
Unemployment Facts

704 Macroeconomics II

Topic 1

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2026 Spring

Course Logistics

- Lecture:
 - Tuesdays, Thursdays, 11-12:15, in CAS 233
- Instructor:
 - Masao Fukui (mfukui@bu.edu)
 - Office hours: Mon 2:45-5:45pm in Room 400
- TA:
 - Shraddha Mandi (mandis@bu.edu)
 - Office hours: 12:30-2:30 in Room 514
- Sections: Tu 3:30-4:45 in CAS 228

Grades

- Grades:
 - 10% problem sets
 - 90% final exam
- There will be 3 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 April 2nd.

Coding

- Coding skills are extremely important but under-emphasized at BU
- I put emphasis on coding and post all the underlying codes at https://github.com/masaofukui/704_Julia
- Tips:
 - For simulation, use Julia or Python (stop using matlab)
 - Use Github for version control
 - Use VS Code + GitHub Copilot as an editor
 - I use Cursor, which is strictly better but costs \$20/month

Course Overview

Frictionless models
(Neoclassical growth, RBC)

1. Goods market friction:
Price stickiness (NK)

2. Labor market friction:
Search & matching

3. Financial market friction

- First half: labor market frictions
- Second half: financial market frictions

What is Unemployment?

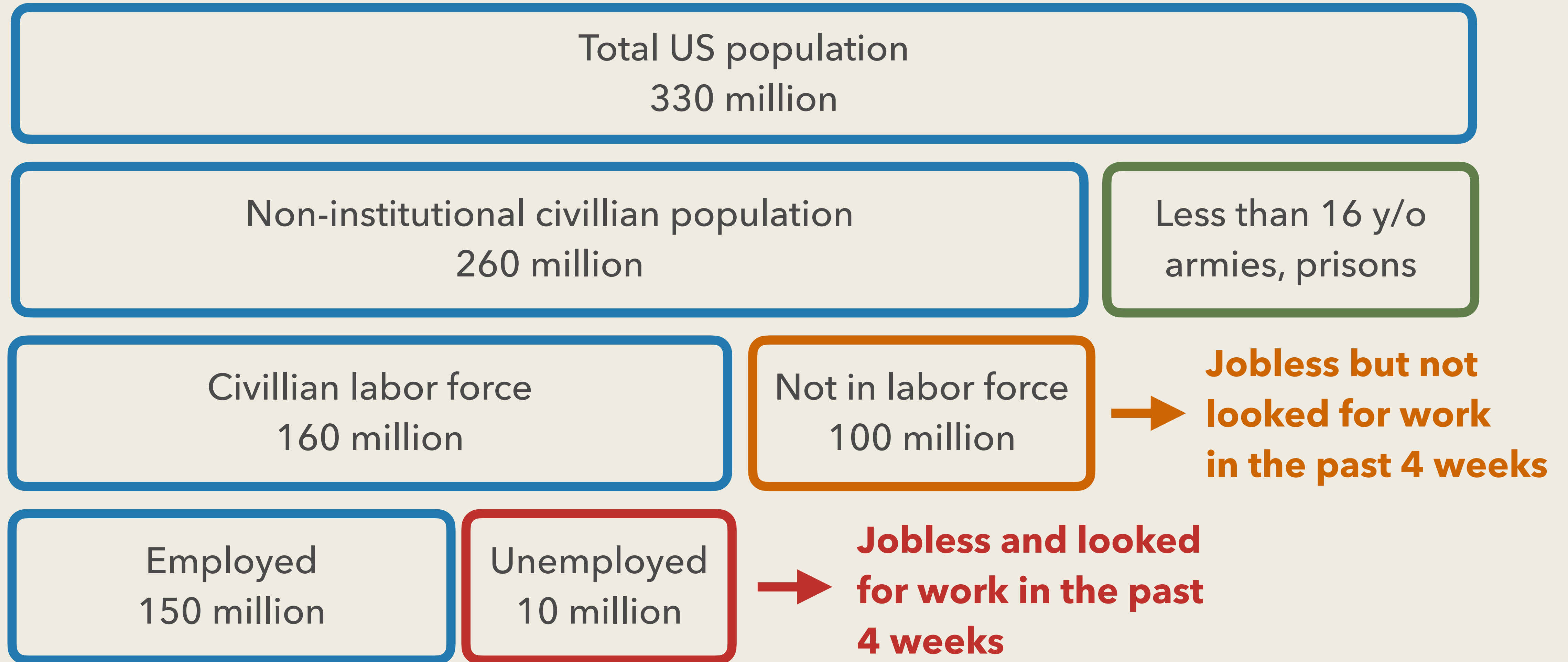
Why Study Unemployment?

- Unemployment is often a central focus in business cycles
- Why care about unemployment?
 - 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

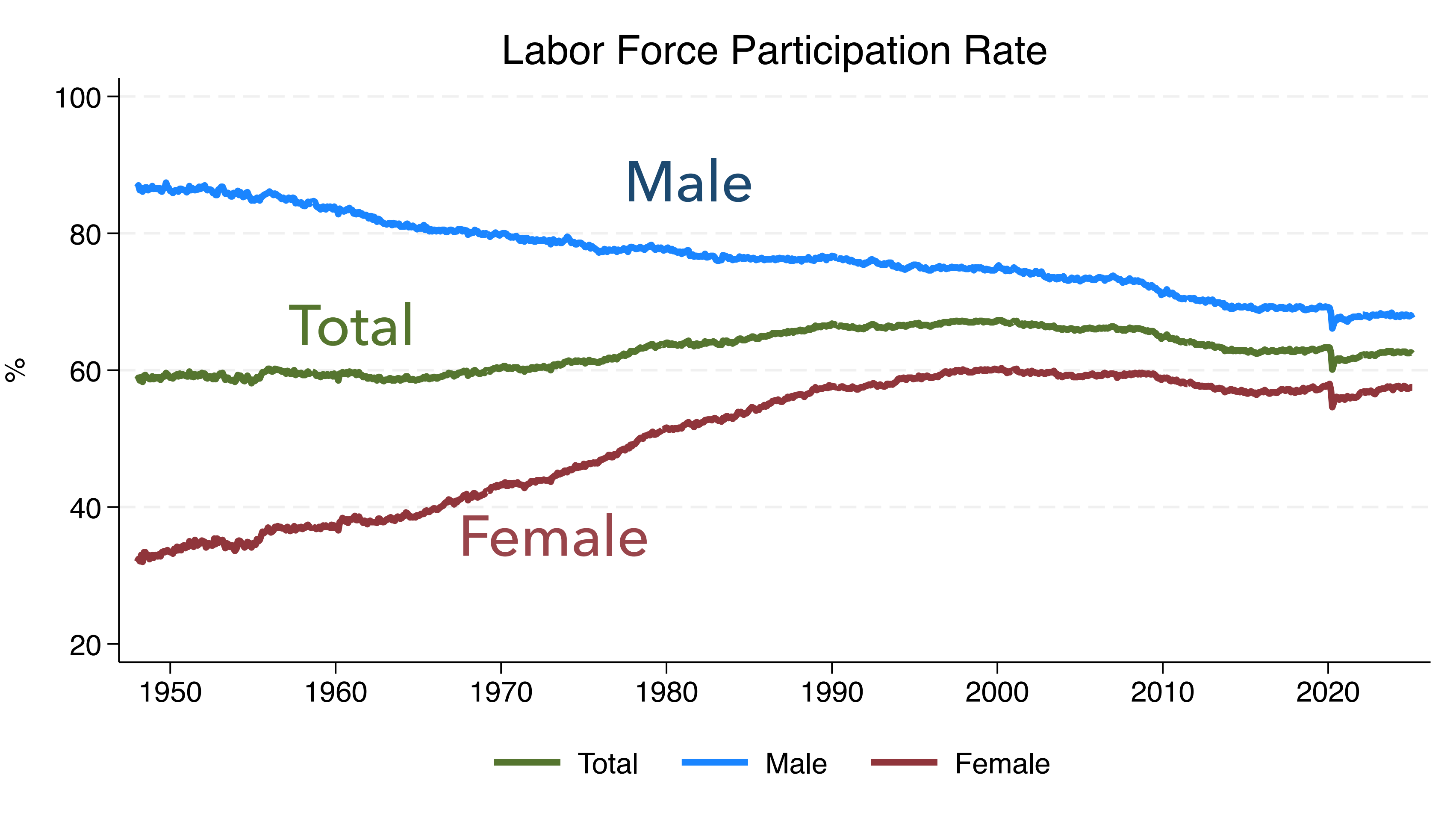
→ Ganong-Noel (2018)

→ Krueger-Meuller (2012)

Defining Unemployment

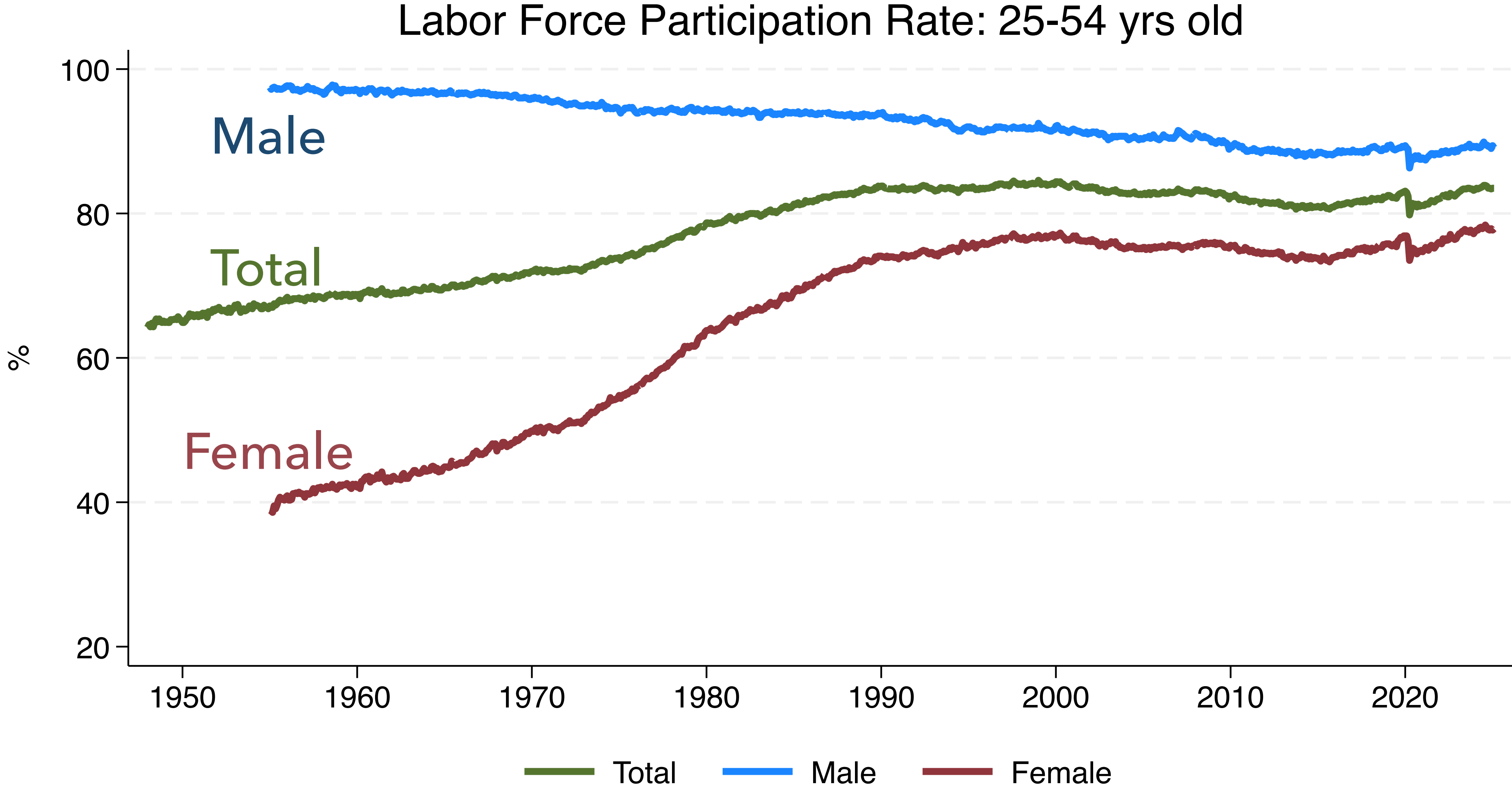


Labor Force Participation Rate



- 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



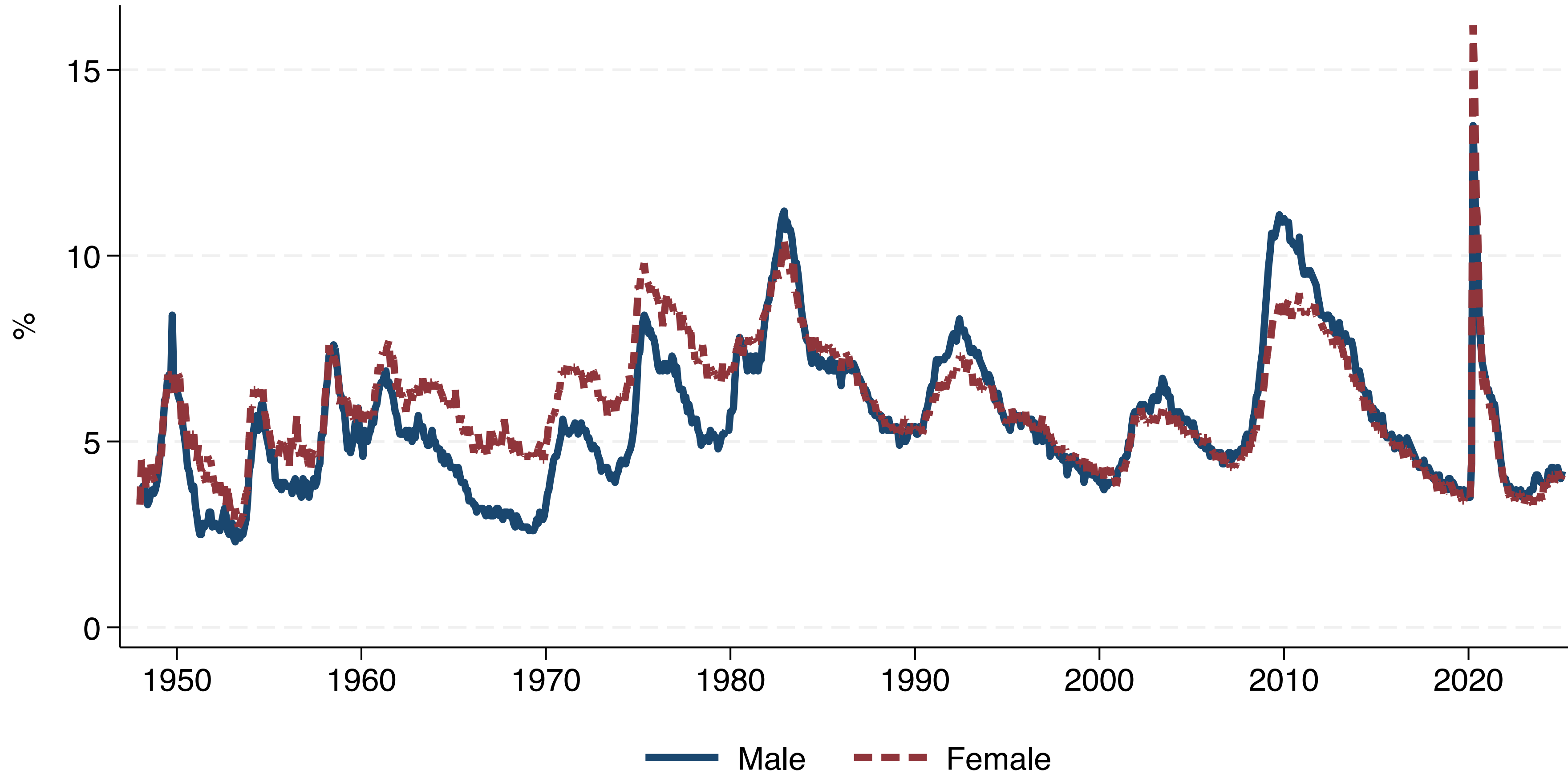
Unemployment Rate



Data: NBER Macro History Database and CPS

Unemployment Rate by Gender

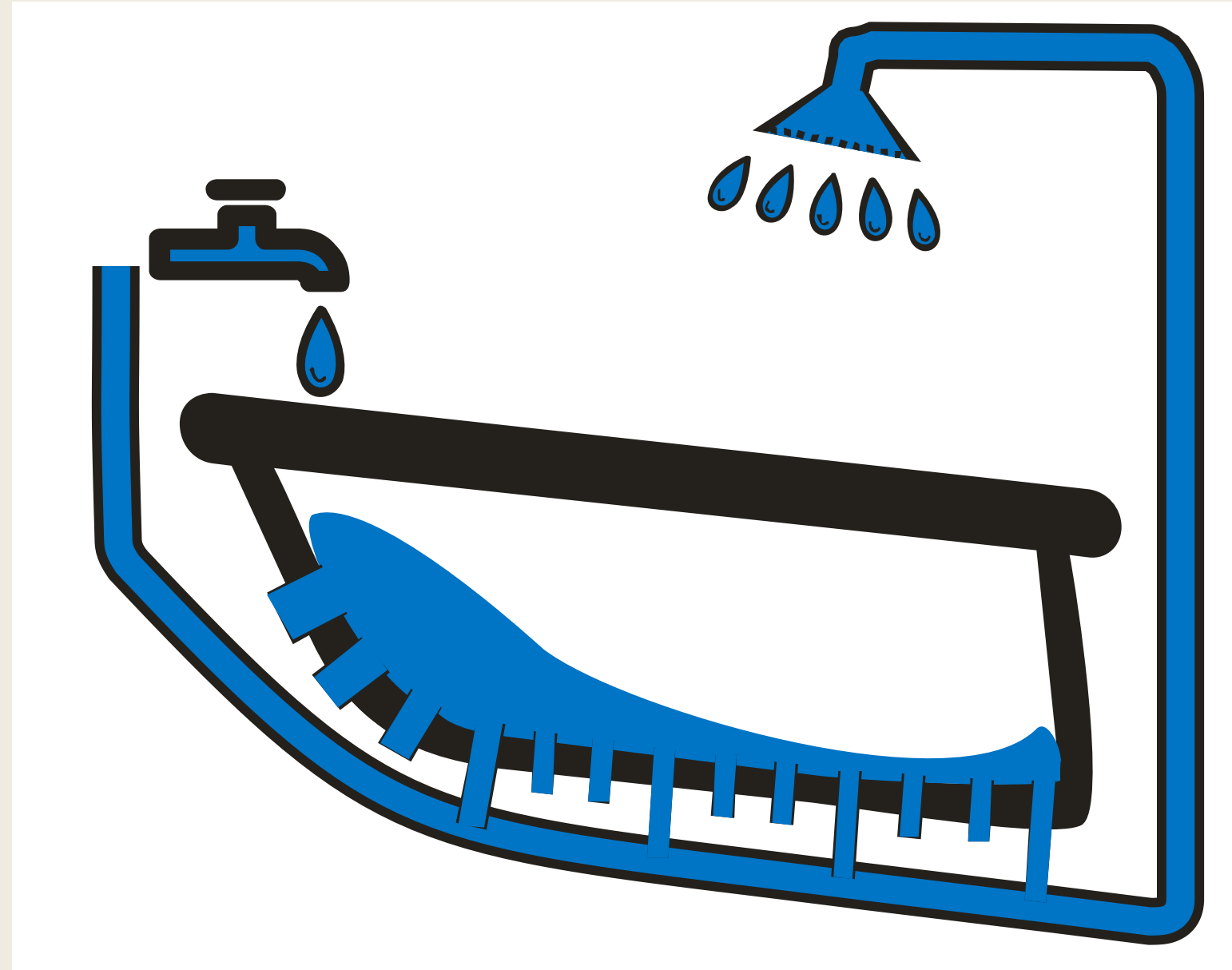
Unemployment Rate by Gender



■ Female less cyclical before COVID

Flows Into and Out of Unemployment

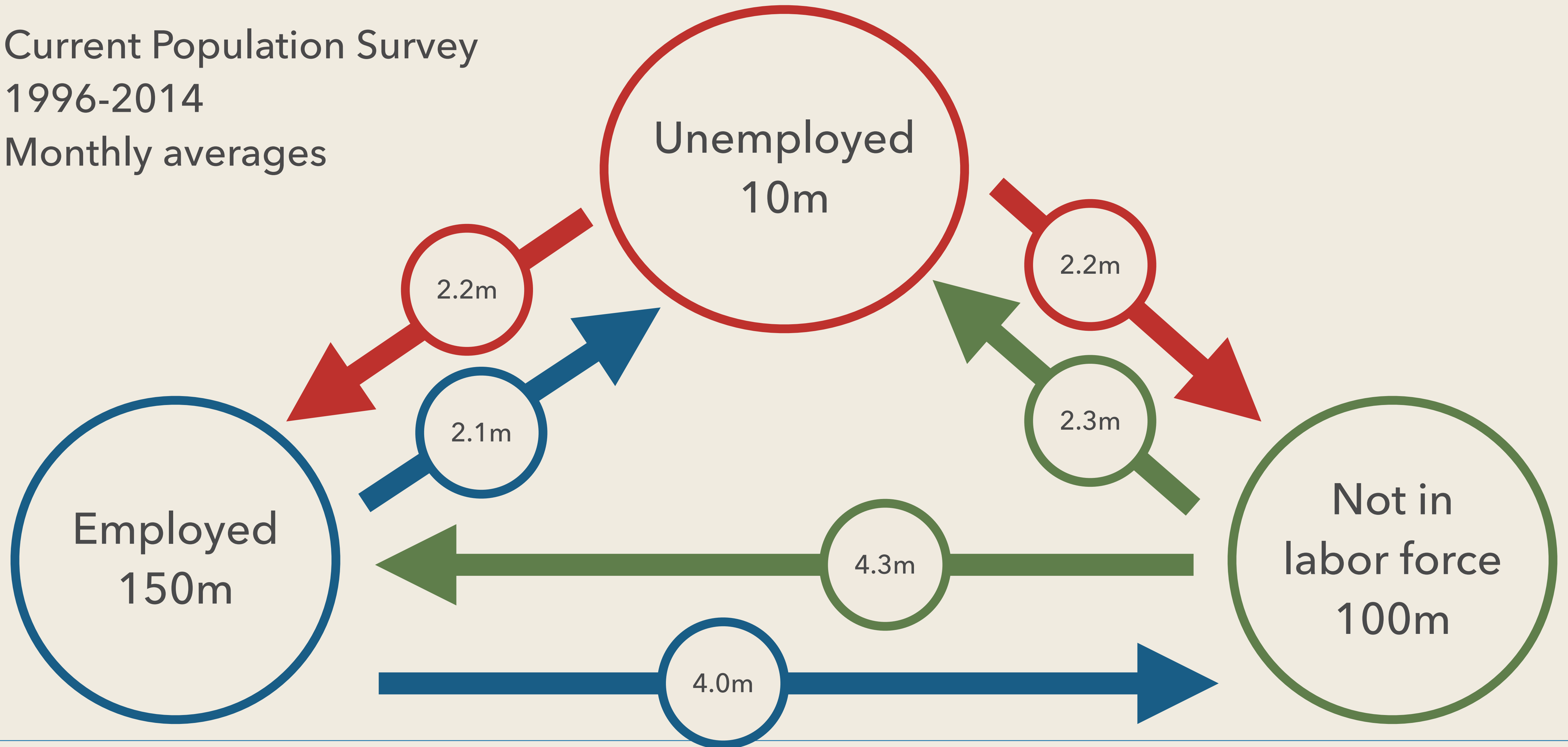
Stock-Flow Accounting Model



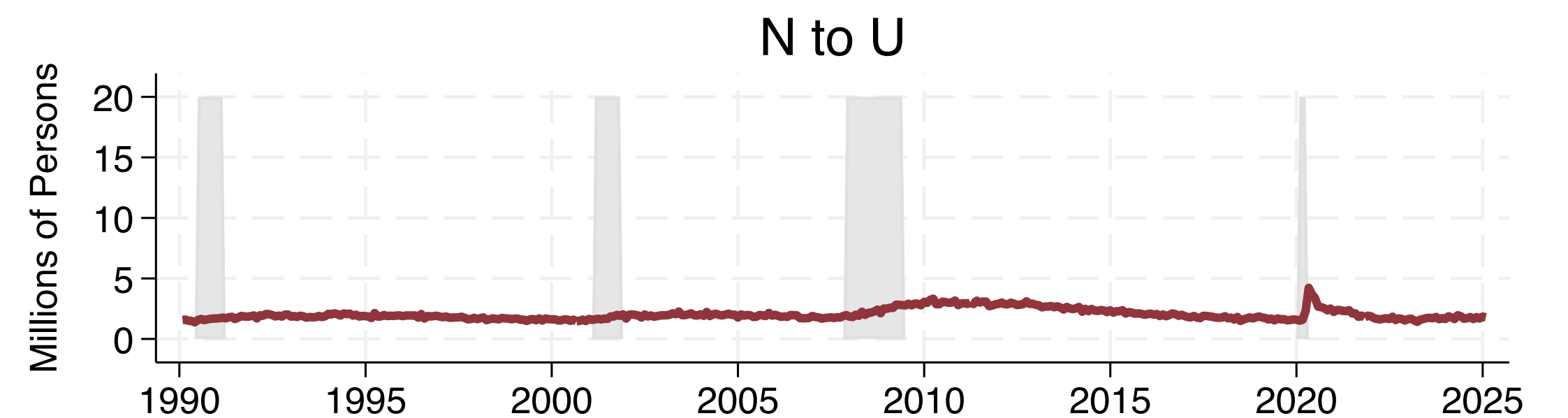
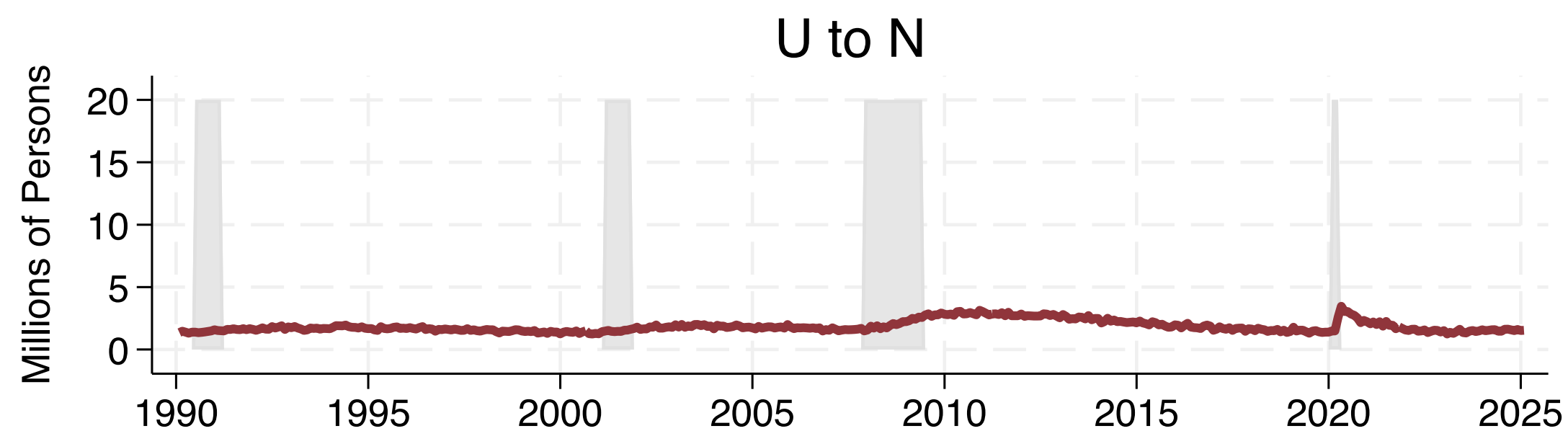
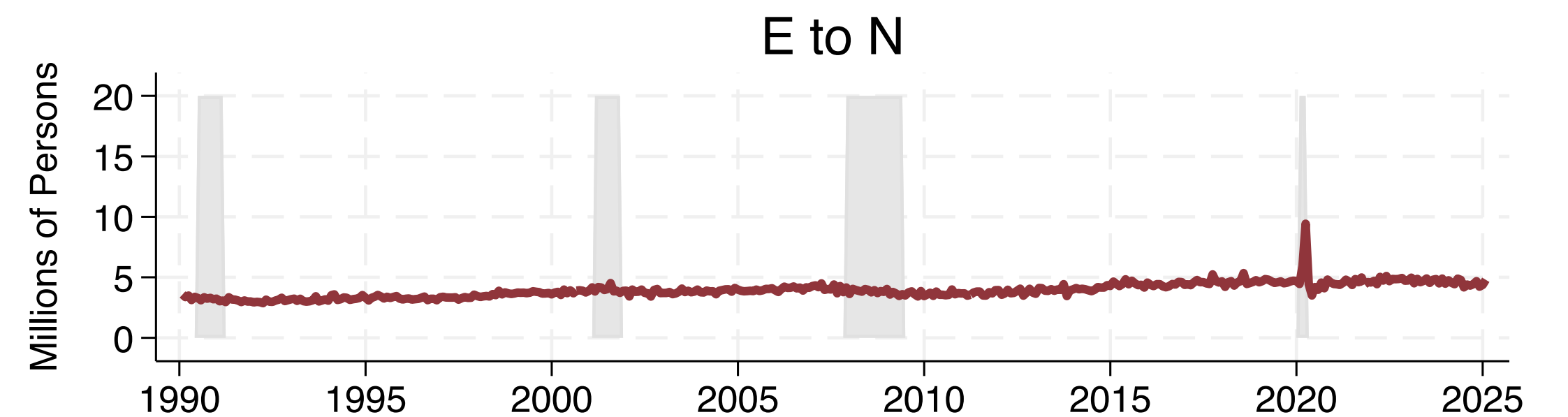
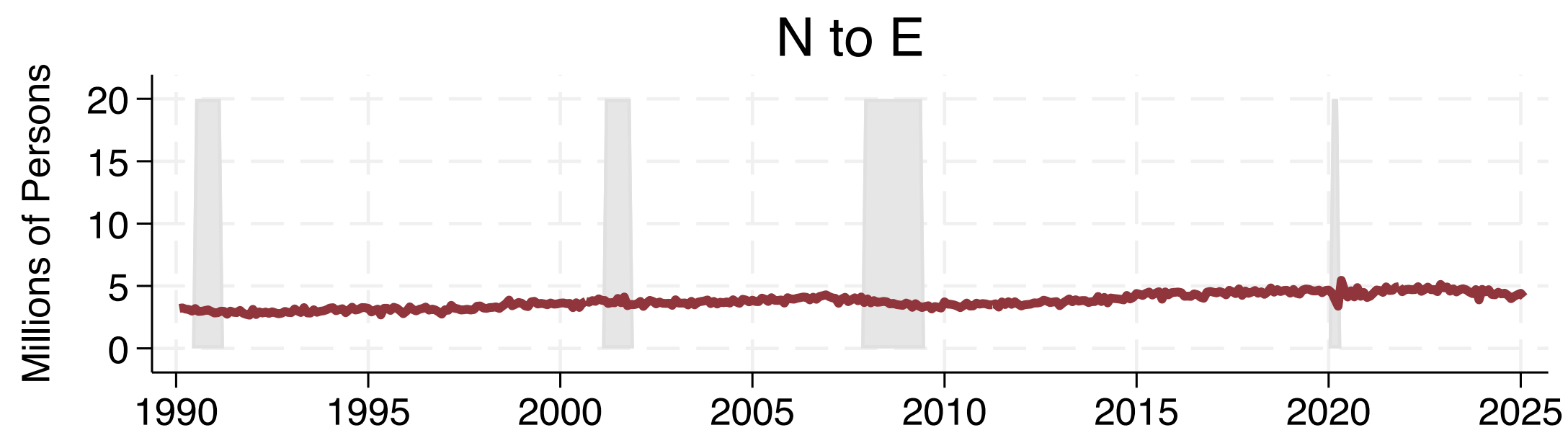
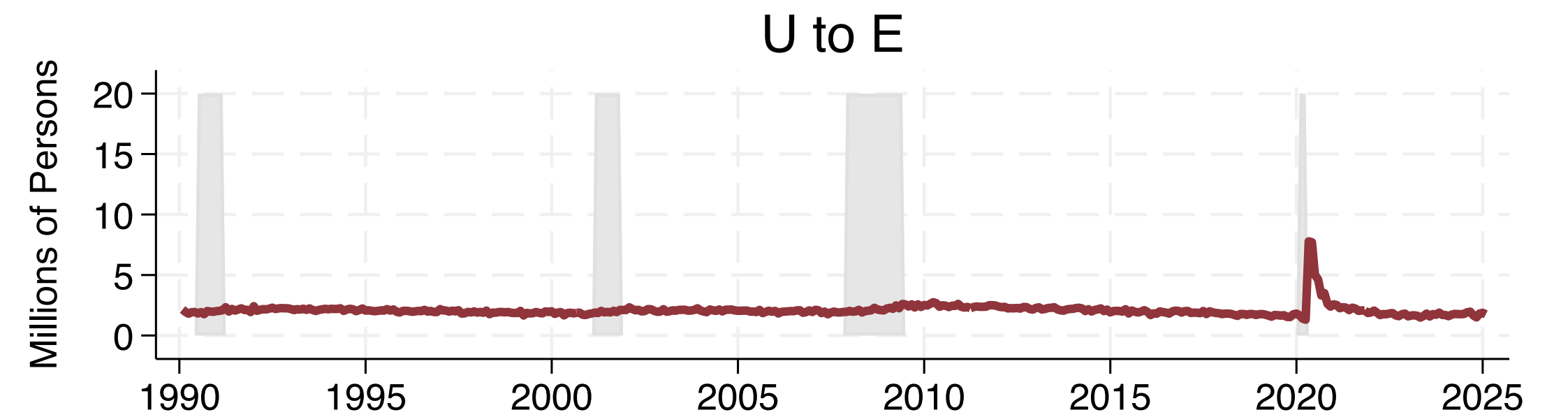
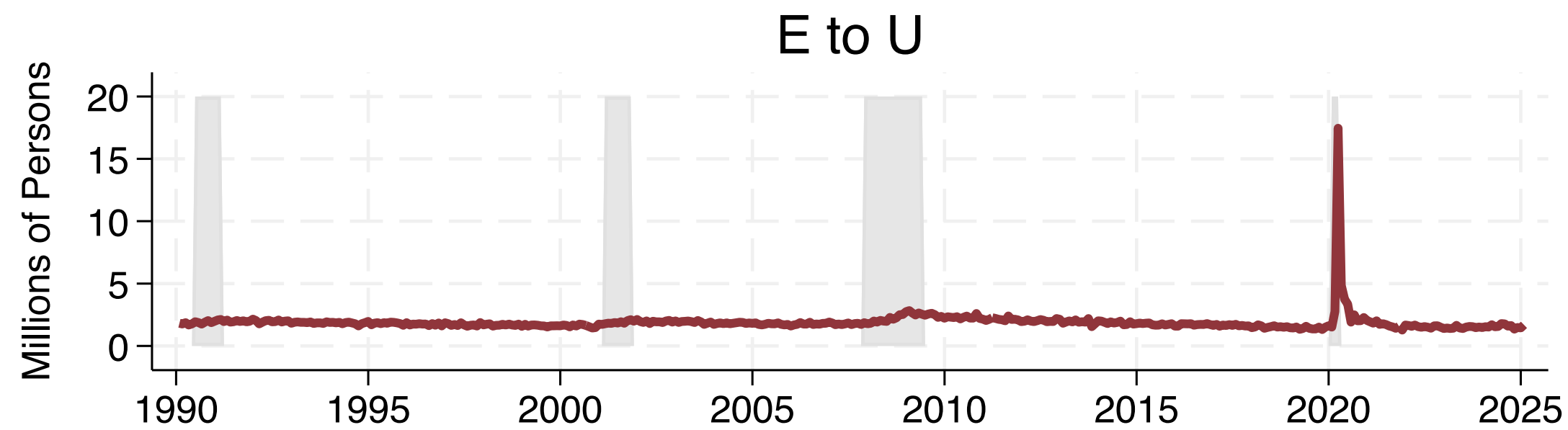
- Unemployment represents a stock of workers
 - Determined through a balance between inflows and outflows
- Useful to break down the role of inflows vs. outflows
 - Disciplines the model we should be writing down

Flows are Large on Average

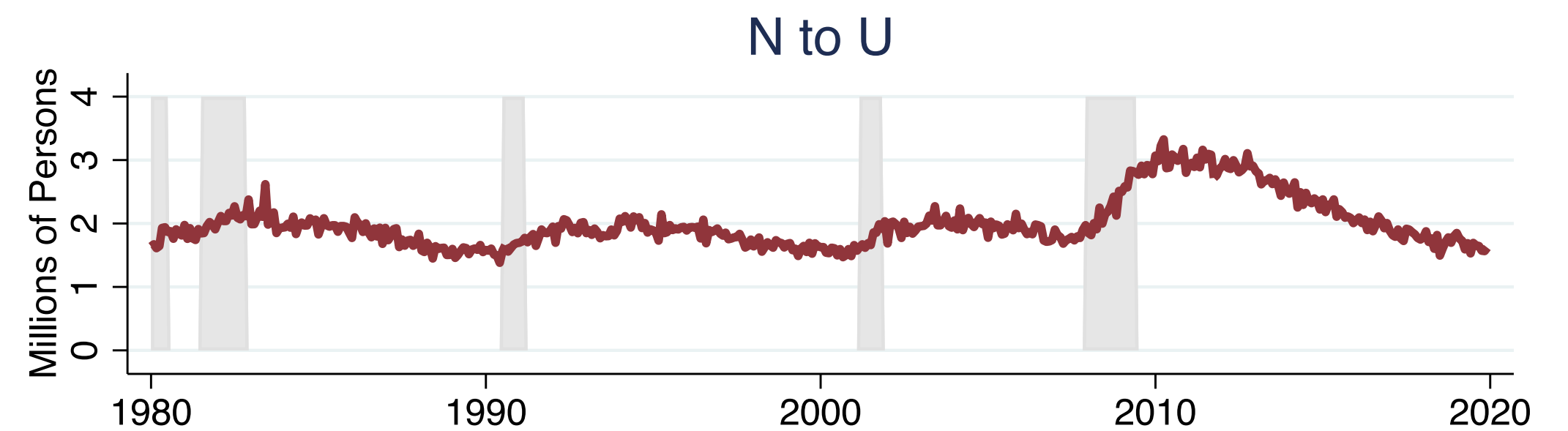
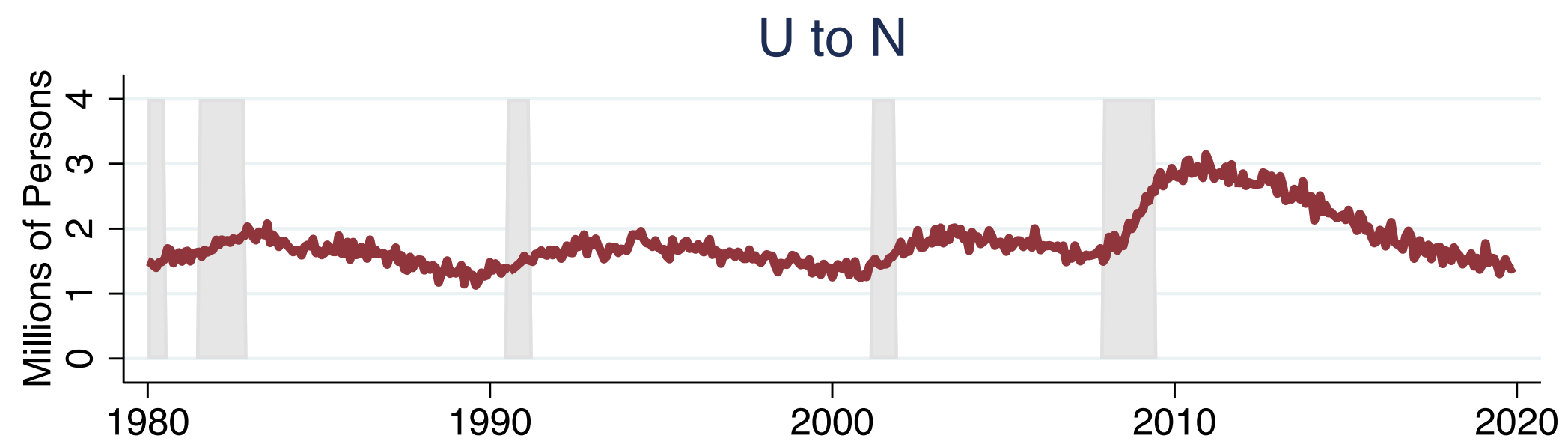
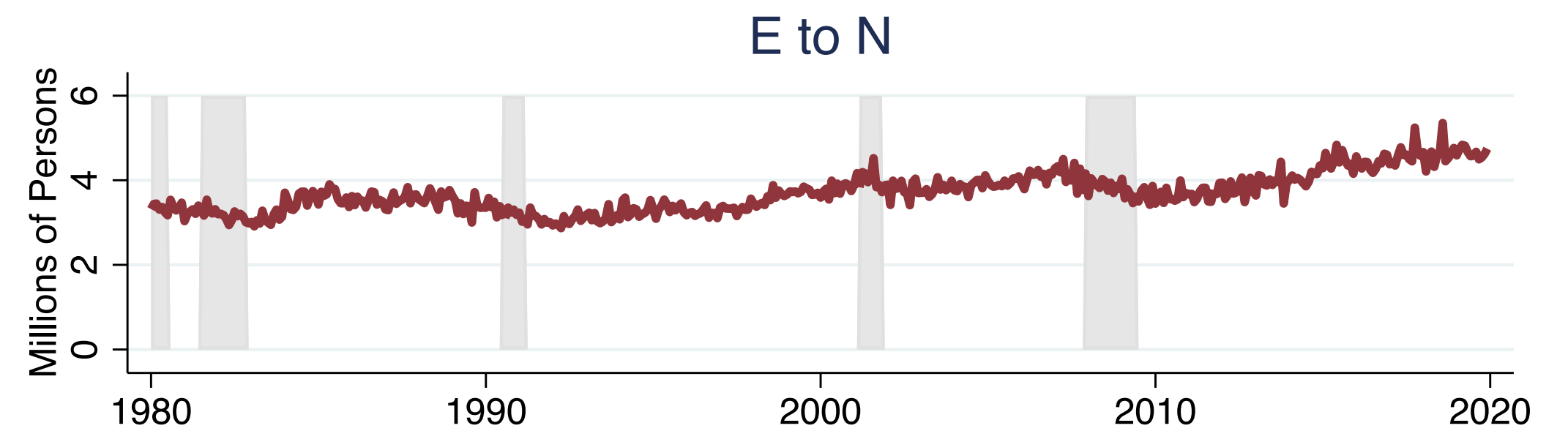
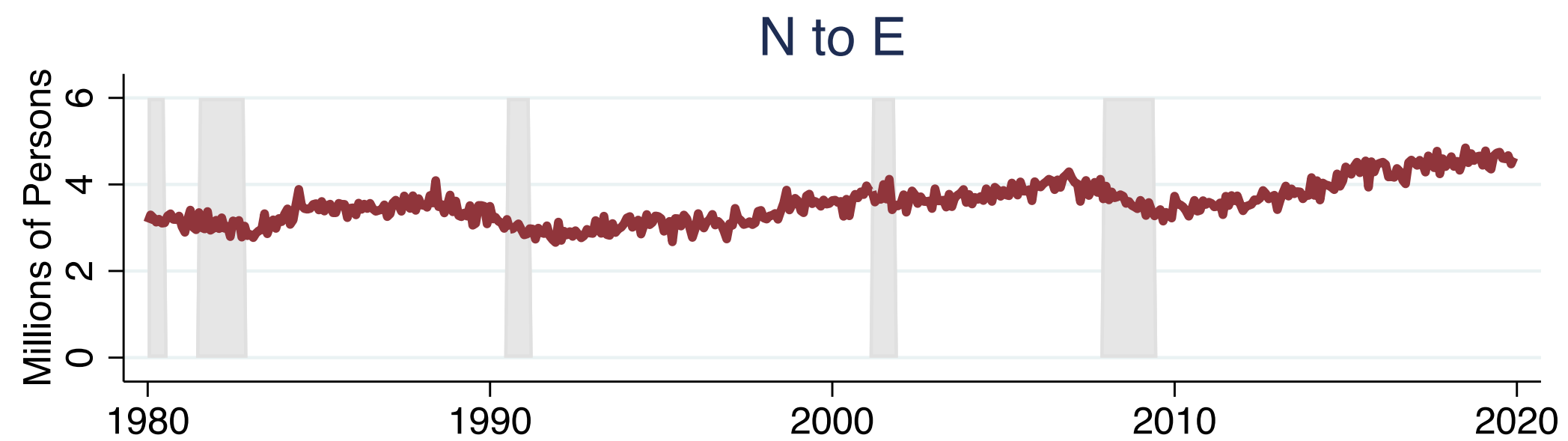
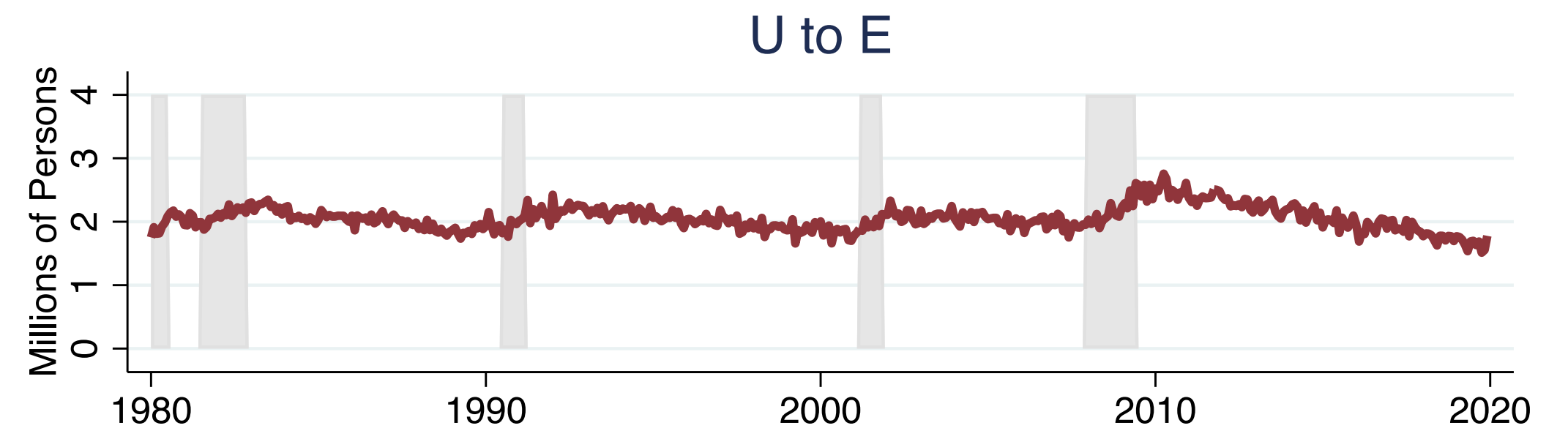
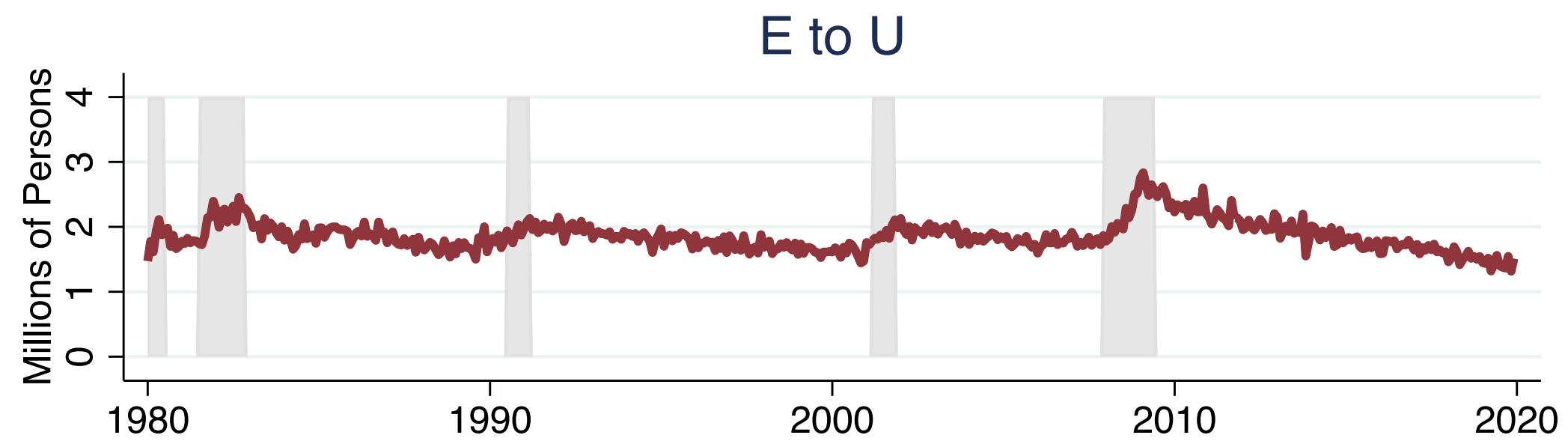
Current Population Survey
1996-2014
Monthly averages



Labor Market Flows over Time

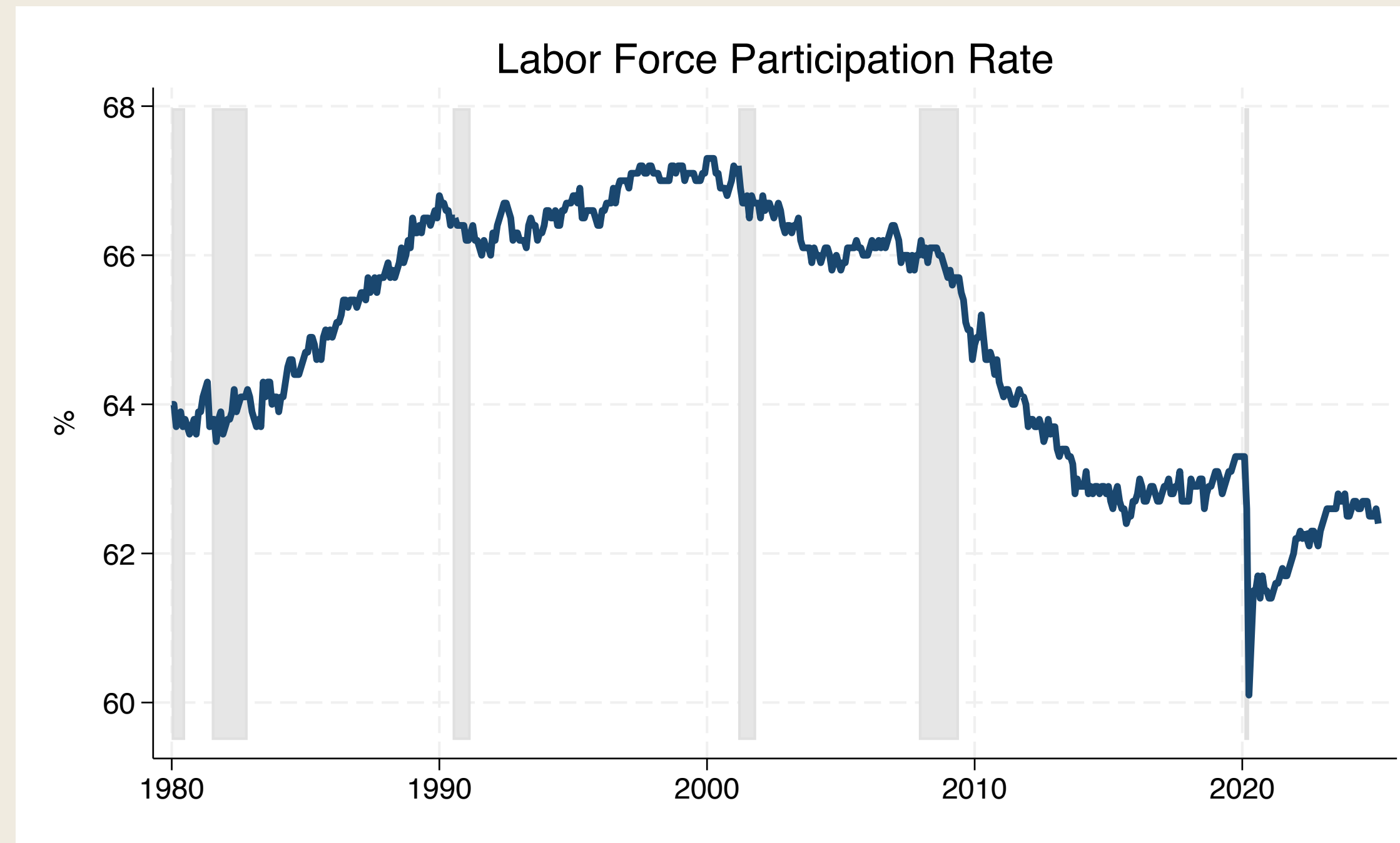


Labor Market Flows before COVID



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.

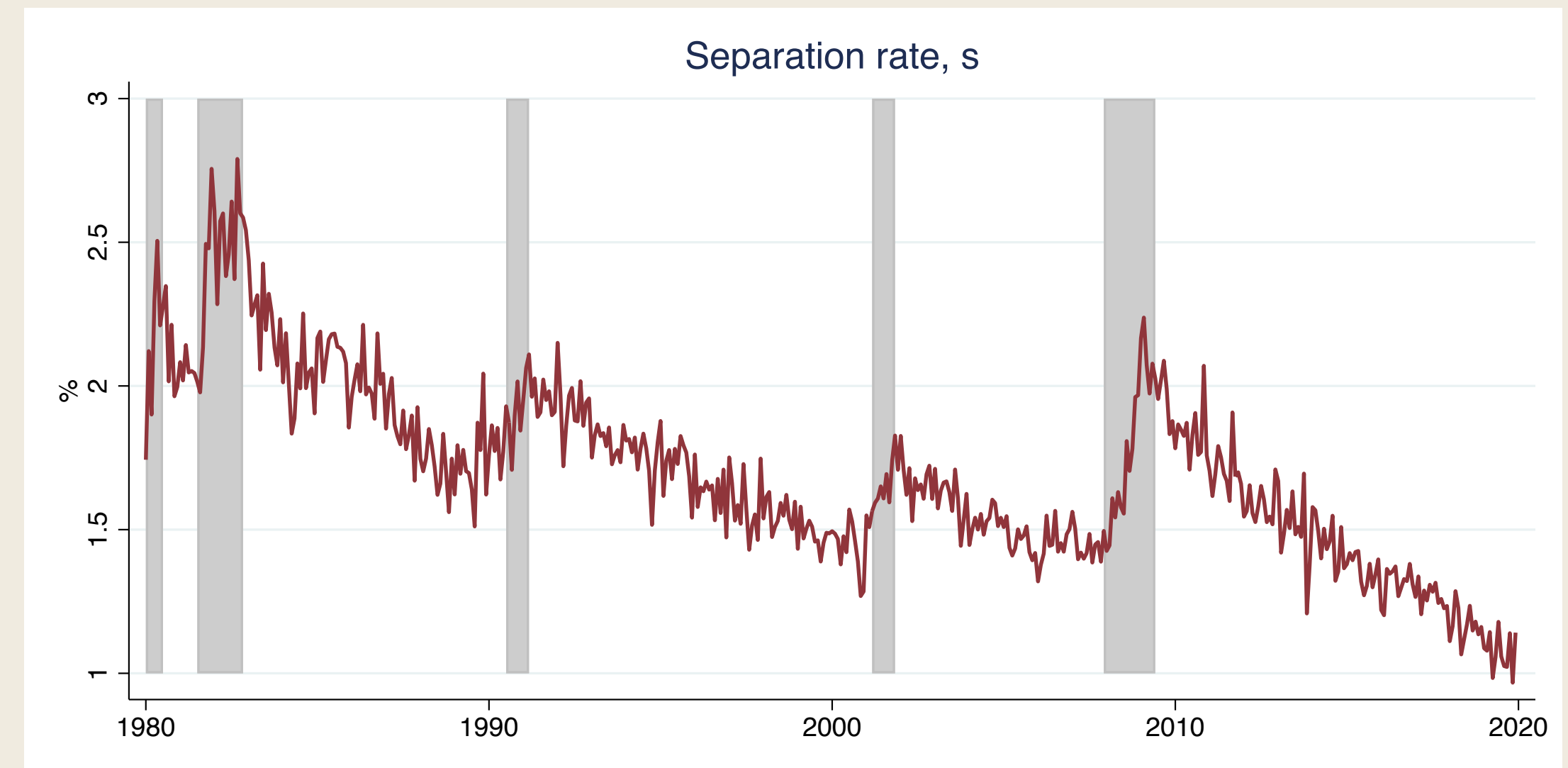
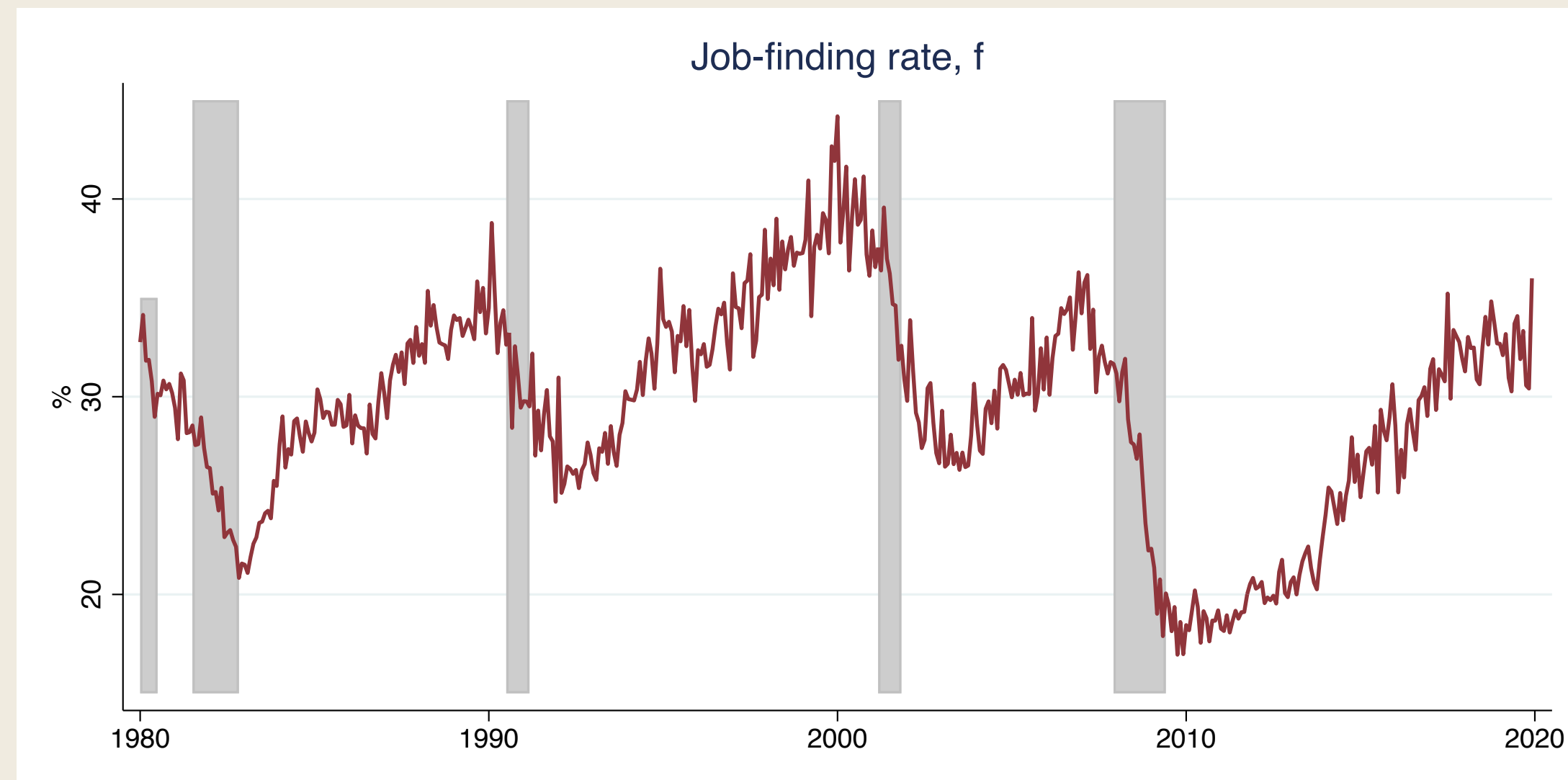


- Normalize: $U + E = 1$

Stock-Flow Model

- Basic stock-flow accounting equation:

$$\underbrace{u_{t+1} - u_t}_{\text{changes in unemployment}} = \underbrace{s_t(1 - u_t)}_{\text{separation (inflow into U)}} - \underbrace{f_t u_t}_{\text{job-finding (outflow from U)}}$$



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

Approximate Unemployment Rate

- In the steady state,

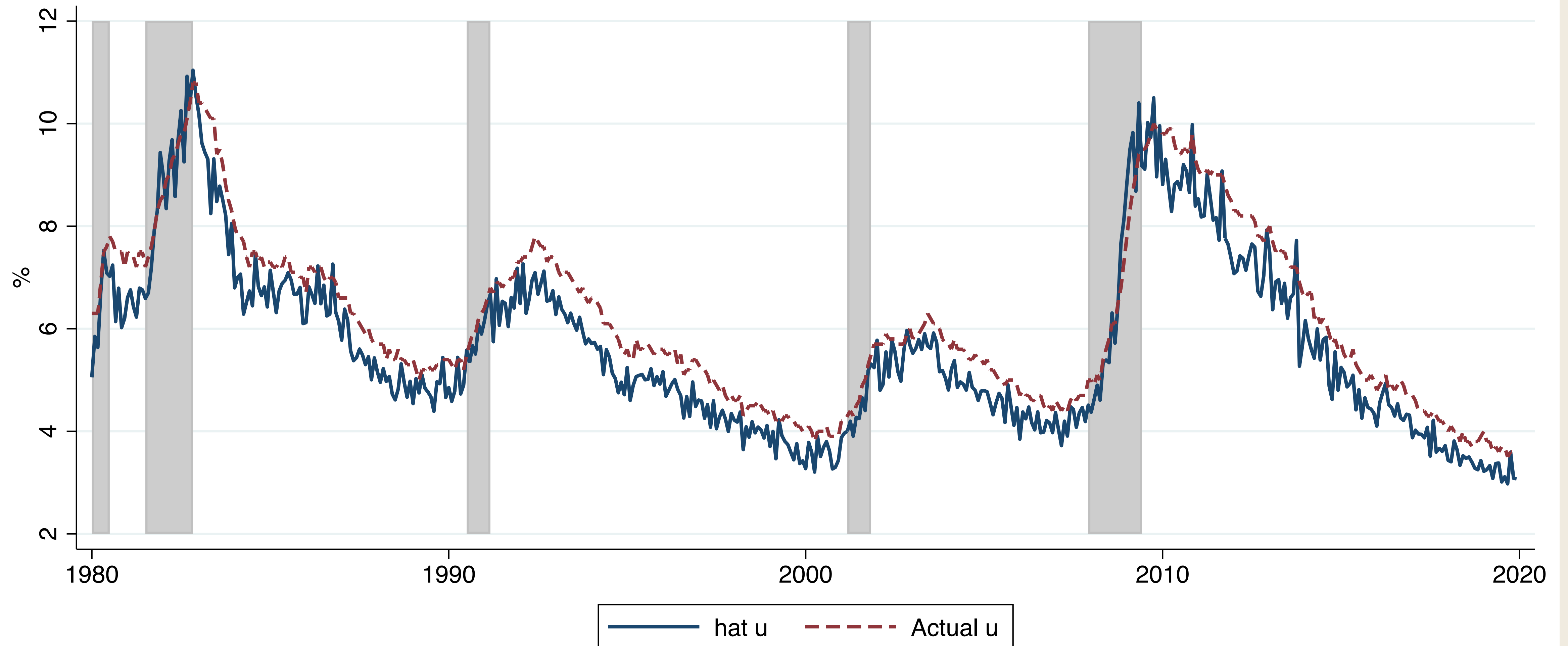
$$\bar{u} = \frac{\bar{s}}{\bar{s} + \bar{f}}$$

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

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

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

Approximation is Excellent



How Much Fluctuations in u due to s or f ?

- 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 into

$$\text{Var} \left[\log \frac{\hat{u}_t}{1 - \hat{u}_t} \right] = \underbrace{\text{Cov} \left[\log \frac{\hat{u}_t}{1 - \hat{u}_t}, \log s_t \right]}_{\text{flutuations due to } s} + \underbrace{\text{Cov} \left[\log \frac{\hat{u}_t}{1 - \hat{u}_t}, -\log f_t \right]}_{\text{flutuations due to } f}$$

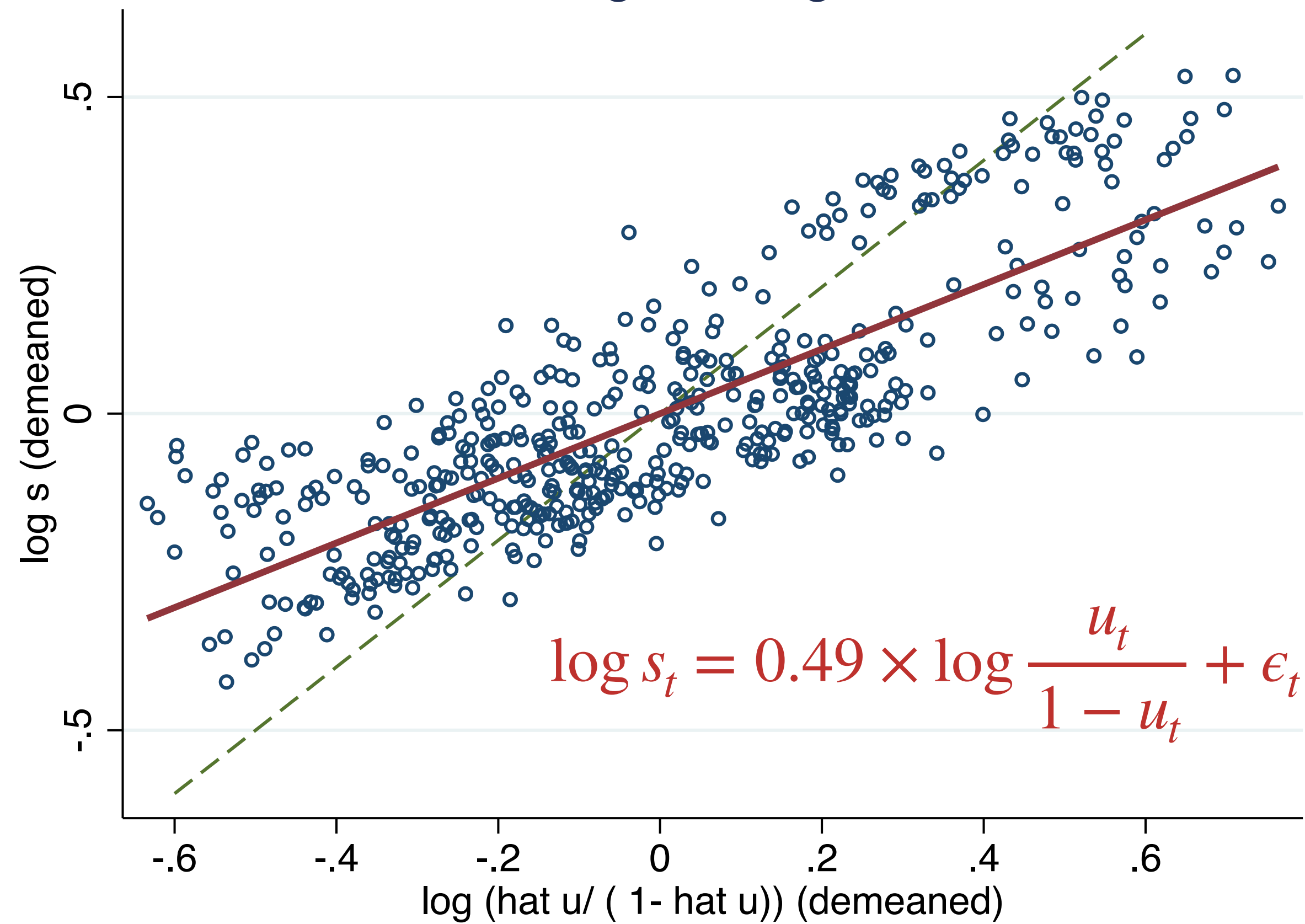
- Consider the following OLS regression

$$\log s_t = \alpha + \beta \log(\hat{u}_t/(1 - \hat{u}_t)) + \epsilon_t$$

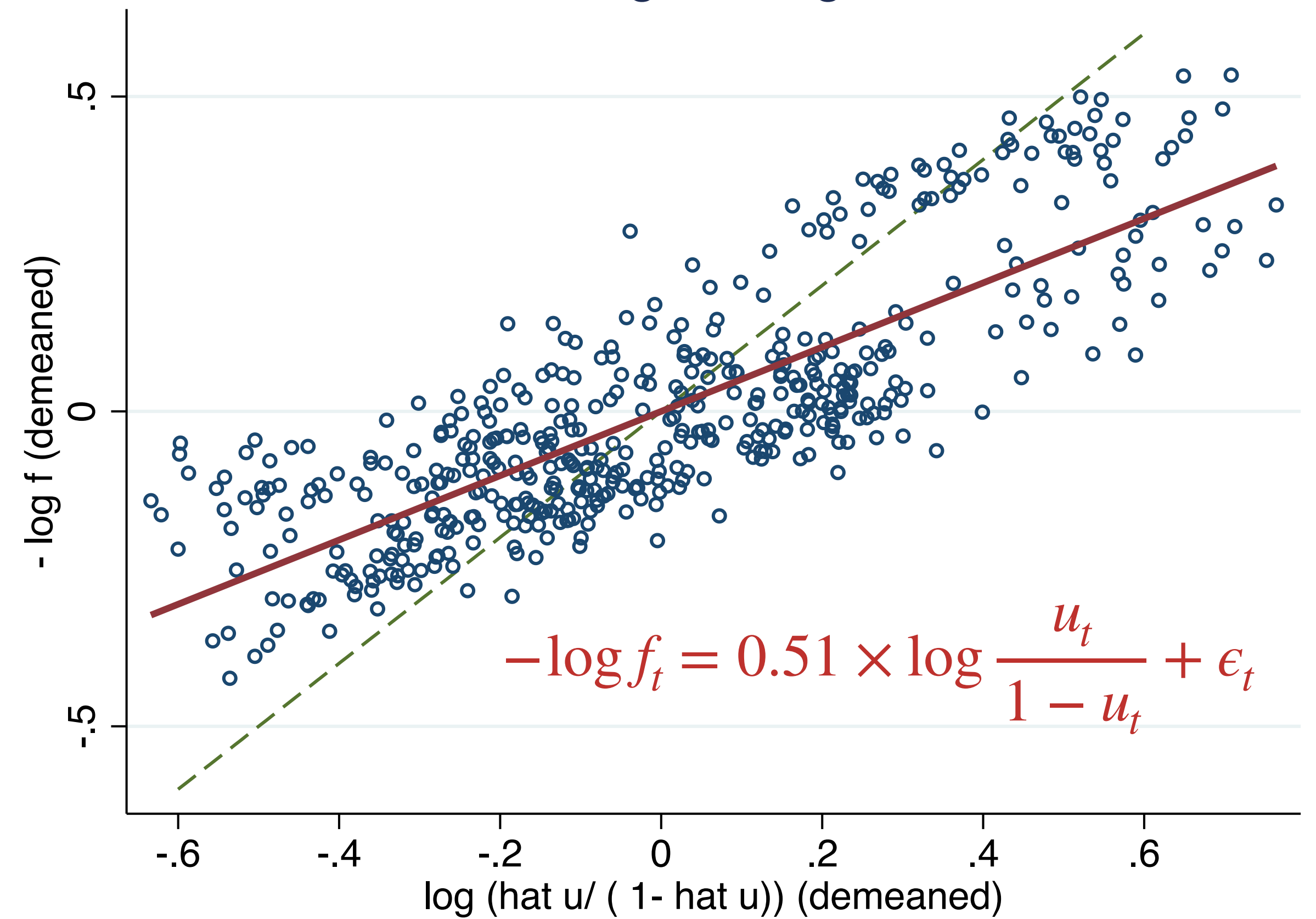
$$\text{Then } \beta = \frac{\text{Cov}(\log s_t, \log \hat{u}_t/(1 - \hat{u}_t))}{\text{Var}(\log \hat{u}_t/(1 - \hat{u}_t))} \Rightarrow \text{Variance share!}$$

Variance Decomposition through Regression

log s vs log u



- log f vs log u



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 hysteresis from Shimer

Unpacking Job-finding Rate

Matching Friction

- Why can't workers find a job immediately? Why does job-finding rate fluctuate?
- 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
$$m_t = M(u_t, v_t)$$
 - 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)

Deriving Beveridge Curve

- It is convenient to assume M is constant returns to scale (e.g., $M(u, v) = \bar{m}u^{1-\alpha}v^\alpha$)
 - Not empirically settled. Interesting area to explore.

- The job-finding probability can be written as

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

- $\theta_t \equiv v_t/u_t$ is labor market tightness
- Plug the above expression into the approx. unemp. rate formula ($s_t = f_t u_t / (1 - u_t)$):

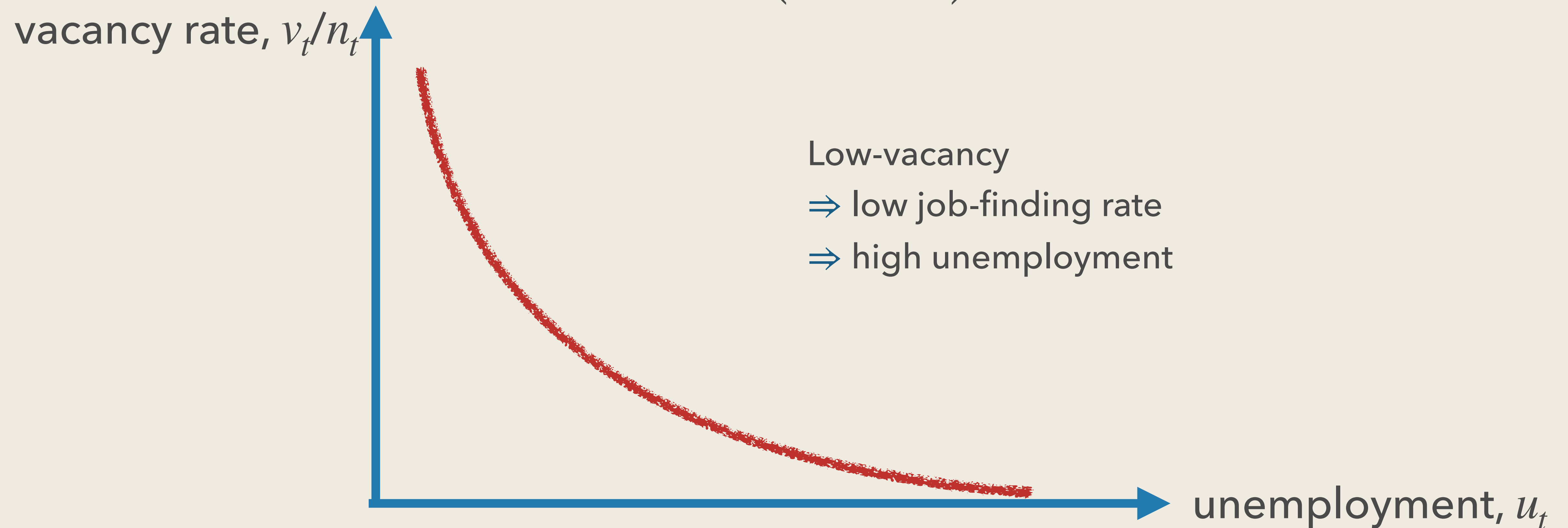
$$s_t = M\left(\frac{v_t}{n_t}, \frac{u_t}{1 - u_t}\right), \quad n_t \equiv 1 - u_t$$

- A relationship between vacancy rate, v_t/n_t , and unemp. rate, u_t (for given s_t)
 - Popularly referred to as "**Beveridge curve**"

Beveridge Curve

- Assuming s is a constant

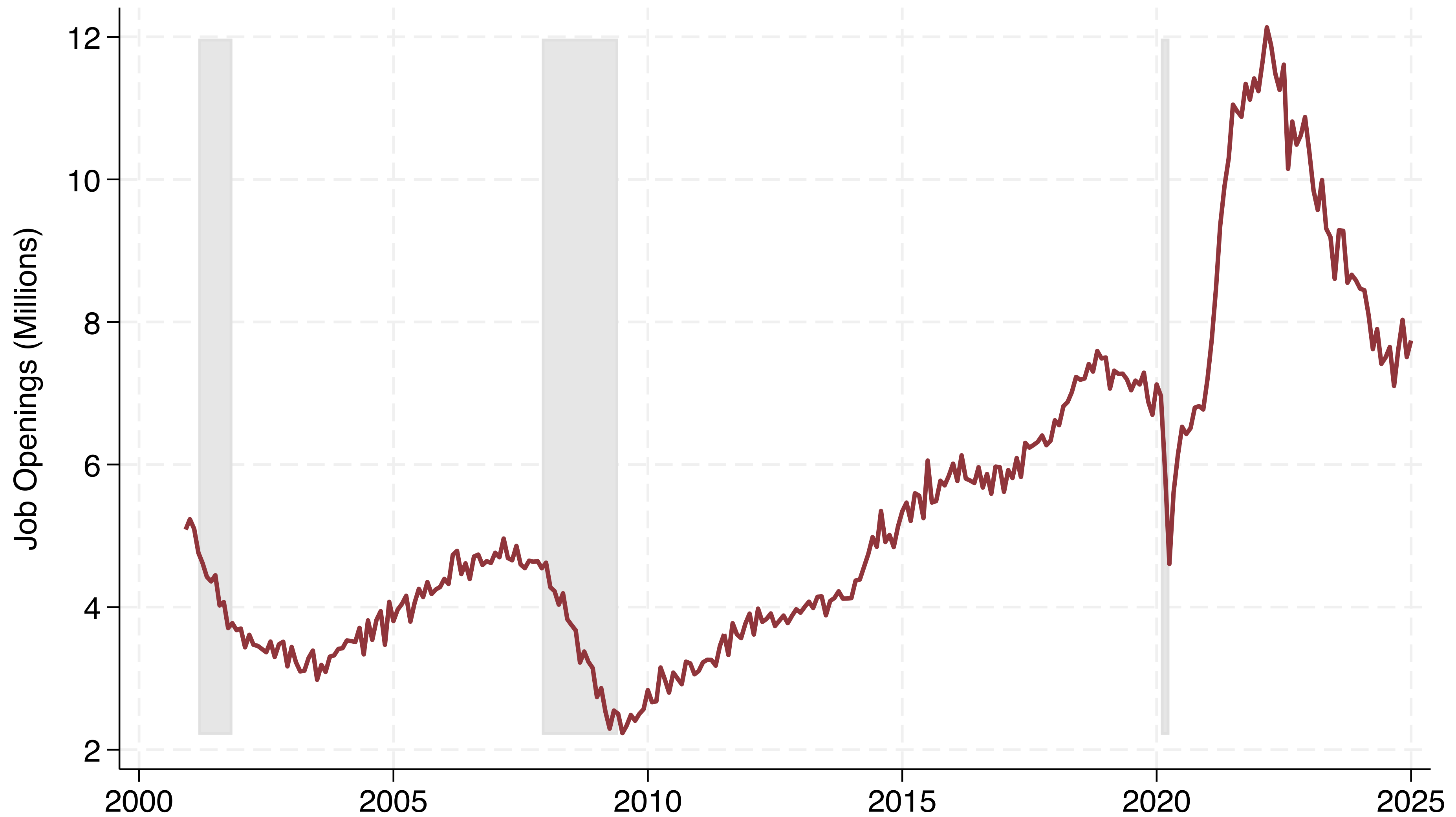
$$s = M \left(\frac{v_t}{n_t}, \frac{u_t}{1 - u_t} \right)$$



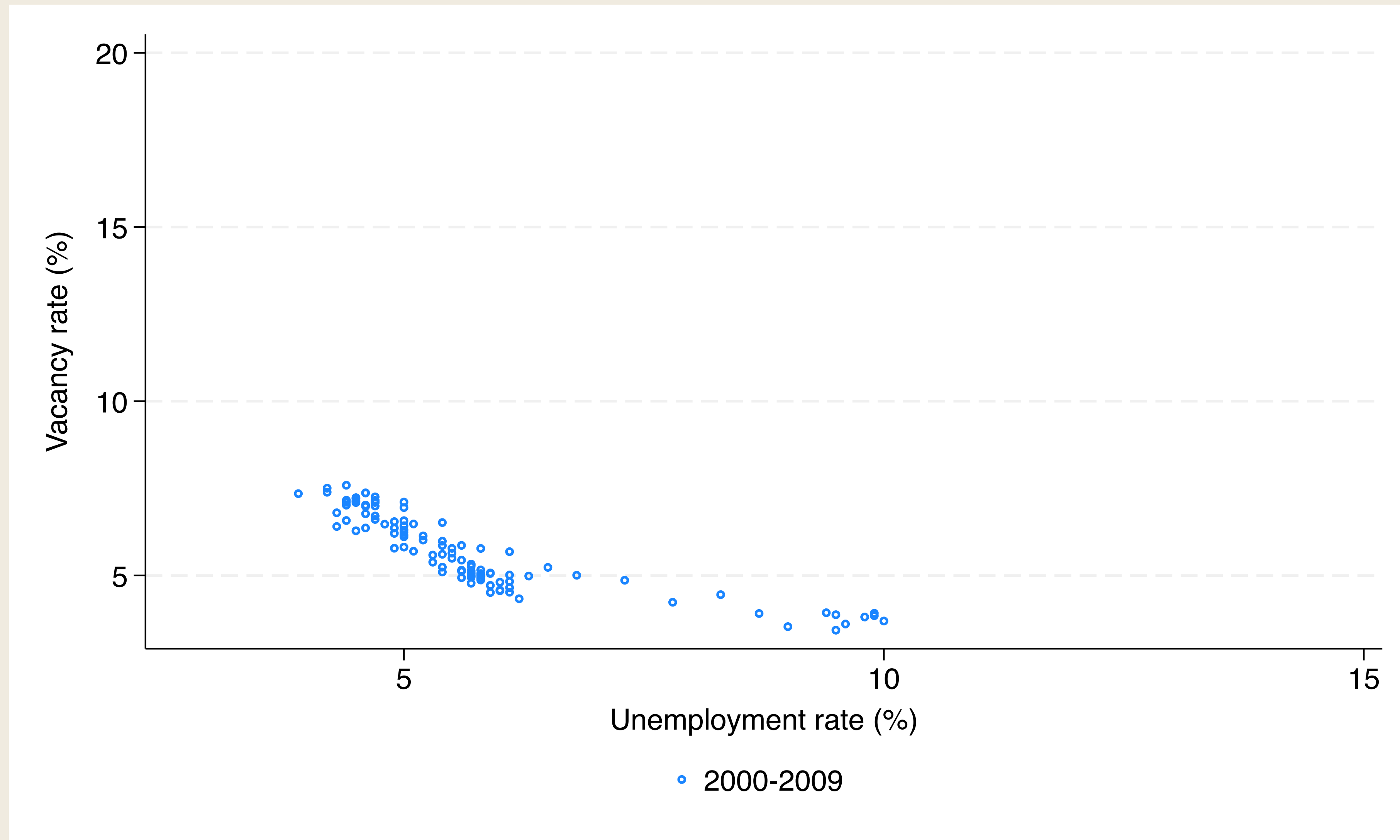
What is Vacancy?

- 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

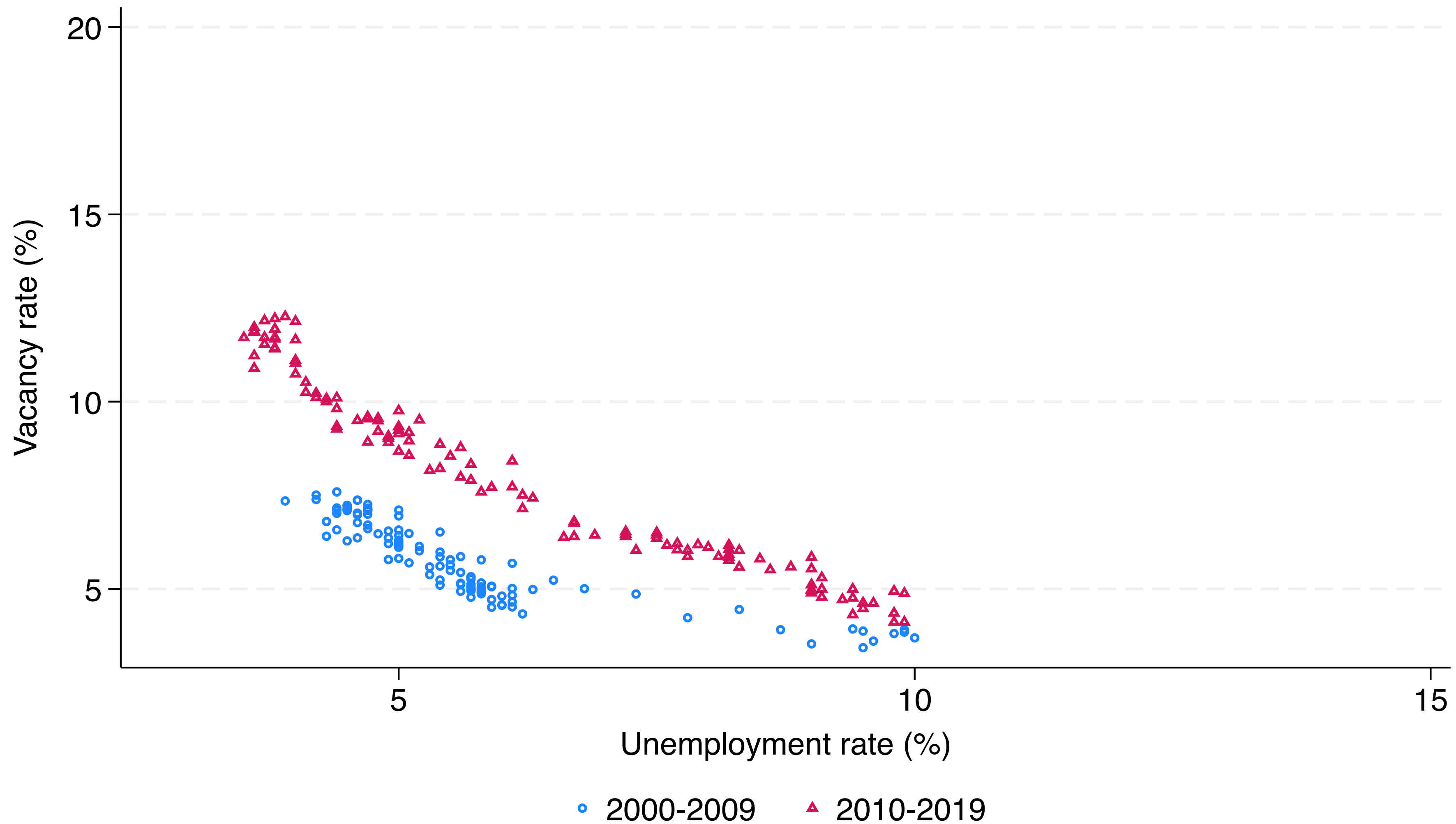
Vacancy in the Data



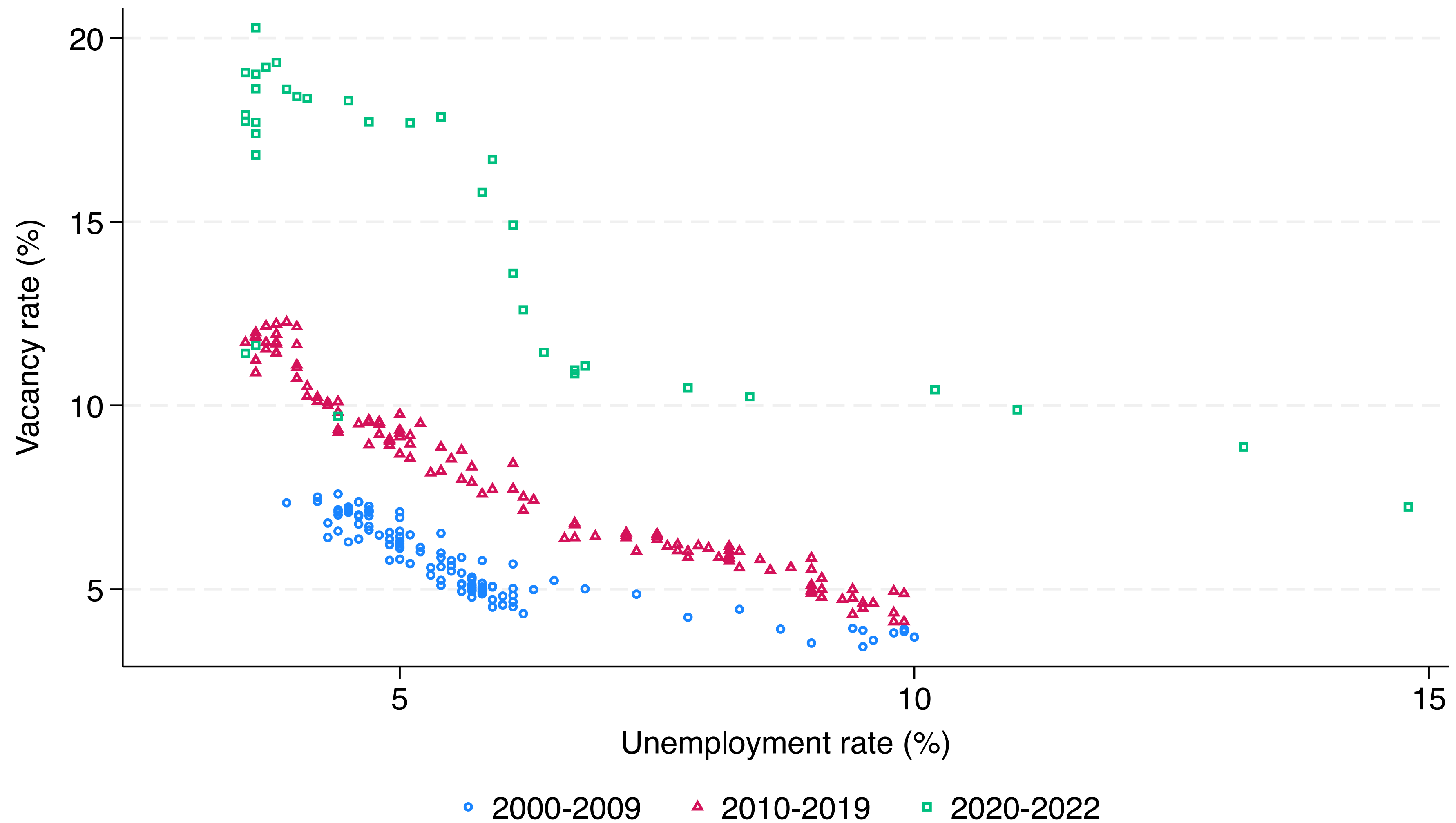
Empirical Beveridge Curve



Empirical Beveridge Curve

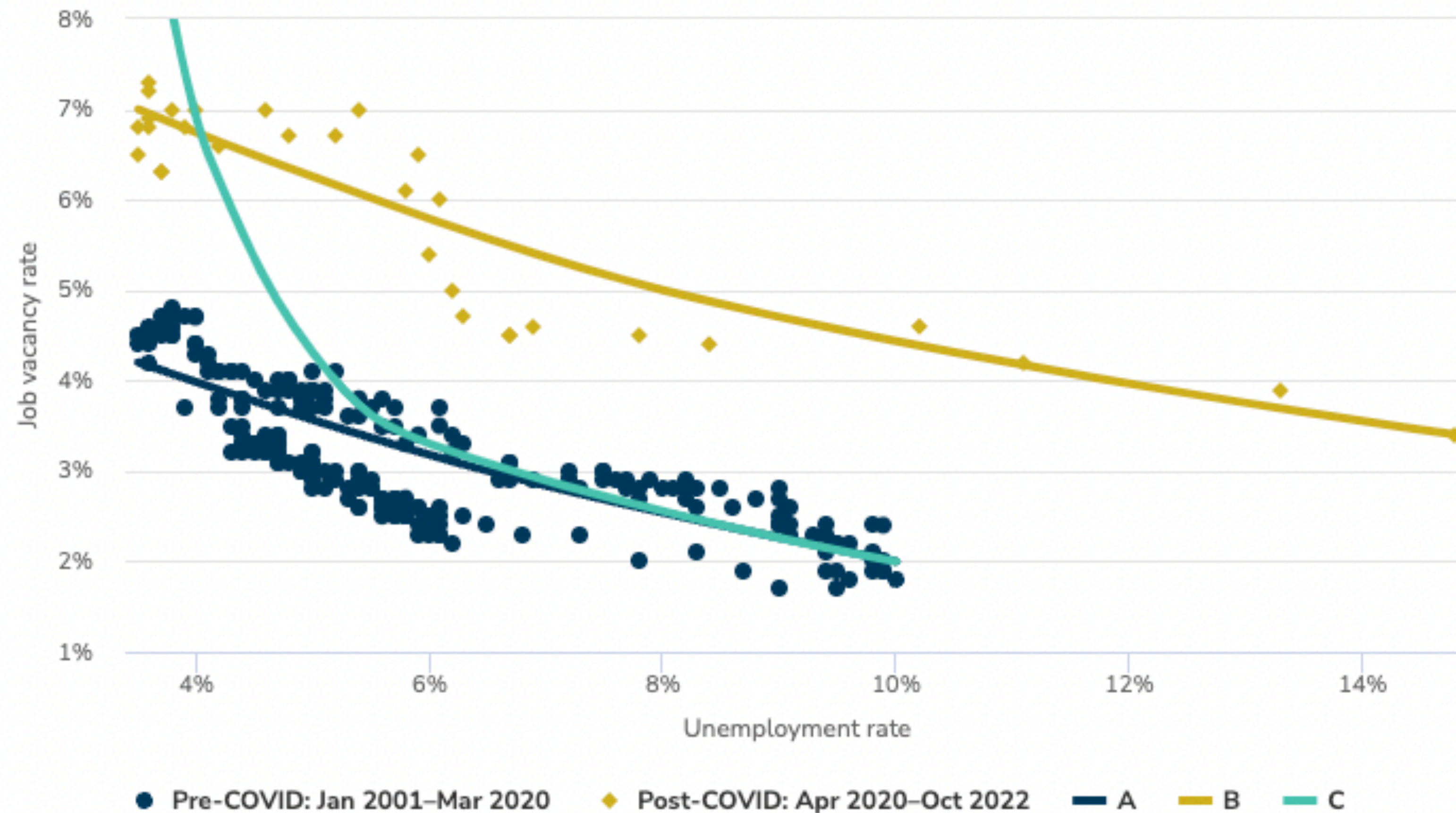


Empirical Beveridge Curve



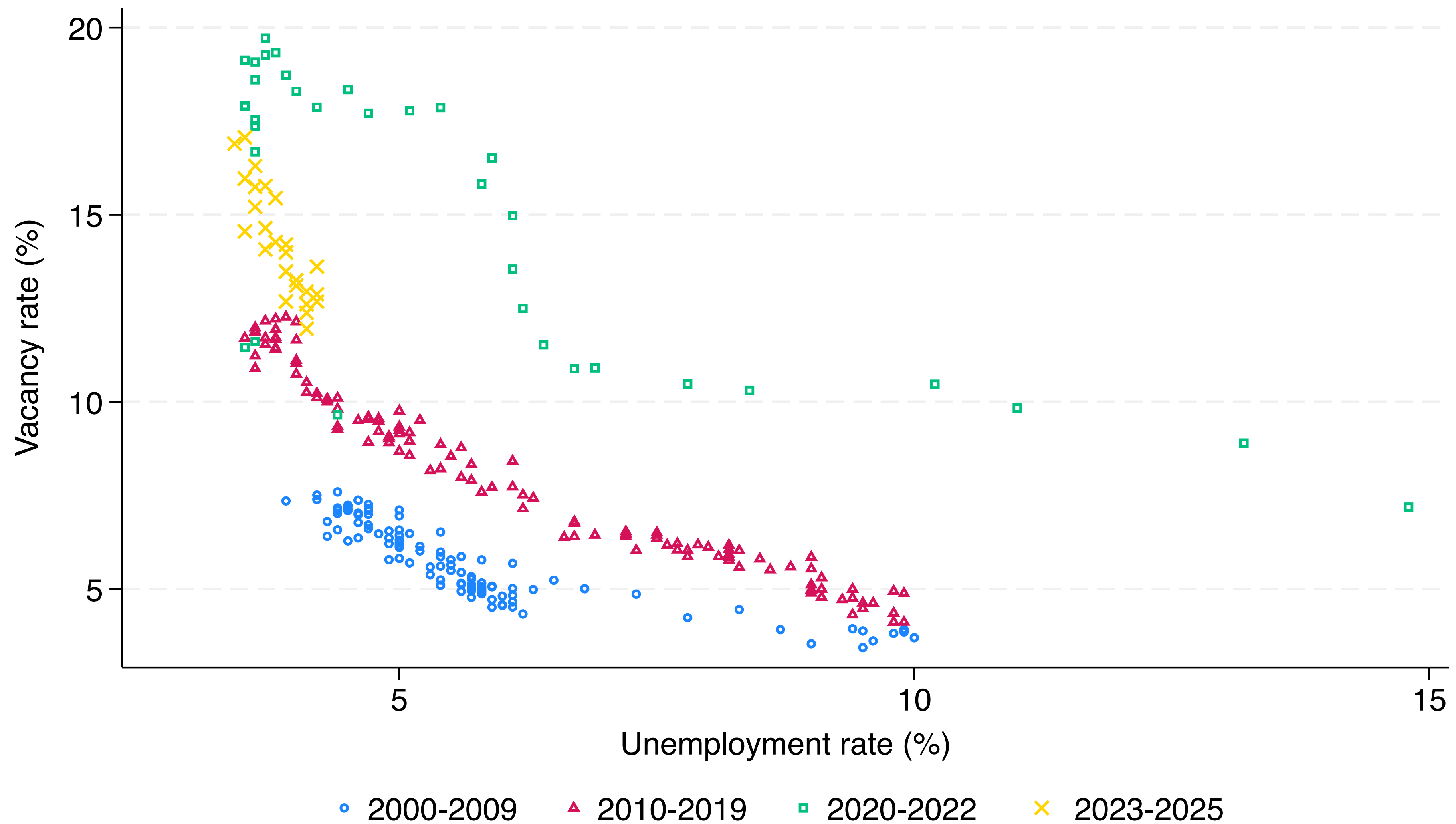
Soft-Landing or Hard-Landing?

Which Beveridge curve are we on?



- **Blanchard & Summers:**
We are on B. If the Fed brings down v to pre-COVID level, we will see a massive increase in u .
⇒ hard-landing
- **Mongey:**
We are on C. Reducing v doesn't increase u much.
⇒ soft-landing

Who was Right?



What Can Beveridge Curve Tell?

- As predicted by DMP paradigm, there appears to be a negative correlation ... 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

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

\bar{m}_t : match efficiency shock

Beveridge Curve

- Taking log, the Beveridge curve (expressed in logs) is now

$$\log(v_t/n_t) = \tilde{m}_t - \frac{1-\alpha}{\alpha} \log \frac{u_t}{1-u_t}$$

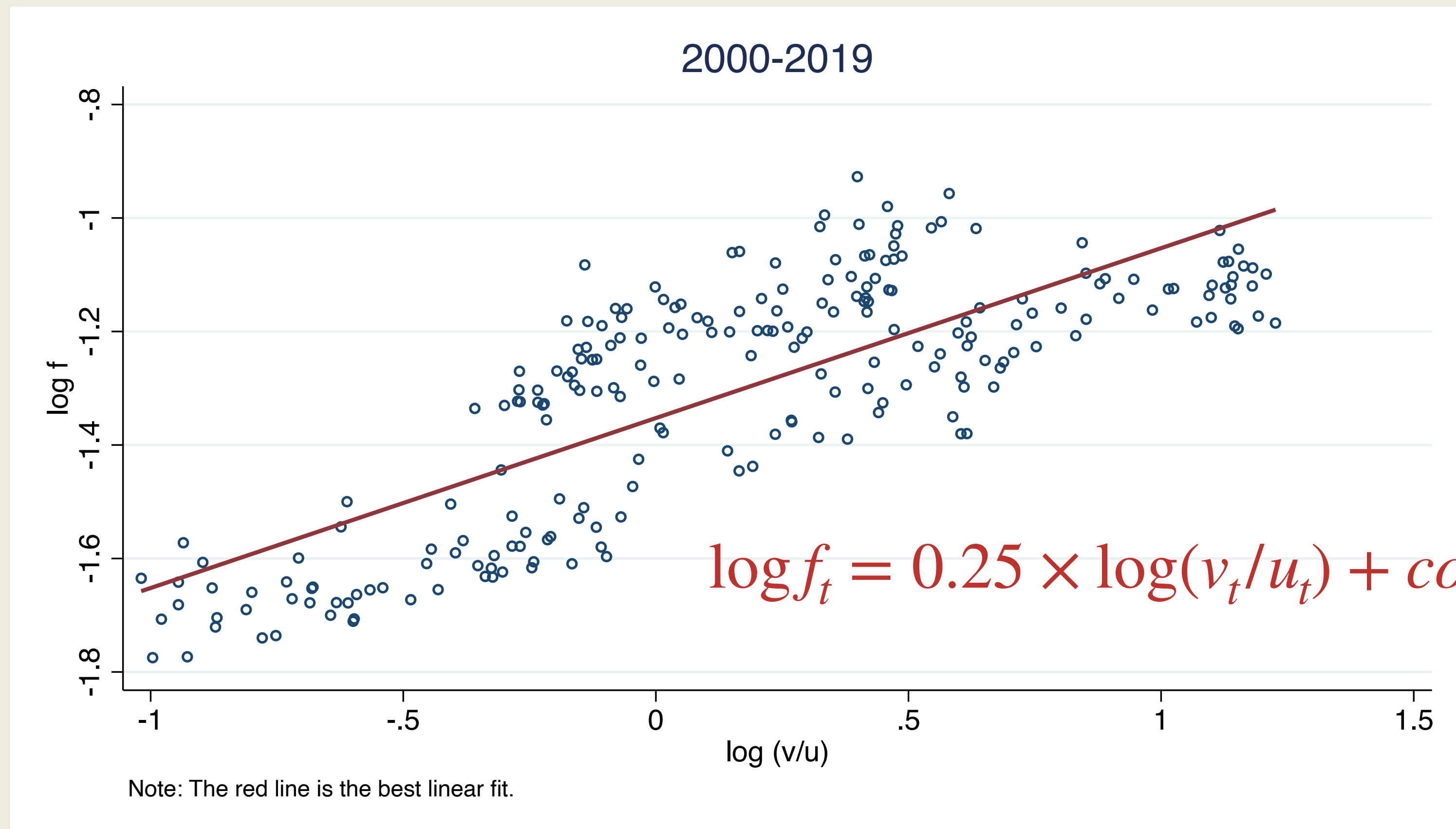
where $\tilde{m}_t \equiv (1/\alpha) [\log s_t - \log \bar{m}_t]$

- 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 $\text{corr}(q, p)$ tells us neither supply nor demand curve
 - In my view, this is an important open question
- Still, $\text{corr}(v, u) < 0$ is suggestive that v is an important determinant of u

Job-Finding and Market Tightness

- Another way to see the prediction of DMP paradigm is (under Cobb-Douglas)

$$\log f_t = \log \hat{f}(\theta_t) = \log \bar{m} + (1 - \alpha) \log(v_t/u_t)$$



Taking Stock

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_t

Appendix: Cross-Country Perspective

