Phillips meets Beveridge

Régis Barnichon - *Federal Reserve Bank of San Francisco*
Adam Shapiro - *Federal Reserve Bank of San Francisco*

NBER Conference: Inflation in the COVID Era and Beyond
May 16, 2024

The views expressed in the paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of San Francisco or the Federal Reserve System.

The Phillips curve

- The Phillips curve is the main macro framework to understand inflation fluctuations
- The New-Keynesian Phillips curve

$$\pi_t = \gamma E_t \pi_{t+1} + \kappa x_t + \nu_t,$$

- How excess Aggregate Demand affects Inflation
  $\rightarrow$ From unused capacity (or slack) to inflation
- x_t is the "forcing variable"

This paper

- Systematic evaluation of competing forcing variables
- Two angles:
    1. Forecasting inflation
    2. Explaining inflation with structural Phillips curve
- Using
    1. Time series variation
    2. Cross-sectional (MSA) variation

Findings

- V/U ratio and vacancy filling cost proxies perform best
- V/U ratio performs better than UR
- Beveridge curve shifts contain information about inflation
  $\Rightarrow$ Phillips meets Beveridge
- Matching efficiency affects inflation?

This talk

1. Candidate forcing variables
2. Evaluation
   - Out-of-sample forecasting
   - Structural Phillips curve
3. Beveridge curve shifts and inflation

Candidate forcing variables

1. Forcing variables: economic slack

Idea: get a measure of "unused capacity"

1. u, $u^{gap} = u - u^*$, y^{gap}
2. Non-Employment Index (NEI) includes job seekers outside LF

   Hornstein et al. 2014
3. V/U ratio: $\frac{\text{job openings}}{\text{job seekers}}$, $\theta = \frac{v}{u}$

   Barnichon and Shapiro 2022, Ball et al. 2022
4. Generalized $\frac{v}{u^*}$ ratio with u^* including job seekers from U, N, E

   Abraham et al. 2020
5. Board Fed measure of *Capacity Utilization* in manufacturing, mining, utilities

2. Forcing variables: firms' marginal cost

From New-Keynesian literature

1. Labor share (average labor cost) Gali-Gertler, 1999
2. Proxy for cost from material inputs: Share of IP in GDP Shapiro, 2008
3. V/U ratio or job switching rate (p_t^{ee}) as proxy for firms' hiring cost

   Krause and Lubik (2007), Blanchard and Gali (2010), Moscarini and Postel-Vinay (2017)
4. Vacancy filling cost —cost of hiring a marginal worker—: χ

Vacancy filling cost (1)

- In models with search frictions, firms' *vacancy filling cost* is

$$\chi_t = \frac{c}{q_t} \qquad \text{where} \qquad q_t \equiv \frac{m_t}{V_t}$$

  - c: vacancy posting cost
  - q_t: vacancy filing rate
  - m_t: flow of new matches at t

Vacancy filling cost (1)

- In models with search frictions, firms' *vacancy filling cost* is

$$\chi_t = \frac{c}{q_t} \qquad \text{where} \qquad q_t \equiv \frac{m_t}{V_t}$$

  - c: vacancy posting cost
  - q_t: vacancy filing rate
  - m_t: flow of new matches at t

- Cobb-Douglas matching function $m_t = m_{0t} U_t^{\sigma} V_t^{1-\sigma}$

$$q_t = m_{0t} \theta_t^{-\sigma}$$

Vacancy filling cost (1)

- In models with search frictions, firms' *vacancy filling cost* is

$$\chi_t = \frac{c}{q_t} \qquad \text{where} \qquad q_t \equiv \frac{m_t}{V_t}$$

  - c: vacancy posting cost
  - q_t: vacancy filing rate
  - m_t: flow of new matches at t

- Cobb-Douglas matching function $m_t = m_{0t} U_t^{\sigma} V_t^{1-\sigma}$

$$q_t = m_{0t} \theta_t^{-\sigma}$$

- Log-linearized vacancy filling cost

$$\hat{\chi}_t = \sigma \hat{\theta}_t - \hat{m}_{0t}.$$

$\Rightarrow$ With constant matching efficiency, V/U proxies for firms' vacancy filling cost

Vacancy filling cost (2)

Using data on worker transition rates:

- With hiring from unemployment, vacancy filling rate is

$$q_t = \frac{m_t}{V_t} = \frac{p_t^{ue} U_t}{V_t}$$

- Log-linearized vacancy filling cost $\chi = \frac{c}{q_t}$

$$\hat{\chi}_t = \hat{\theta}_t - \hat{p}_t^{ue}$$

With hiring from nonparticipation

More generally:

- Hiring from unemployment and non-participation
- Vacancy filling rate is

$$q_t = \frac{m_t}{V_t} = \frac{p_t^{ue} U_t + p_t^{ne} N_t}{V_t}$$

With hiring from nonparticipation

More generally:

- Hiring from unemployment and non-participation
- Vacancy filling rate is

$$q_t = \frac{m_t}{V_t} = \frac{p_t^{ue} U_t + p_t^{ne} N_t}{V_t}$$

- Log-linearized vacancy filling cost $\chi = \frac{c}{q_t}$

$$\hat{\chi}_t = \hat{\theta}_t - \hat{p}_t^{ue} - \hat{\gamma}_t \qquad \text{where} \qquad \gamma_t = 1 + \frac{p_t^{ne}}{p_t^{ue}} \frac{1 - l_t}{l_t u_t}$$

  - unemployment rate u_t and lfpr l_t
  - p_t^{ue} and p_t^{ne} measurable from CPS micro data

Evaluation: forecasting

Forecasting exercise

Idea: assess inflation information content in x_t while limiting over-fitting

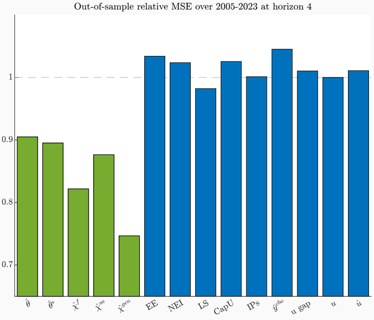
$$\pi_{t+h} = \gamma \pi_{t-1} + \lambda x_t + \eta_{t+h}$$

- One-year ahead out-of-sample forecast ($h = 4$)
- 10-year rolling window
- Sample periods
  - 1995-2023: Largest set of forcing variable
  - 1960-2023: v/u, χ, u
  - 1919-1941: v/u, u

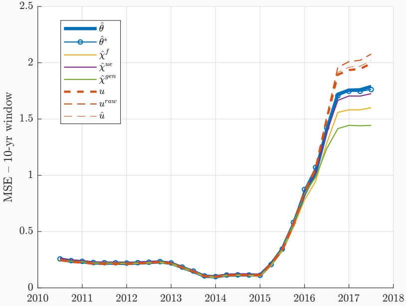
Data issues

- Measuring job openings from Help-Wanted ads (print and then online): 1951-2023 Barnichon (2010)
- Measuring worker transition rates (p_t^{ue}, p_t^{ne}) from CPS micro data: 1967-2023 Shimer (2012)
- Measuring job switching rate (p_t^{ee}) from CPS micro data: 1995-2023 Fujita et al. (2020)
- U and Y gaps: CBO

Forecasting performances, 1995-2024

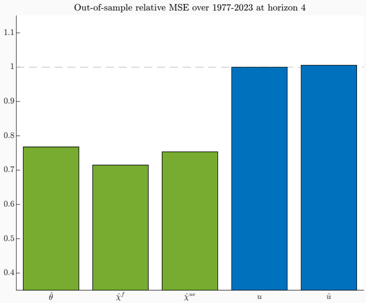


(a) Relative MSEs

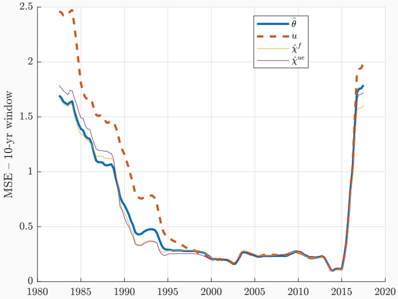


(b) 10-year Rolling MSEs

Forecasting performances, 1968-2024

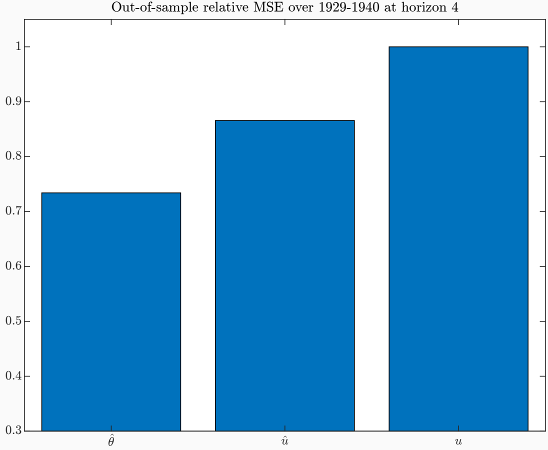


(c) Relative MSEs



(d) 10-year Rolling MSEs

Forecasting performances, 1919-1941



Evaluation: Phillips curve

Structural Phillips curve

- Follow Hazell et al. (2022) with

$$\pi_t = \mathrm{E}_t \pi_\infty + \kappa \left(\hat{x}_t - E_t \hat{x}_\infty \right) + \omega_t$$

- Estimate on quarterly data

$$\pi_t = \alpha + \beta_x \hat{x}_{t-4} + \beta_\pi E_t \pi_\infty + \upsilon_t$$

Philips Curve Estimates, 1995-2023

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
u_t	-0.19^{***} (0.08	-0.84^{***} (0.12)	—	—	—	—	—	—
$\hat{\theta}_t$	—	—	0.28^{***} (0.08)	1.08^{***} (0.10)	—	—	—	—
$\hat{\chi}_t$	—	—	—	—	0.30^{***} (0.09)	1.07^{***} (0.11)	—	—
$\hat{\theta}_t^*$	—	—	—	—	—	—	0.35^{***} (0.09)	1.17^{***} (0.10)
Inflation	core	cyclical	core	cyclical	core	cyclical	core	cyclical
Sample	95-23	05-23	95-23	05-23	95-23	05-23	95-23	05-23
Adjusted R^2	0.223	0.614	0.267	0.755	0.265	0.731	0.291	0.790

Notes: The forcing variables were z-scored (demeaned and normalized to unit standard-deviation) for comparability across columns.

Philips Curve Estimates, 1960-2023

	(1)	(2)	(3)	(4)	(5)	(6)
u_t	-0.27^{***} (0.06	-1.12^{**} (0.57)	—	—	—	—
$\hat{\theta}_t$	—	—	0.33^{***} (0.06)	1.00^{**} (0.51)	—	—
$\hat{\chi}_t$	—	—	—	—	0.27^{***} (0.07)	1.05^{**} (0.63)
$E_t \pi_\infty$	1.04^{***} (0.04)	0.79^{*} (0.50)	0.95^{***} (0.07)	0.86^{*} (0.46)	0.95^{***} (0.07)	0.90^{*} (0.49)
Adjusted R^2	0.815		0.824		0.829	
Partial R^2	0.039		0.080		0.092	
IV	No	Yes	No	Yes	No	Yes

Notes: The forcing variables were z-scored (demeaned and normalized to unit standard-deviation) for comparability across columns.

Structural Phillips curve

- Endogeneity issues
  - Supply shocks
  - Measurement error in inflation expectations
  - Long-run level $E_t \hat{x}_\infty$ in error term
- "Solutions"
  1. Use FRBSF cyclical core inflation measure
     $\rightarrow$ alleviates bias from supply shocks
  2. Use monetary shocks as IV

     Barnichon-Mesters, 2020
  3. Use MSA-level cross-sectional variation

Philips Curve Estimates, 1995-2023

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
u_t	-0.19^{***} (0.08	-0.84^{***} (0.12)	—	—	—	—	—	—
$\hat{\theta}_t$	—	—	0.28^{***} (0.08)	1.08^{***} (0.10)	—	—	—	—
$\hat{\chi}_t$	—	—	—	—	0.30^{***} (0.09)	1.07^{***} (0.11)	—	—
$\hat{\theta}_t^*$	—	—	—	—	—	—	0.35^{***} (0.09)	1.17^{***} (0.10)
Inflation	core	cyclical	core	cyclical	core	cyclical	core	cyclical
Sample	95-23	05-23	95-23	05-23	95-23	05-23	95-23	05-23
Adjusted R^2	0.223	0.614	0.267	0.755	0.265	0.731	0.291	0.790

Notes: The forcing variables were z-scored (demeaned and normalized to unit standard-deviation) for comparability across columns.

Philips Curve Estimates, 1960-2023

	(1)	(2)	(3)	(4)	(5)	(6)
u_t	-0.27^{***} (0.06)	-1.12^{**} (0.57)	—	—	—	—
$\hat{\theta}_t$	—	—	0.33^{***} (0.06)	1.00^{**} (0.51)	—	—
$\hat{\chi}_t$	—	—	—	—	0.27^{***} (0.07)	1.05^{**} (0.63)
$E_t \pi_\infty$	1.04^{***} (0.04)	0.79^{*} (0.50)	0.95^{***} (0.07)	0.86^{*} (0.46)	0.95^{***} (0.07)	0.90^{*} (0.49)
Adjusted R^2	0.815		0.824		0.829	
Partial R^2	0.039		0.080		0.092	
IV	No	Yes	No	Yes	No	Yes

Notes: The forcing variables were z-scored (demeaned and normalized to unit standard-deviation) for comparability across columns.

MSA level regression

- MSA-level Phillips curve

$$\pi_{it} = \mathrm{E}_t \pi_{i\infty} + \psi \left(\hat{x}_{it} - E_t \hat{x}_{i\infty} \right) + \omega_{it} \ .$$

- Estimate

$$\pi_{i,t} = \psi \hat{x}_{i,t-4} + \delta_t + \alpha_{i0} + \alpha_{i1} t + \beta \mathbf{X}_{i,t-4} + \upsilon_{it},$$

- Endogeneity issues
  - Time FE gets rid of (AS) shocks and monetary policy
  - MSA FE and linear trend to capture $\mathrm{E}_t \pi_{i,\infty} - \mathrm{E}_t \pi_{\infty}$ and $E_t \hat{x}_{i,\infty} - E_t \hat{x}_{\infty}$

MSA level data

- Unemployment
  - 1990-2023: Local Area Unemployment Statistics
  - 1982-1989: Construct from CPS micro data, adjusting for MSA defn
- Vacancies
  - 1951-2008: Conference Board *print* Help Wanted ads
  - 2005-2010: Conference Board *online* Help Wanted ads
    $\rightarrow$ Spliced as in Barnichon (2010)
  - 2010-2022: Burning Glass data
- 1982-2022: core CPI inflation

Philips Curve Estimates, MSA Level 1982-2022

	Dep. variable: Core Inflation (Δ4Q)					
	(1)	(2)	(3)	(4)	(5)	(6)
u	-0.0957***	-0.647***			0.392***	-0.308**
	(0.0282)	(0.114)			(0.0644)	(0.123)
$\hat{\theta}$			0.280***	0.809***	0.584***	0.591***
			(0.0351)	(0.102)	(0.0625)	(0.128)
Observations	2431	2431	2431	2431	2431	2431
Adjusted R^2	0.329	0.689	0.358	0.695	0.378	0.698
Adj. Within R^2	0.329	0.199	0.358	0.215	0.378	0.223
MSA Fixed Effects	No	Yes	No	Yes	No	Yes
MSA Time Trends	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes

All variables z-scored (demeaned and normalized to unit standard-deviation) for comparability across columns.

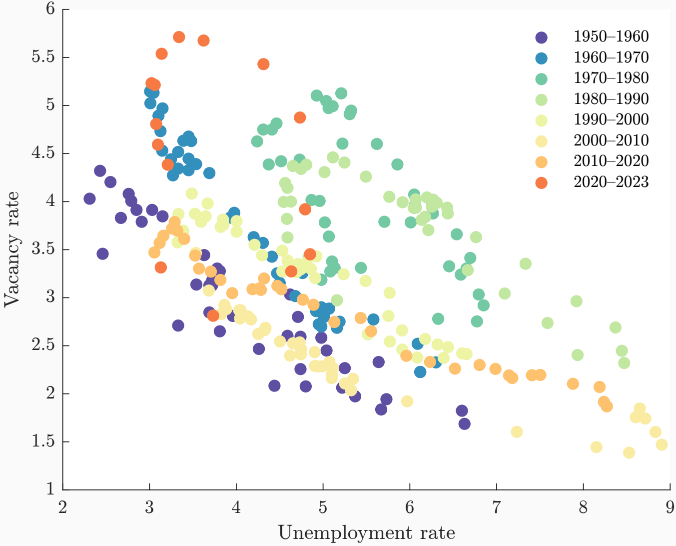
Controls included lagged inflation and the lagged ratio of the goods and services price level.

Standard errors clustered by MSA

Phillips meets Beveridge

The Beveridge curve

- Tight relation between V and U



Question

- $Corr(u, v) \approx -.9$ but superior performances of V/U over U
- What additional information does V brings over U?

  $\Rightarrow$ **Beveridge curve shifts**

The Beveridge curve in theory (1)

$$\begin{cases} \dot{U}_t = p_t^{EU} E_t + p_t^{NU} N_t - (p_t^{UE} + p_t^{UN}) U_t \\ \dot{E}_t = p_t^{UE} U_t + p_t^{NE} N_t - (p_t^{EU} + p_t^{EN}) E_t \\ \dot{N}_t = p_t^{EN} E_t + p_t^{UN} U_t - (p_t^{NE} + p_t^{NU}) N_t \end{cases}$$

- "Steady-state" approximation ($\dot{X}_t = 0$)

$$u_t \simeq u_t^{ss} \equiv \frac{s_t}{f_t}$$

with s_t and f_t defined by

$$\begin{cases} s_t = p_t^{EU} + \frac{p_t^{EN} p_t^{NU}}{1 - p_t^{NN}} \\ f_t = p_t^{UE} + \frac{p_t^{UN} p_t^{NE}}{1 - p_t^{NN}}. \end{cases}$$

The Beveridge curve in theory (2)

Use Cobb-Douglas matching function

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

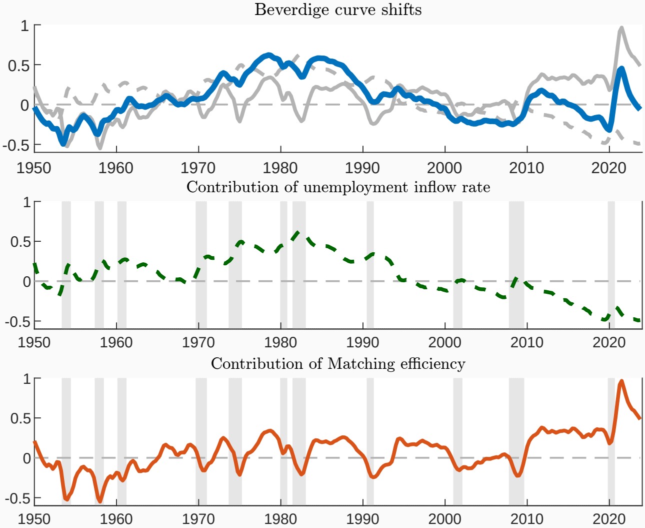
- Combine

$$f_t = \frac{m_t}{U_t} = m_{0t} \left(\frac{v_t}{u_t} \right)^{1-\sigma} \quad \text{and} \quad u_t = \frac{s_t}{f_t}$$

- Get

$$\hat{v}_t = -\frac{\sigma}{1-\sigma} \hat{u}_t + \underbrace{\hat{\mu}_t}_{\text{BC shifts}} \qquad \text{where} \qquad \hat{\mu}_t = \frac{1}{1-\sigma} \hat{s}_t - \frac{1}{1-\sigma} \hat{m}_{0t}.$$

The shifting Beveridge curve



Phillips meets Beveridge

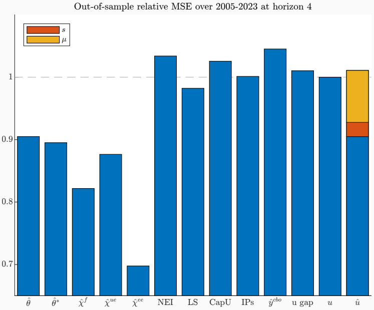
- Phillips curve

$$\pi_t = \mathrm{E}_t \pi_\infty + \kappa \left(\hat{\theta}_t - E_t \hat{\theta}_\infty \right) + \omega_t$$

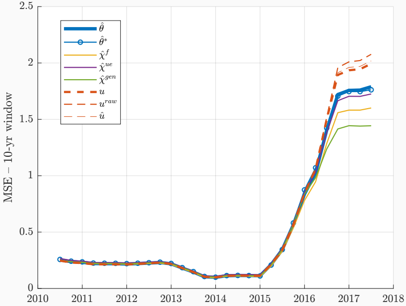
- Beveridge curve

$$\hat{\theta}_t = \underbrace{-\frac{1}{1-\sigma} \hat{u}_t}_{\text{Mvts along BC}} + \underbrace{\frac{1}{1-\sigma} \hat{s}_t - \frac{1}{1-\sigma} \hat{m}_{0t}}_{\text{Shifts in BC}}$$

Forecasting performances, 1995-2024

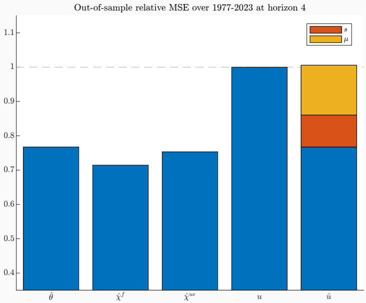


(e) Relative MSEs

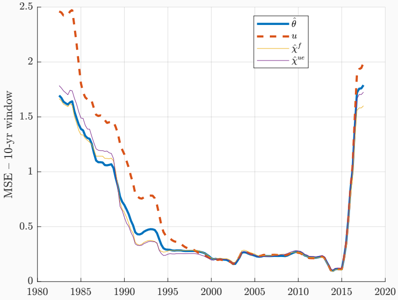


(f) 5-year Rolling MSEs

Forecasting performances, 1968-2024



(g) Relative MSEs



(h) 10-year Rolling MSEs

Testing for Beveridge curve shifts, 1960-2023

	(1)	(2)	(3)	(4)	(5)
$\hat{u}_t$	-0.91^{***} (0.13)	1.45^{*} (0.75)	-0.42 (0.30)	-0.55^{**} (0.28)	—
$\hat{\theta}_t$	—	1.36^{***} (0.39)	—	—	0.52^{***} (0.13)
$\hat{\mu}_t$	—	—	-1.36^{***} (0.40)	—	—
$\hat{s}_t$	—	—	—	1.03^{*} (0.54)	—
$\hat{m}_{0t}$	—	—	—	-1.43^{***} (0.40)	-0.67^{***} (0.32)
$E_t\pi_\infty$	1.01^{***} (0.07)	0.88^{***} (0.07)	0.88^{***} (0.07)	0.89^{***} (0.07)	0.91^{***} (0.07)

Philips Curve Estimates, MSA Level 1982-2022

	Dep. variable: Core Inflation (Δ4Q)		
	(1)	(2)	(3)
$\hat{u}$	-0.687***	-0.368**	-0.695***
	(0.0925)	(0.140)	(0.0856)
$\hat{\theta}$		0.506***	
		(0.159)	
$\hat{\mu}$			-0.122***
			(0.0384)
Observations	2431	2431	2431
Adjusted R^2	0.694	0.699	0.699
Adj. Within R^2	0.211	0.225	0.225
MSA Fixed Effects	Yes	Yes	Yes
MSA Time Trends	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes

All variables z-scored (demeaned and normalized to unit standard-deviation) for comparability across columns. Controls include lagged inflation and the lagged ratio of the goods and services price level. Standard errors clustered by MSA.

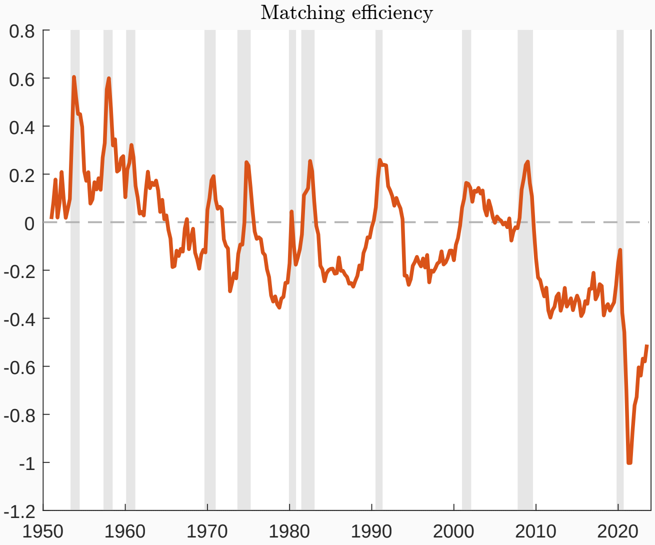
Conclusion

- The V/U rate and vacancy filling cost proxies outperform other forcing variables in a Phillips framework
- Shifts in the Beveridge curve —mvts in matching efficiency— contain information about future inflation

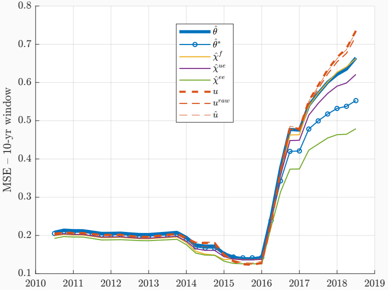
Conclusion

- The V/U rate and vacancy filling cost proxies outperform other forcing variables in a Phillips framework
- Shifts in the Beveridge curve —mvts in matching efficiency— contain information about future inflation
- Determinants of matching efficiency
  - Search and recruiting intensity/technology
  - Composition of pool of job seekers matter Barnichon-Figura 2015, Abraham et al. 2022
  - Mismatch Sahin et al. 2014
  - Out-of-steady-state dynamics
- Open question: Does higher matching efficiency *cause* lower inflation?
- Need an Instrumental Variable
  - Post-Covid Great Resignation responsible for drop in matching efficiency?

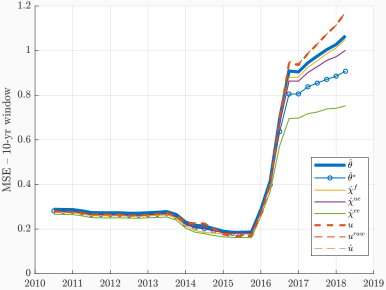
Open question: What happened to matching efficiency?



Forecasting performances, varying h

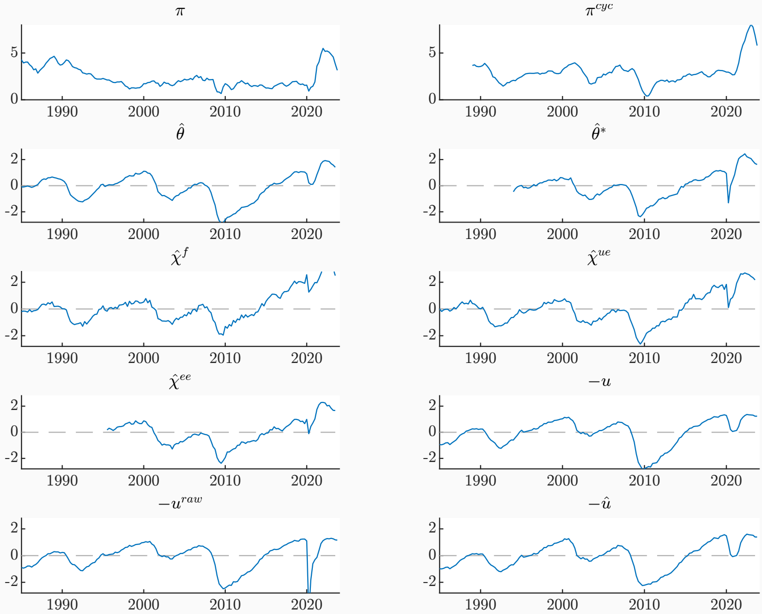


(i) 10-yr Rolling MSEs, $h = 0$

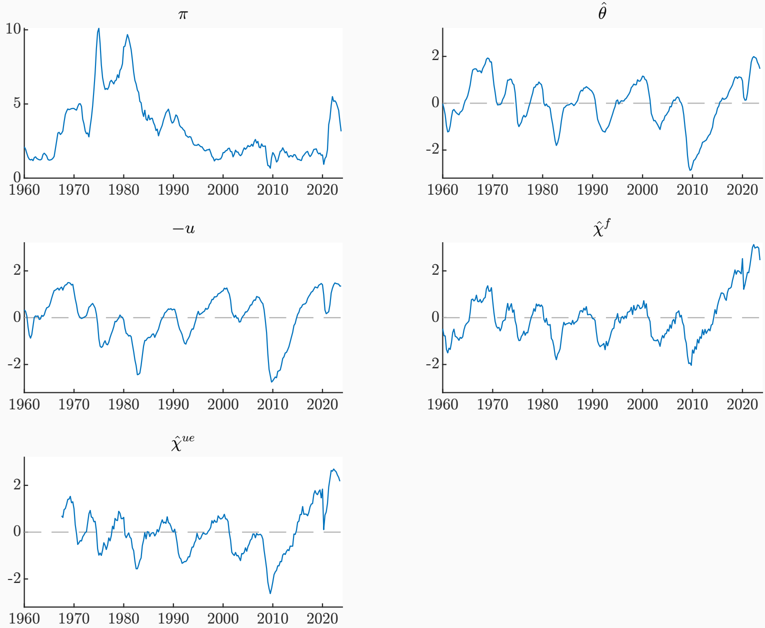


(j) 10-yr Rolling MSEs, $h = 1$

Raw series


π
π^{cyc}
$\hat{\theta}$
$\hat{\theta}^*$
$\hat{\chi}^f$
$\hat{\chi}^{ue}$
$\hat{\chi}^{ee}$
$-u$
$-u^{raw}$
$-\hat{u}$
5
0
2
-2
1990
2000
2010
2020

Raw series



π
10
5
0
1960
1970
1980
1990
2000
2010
2020
$\hat{\theta}$
2
0
-2
$-u$
$\hat{\chi}^f$
$\hat{\chi}^{ue}$