Decomposing Shifts in the Beveridge Curve: Implications for Labor Market Dynamics and Inflation

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NBER Conference on Inflation: Frontiers of Research and Policy

March 12-13, 2026

Preview

- Several recent papers find vacancy-to-unemployment ratio outperforms unemployment rate in Phillips curve models (Ball, Leigh and Mishra 2022; Barnichon and Shapiro 2024; Benigno and Eggertsson 2024)
- Majority of hires don't come from unemployment; effective searchers (sum of all population groups weighted by relative search intensities) conceptually preferable to unemployment as measure of availability of potential hires
  - Abraham, Haltiwanger and Rendell (2020) find vacancy-to-effective searcher ratio better predicts job filling and job finding rates than vacancy-to-unemployment ratio
- Goals of present paper:
  1) Analyze drivers of standard tightness (*v/u*) and generalized tightness (*v/ES*) and show how they are related;
  2) Explore the performance of standard and generalized tightness measures for Phillips curve analysis

Measuring labor market tightness

Standard matching function

- Hires depend on vacancies and unemployment:

  $$(1)\ \ h_t = m(v_t, u_t) = \mu_t^s v_t^{1-\alpha_s} u_t^{\alpha_s}$$

- Labor market tightness: $(2)\ \ \theta_t = \dfrac{v_t}{u_t}$
- In steady state, separations equal hires; vacancies and unemployment move inversely along Beveridge curve:

  $$(3)\ \ \delta_t = h_t = m(v_t, u_t) = \mu_t^s v_t^{1-\alpha_s} u_t^{\alpha_s}$$

  - Changes in either separations or matching efficiency shift curve
- Standard matching function mis-specified
  - Potential hires come not just from unemployment but also from out of the labor force or job-to-job transitions
  - Employer recruiting intensity may vary over time
  - Paper addresses first of these issues

Generalized matching function

- Hires depend on vacancies and *effective searchers*:

$$(4)\ \ h_t = m\left(v_t, \sum_i \rho_t^{l_i} l_{it}\right) = \mu_t^g v_t^{1-\alpha_g} \left(\sum_i \rho_t^{l_i} l_{it}\right)^{\alpha_g}$$

- Labor market tightness: $(5)\ \ \tilde{\theta}_t = \dfrac{v_t}{\sum_i \rho_t^{l_i} l_{it}}$
- In steady state, separations equal hires; vacancies and *effective searchers* move inversely along Beveridge curve:

$$(6)\ \ \delta_t = h_t = m\left(v_t, \sum_i \rho_t^{l_i} l_{it}\right) = \mu_t^g \left(v_t\right)^{1-\alpha_g} \left(\sum_i \rho_t^{l_i} l_{it}\right)^{\alpha_g}$$

  – Changes in either separations or matching efficiency shift curve
- In empirical implementation, *effective searchers* are weighted sum of people in each of 22 population groups
  – Weights equal relative base period job finding rates

Standard matching efficiency depends on ratio of effective searchers to unemployment

- Log linearization of standard matching function:

$$(7)\quad \log(\mu_t^s) = \log(h_t) - (1-\alpha^s)\log(v_t) - \alpha^s \log(u_t)$$

- Log linearization of generalized matching function:

$$(8)\quad \log(\mu_t^g) = \log(h_t) - (1-\alpha^g)\log(v_t) - \alpha^g \log(ES_t) \quad \text{where } ES_t = \sum_i \rho_t^{l_i} l_{it}$$

- Subtracting and rearranging terms:

$$(9)\quad \underbrace{\log(\mu_t^s)}_{\substack{\text{Standard}\\ \text{matching}\\ \text{efficiency}}} = \underbrace{\log(\mu_t^g)}_{\substack{\text{Generalized}\\ \text{matching}\\ \text{efficiency}}} + \underbrace{\alpha^g \log(ES_t / u_t)}_{\substack{\text{Ratio of effective}\\ \text{searchers to}\\ \text{unemployment}}} + \underbrace{(\alpha^s - \alpha^g)\log(\theta_t)}_{\substack{\text{Difference between standard and}\\ \text{generalized elasticities times}\\ \text{standard labor market tightness}}}$$

Two ways to decompose standard tightness

- Log-linear approximate decomposition that starts with standard matching function (Notation: $\hat{y}_t = \ln(y_t) - \ln(\bar{y})$)

$$(14)\quad \underbrace{\hat{v}_t - \hat{u}_t}_{\text{Standard tightness}} = \underbrace{-\left(\frac{\alpha^s}{1-\alpha^s}+1\right)\hat{u}_t}_{\text{Movements along Beveridge curve}} \underbrace{-\frac{1}{1-\alpha^s}\hat{\mu}_t^s}_{\text{Matching efficiency}} \underbrace{+\widehat{x_t^s}}_{\text{Other shifters}}$$

- Log-linear approximate decomposition that starts with generalized matching function:

$$(15)\quad \underbrace{\hat{v}_t - \hat{u}_t}_{\text{Standard tightness}} = \underbrace{-\left(\frac{\alpha^g}{1-\alpha^g}+1\right)\hat{u}_t}_{\text{Movements along Beveridge curve}} \underbrace{-\frac{1}{1-\alpha^g}\hat{\mu}_t^g}_{\text{Matching efficiency}} \underbrace{+\widehat{x_t^g}}_{\text{Other shifters}} \underbrace{-\frac{\alpha^g}{1-\alpha^g}\hat{Z}_t}_{\text{Effective searchers among unemployed}}, \text{ where } Z_t = \sum_{i\in u} \rho_t^{l_i} l_{it} / u_t$$

Decomposing generalized tightness

- Log-linear approximate decomposition that starts with generalized matching function:

(16) $$\underbrace{\hat{v}_t - \widehat{\mathrm{ES}}_t}_{\text{Generalized tightness}} = \underbrace{-\left(\frac{\alpha^g}{1-\alpha^g}+1\right)\widehat{ES}_t}_{\text{Movements along generalized Beveridge curve}} \underbrace{- \frac{1}{1-\alpha^g}\hat{\mu}_t^g}_{\text{Generalized matching efficiency}} \underbrace{+ \hat{x}_t^g}_{\text{Other shifters}}$$

Data and measurement

Vacancies and effective searchers

- Vacancies: Job openings from JOLTS for 2001Q1-2025Q2; back cast to 1994 using method of Davis, Faberman, and Haltiwanger (2012)
- Effective searchers: Sum of 22 population groups weighted by relative job finding rates
  - Constructed using CPS data (monthly estimates averaged by quarter)
  - Weights based on 2006 job finding rates
  - Job finding rates vary over time, but *relative* job finding rates quite stable
- Population groups include:
  - 13 groups among unemployed
  - 3 groups among out of labor force and want a job
  - 4 groups among out of labor force and don’t want a job
  - 2 groups among employed

Inflation and inflation expectations

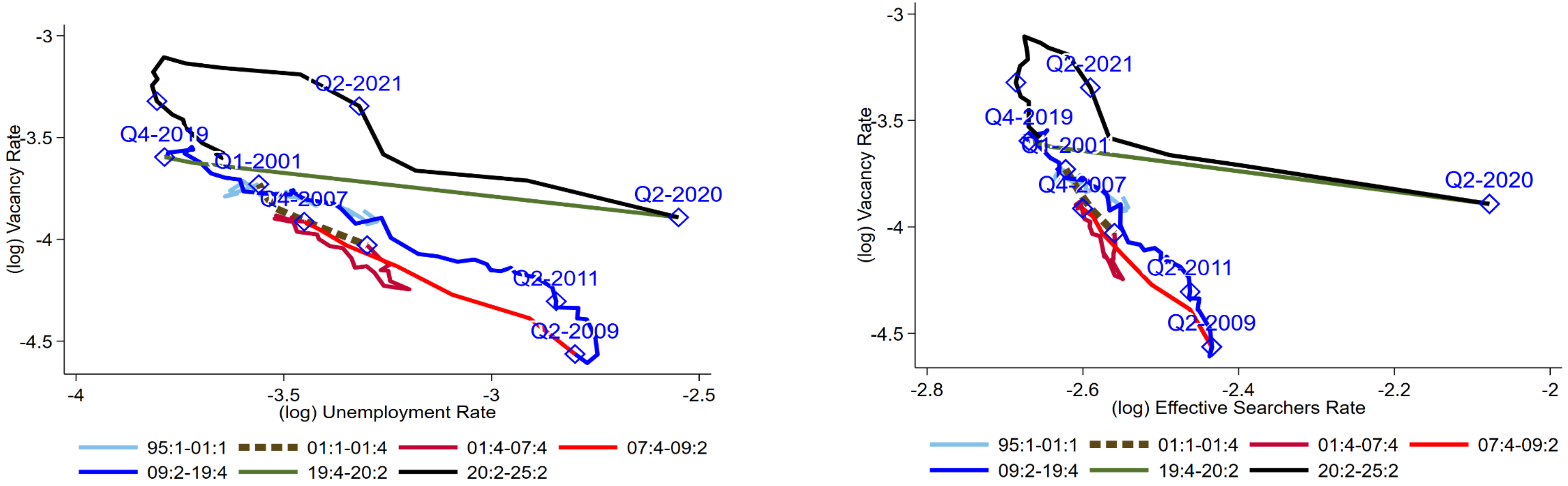
- Inflation measure for baseline analysis: PCE core inflation
  - All results replicated using Cleveland Federal Reserve Bank median CPI inflation
- Inflation expectations: Livingston survey 10-year CPI forecasts
- Model gap between inflation and inflation expectations:

$$\pi_t - \pi_t^e = \alpha + \beta\theta_t^i + \varepsilon_t$$

  - Seasonally adjusted quarterly data
  - Dependent variable: Year-over-year change in inflation [*t* – (*t-4*)] minus expected inflation in *t*
  - Tightness measure: Standard tightness or generalized tightness; average value from *t-4* through *t-1*
    - All results replicated using tightness measure from *t-4*
  - In addition to baseline model, fit models that allow for nonlinearities and/or allow changes in tightness for different reasons to have different effects
  - All explanatory variables z-scored (subtract mean and divide by standard deviation)

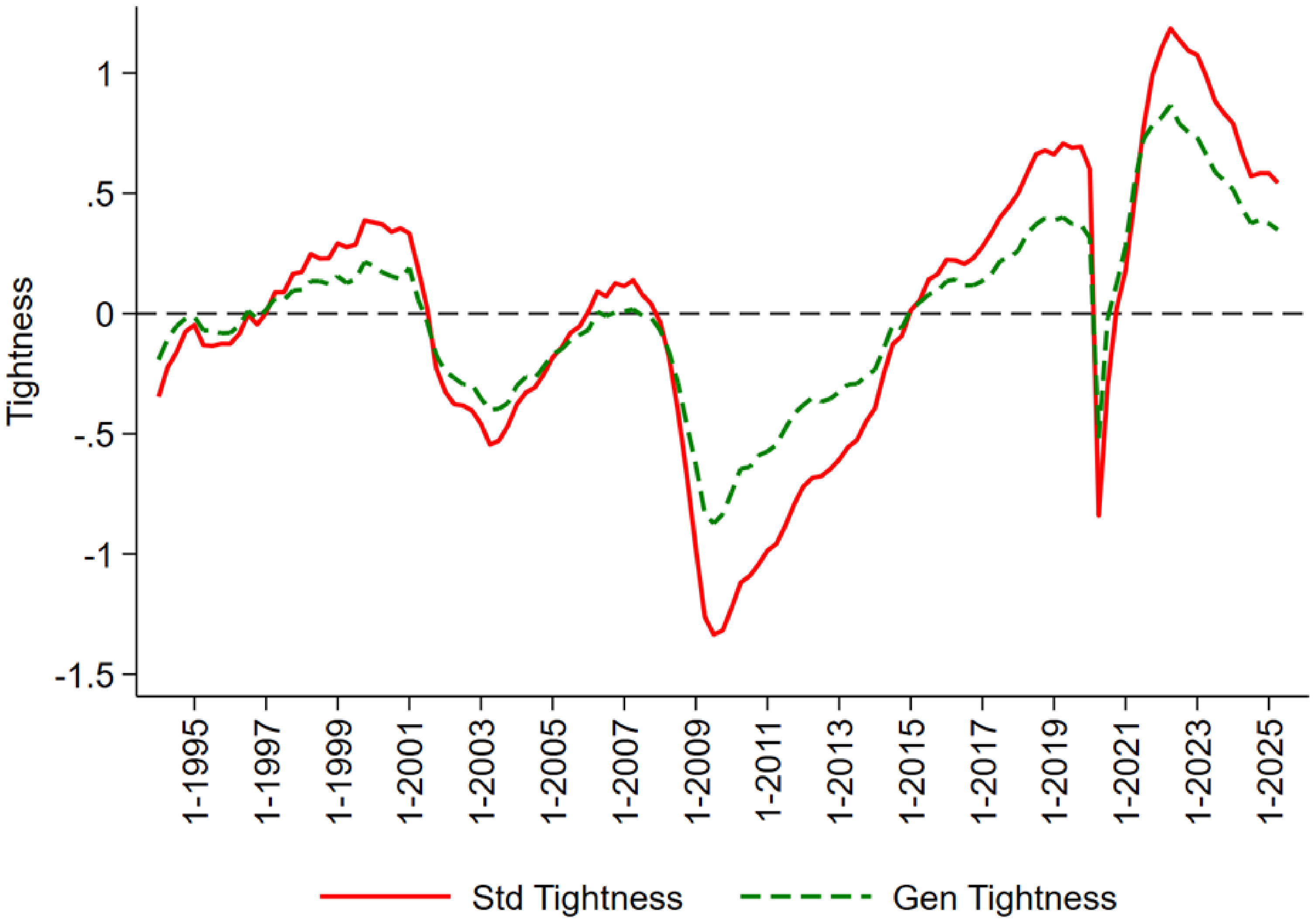
Beveridge curve decomposition

Figure 1: Standard and generalized Beveridge curves



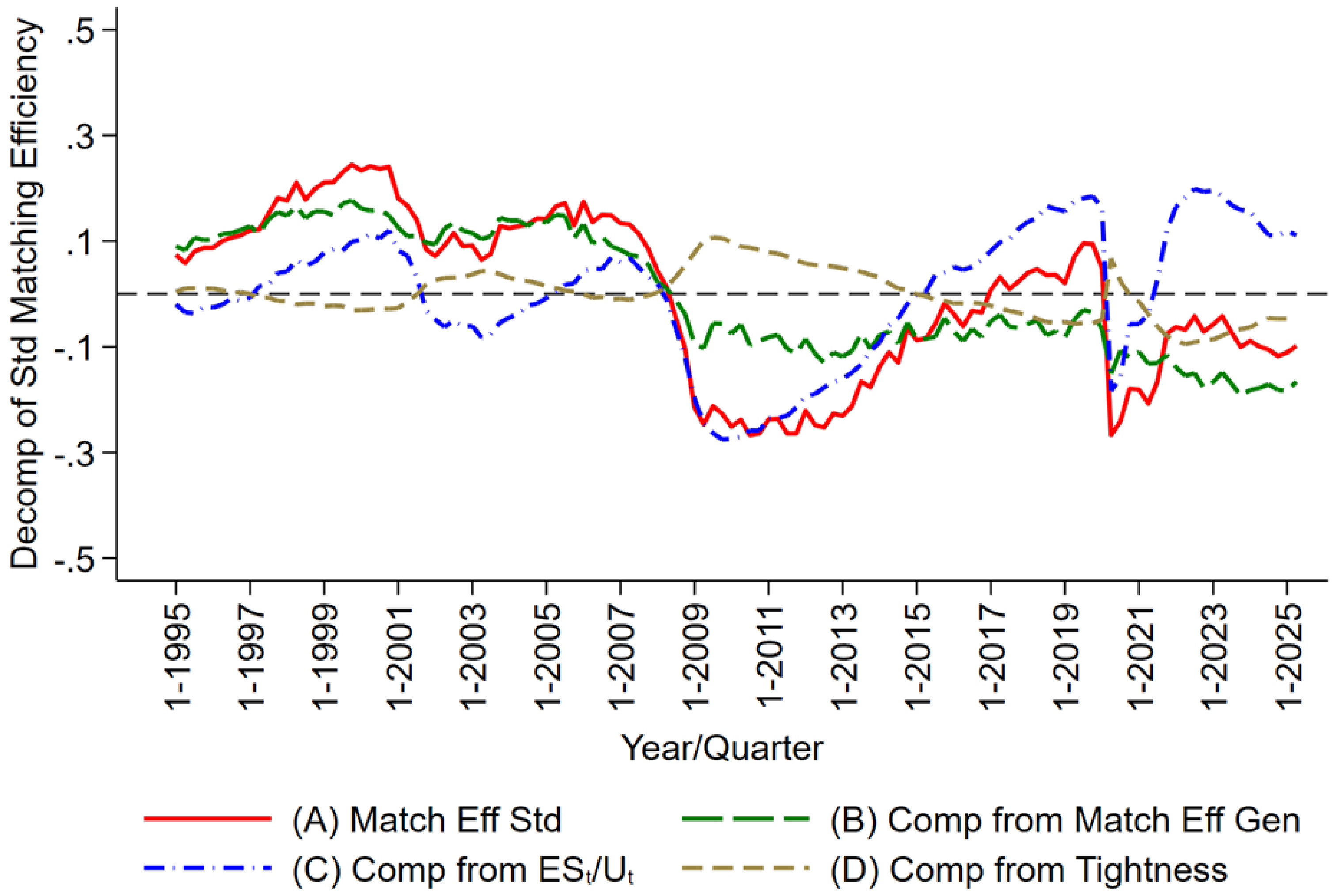
- Both curves slope downward and both exhibit cyclical looping
- Generalized curve varies proportionally less along X axis than standard curve

Figure 2: Standard and generalized labor market tightness



- Generalized tightness less cyclical than standard tightness
- Reflects that changes over cycle in effective searchers are proportionally smaller than changes in unemployment

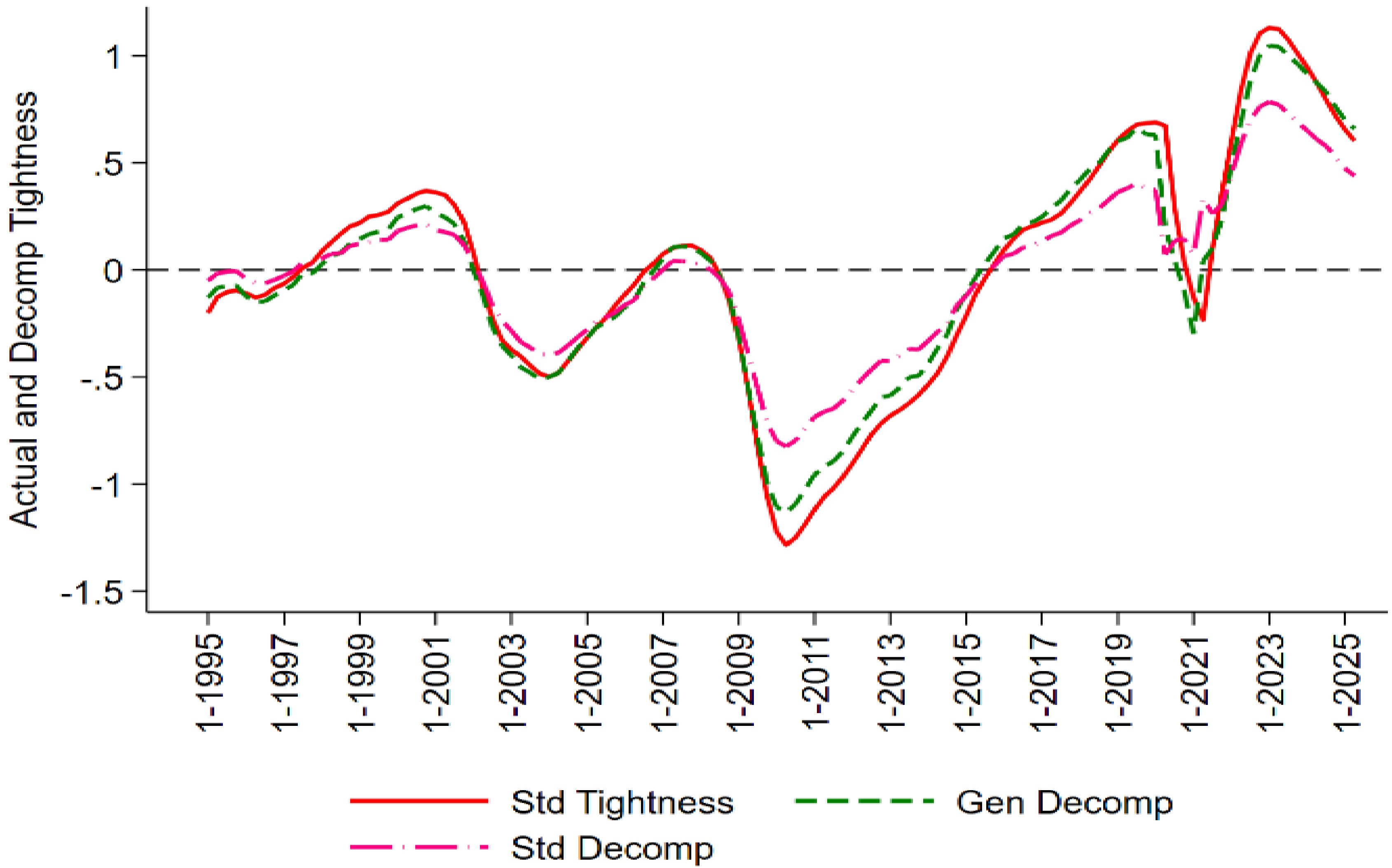
Figure 3: Decomposition of standard matching efficiency



Note: By construction, Shift (A) = Shift (B) + Shift (C) + Shift (D).

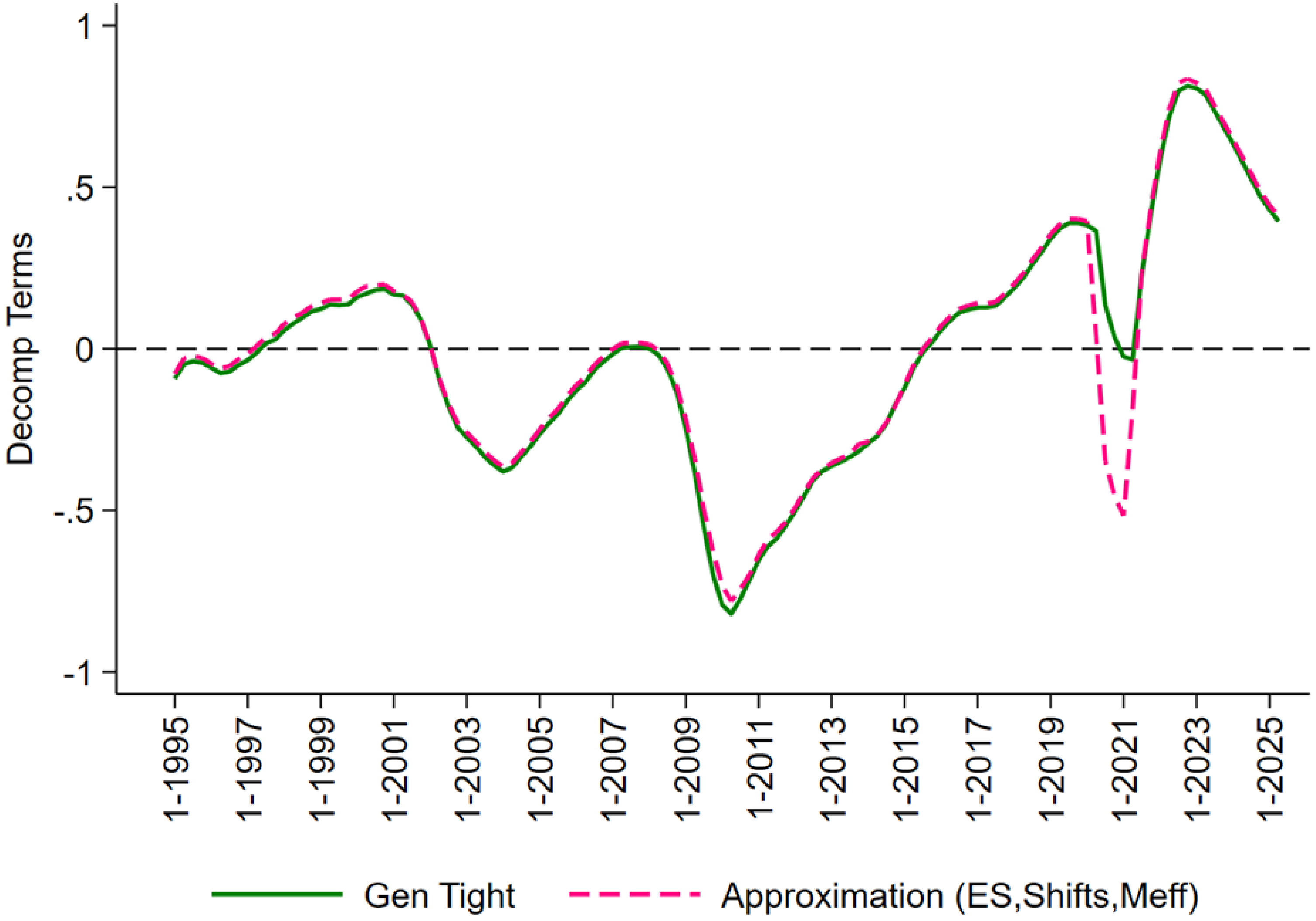
- Standard and generalized matching efficiency follow distinct paths
- Much of movement in standard matching efficiency due to changes in ratio of effective searchers to unemployment

Figure 4: Actual and approximated standard tightness



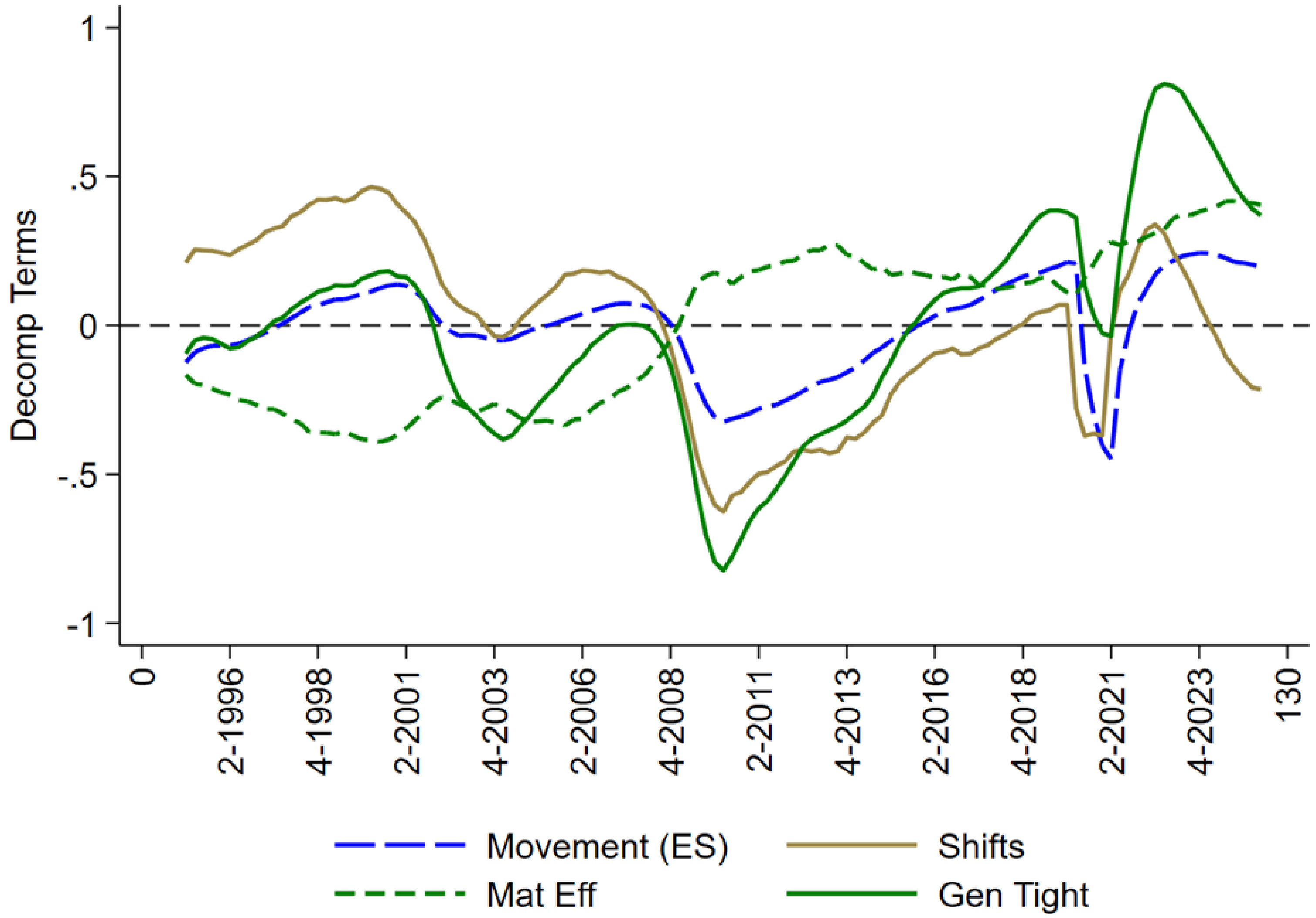
- Approximation based on decomposition of standard tightness using standard matching model (equation 14) does not track actual standard tightness especially well
- Approximation based on decomposition using generalized matching model (equation 15) does considerably better
  - Can think of this as an informal specification test

Figure 6: Actual and approximated generalized tightness



- Except for brief period during pandemic, approximation based on decomposition of generalized tightness using generalized matching model (equation 16) tracks generalized tightness closely

Figure 7: Decomposition of generalized tightness



- Movements along the generalized Beveridge curve, shifts in the curve due to changes in matching efficiency and other shifts all have contributed to changes in generalized tightness

- Generalized matching efficiency worsened following the Great Financial Crisis

- Generalized matching efficiency also has been low since the pandemic

Labor market tightness and inflation

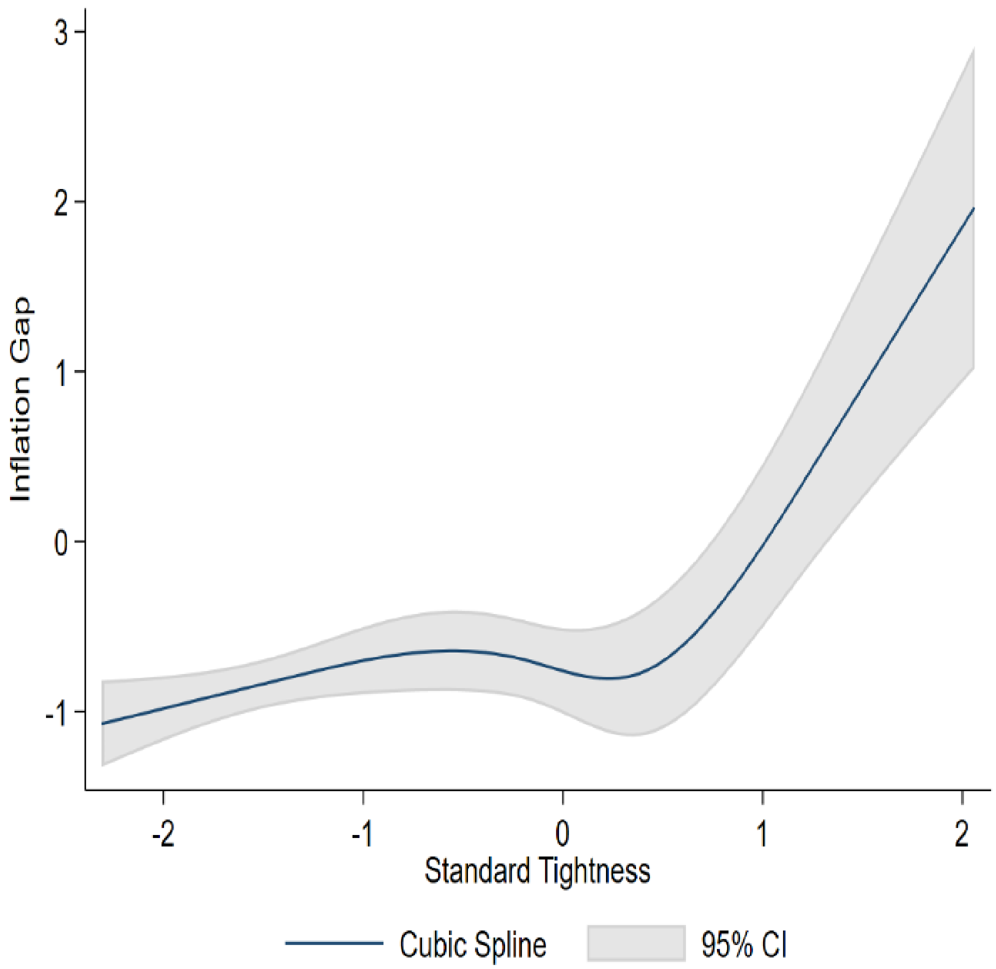
χ^2

Table 1: Inflation gap and labor market tightness

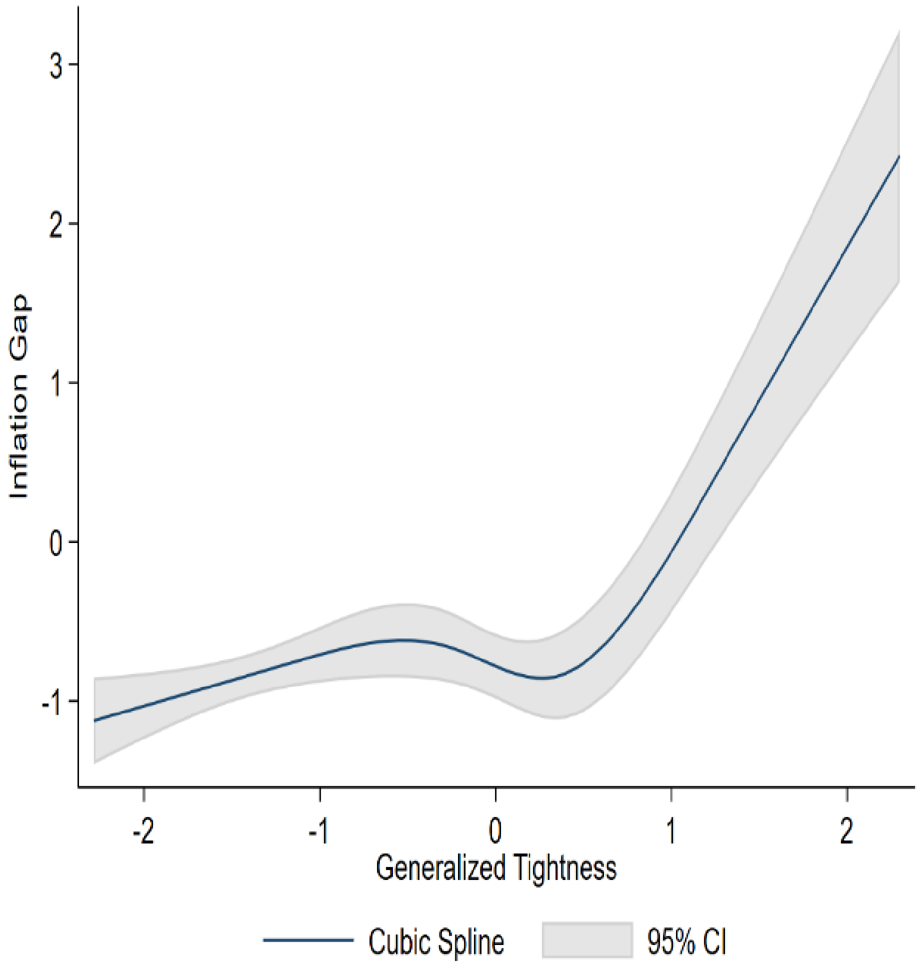
Standard Tightness	0.501***			
	(0.187)			
Generalized Tightness			0.583***	
			(0.194)	
Std Tightness (Spline 1)		0.289**		
		(0.138)		
Std Tightness (Spline 2)		-0.984*		
		(0.551)		
Std Tightness (Spline 3)		9.298***		
		(2.932)		
Gen Tight (Spline 1)				0.324**
				(0.138)
Gen Tight (Spline 2)				-1.660**
				(0.670)
Gen Tight (Spline 3)				9.560***
				(2.467)
R-sq.	0.277	0.503	0.375	0.671
Adj. R-sq.	0.271	0.490	0.370	0.663
AIC	297.7	256.0	279.9	205.5
BIC	303.3	267.2	285.5	216.7
Wald χ^2 test	p<0.001		p<0.001	
Obs.	122	122	122	122

Figure 9: Nonlinear relationship between inflation gap and tightness

Standard model



Generalized model



Actual and predicted inflation gap

Figure 8: Linear models

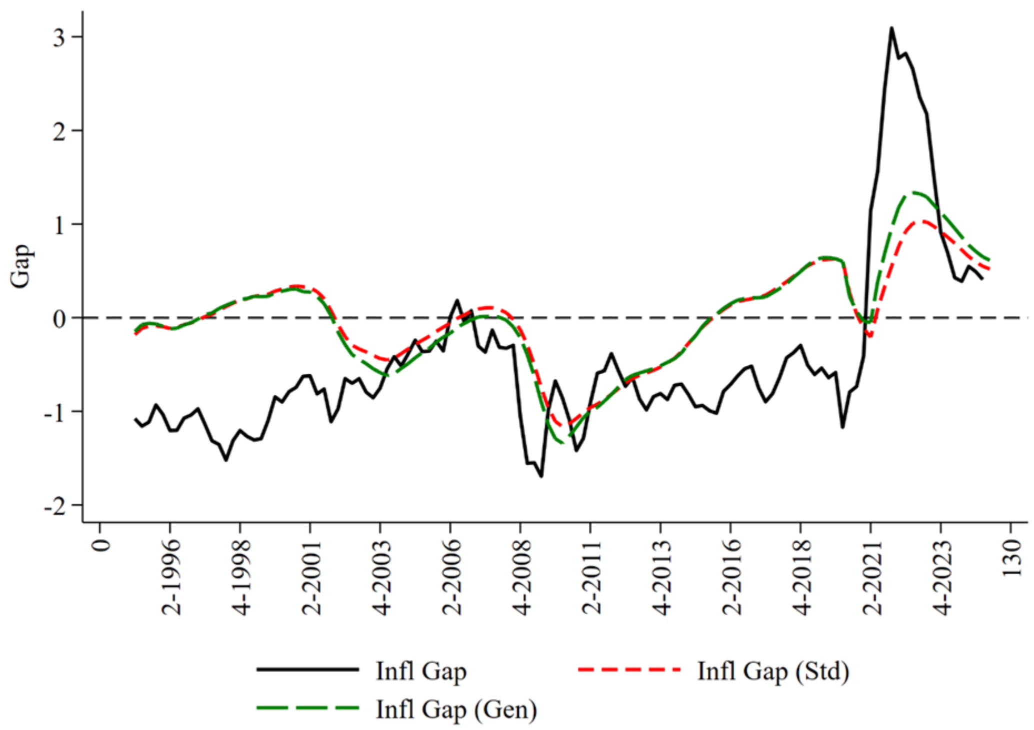
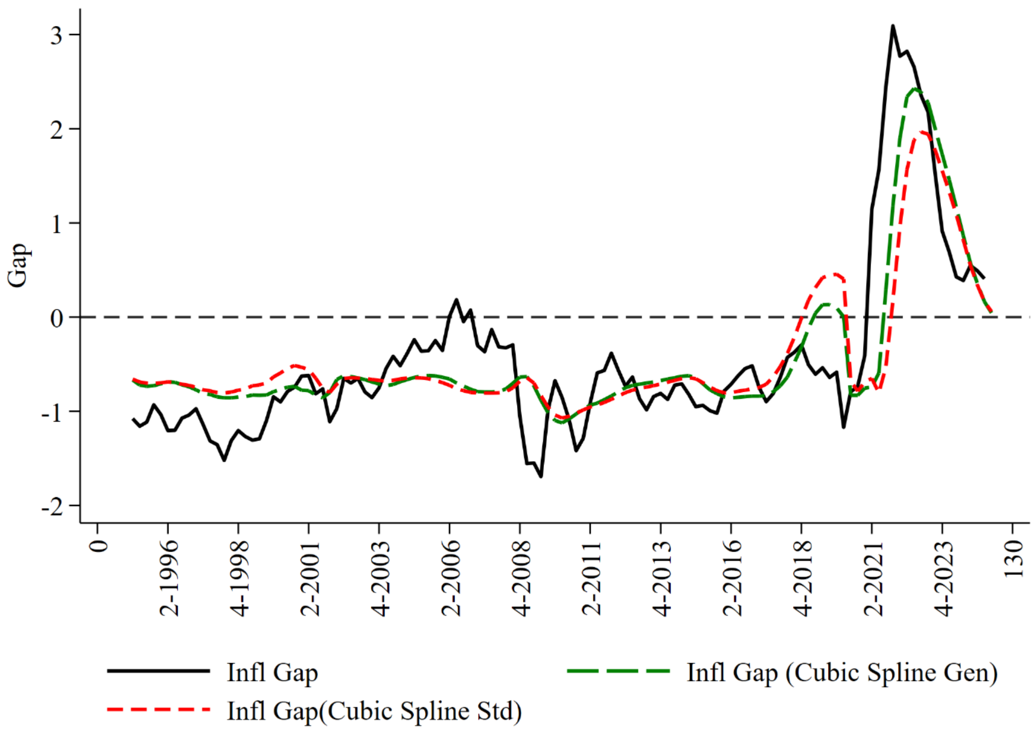


Figure 10: Cubic spline models

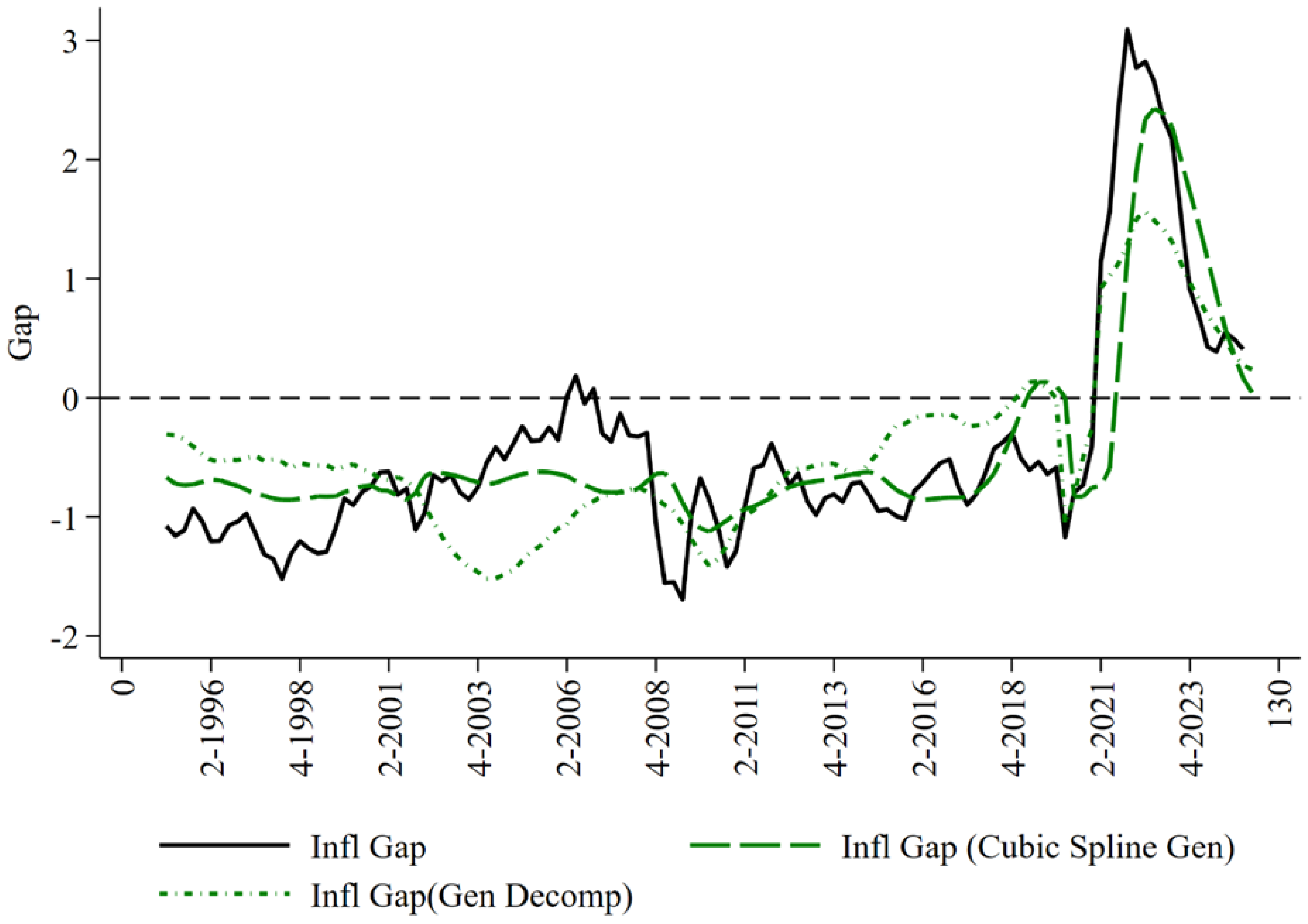


χ^2

Table 2: Inflation gap and decomposed generalized tightness

	Inflation Gap	Inflation Gap	Shapley-Owen Contribution from Column (2)
Gen Tightness	0.583***		
	(0.194)		
ES term		-0.133	14%
		(0.148)	
Shifts term		0.863***	21%
		(0.294)	
Matching Eff term		0.962***	61%
		(0.261)	
R-sq.	0.375	0.564	
Adj. R-sq.	0.370	0.553	
AIC	279.9	240.0	
BIC	285.5	251.3	
Wald χ^2 test		p=0.007	
Obs.	122	122	

Figure 11: Actual and predicted inflation gap, cubic spline vs. decomposed generalized models



- Decomposed model does not perform quite as well as cubic spline (adjusted R^2 0.553 vs 0.663), but captures much of same variation in inflation gap
- Stronger effect on inflation for changes in tightness due to shifts in generalized Beveridge curve versus changes due to movements along generalized Beveridge curve
  - Changes due to shifts seen as more likely to persist?
  - Correlation across quarters for three terms: 0.98 for matching efficiency, 0.85 for other shifters terms vs. 0.71 for effective searchers

Robustness checks

- Have replicated national analysis
  - Using Cleveland Federal Reserve Bank's median inflation series
  - Using tightness measures from *t-4* rather than average for *t-4* through *t-1*
  - Results generally similar
- Have carried out an exploratory MSA-level analysis
  - Vacancies: Help Wanted Index data from Barnichon and Shapiro (2024)
  - Unemployment and 4-group effective searcher measure: Constructed using CPS micro-data
  - Inflation: Core CPI
  - Inflation gap models for 1995-2022; controls for MSA, MSA-specific time trends, recession indicators, national GDP growth and national core CPI inflation
  - Even defining effective searchers using just four groups, generalized tightness outperforms standard tightness

Summing up inflation results

1) Generalized tightness (vacancies-to-effective searchers ratio) better predicts inflation than standard tightness (vacancies-to-unemployment ratio)
2) Relationship of inflation to generalized tightness strongly nonlinear
3) Decomposed models show inflation responds more strongly to changes in generalized tightness due to changes in matching efficiency or other Beveridge curve shifters than to changes in generalized tightness due to movements along the generalized Beveridge curve

Conclusion

Caveats, conclsions and future directions

- Acknowledge reported analysis has limitations
  - Time period relatively short (1994-2025); just one high inflation episode
  - Many Phillips curve specification issues we have not attempted to explore
- Paper's contribution: Demonstrate the limitations of the standard framework for understanding labor market tightness and the effects of tightness on inflation; show the value of a generalized framework that allows for hires from all sources
- We think our measure of generalized matching efficiency improves on the standard measure, but it is still a residual. Better understanding what underlies it a priority. Some directions for future research
  - Allow for variation in within-group search intensity over time
  - Incorporate variation in employer recruiting intensity

Thank you!

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