Directed Search with Phantom Vacancies

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Motivation

This paper is based on two premises:

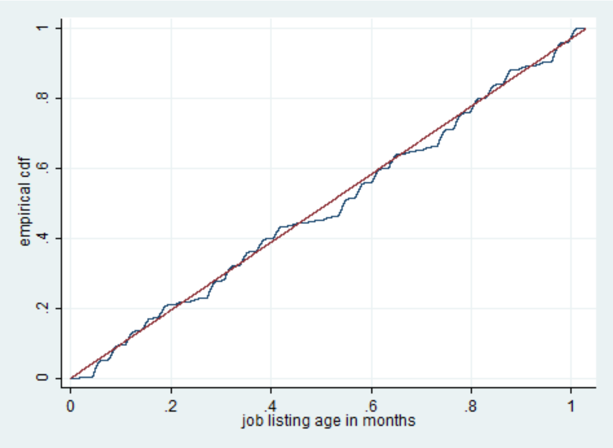
1. Much of the information available to job seekers about possible job openings is out of date.

2. Job seekers are aware of this, and they adjust their search behavior accordingly.

Phantom vacancies

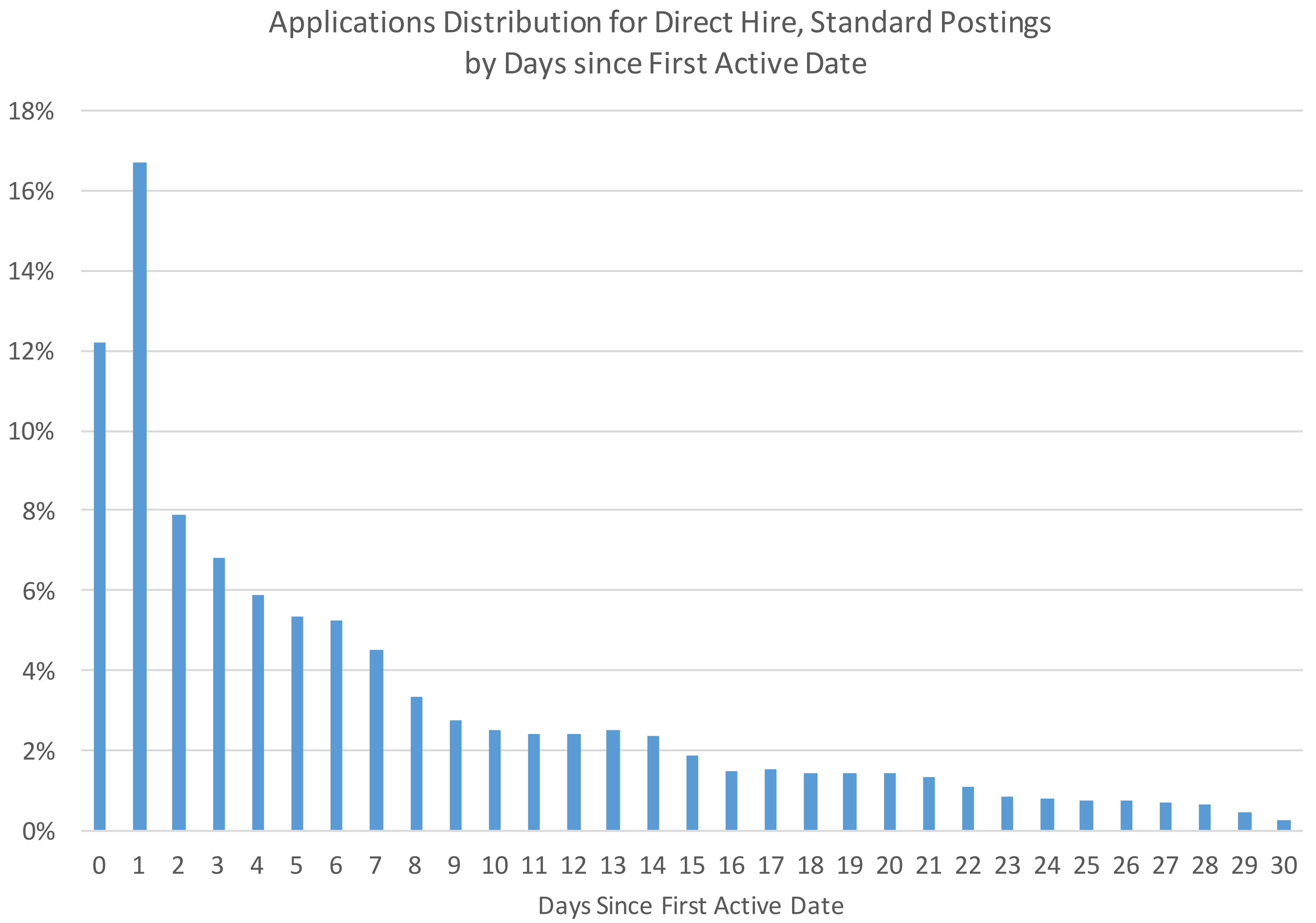
- We use the idea of *phantom vacancies* to model out-of-date information.
- By a phantom vacancy we mean a listing that remains on a job board (like Craigslist or Monster.com) for some time even though the vacancy has already been filled.
- Of course, the idea is more general; e.g., word-of-mouth information about possible job openings is also often out of date.

Evidence – Using Craigslist data, the distribution of job listings by age over one month (the time at which Craigslist destroys ads) is uniform. (Data from June 10, 2015)



Workers react to phantoms

- Job seekers observe the ages of job listings and adjust their application strategies accordingly.
- Workers are much more likely to apply for recently posted positions than they are to pursue older listings.
- *Evidence* – See the following figure from Davis and Samaniego de la Parra (work in progress)


Applications Distribution for Direct Hire, Standard Postings
by Days since First Active Date
18%
16%
14%
12%
10%
8%
6%
4%
2%
0%
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
Days Since First Active Date

Directed search

- On job boards such as Craigslist, searchers can observe the posting date for job listings. Similarly, job seekers have an idea about "how up to date" word-of-mouth information might be. They understand that older information is more likely to be out of date.
- Job seekers react by directing their search based on listing age. They know that an older listing is more likely to be out of date, i.e., is more likely to be a phantom.
- At the same time, however, job seekers recognize that other searchers also understand that younger job listings are less likely to be phantoms. There is therefore likely to be more competition for the younger listings.

Summary of Results

1. We characterize the directed search allocation of job seekers across listing ages using a simple no-arbitrage condition. The allocation of job seekers must be such that the expected payoffs associated with searching in various submarkets should be equalized, i.e., the job-finding rate is the same in all submarkets.

2. We characterize the constrained efficient allocation and identify a dynamic composition externality associated with phantoms. We find that workers overapply to young listings.

3. Finally, we calibrate our model to US data over 2000-2008 and provide evidence that phantoms may have a quantitatively important effect.

Model assumptions

- We consider the steady state of a continuous-time model. There is a continuum of workers of mass one. A fraction $1 - \mathbf{u}$ of workers is employed; a fraction $\mathbf{u}$ is unemployed.
- There is also a continuum of vacancies of mass $\mathbf{v}$. Each vacancy is associated with a listing, and listings differ in age, $a \geq 0$.
- There are K jobs so that $\mathbf{v} + 1 - \mathbf{u} = K$. (We allow for free entry of vacancies in our current revision.)

Output and Wages

- Filled jobs produce y and are destroyed at Poisson rate λ. Newly separated workers join the pool of unemployed.
- Here, we assume a fixed exogenous wage. (In our revision, the wage is determined by Nash bargaining over the match surplus.)

Matching in Submarkets

- The market is segmented by listing age, a. In each submarket, there are $u(a)$ unemployed, $v(a)$ vacancies, and $p(a)$ phantoms.

- Job seekers cannot distinguish between phantoms and vacancies.
- The flow of new matches in submarket a is

$$M(a) = \pi(a) m(u(a), v(a) + p(a)),$$

where $\pi(a)$, the *nonphantom proportion*, is

$$\pi(a) = \frac{v(a)}{v(a) + p(a)}.$$

Matching in Submarkets

$$M(a) = \pi(a)m(u(a), v(a) + p(a))$$

- Two components of the matching function:
  - *meeting function m*; standard DMP properties, strictly concave with CRS, etc.
  - *nonphantom proportion* $\pi(a)$
- The job-finding rate by listing age is $\mu(a) = M(a)/u(a)$, the rate of filling vacancies is $\eta(a) = M(a)/v(a)$, and submarket tightness is $\theta(a) \equiv (v(a) + p(a))/u(a)$.
- By CRS, $\mu(a) = \pi(a)m(\theta(a))$ and $\eta(a) = m(\theta(a))/\theta(a)$.

Phantoms and vacancies

- When a vacancy is filled, a phantom is created. However, job listings – both vacancies and phantoms – have finite lifetimes. When a vacancy reaches age A, it is renewed; i.e., it is relisted as a new vacancy ($a = 0$). When a phantom reaches age A, it disappears. In this version of the model, A is exogenous.
- Between $a = 0$ and $a = A$, vacancies and phantoms evolve according to:

$$\begin{aligned} \frac{dv(a)}{da} &= -M(a) = -\eta(a)v(a), \\ \frac{dp(a)}{da} &= M(a) = \eta(a)v(a), \end{aligned}$$

  with $v(0) = \lambda(1-u) + v(A)$ and $p(0) = 0$.
- The nonphantom proportion evolves according to:

$$\frac{d\pi(a)}{da} = -\frac{M(a)}{v(a)}\pi(a) = \eta(a)\pi(a) \quad \text{with } \pi(0) = 1.$$

Closing the model

- The unemployed are spread over the different submarkets with

$$\mathbf{u} = \int_0^A u(a)da$$

- We need a rule that allocates the unemployed across submarkets, i.e., across listing ages.
- We consider three allocations: (i) the directed search allocation, (ii) the random search allocation, and (iii) the constrained efficient allocation.

What directed search means

- Agents observe listing age a and decide which market segment to search in.

- In equilibrium, the job-finding rate is the same in all submarkets. That is,

$$\mu(a) = \pi(a)m(\theta(a)) = m(\theta(0)) \text{ for all } a$$

  Differentiating gives:

$$-\alpha(\theta)\frac{\dot{\theta}}{\theta(a)} = \frac{\dot{\pi}}{\pi(a)}$$

  where $\alpha(\theta)$ is the elasticity of the meeting function wrt $\theta(a)$ and a dot denotes the derivative wrt age, e.g., $\dot{\theta} = d\theta(a)/da$.

Directed Search Equilibrium

- Using $\frac{\dot{\pi}}{\pi(a)} = \frac{-m(\theta(a))}{\theta(a)}$, we have a pair of differential equations,

$$\begin{aligned} \alpha(\theta)\frac{\dot{\theta}}{\theta(a)} &= \frac{m(\theta(a))}{\theta(a)} \\ \frac{\dot{\pi}}{\pi(a)} &= \frac{-m(\theta(a))}{\theta(a)}. \end{aligned}$$

These can be solved given $\pi(0) = 1$ and $\theta(0) = \theta_0^{ds}$. The latter value is found using the resource constraint once the equilibrium is solved; i.e., there is a fixed point problem.

Directed Search Allocation- Results

1. There exist functions $\theta^{ds}(a) : [0, A] \to \mathbb{R}_+$ and $\pi^{ds}(a) : [0, A] \to [0, 1]$ that characterize the directed search allocation. They have the following properties:

$$\pi^{ds}(a)m(1, \theta^{ds}(a)) = \pi^{ds}(0)m(\theta^{ds}(0)) = m(\theta_0^{ds})$$

$$\alpha(\theta^{ds})\frac{\dot{\theta}^{ds}}{\theta^{ds}(a)} = -\frac{\dot{\pi}^{ds}}{\pi^{\mathrm{ds}}} = \frac{m(\theta^{ds}(a))}{\theta^{ds}(a)}$$

   with initial conditions $\pi^{ds}(0) = 1$ and $\theta^{ds}(0) = \theta_0^{ds}$, where θ_0^{ds} is defined implicitly by the resource constraint.
2. $\eta^{ds}(a)$ and $\pi^{ds}(a)$ are strictly decreasing in a, $\theta^{ds}(a)$ is strictly increasing in a, and $\mu^{ds}(a)$ is constant in a.

Random Search Allocation

- For the purpose of comparison, we consider the allocation of job seekers across submarkets that obtains when workers cannot observe listing age.
- When the unemployed cannot observe listing age, the ratio of listings (vacancies + phantoms) to job seekers is constant across submarkets. That is,

$$\theta(a) = \frac{v(a) + p(a)}{u(a)} = \theta \text{ for } 0 \leq a \leq A$$

- We close the model using the resource constraint, namely, $\mathbf{v} + 1 - \mathbf{u} = K$.

Random Search Allocation - Results

1. With random search, there exists a unique tightness θ^{rs} satisfying the resource constraint.
2. The nonphantom proportion, $\pi(a)$, declines at a constant rate with listing age.
3. The job-filling rate, $\eta(a) = m(\theta^{rs})/\theta^{rs}$ is constant over listing age.
4. The job-finding rate $\mu(a) = \pi(a)m(\theta^{rs})$ decreases with listing age.
5. Aggregate unemployment, $\mathbf{u}$, and tightness, θ^{rs}, increase with A.

Social Planner Problem

- The social planner allocates job seekers across listing ages to minimize aggregate unemployment. Since $1 - \mathbf{u} + \mathbf{v} = K$, the SP problem can be expressed as

$$\max_{\theta(.)} \; -\int_0^A v(a)da$$

- This maximization is constrained by

  1. The laws of motion for $v(a)$ and $p(a)$
  2. The resource constraint: $(1 - \mathbf{u}) + \mathbf{v} = K$.

Details

$$\max_{\theta(.)} \; -\int_0^A v(a)da$$

subject to

$$\begin{aligned}
\dot{v} &= -\eta(\theta(a))v(a) \\
v(0) &= \lambda\left(K - \int_0^A v(a)da\right) + v(A) \\
\dot{p} &= \eta(\theta(a))v(a) \\
p(0) &= 0 \\
K &= 1 - \int_0^A \frac{v(a)+p(a)}{\theta(a)}da + \int_0^A v(a)da
\end{aligned}$$

The Constrained Efficient Allocation

- There exist functions $\theta^{eff}(a) : [0, A] \to \mathbb{R}_+$ and $\pi^{eff}(a) : [0, A] \to [0, 1]$ that characterize the constrained efficient allocation. Again, the initial condition $\theta^{eff}(0) = \theta_0^{eff}$ is defined implicitly by the resource constraint.
- Characterizing this allocation is complicated, but it is relatively easy to understand the difference between the directed search and the constrained efficient allocations.
- To do this, it is useful to define $s_1(a)$ and $s_2(a)$, the shadow values associated with vacancies and phantoms of age a, respectively.

Inefficiency of Directed Search

- The rules allocating job seekers across listing ages in the directed search and constrained efficient allocations are, respectively

$$\begin{aligned} \pi^{ds}(a)m(\theta^{ds}(a)) &= m(\theta_0^{ds}) \\ (s_2(a)-s_1(a))(1-\alpha(\theta^{eff}(a)))\pi^{eff}(a)m(\theta^{eff}(a)) &= 1. \end{aligned}$$

- These rules differ in two respects. The first is the term $1-\alpha(\cdot)$ in the constrained efficient rule. This captures the idea that when an additional job seeker is allocated to submarket a, the elasticity of the matching function may change as a result. Second, there is the term $s_2(a)-s_1(a)$. Adding job seekers to submarket a translates to more matches, i.e., fewer vacancies and more phantoms, and $s_2(a)-s_1(a)$ reflects the corresponding change in value. The magnitude of the externality captured in $s_2(a)-s_1(a)$ varies with age – it reflects a dynamic composition externality.

Efficient allocation (cont'd)

As we did in the directed search case, we can substitute for $\pi(a)$ and use the resource constraint to solve for $\theta^{eff}(0)$, giving us a differential equation for $\theta^{eff}(a)$.

We can use this to show that in the efficient allocation:

1. $\theta(a)$ is increasing in a
2. $\pi(a)$ is decreasing in a
3. $\mu(a)$ is decreasing in a
4. $\eta(a)$ is decreasing in a

Inefficiency

1. The random search allocation is never constrained efficient;
2. The directed search allocation generically differs from the efficient allocation.

Calibration

- The meeting technology is Cobb-Douglas, i.e.,

$$m(u, v + p) = m_0 u^{1-\alpha}(v + p)^{\alpha}, \;\; m_0 > 0, \;\; \alpha \in (0, 1)$$

- Given this assumption, we can solve for the $\theta(a)$ in the directed search and constrained efficient allocations. In both cases, this involves solving a fixed point problem, namely, using the resource constraint to find the initial value of θ.

Parameters

- We use BLS data over the period 2000-2008
  - monthly job-finding probability:
    $\mu_m = 0.4 \Leftrightarrow 1 - \exp(-\mu) = 0.4$
    so $\mu = -\ln(1 - 0.4) \approx 0.51$
  - monthly job-loss probability:
    $\lambda_m = 0.03 \Leftrightarrow \lambda = -\ln(1 - 0.03) \approx 0.03$
  - this implies $\mathbf{u} = \lambda/(\lambda + \mu) \approx 0.0563$
- We set $A = 1$ (corresponds to Craigslist)

Parameters (cont'd)

- Two important parameters are K and α. Since $\mathbf{v} + 1 - \mathbf{u} = K$, to set K we need to estimate $\mathbf{v}$ or equivalently, since we observe $\mathbf{u}$, we need to estimate $x \equiv \mathbf{v}/\mathbf{u}$. We do this using data on vacancy durations and set $x = 0.33$.

  - To set α, we note that the aggregate matching rate is

$$M = m_0 \int_0^A \pi(a) u(a) \theta(a)^\alpha da$$

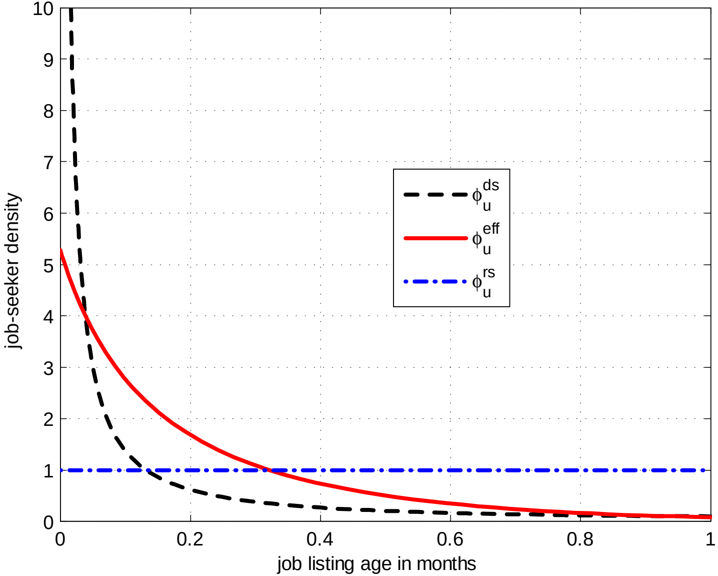
  - the elasticity of this function wrt overall tightness, x, is larger than α
  - We use $\alpha = 0.15$, which implies a matching function elasticity of 0.4.

- We set m_0 so that $\mathbf{u} = 0.0563$ and we set $K = 0.9623$ to match $x = 0.33$.
- This implies that $\mathbf{u}$ is 0.0377 in the absence of meeting frictions and phantoms

Summary

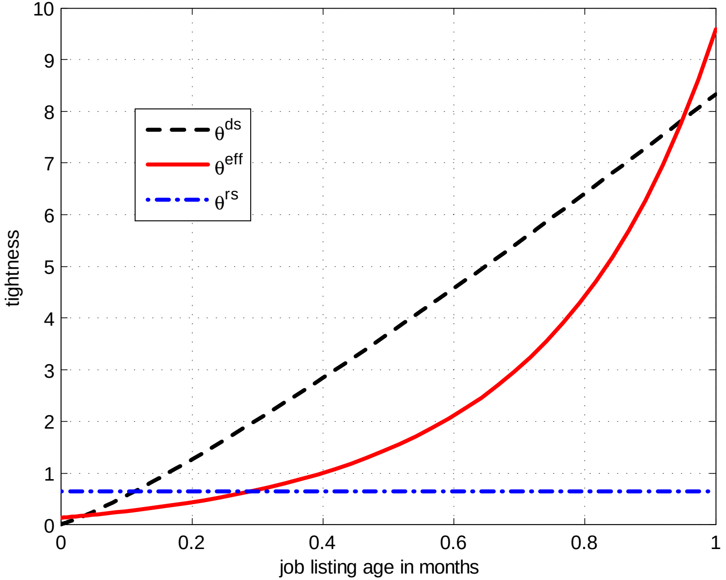
m_0	α	A	λ	K	μ	u
1.0671	0.15	1	0.0305	0.9623	0.5108	0.0563

Table 1: Parameter values in the baseline calibration

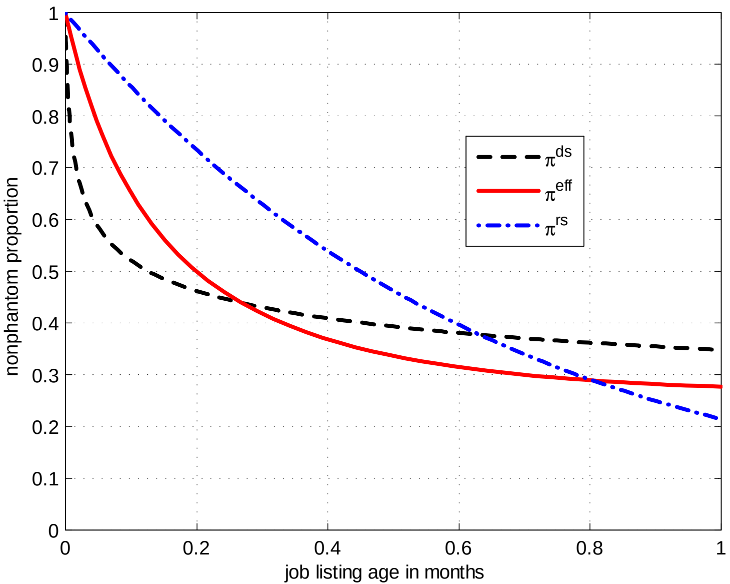

job-seeker density
job listing age in months
0
0.2
0.4
0.6
0.8
1
0
1
2
3
4
5
6
7
8
9
10
ϕ_u^{ds}
ϕ_u^{eff}
ϕ_u^{rs}

	Density of job seekers	Mean job queue
Day 1	0.5834	20.8422
Day 2	0.1044	3.7329
Day 3	0.0569	2.0321
Day 4	0.0382	1.3697
Week 1	0.8527	4.3530
Week 2	0.078	0.3981
Week 3	0.0415	0.2120
Week 4	0.0278	0.1417

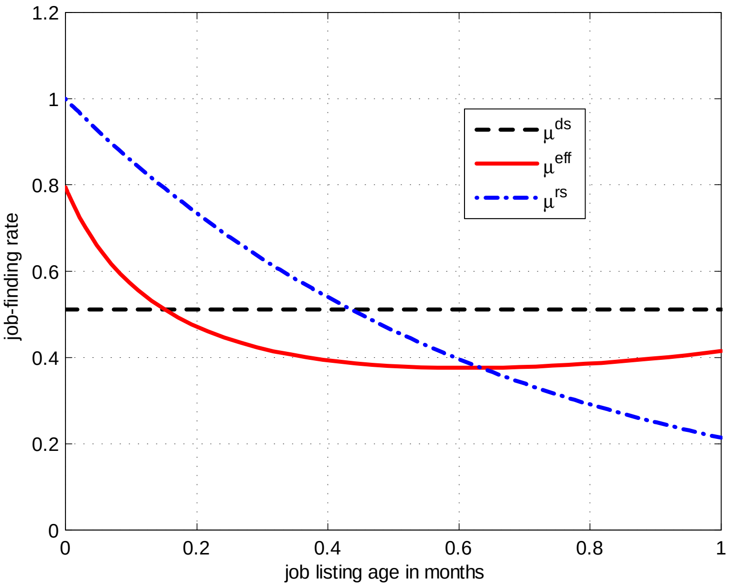
Table 2: Mass of job seekers and job queues at various intervals of listing age.



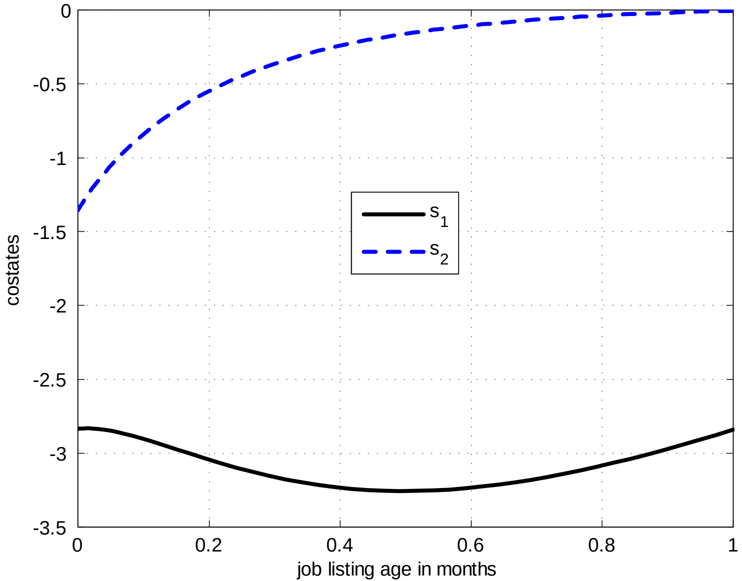
tightness
job listing age in months
θ^{ds}
θ^{eff}
θ^{rs}
0
1
2
3
4
5
6
7
8
9
10
0
0.2
0.4
0.6
0.8
1



nonphantom proportion
job listing age in months
π^{ds}
π^{eff}
π^{rs}
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1



job-finding rate
job listing age in months
μ^{ds}
μ^{eff}
μ^{rs}
0
0.2
0.4
0.6
0.8
1
1.2



costates
job listing age in months
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
0
0.2
0.4
0.6
0.8
1
s_1
s_2

Quantitative implications

- Efficiency gains achieved by the efficient allocation are modest
  - search strategies that produce more matches also produce more phantoms
  - the unemployment rates across the 3 allocations are: $\mathbf{u}^{rs} = 5.64\%, \mathbf{u}^{ds} = 5.63\%, \mathbf{u}^{eff} = 5.39\%$
- Contribution of information obsolescence to unemployment is nonetheless large
  - nonfrictional unemployment rate is $\min(1 - K, 0) = 3.77\%$
  - matching frictions account for $(5.63 - 3.77)/5.63 \approx 33\%$ of unemployment
  - with frictions but no phantoms, the unemployment rate would be 4.06%
  - phantoms account for $(5.63 - 4.06)/(5.63 - 3.77) \approx 85\%$ of overall frictions and $(5.63 - 4.06)/5.63 \approx 28\%$ of unemployment

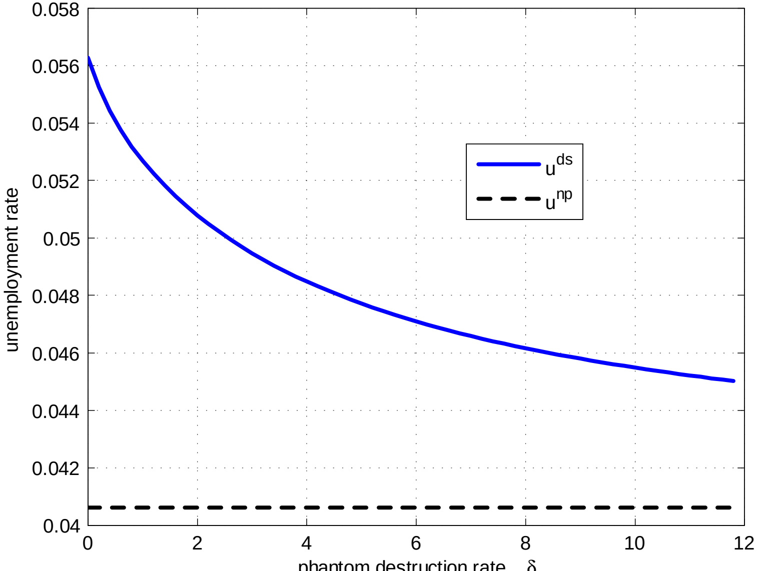
Extensions

1. Phantom Death Rate
2. Vacancy Renewals
3. Lemons
4. Nash Bargained Wages

Phantom Death Rate

- We introduce a new parameter, δ, the rate at which phantoms die. This changes the laws of motion for p and π.
- As we vary δ from 0 (the baseline case) to ∞ (no phantoms), the unemployment rate varies from 5.63% to 4.06%
- With $\delta = 4$ (employers withdraw obsolete ads after one week on average), the unemployment rate is 4.85%.

Phantom Death Rate

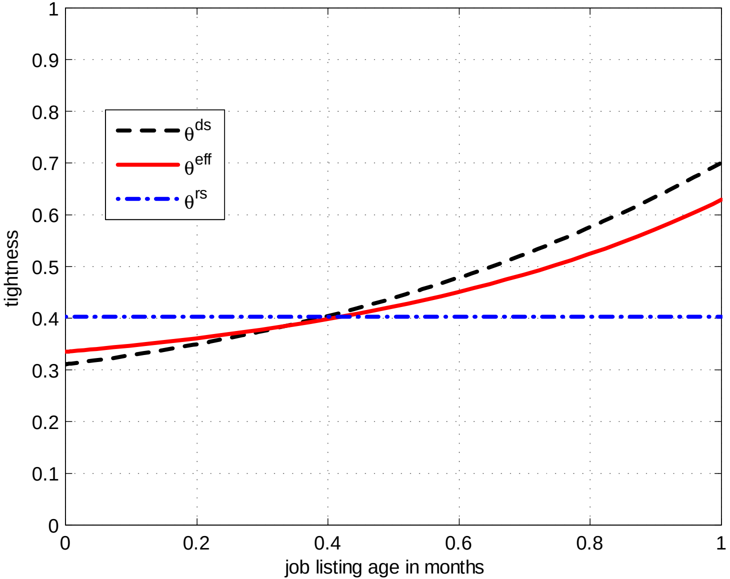


Vacancy Renewals

- Some websites allow employers to relist vacancies ($a = 0$) before the termination age A is reached.
- We assume that vacancies are renewed at exogenous Poisson rate γ between ages 0 and A. This changes the laws of motion for v and π.
- To calibrate γ, we use information from Craigslist on the fraction of newly created vacancies in a new cohort of listings. We set $\gamma = 0.3438$.
- Bottom line: Vacancy renewal does not qualitatively affect our conclusions.

Lemons

- Next we consider the possibility that some jobs may be lemons so that workers who meet them won't take them. Lemons are another reason that workers pay attention to listing age.
- To isolate the effect of lemons, we shut down phantom creation.
- Unlike phantoms, lemons are created at age zero, and no new lemons are created after this. We assume the inflow of lemons is proportional to the inflow of newly listed vacancies, $l_0 = \beta v(0)$, with $\beta = 0.1$
- Lemons create an inefficiency because when a match is formed, there is a compositional externality – a job seeker responding to an ad is less likely to find a vacancy. However, quantitatively the effect of lemons is small.



tightness
job listing age in months
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.2
0.4
0.6
0.8
1
θ^{ds}
θ^{eff}
θ^{rs}

Nash-Bargained Wages

- With Nash bargaining, workers receive a share $\upsilon \in [0, 1]$ of the match surplus, $S(a)$ and the firm receives the remaining $1 - \upsilon$.
- Workers direct their search to allocate themselves over job listings so that

$$\pi(a) m(1, \theta(a)) S(a) = m(1, \theta(0)) S(0) \quad \text{for all } a \geq 0.$$

  Taking derivatives of both sides yields

$$\alpha \frac{\dot{\theta}}{\theta(a)} = -\left(\frac{\dot{\pi}}{\pi(a)} + \frac{\dot{S}}{S(a)} \right).$$

- Even though the match surplus (and therefore the wage) vary with listing age, there is no $\upsilon \in [0, 1]$ that implements the constrained efficient allocation.

Summing Up

- When vacancies are filled, the ads that were posted are often not withdrawn creating phantom vacancies.
- Directed search by workers who observe the age of job listings then leads workers to overapply to young ads.
- Thus filling a vacancy of a given age creates a negative informational externality that affects all cohorts of listings that are older.
- We calibrate our model of directed search with phantoms to US data and find that phantoms contribute significantly to unemployment and market frictions. The externality, however, is not large if the social planner is unable to eliminate the phantoms.