# Making Sense of Labor Market Indicators Amid Data Imperfections

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**Who said this?**

1. "*In the labor market, *supply and demand* conditions have come into better balance.*"

2. "*One possibility is that the recent improvement in *matching efficiency* [...] may reflect post-COVID renormalization.*"

3. "*Moreover, underlying *labor demand* appears to be improving.*"

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1. "*In the labor market, supply and demand conditions have come into better balance.*"
   ***Hint:*** FOMC press conference, June 12, 2024.

2. "*One possibility is that the recent improvement in matching efficiency [...] may reflect post-COVID renormalization.*"
   ***Hint:*** Economic Report of the President, 2024.

3. "*Moreover, underlying labor demand appears to be improving.*"
   ***Hint:*** U.S. Department of the Treasury Press Release, February 4, 2013.

# Labor market narratives commonly used by policymakers

**Who said this?**

1. "*In the labor market, supply and demand conditions have come into better balance.*"
   ***Hint:*** FOMC press conference, June 12, 2024.
   ***Answer:*** **Chair Jerome H. Powell**

2. "*One possibility is that the recent improvement in matching efficiency [...] may reflect post-COVID renormalization.*"
   ***Hint:*** Economic Report of the President, 2024.
   ***Answer:*** **Council of Economic Advisers**

3. "*Moreover, underlying labor demand appears to be improving.*"
   ***Hint:*** U.S. Department of the Treasury Press Release, February 4, 2013.
   ***Answer:*** **Assistant Secretary for Economic Policy Jan Eberly**

# We provide time-series estimates of these narrative factors

**Make sense of wealth of monthly and quarterly U.S. labor market indicators**

- 94 indicators, 1960–2026 <span>from BLS, NFIB, Michigan Survey, Revelio, ADP, Indeed, LMU, and others</span>
- Exploit cross-section to overcome data limitations: missing values, jagged edges, multiple measures of same concept, and revisions.
- Introduce two-step methodology to construct estimates

**Narrative factors provide concise summary of labor market conditions**

- Tightly identified based on small set of inequality constraints
- Labor demand and short-run labor supply explain bulk of cyclical fluctuations
- "Soft Landing" since 2021 the result of joint declines in labor demand and labor supply

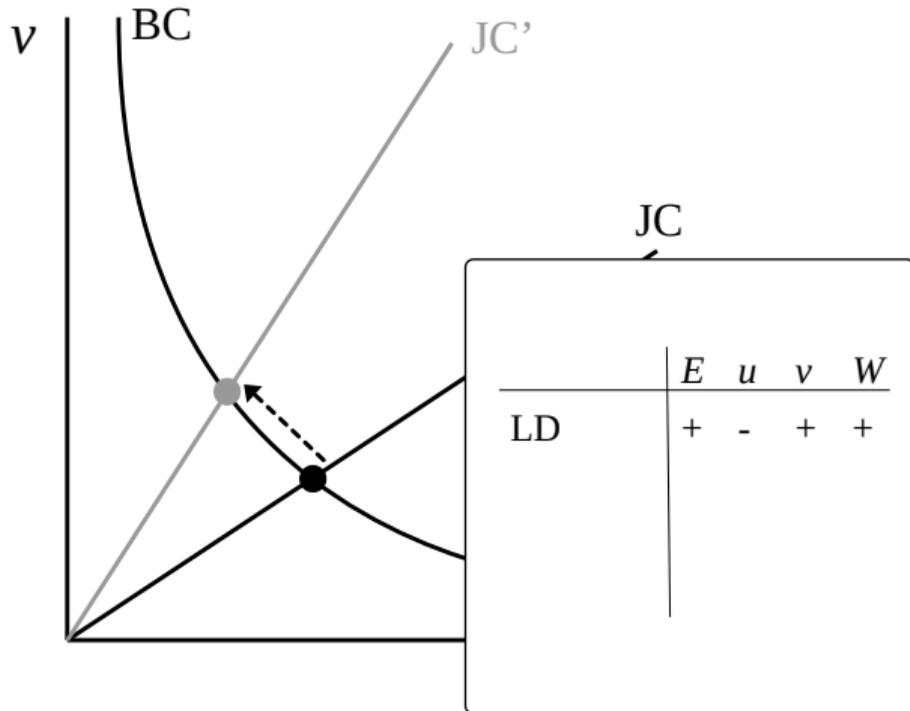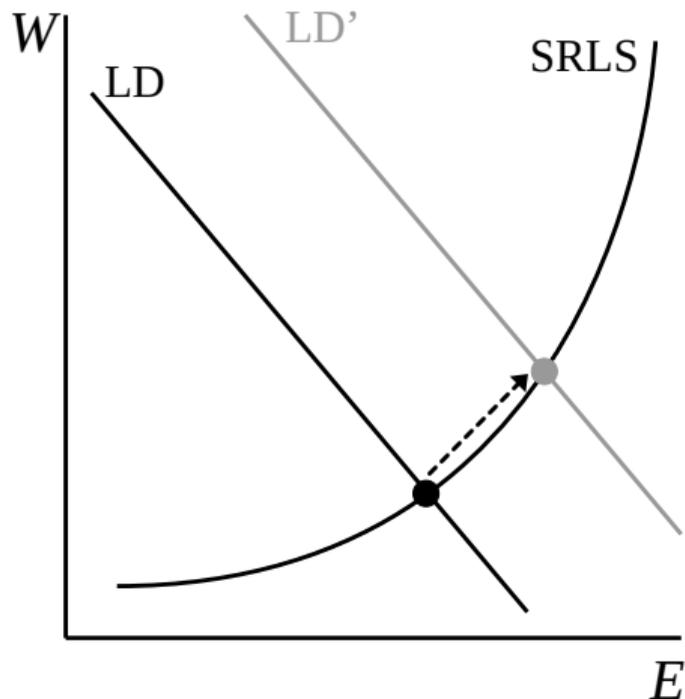# Textbook Intuition Behind Labor-Market Narratives

Labor-market narrative terminology used in context of relatively uncontroversial textbook assumptions
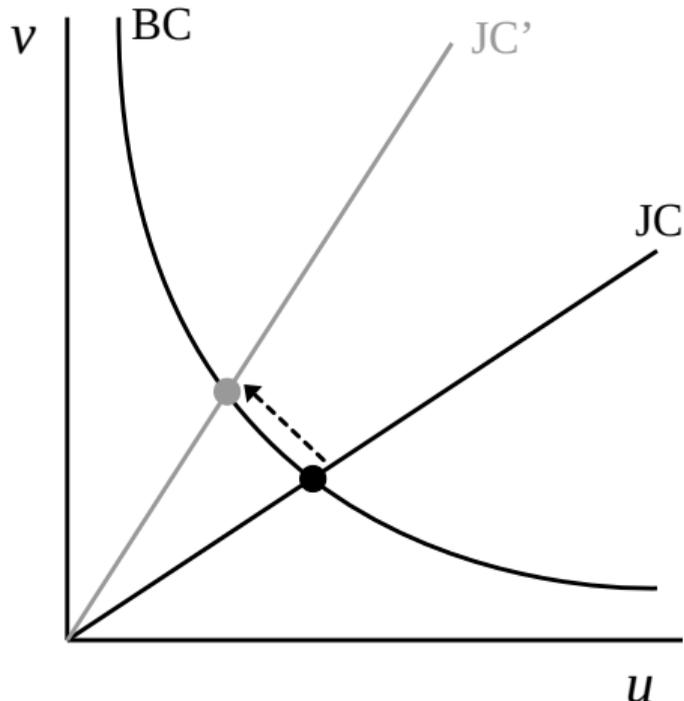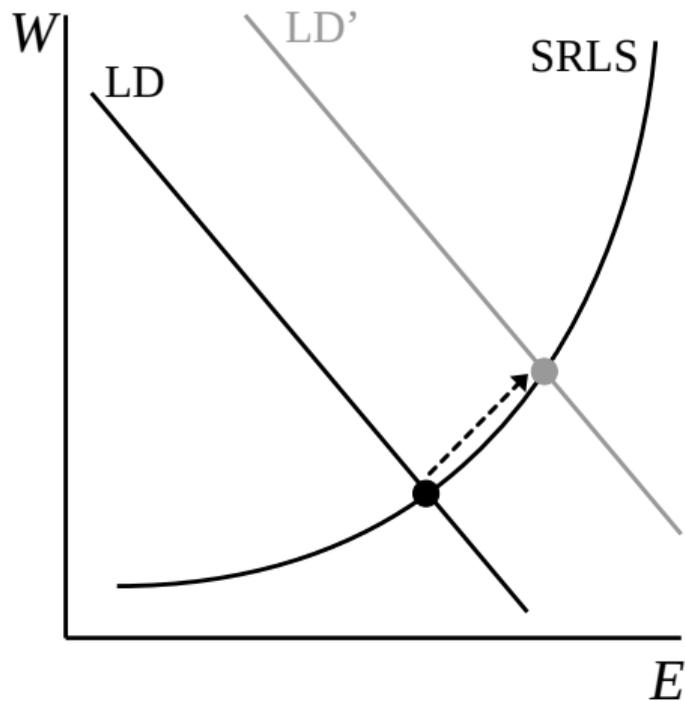
Employment increases, vacancies increase, wages increase, and unemployment decreases

| | E | u | v | W |
|----|---|---|---|---|
| LD | + | - | + | + |

Employment increases, vacancies increase, wages increase, and unemployment decreases

# Long-Run Labor Supply: Demand adjusts to change in labor supply
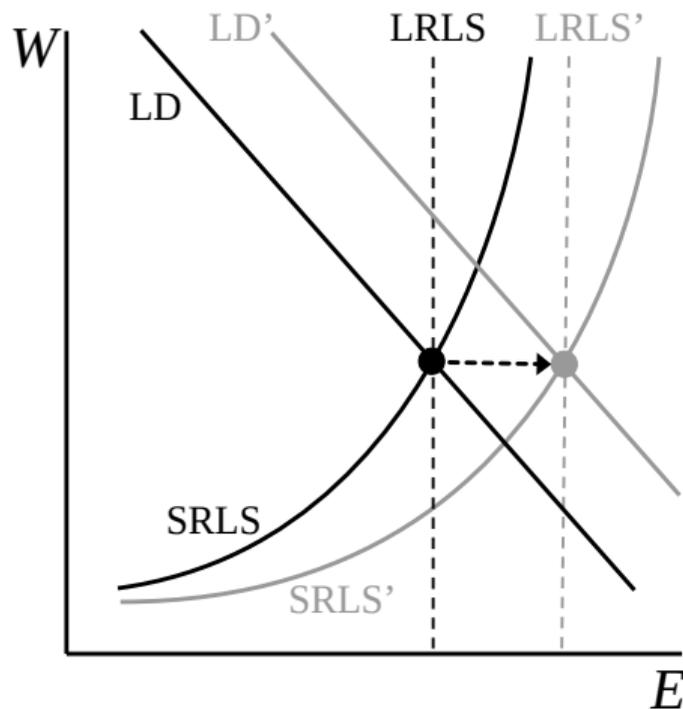


|      | $E$ | $u$ | $v$ | $W$ |
|------|-----|-----|-----|-----|
| LD   | +   | -   | +   | +   |
| LRLS | +   | 0   | 0   | 0   |

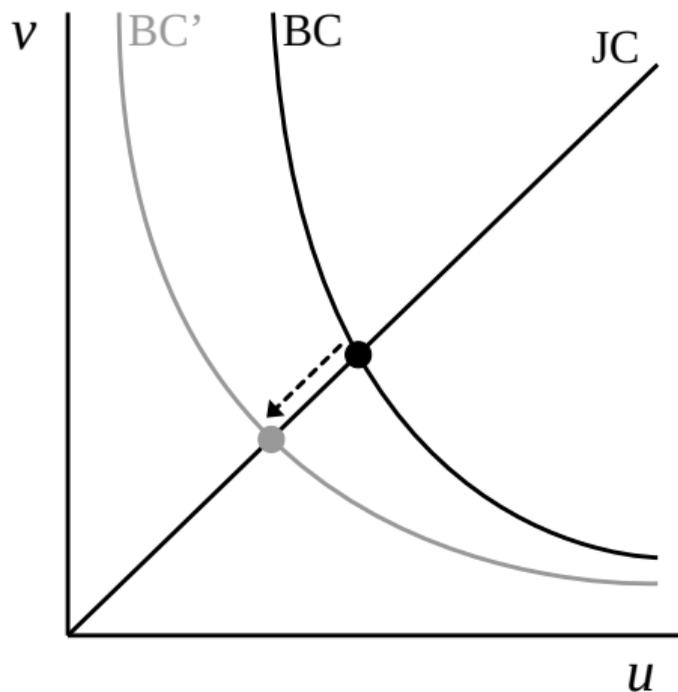Employment increases and wages as well as unemployment, vacancy, and participation rates mostly unchanged
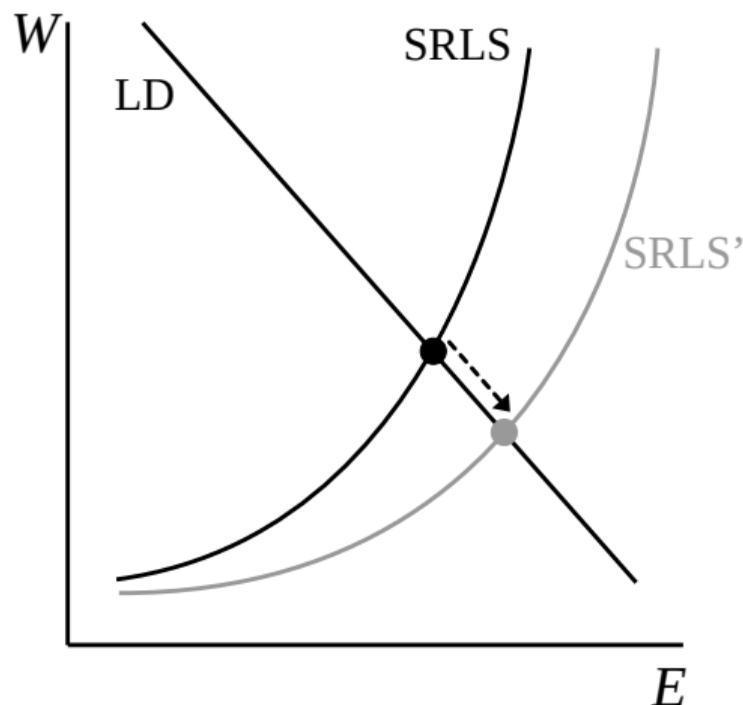
Employment increases (through increased participation and attachment) and wages decrease

|      | *E* | *u* | *v* | *W* |
|------|-----|-----|-----|-----|
| LD   | +   | -   | +   | +   |
| LRLS | +   | 0   | 0   | 0   |
| SRLS | +   | ~   | ~   | -   |
| ME   | ~   | -   | -   | ~   |

Unemployment and vacancies decrease (move in the same direction)

## Making Sense of Labor-Market Indicators

### From many indicators to four narrative factors

Introduce methodology to construct measures of *Labor Demand*, *Long-Run Labor Supply*, *Long-Run Labor Supply*, and *Matching Efficiency*

**94 monthly/quarterly labor market indicators 1960-2026, $y_t$**

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$\Downarrow$

Step 1: Dimension reduction using PCA

Stock & Watson (2002), Hakkio & Willis (2014), and Brave *et al.* (2019)

$\Downarrow$

**Five principal components, $y_t = \Lambda v_t + \varepsilon_t$**

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Stock & Watson (2002), Hakkio & Willis (2014), and Brave *et al.* (2019)

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**Five principal components,** $y_t = \Lambda v_t + \varepsilon_t$

$\Downarrow$

Step 2: Sample rotations of principal components, $f_t = R v_t$, such that
$y_t = \Gamma f_t + \varepsilon_t$, where $\Gamma = \Lambda R^{-1}$.
Select those that satisfy inequality restrictions on $\Gamma$.

Restrictions do not uniquely pin down narrative factors – set identification (Rubio-Ramírez *et al.*, 2010; Baumeister & Hamilton, 2015; Korobilis, 2022)

## Two-step methodology to get measures of narrative factors

**94 monthly/quarterly labor market indicators 1960-2026, $y_t$**

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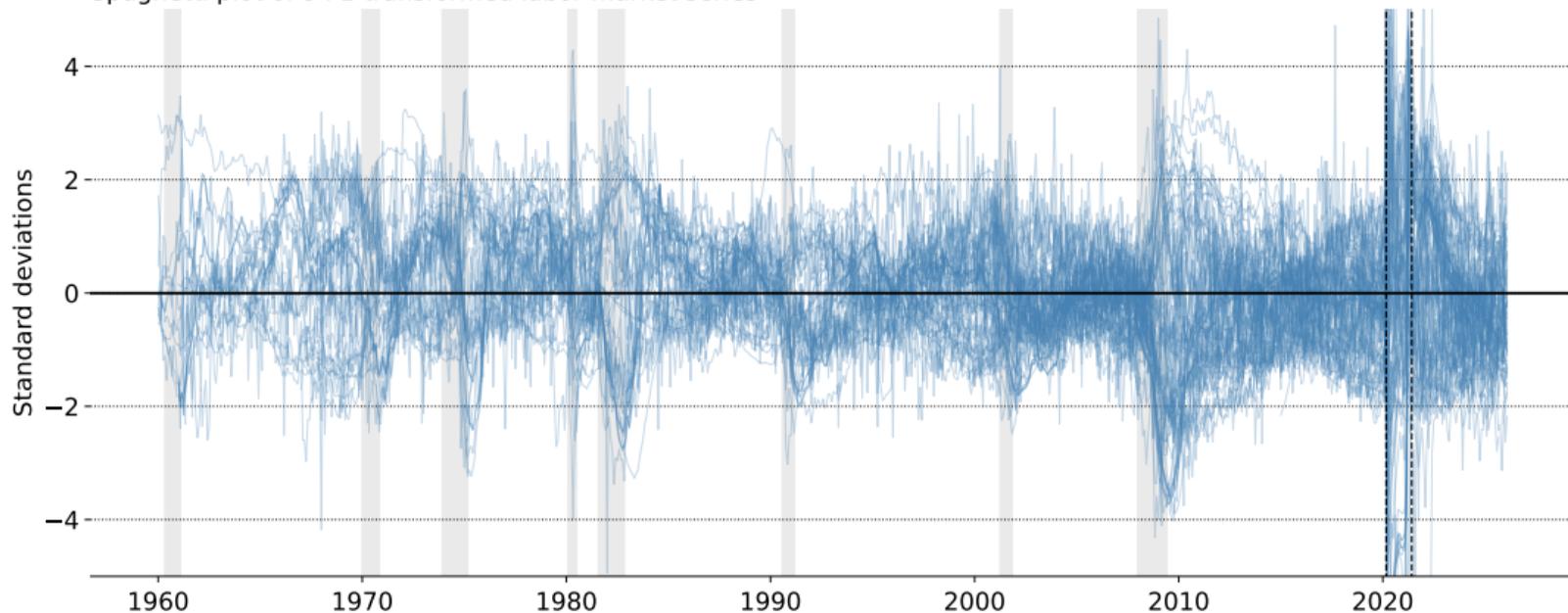
$\Downarrow$

**Narrative factors, $f_t$**

Labor Demand, Long-Run Labor Supply, Short-Run Labor Supply, Matching Efficiency

Kitchen Sink is residual fifth factor. Factors can be correlated

## Indicators in the Data Set

Spaghetti plot of 94 z-transformed labor market series



Source: Authors' calculations

Wealth of monthly U.S. labor-market indicators

## **First 5 principal components**
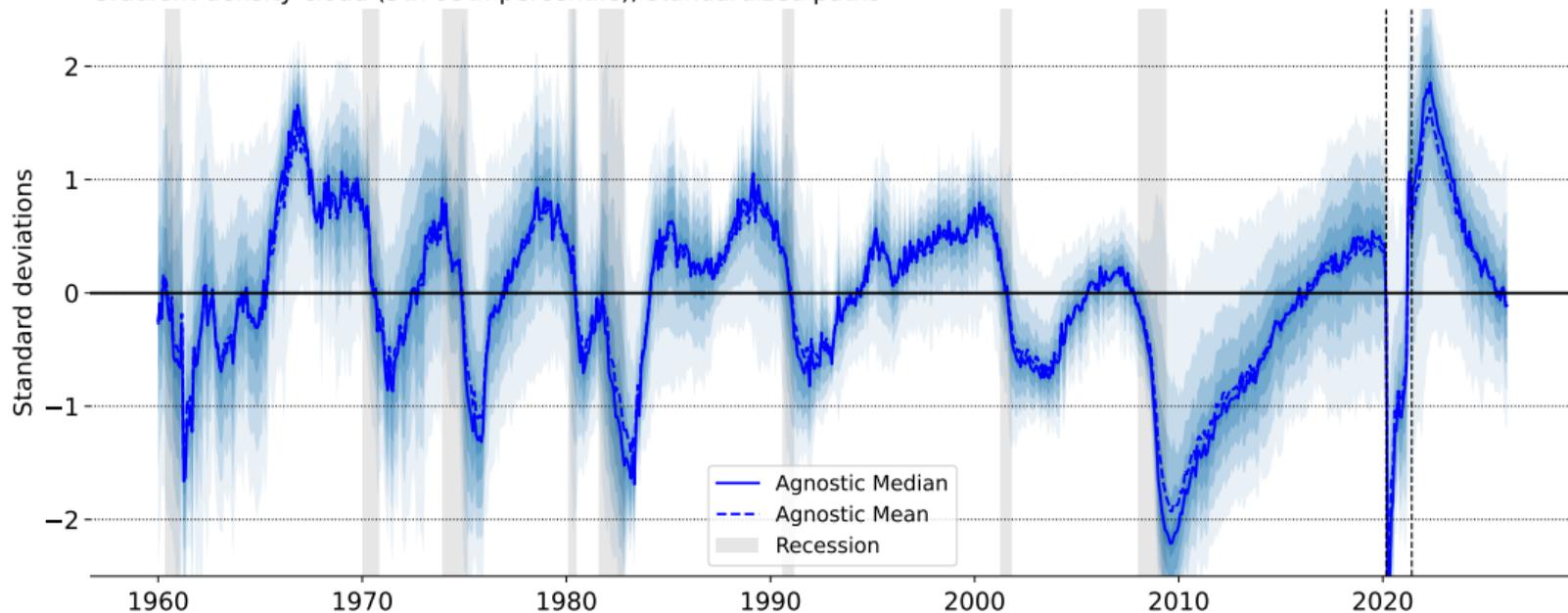Monthly data; seasonally adjusted; standard deviations from mean; z-transformed
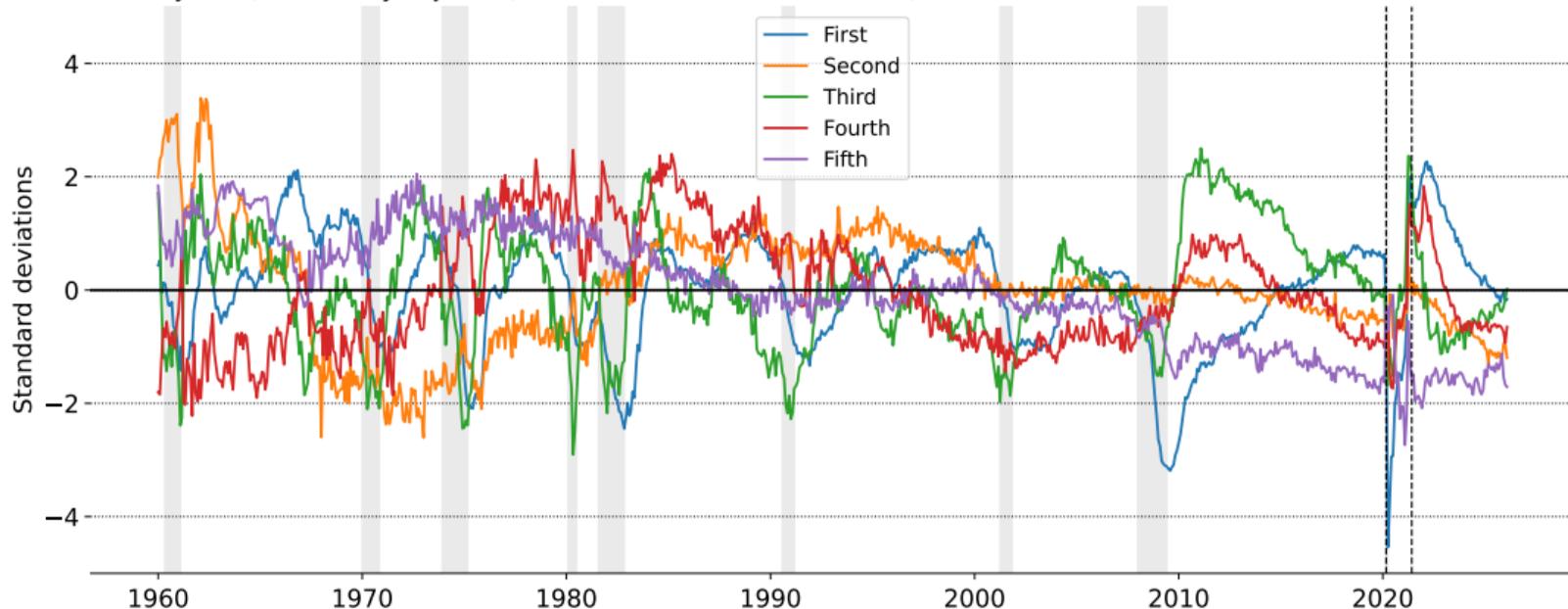


Source: Authors' calculations

First five principal components explain more than three-quarters of variation in data. But have no economic interpretation

## Narrative Identity: Labor demand
Gradient density cloud (5th-95th percentile); standardized paths



Source: Authors' calculations

Limited inequality restrictions give relatively tight set identification

## Narrative Identity: LR labor supply
Gradient density cloud (5th-95th percentile); standardized paths
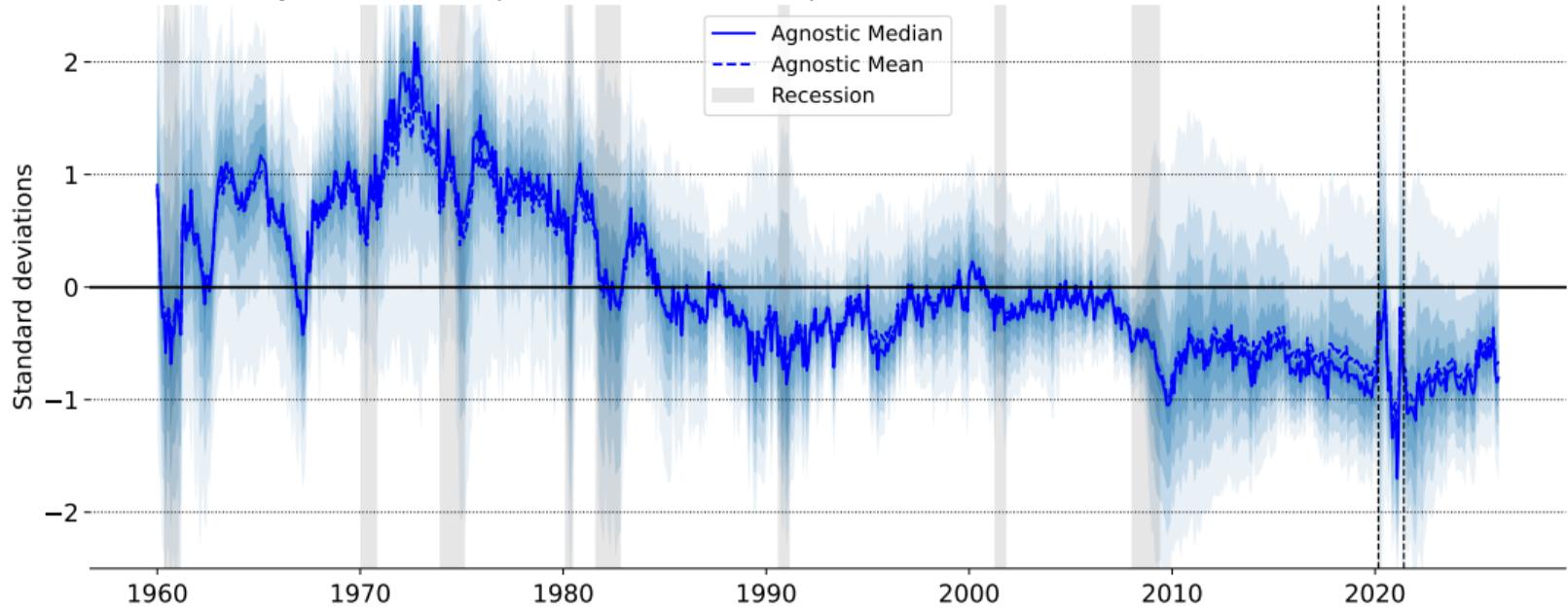


Source: Authors' calculations

Anchored by harmonized population growth (Coglianese *et al.*, 2025)

# Narrative Identity: SR labor supply
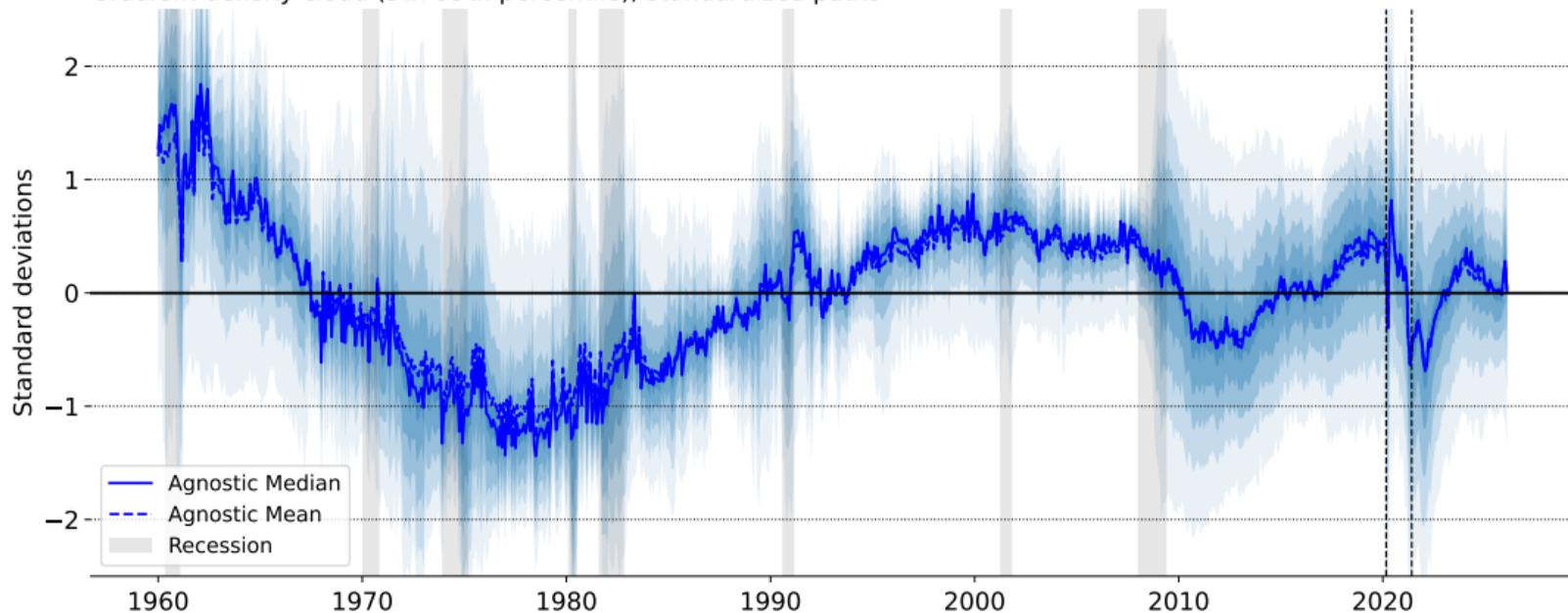Gradient density cloud (5th-95th percentile); standardized paths
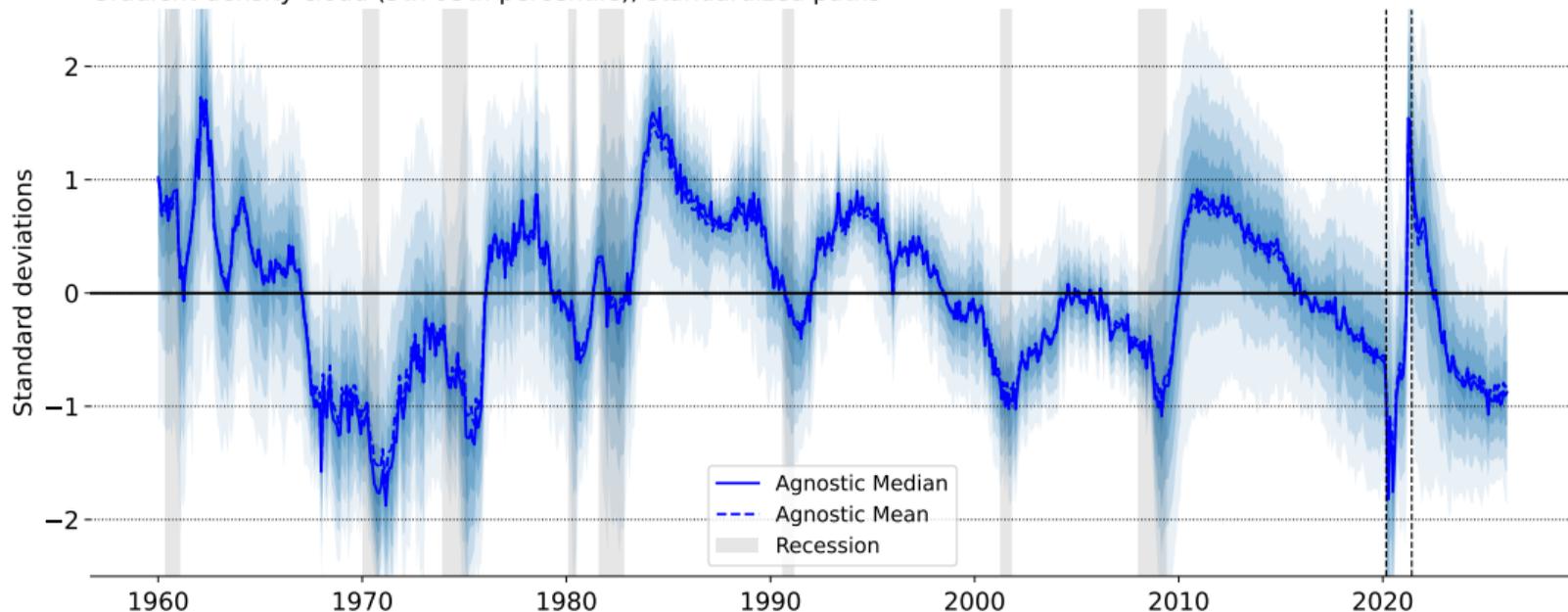


Source: Authors' calculations

Best interpreted as "effective" short-run labor supply: Both the availability of workers and their responsiveness to labor demand

## Narrative Identity: Matching efficiency

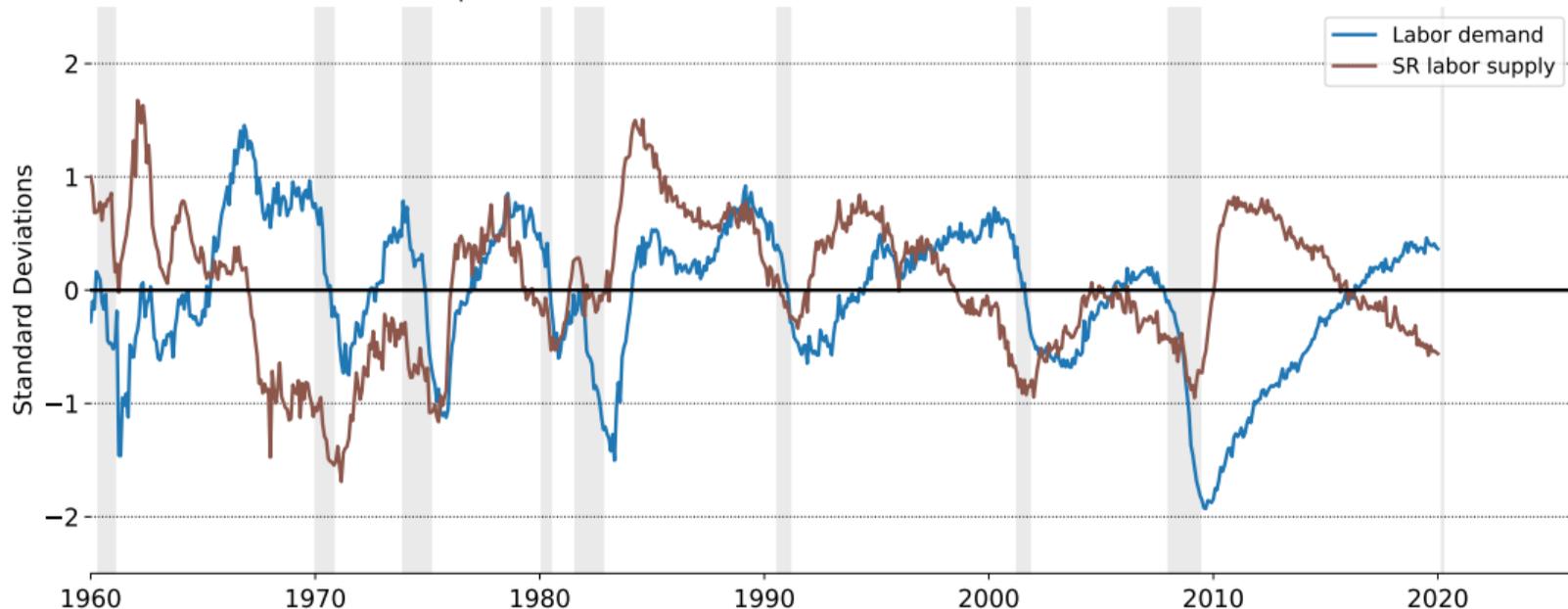Gradient density cloud (5th-95th percentile); standardized paths



Source: Authors' calculations

Follows historical shifts in the Beveridge curve (Barlevy *et al.*, 2024)

## Narrative Factor Comparison
Means of identified structural paths; standardized units



Source: Authors' calculations

SRLS tends to decline in mature part of business cycle and onset of recessions. Partly captures declining elasticity of SRLS curve as demand increases.

## Narrative Factor Comparison
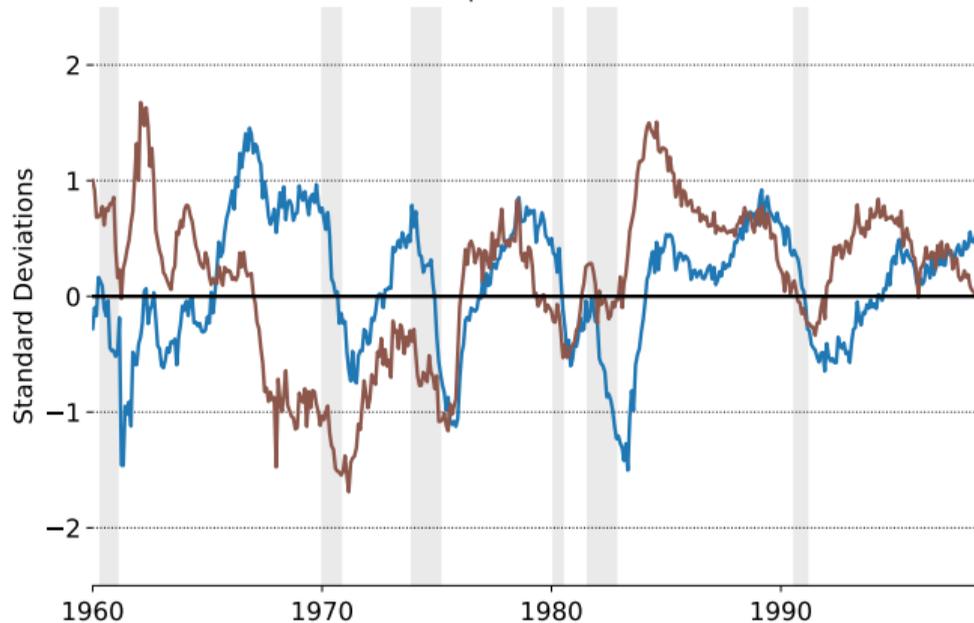Means of identified structural paths; standardized units



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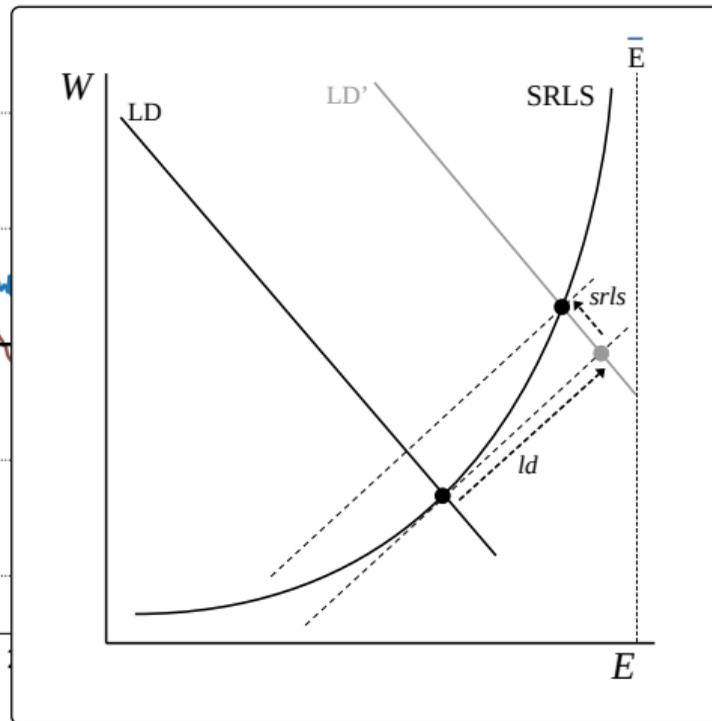
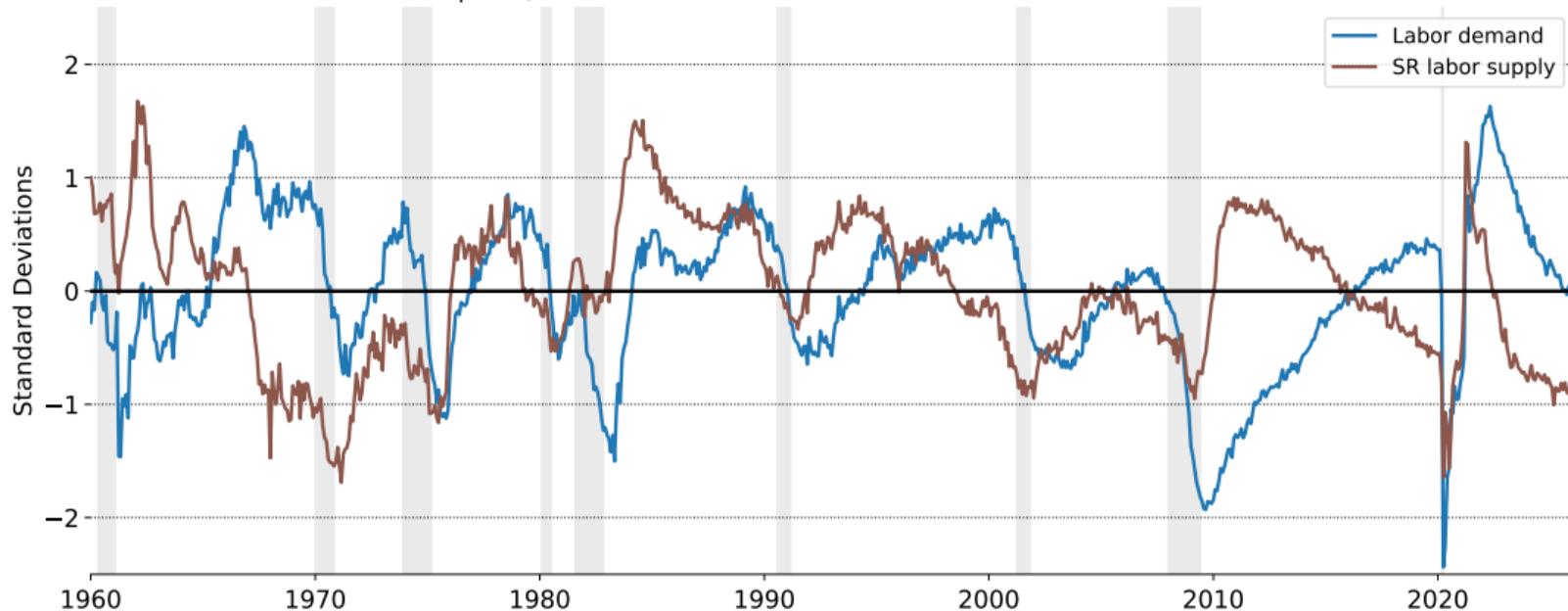## What Results Teach us About Labor Market Since 2021

Decline in Labor Demand coincides with unusual decline in Short-Run Labor Supply

# Narrative Factor Comparison
Means of identified structural paths; standardized units



Source: Authors' calculations

Joint decline in Labor Demand and Short-Run Labor Supply

# Historical Decomposition: Nonfarm payroll growth

Agnostic mean contributions; standardized units (2021:6 - 2026:2)
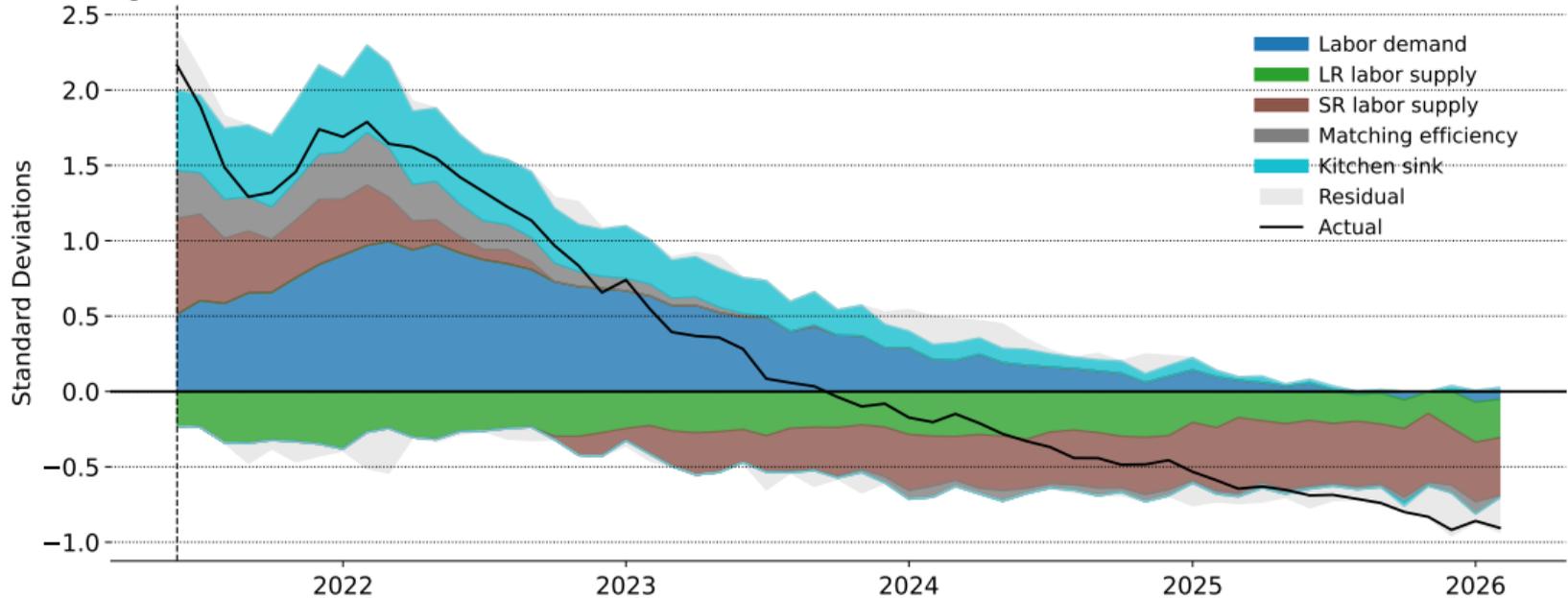


Source: Authors' calculations
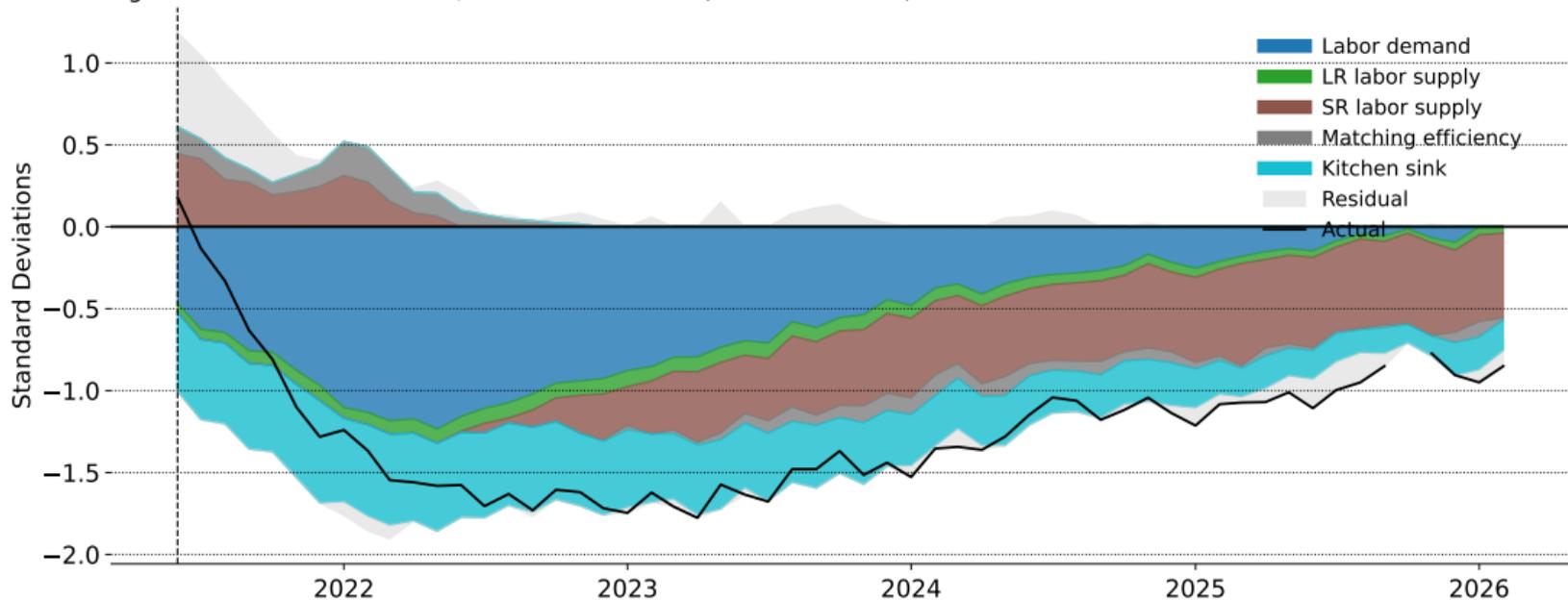
Conversion: Short-Run Labor Supply has reduced payroll growth by about 90 thousand jobs a month over past year

## Historical Decomposition: Unemployment rate (U3) (CPS)
Agnostic mean contributions; standardized units (2021:6 - 2026:2)



Source: Authors' calculations

Conversion: Short-Run Labor Supply is suppressing unemployment rate by about 0.75 percentage points in February 2026

# Historical Decomposition: Job openings rate (JOLTS)

Agnostic mean contributions; standardized units (2021:6 - 2026:2)
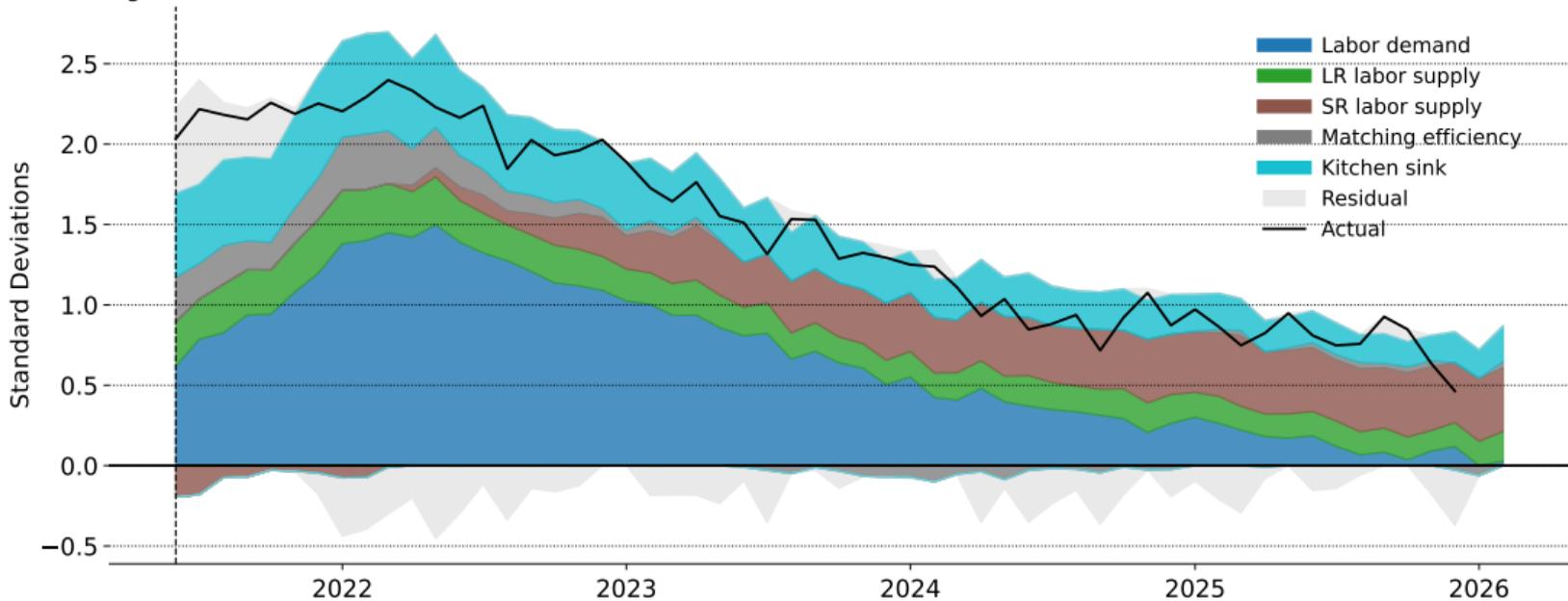


Legend:
- Labor demand
- LR labor supply
- SR labor supply
- Matching efficiency
- Kitchen sink
- Residual
- Actual

Y-axis: Standard Deviations

Source: Authors' calculations

# Main Takeaways

**Narrative factors provide concise summary of labor market conditions**

- Estimated by exploiting cross-sectional variation across broad set of labor-market indicators
- Handles data imperfections: missing values, jagged edges, multiple measures of same concept, and data revisions
- Tightly identified based on small set of inequality constraints
- Labor demand and short-run labor supply explain bulk of cyclical fluctuations
- "Soft Landing" since 2021 the result of joint declines in labor demand and labor supply

# References I

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