## **Unemployment Facts** 704 Macroeconomic Theory II Topic 1

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#### Lecture:

Tuesdays, Thursdays, 11-12:15, in CDS 463

#### Instructor:

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#### **TA:**

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- Office hours: 12:30-2:30 in room 413
- Sections: Tu 3:30-4:45 in CAS 116







#### Grades:

- 40% problem sets
- 60% final exam

#### There will be 4 problem sets

- Strongly encouraged to work in a group
- But each student must hand in their own write-up.
- Strongly encouraged to write in LaTeX
- Write as if you were writing a paper and submitting it to a journal. Don't paste the screenshot of Stata output window!

The first problem set is already posted. Due March 29th.







#### **Frictionless models** (Neoclassical growth, RBC)

**1. Goods market friction:** Price stickiness (NK)

#### First half: labor market frictions

Second half: financial market frictions



#### **2. Labor market friction:** Seach & matching

#### **3. Financial market** friction







### What is Unemployment?





## Why Study Unemployment?

- Unemployment is often a central focus in business cycles
- - Krueger-Meuller (2012)
- Why care about unemployment? Ganong-Noel (2018) Individual: lower income, consumption, and emotional well-being • Aggregate: Potentially under-utilization of resources
- Questions:
  - 1. Why is there unemployment? Why does it fluctuate?
  - 2. Is unemployment inefficient?
  - 3. What policies should we implement?
- But before theorizing, we need to define and measure unemployment



## **Defining Unemployment**

330 million Less than 16 y/o armies, prisons **Jobless but not** Not in labor force looked for work 100 million in the past 4 weeks **Jobless and looked** 

**Total US population** Non-institutional civillian population 260 million 160 million Unemployed

**Civillian labor force** 

Employed 150 million

for work in the past 10 million

4 weeks



### Labor Force Participation Rate



Male: declining trend

- aging
- longer education
- wealth effect
- leisure tech

Female: rising trend

- social norm
- home production technology
- service sector



### **Prime Age Labor Force Participation Rate**



#### Labor Force Participation Rate: 25-54 yrs old

![](_page_8_Picture_4.jpeg)

![](_page_9_Figure_1.jpeg)

![](_page_9_Picture_2.jpeg)

![](_page_9_Picture_4.jpeg)

## **Unemployment Rate by Gender**

#### Unemployment Rate by Gender

![](_page_10_Figure_2.jpeg)

#### Female less cyclical before COVID

![](_page_10_Picture_5.jpeg)

### Flows Into and Out of Unemployment

![](_page_11_Picture_1.jpeg)

![](_page_12_Picture_1.jpeg)

- Unemployment represents a stock of workers
  - Determined through a balance between inflows and outflows
- Useful to break down the role of inflows vs. outflows
  - Disciplines the model we should be writing down

![](_page_12_Picture_7.jpeg)

![](_page_13_Picture_0.jpeg)

#### Labor Market Flows over Time

![](_page_14_Figure_1.jpeg)

![](_page_14_Picture_2.jpeg)

![](_page_14_Picture_16.jpeg)

#### Labor Market Flows before COVID

![](_page_15_Figure_1.jpeg)

![](_page_15_Figure_2.jpeg)

![](_page_15_Figure_3.jpeg)

E to N

N to U

![](_page_15_Picture_6.jpeg)

### Not in the Labor Force

#### We will abstract from individuals not in the labor force

- One justification is that the labor force participation is not very cyclical • Active research on how flows in to and out of N matters.

![](_page_16_Figure_4.jpeg)

![](_page_16_Picture_5.jpeg)

![](_page_16_Picture_7.jpeg)

![](_page_16_Picture_22.jpeg)

#### **Stock-Flow Model**

Basic stock-flow accounting equation:

![](_page_17_Figure_2.jpeg)

Is unemployment fluctuations due to fluctuations in  $f_t$  or  $s_t$ ?

## $separation = \underbrace{s_t(1 - u_t)}_{separation} - \underbrace{f_t u_t}_{job-finding}$ (inflow into U) (outflow from U)

Separation rate, s

![](_page_17_Figure_6.jpeg)

![](_page_17_Picture_7.jpeg)

### **Approximate Unemployment Rate**

In the steady state,

 $\bar{u}$  :

- Out of steady state, no such simple formula
- But if transitions are "fast enough", we can approximate

 $\mathcal{U}_t \approx$ 

- Unemployment is "as if" steady-state with contemporaneous flow Can use this approximate formula to unpack the role of inflows vs. outflows

$$= \frac{\bar{s}}{\bar{s} + \bar{f}}$$

$$\neq \frac{s_t}{s_t + f_t} \equiv \hat{u}_t$$

![](_page_18_Picture_11.jpeg)

![](_page_19_Picture_0.jpeg)

![](_page_19_Figure_1.jpeg)

### **Approximation is Excellent**

How Much Fluctuations in 
$$u$$
 due to  $s$   
Rewrite  $\hat{u}_t = s_t/(s_t + f_t)$  as  
 $\frac{\hat{u}_t}{1 - \hat{u}_t} = \frac{s_t}{f_t}$   
Taking log of both sides, the variance of  $\log(\hat{u}_t/(1 - \hat{u}_t))$  can be decomposed  
Var  $\left[\log \frac{\hat{u}_t}{1 - \hat{u}_t}\right] = \operatorname{Cov}\left[\log \frac{\hat{u}_t}{1 - \hat{u}_t}, \log s_t\right] + \operatorname{Cov}\left[\log \frac{\hat{u}_t}{1 - \hat{u}_t}, -\log f_t\right]$   
flutuations due to s  
Fluctuations due to s  
Consider the following OLS regression  
 $\log s_t = \alpha + \beta \log(\hat{u}_t/(1 - \hat{u}_t)) + c_t$   
Then  $\beta = \frac{\operatorname{Cov}(\log s_t, \log \hat{u}_t/(1 - \hat{u}_t))}{\operatorname{Var}(\log \hat{u}_t/(1 - \hat{u}_t))} \Rightarrow$  Variance share!

### **or** *f* **?**

posed into

![](_page_20_Picture_7.jpeg)

### Variance Decomposition through Regression

log s vs log u

![](_page_21_Figure_2.jpeg)

- log f vs log u

![](_page_21_Picture_4.jpeg)

#### Variance Decomposition

#### Decomposition:

- Job-finding: 51%
- Job-separation: 49%
- This is in line with Fujita-Ramey (2009)
- In contrast, using different data/methodology, Shimer (2012) argued
  - Job-finding: 90%
  - Job-separation: 10%
- Consensus nowadays is 50:50

#### Literature has been mostly focusing on job-finding due to hysterisis from Shimer

![](_page_22_Picture_13.jpeg)

### Unpacking Job-finding Rate

![](_page_23_Picture_2.jpeg)

### **Matching Friction**

- Dominant views until 1970s:
  - wage rigidity  $\Rightarrow$  labor supply > labor demand
- Diamond-Mortensen-Pissarides (DMP) paradigm:
  - Workers look for a job. Firms look for workers.
  - But it takes time to find a match
- Assume that the number of matches in each period is given by

- M: matching function,  $u_t$ : unemployment,  $v_t$ : vacancies
- *M* is nonnegative, increasing, and concave in both arguments
- Reduced form way to capture various frictions (e.g., physical and informational)

Why can't workers find a job immediately? Why does job-finding rate fluctuate?

 $m_t = M(u_t, v_t)$ 

![](_page_24_Picture_14.jpeg)

## **Deriving Beveridge Curve**

- Not empirically settled. Interesting area to explore.
- The job-finding probability can be written as

$$f_t = \frac{M(u_t, v_t)}{u_t}$$

•  $\theta_t \equiv v_t/u_t$  is labor market tightness

- - Popularly referred to as "**Beveridge curve**"

It is convinient to assume M is constant returns to scale (e.g.,  $M(u, v) = \overline{m}u^{1-\alpha}v^{\alpha}$ )

$$= M(1, v_t/u_t) \equiv \hat{f}(\theta_t)$$

If Plug the above expression into the approx. unemp. rate formula ( $s_t = f_t u_t / (1 - u_t)$ ):  $s_t = M\left(\frac{v_t}{n_t}, \frac{u_t}{1 - u_t}\right), \quad n_t \equiv 1 - u_t$ • A relationship between vacancy rate,  $v_t/n_t$ , and unemp. rate,  $u_t$  (for given  $s_t$ )

![](_page_25_Picture_12.jpeg)

![](_page_25_Picture_27.jpeg)

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#### Assuming s is a constant

# vacancy rate, $v_t/n_t$

# **Beveridge Curve** $s = M\left(\frac{v_t}{n_t}, \frac{u_t}{1 - u_t}\right)$

#### Low-vacancy ⇒ low job-finding rate ⇒ high unemployment

![](_page_26_Picture_6.jpeg)

![](_page_26_Picture_7.jpeg)

#### How does Beveridge curve look in the data?

• Before that, what is "vacancy" in the data?

#### BLS Job Openings and Labor Turnover Survey (JOLTS) definition:

- 1. A specific position exists and there is work available for that position
- 2. The job could start within 30 days
- 3. There is active recruiting for workers from outside the establishment location

![](_page_27_Picture_7.jpeg)

![](_page_27_Picture_10.jpeg)

![](_page_28_Picture_0.jpeg)

![](_page_28_Figure_1.jpeg)

#### Vacancy in the Data

![](_page_28_Picture_3.jpeg)

### **Empirical Beveridge Curve**

![](_page_29_Figure_1.jpeg)

![](_page_29_Picture_2.jpeg)

### **Empirical Beveridge Curve**

![](_page_30_Figure_1.jpeg)

![](_page_30_Picture_2.jpeg)

### **Empirical Beveridge Curve**

![](_page_31_Figure_1.jpeg)

![](_page_31_Picture_2.jpeg)

### **Soft-Landing or Hard-Landing?**

14%

#### Which Beveridge curve are we on? 8% 7% 6% ob vacancy rate 5% 3% 2% 1% 4% 6% 8% 10% 12% Unemployment rate Post-COVID: Apr 2020–Oct 2022 Pre-COVID: Jan 2001–Mar 2020

https://www.minneapolisfed.org/article/2022/us-job-matching-holds-up-keeping-a-soft-landing-in-sight

**Blanchard & Summers:** We are on B. If the Fed brings down v to pre-COVID level, we will see a massive increase in u.  $\Rightarrow$  hard-landing

Mongey: We are on C. Reducing v doesn't increase *u* much.  $\Rightarrow$  soft-landing

![](_page_32_Picture_5.jpeg)

![](_page_32_Picture_6.jpeg)

![](_page_33_Picture_0.jpeg)

![](_page_33_Figure_1.jpeg)

### Who was Right?

![](_page_33_Picture_3.jpeg)

## What Can Beveridge Curve Tell?

- As predicted by DMP paradigm, there appears to be a negative correltaion ... with ongoing outward shifts in the relationship
  - For any given  $u_t$ , we have more vacancies now than before
- Suppose the matching function is time-varying and now given by

 $\bar{m}_t$ : match efficiency shock

 $M_t(v_t, u_t) = \bar{m}_t(v_t)^{\alpha}(u_t)^{1-\alpha}$ 

![](_page_34_Picture_7.jpeg)

### **Beveridge Curve**

- Taking log, the Beverage curve (expressed in logs) is now
  - $\log(v_t/n_t) = \tilde{m}_t$
  - where  $\tilde{m}_t \equiv (1/\alpha) \left[ \log s_t \log \bar{m}_t \right]$
- Any shock to  $s_t$  or  $\bar{m}_t$  will show up as the shifts in the empirical Beveridge curve
- If  $\tilde{m}_t$  is correlated with  $u_t$ , the empirical Beveridge curve lacks structural interpretation • Just as in corr(q, p) tells us neither supply nor demand curve In my view, this is an important open question

- Still, corr(v, u)<0 is suggestive that v is an important determinant of u</p>

$$t - \frac{1 - \alpha}{\alpha} \log \frac{u_t}{1 - u_t}$$

![](_page_35_Picture_10.jpeg)

![](_page_35_Picture_11.jpeg)

### **Job-Finding and Market Tightness**

![](_page_36_Figure_2.jpeg)

Another way to see the prediction of DMP paradigm is (under Cobb-Douglas)  $\log f_t = \log \hat{f}(\theta_t) = \log \bar{m} + (1 - \alpha)\log(v_t/u_t)$ 

![](_page_36_Figure_5.jpeg)

 $\log f_t = 0.25 \times \log(v_t/u_t) + const + \epsilon_t$ 

![](_page_36_Picture_7.jpeg)

## Taking Stock

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### **Taking Stock**

- Unemployment rate fluctuates between 5-10p.p.
- On average, 30% of workers find a job every month; 2% of workers loose their job
- Job-finding and separation play roughly equally important role in fluctuations in u
- DMP paradigm views unemployment as the outcome of matching frictions
- Next lecture: understand the determinants of v<sub>t</sub>

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![](_page_38_Picture_9.jpeg)

### **Appendix: Cross-Country Perspective**

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