrightarrow$ With ω=0.3, increase in dispersion explains $\Delta mm_t \simeq$0.17 log points, i.e. all decline in match efficiency

Conclusion

- Labor market heterogeneities important to understand behavior of JF
  - Unobserved workers' charact. , e.g., ability (captured by U reason and U duration)
  - Labor market is segmented (large increase in dispersion that $\uparrow$ U by $1\frac{3}{4}$ ppt)
- Matching function is not a palliative to modeling workers heterogeneities (e.g., Merkl and van Rens, 2011)
- Model mobility decisions across markets (Alvarez and Shimer (2010), Birchenall (2010), Carrillo-Tudela and Visscher (2010), and Hertz and Van Rens (2011))

Corollary: reverse-engineering

Measuring mismatch from aggregate published data

- Since composition accounts perfectly for m_{0t} in the absence of "abnormal" dispersion/mismatch
- One does not need extensive data to survey the extent of dispersion/mismatch

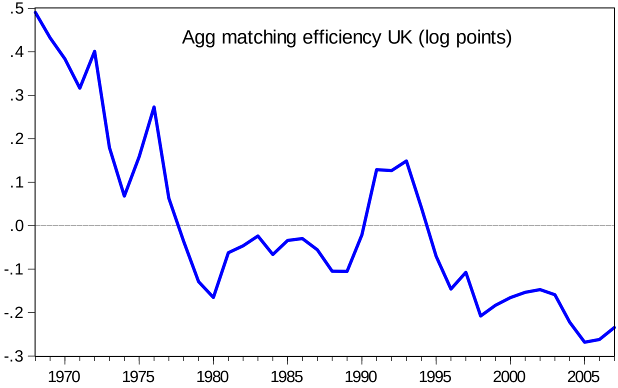
$$mm_t \simeq -jf_t + m_0\theta_t^{1-\sigma} + \beta^{dur}(Udur_t - \overline{Udur}) \\ +\beta^{layoff}\left(\frac{U_t^{layoff}}{U_t} - \overline{\frac{U_t^{layoff}}{U_t}}\right) + \beta^{quit}\left(\frac{U_t^{quit}}{U_t} - \overline{\frac{U_t^{quit}}{U_t}}\right) + etc..$$

Future work

- Just like TFP, study matching efficiency across countries

UK

Declining trend in matching efficiency



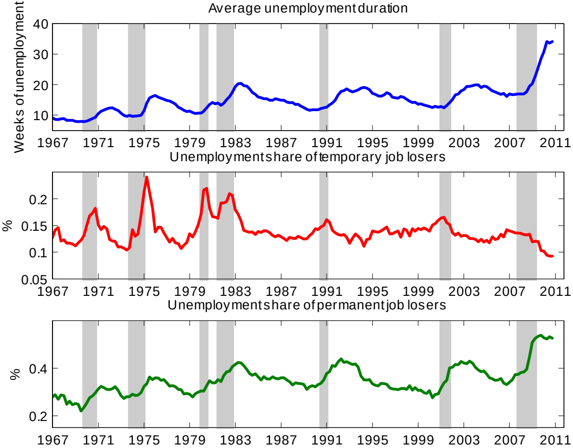
Comparison with previous measures of mismatch

In the literature, various measures to quantify the effect of misallocation on the unemployment rate

- $\sum_i \left| \frac{U_i}{U} - \frac{V_i}{V} \right|$ (Jackman and Roper 1987, Franz 1991, Brunello 1991), $\sum_i \left(\frac{U_i}{U} \frac{V_i}{V} \right)^{1/2}$ (Bean and Pissarides, 1991), and others $\sum_i \frac{E_i}{E} \left(\frac{U_i/E_i}{U/E} - \frac{V_i/E_i}{V/E} \right)^2$ (Layard, Nickell and Jackman, 1991)
- Unemployment rate dispersion measures $\sum_i u_i^2$ or $\sum_i \left(\frac{u_i}{u} \right)^2$ (e.g., Jackman, Layard and Savouri (1991), Attanasio and Padoa Schioppa (1991)),
- Some measures weighted, some not

$\Rightarrow$ Absent a unifying framework, no consensus on the most appropriate measure

- The measure we propose can be directly related to aggregate matching efficiency and thus to the equilibrium unemployment rate


Average unemployment duration
Weeks of unemployment
40
30
20
10
1967 1971 1975 1979 1983 1987 1991 1995 1999 2003 2007 2011
Unemployment share of temporary job losers
%
0.2
0.15
0.1
0.05
1967 1971 1975 1979 1983 1987 1991 1995 1999 2003 2007 2011
Unemployment share of permanent job losers
%
0.4
0.2
1967 1971 1975 1979 1983 1987 1991 1995 1999 2003 2007 2011

Dispersion by geography over 2000-2010 (22 locations)

- Splice print and online help-wanted ads data (Conference Board) over 22 cities (MSAs)

Barnichon (2010)