Making Sense of Labor-Market Indicators Amid Data Imperfections

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ABSTRACT Interpreting real-time labor market conditions is challenging because commonly used indicators are noisy, revised over time, and often send conflicting signals. In practice, policymakers and market participants describe labor market developments using a shared narrative language centered on labor demand, labor supply, and matching frictions. In this paper, we show that empirical measures of these narrative concepts can be recovered from latent factors that summarize the joint movements of a broad set of high-frequency U.S. labor-market indicators. We use ninety-four labor-market indicators, over the period from 1960 to 2026, and construct measures for labor demand, long-run labor supply, short-run labor supply, and matching efficiency by selecting the factors that satisfy a limited set of restrictions on how underlying forces map into observed data. We find that labor demand and short-run labor supply account for most of the common variation in labor-market indicators. Our results also show that assigning narrow interpretations to individual indicators can lead to misleading conclusions about underlying labor market conditions. Applying the framework to the post-pandemic period reveals that although labor demand recovered briskly after the acute phase of the pandemic, it cannot account for the large rise in vacancies and quits. Instead, movements in short-run labor supply and matching efficiency play a central role. We also show that the "soft-landing" episode from 2023 through 2025 was characterized by a joint decline in labor demand and short-run labor supply, which slowed payroll growth while generating only a moderate increase in the unemployment rate.

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Policymakers and analysts who follow the U.S. labor market in real time monitor a wide range of high-frequency indicators, many produced by the Bureau of Labor Statistics, that provide overlapping and sometimes conflicting signals about the state of the labor market.[1] The challenge is therefore not a lack of information, but how to summarize the joint movements in these data in ways that are clear to a broad audience with diverse views about the forces shaping labor market outcomes. In practice, real-time discussions of the labor market therefore rely on a shared narrative vocabulary built around a small number of broad concepts—such as labor demand, labor supply, and matching efficiency (often discussed in terms of structural unemployment). Policymakers, analysts, and academics regularly use these terms when interpreting incoming data. Their use creates a common language for describing labor market developments, implicitly grounded in simple textbook-style assumptions about how these underlying forces should co-move with the indicators that are monitored broadly from month to month.

These narrative terms serve as informal summary statistics for the wide range of indicators that are tracked in real time.[2] Discussions of labor market developments often proceed by asking whether recent data point to stronger labor demand, increased labor supply, or changes in the efficiency with which workers and jobs are matched. For example, payroll growth, job openings, and hiring rates are commonly interpreted as signals of labor demand, while labor force participation and population growth are associated with labor supply, and the joint behavior of vacancies and unemployment is often taken as evidence of changes in matching efficiency or structural unemployment. Importantly, the use of these concepts also reflects expectations about how groups of indicators should move together. For instance, stronger labor demand is typically associated with rising employment, declining unemployment, and elevated vacancies, while increases in labor supply are expected to raise employment while putting upward pressure on participation.

We begin by summarizing these implicit assumptions using two familiar benchmark environments: the frictionless textbook labor-market equilibrium and the Diamond–Mortensen–Pissarides model in which unemployment and vacancies coexist because of search frictions. Rather than building a fully specified structural model, we rely on simple textbook diagrammatic representations of these frameworks to illustrate how the narrative vocabulary used in real-time labor-market analysis implicitly links observable indicators—and their co-movements—to a small set of underlying economic forces. These implied co-movements form the basis of our identification strategy when we develop our econometric framework. We then conduct a textual analysis of all currently available speeches and statements by members of the Federal Reserve Board, as well as the Economic Reports of the President issued by the Council of Economic Advisers for the period 2013–2015, to more systematically characterize how policymakers use narrative concepts when discussing

[1] See, for example, Foote et al. (2025), who discuss how a range of indicators are used to assess labor market conditions and maximum employment.

[2] Our use of the term "narrative" differs from the narrative identification approach commonly used in macroeconomics, where historical records, policy documents, newspaper articles, and social media posts are used to identify exogenous shocks (see, for example, Ramey and Shapiro (1998) or Romer and Romer (2010)), economic variables Antenucci et al. (2014), or collective sentiment Shiller (2017). In this paper, the term refers instead to the conceptual language that policymakers and analysts use to interpret labor market developments in real time, and our objective is to extract empirical counterparts to these narrative drivers from the joint movements of a large set of labor-market indicators.

labor-market dynamics. In total, our sample contains 502 unique documents, 310 of which mention labor at least once. This analysis confirms that the narrative concepts we focus on are frequently discussed by policymakers and that their discussions broadly reflect the equilibrium textbook relationships. We find that labor demand and labor supply are the concepts most commonly discussed, with substantial overlap in the indicators referenced for each. Discussions of labor supply are more likely to refer to participation, population, and immigration while references to matching frictions almost exclusively coincide with indicators of unemployment and vacancies.

We then examine the joint movements of headline labor-market indicators using a simple accounting framework. This framework links payroll employment growth to changes in the unemployment rate, labor force participation, and population growth. Because payroll employment is measured in the establishment survey (CES) while unemployment and participation rates come from the household survey (CPS), the identity also includes a survey difference term capturing discrepancies between the two surveys. The accounting relationship provides a useful rule of thumb for break-even payroll growth—the level of payroll gains required to absorb labor force growth while keeping the unemployment rate constant—and helps interpret deviations between payroll and household employment measures. Using current projections from the Congressional Budget Office, we estimate that break-even employment growth lies roughly between 25 and 100 thousand jobs per month. We also show that periods in which payroll employment persistently exceeds household employment—such as in 2022–2023—are often followed by upward revisions to population growth.

While this framework clarifies the mechanical relationships among headline indicators, it is less informative about the underlying economic forces driving labor market developments. In particular, headline indicators do not map cleanly into the narrative concepts discussed above, making it difficult to disentangle the roles of labor demand, labor supply, and matching efficiency in shaping observed outcomes.

Motivated by these observations, we develop an empirical framework that formalizes the narrative language and links it directly to the rich set of labor-market indicators observed in real time. Our approach extracts a small number of common drivers from the joint movements of a broad collection of labor-market indicators using a Principal Components Analysis (PCA) and interprets them through the lens of the narrative concepts commonly used. In particular, we focus on four drivers of labor-market dynamics: *labor demand, long-run labor supply, short-run labor supply*, and *matching efficiency*. By distinguishing between long-run and short-run movements in labor supply, we allow shifts in population growth to be separated from more cyclical labor supply responses—which have received increasing attention over the last two decades.[3] Identifying these drivers in the data provides a disciplined framework to summarize labor market developments using the same conceptual language that policymakers and analysts routinely employ when interpreting incoming information.

At a technical level, our framework combines a statistical model that extracts common movements from

[3] The complex interaction of trend and cyclical factors required policymakers to make *"...difficult judgments about the magnitudes of the cyclical and structural influences affecting labor-market variables, including labor force participation"* (Yellen, 2014). The sudden and drastic drop in the labor force participation rate at the onset of the pandemic in 2020 has made these judgments even more important in the wake of the COVID-19 Recession. It has led policymakers to consider the unemployment rate corrected for changes in labor force participation as a measure of labor market slack (Powell, 2021).

a large panel of labor-market indicators with economically motivated restrictions that map these movements to the narrative drivers.[4] The use of many indicators that capture related aspects of labor market conditions allows the model to pool information across multiple noisy measures of similar concepts—for example, different indicators of hiring, vacancies, or wage growth. This cross-sectional richness also helps mitigate several practical challenges that arise in real-time data analysis, including measurement error, data revisions, and incomplete coverage of particular indicators at certain points in time. After extracting the common movements in the data, we impose a small number of economically motivated sign restrictions on the loadings of selected indicators to map these movements to the four narrative drivers.[5] These uncontroversial restrictions are motivated by textbook models of the labor market and imposed on key labor-market indicators: unemployment, payroll employment, labor force participation rate and its related flows, job openings and measures of compensation. By exploiting the overlapping information contained in a large set of indicators, the framework produces estimates of the underlying drivers that are robust to many data imperfections while remaining interpretable in terms of familiar labor-market narratives.

Our main set of results shows that the narrative framework can separate the underlying forces shaping labor market developments using only a limited set of assumptions about how particular indicators should comove when different narrative drivers are at work. These assumptions do not uniquely pin down the narrative factors in the data but instead restrict them to a tightly defined set of values that is consistent with the observed co-movements across indicators. Within this set, the resulting factors, extracted from 94 monthly labor-market indicators for 1960-2026, account for 76.7% of the variation in the data and display clear and economically intuitive behavior. Labor demand is highly procyclical, the long-run labor supply factor largely follows population growth, and the short-run labor supply factor tends to be countercyclical, reflecting the shifts in the composition of the labor force over the business cycle. Matching efficiency, in turn, closely tracks medium-term shifts in the Beveridge curve. In terms of their contribution to fluctuations in labor-market indicators, labor demand accounts for a large share of the common variation in the data, with short-run labor supply playing an important secondary role, while matching efficiency contributes comparatively little to short-run fluctuations. Importantly, these factors are not identified through a small set of anchor indicators. Instead, they organize the co-movements among the full set of 94 indicators in our dataset in a systematic way, with the headline indicators receiving relatively modest weight in determining the factors.

We conclude the paper with a detailed analysis of the post-pandemic labor market, focusing on the period from July 2021 through early 2026. Following the unprecedented disruption caused by the COVID-19 pandemic and the unusually rapid recovery in 2021–22, our narrative factors point to a phase initially characterized by strong labor demand, a temporary increase in short-run labor supply, and unusually low matching

[4] Our approach builds on the literature on large dynamic factor models, which extract a small number of common components from large panels of macroeconomic indicators. See, for example, Stock and Watson (2002a) and Brave et al. (2019). Applications to real-time macroeconomic monitoring include Bańbura et al. (2010) and the construction of composite indicators such as the Kansas City Fed Labor Market Conditions Index described in Hakkio and Willis (2014).

[5] This approach is related to the use of sign restrictions in structural vector autoregressions to identify economically meaningful shocks; see, for example, Rubio-Ramírez et al. (2010), Baumeister and Hamilton (2015), and Brave et al. (2026). The paper most closely related to ours is Korobilis (2022).

efficiency. Although our labor demand factor rebounds quickly—unlike the slower recovery following the Great Recession—it does not fully account for the surge in quits and vacancies often referred to as the Great Resignation.[6] Beginning in mid-2022, labor demand gradually declined, by magnitudes similar to those observed in typical recessions, though more gradually but this moderation was accompanied by a reduction in short-run labor supply. The combination of recession-like declines in labor demand with offsetting movements in labor supply helps reconcile the coexistence of subdued payroll growth with only a modest rise in the unemployment rate, the so-called *soft landing*. In this sense, the narrative framework provides a coherent interpretation of the post-pandemic soft landing by showing how shifts in both labor demand and labor supply jointly shaped the evolution of key labor-market indicators during this period.

Taken together, these results show how the joint movements in a large and sometimes conflicting set of labor-market indicators, despite measurement noise, data revisions, and gaps in coverage, can be summarized by a small number of narrative drivers, providing a disciplined framework for interpreting labor market developments in real time.

I. Narrative Concepts in Labor Market Discussions

Communication about the real-time state of the labor market often revolves around a small set of narrative drivers of labor market conditions, most prominently *labor demand* and *labor supply*. These concepts are deeply embedded in core economic thinking and provide a convenient shorthand for the mechanisms that determine equilibrium outcomes in standard models of the labor market. In such models, labor demand and labor supply determine employment and wages in equilibrium, while observed labor market outcomes can temporarily deviate from that equilibrium due to adjustment dynamics and frictions.

When interpreting incoming data, economists therefore often refine these concepts to better capture the forces shaping labor market developments. In particular, it is useful to distinguish between *long-run labor supply*, which is determined by structural factors such as population growth, demographics, education, immigration, and retirement patterns, and *short-run labor supply*, which reflects cyclical changes in participation, labor-force attachment, and job search. In addition, economists recognize the role of *matching frictions*, which capture the difficulty of matching workers to available jobs. Search frictions, skill mismatch, and geographic mismatch can all affect the efficiency with which workers and vacancies are matched. Together, these concepts provide a common language for discussing the labor market and for interpreting real-time labor-market data.

These narrative concepts serve as a coordination device for real-time discussions of the labor market. Because they provide a shared vocabulary for describing labor market developments, they allow policymakers, analysts, and market participants to interpret incoming data in a consistent way without committing to a specific formal model. This role distinguishes real-time labor-market analysis from much of the academic analysis of labor market fluctuations. Structural models used in research typically rely on particular

[6]This observation is consistent with recent research such as Bagga et al., 2025, Afrouzi et al., 2026, Pilossoph and Ryngaert, 2024 and Guerreiro et al., 2024 which emphasized additional forces such as the emergence of remote work and the erosion of real wages which triggered a wave of reallocation reducing matching efficiency, and increasing vacancy durations.

assumptions about functional forms, equilibrium relationships, and the sources of shocks, and they rarely provide predictions for the full range of indicators observed in real time. Moreover, these models are not easily adapted to and analyzed at the high frequency at which new labor-market data become available. By organizing discussions around broad narratives such as labor demand, labor supply, and matching frictions, policymakers and analysts instead rely on an informal framework grounded in basic textbook principles of how labor markets operate. This approach allows new data releases to be interpreted as signals about movements in these underlying forces without requiring agreement on a fully specified structural model.

This narrative approach has deep historical roots, and similar language appears repeatedly in policy discussions of labor market conditions. Writing about the causes of unemployment in the United Kingdom, William Beveridge characterized unemployment primarily through a demand-side lens:

> "Of the various factors in unemployment named above, deficiency of total [labour] demand is the most important"
>
> — William H. Beveridge, *Full Employment in a Free Society*, 1944, p. 26

More recently, Federal Reserve Governor Adriana Kugler used similar language when describing vacancies:

> "The vacancy rate, a measure of demand for workers, ..."
>
> — Adriana D. Kugler, Speech on the economic outlook and labor market conditions, Federal Reserve, June 5, 2025.

Implicit in much of this communication is the idea that short-run deviations from equilibrium, arising from frictions and rigidities, are central to assessing labor market conditions in real time:

> "In the labor market, supply and demand conditions have come into better balance."
>
> — Chair Jerome H. Powell, FOMC press conference, June 12, 2024.

Some policymakers go further and explicitly discuss the frictions that can create imbalances between labor demand and labor supply. During the post-COVID recovery, the *Economic Report of the President* put forward changes in matching efficiency as a possible explanation for the observed decline in vacancies and relatively flat unemployment:

> "Thus, one possibility is that the recent improvement in matching efficiency, which reduced job openings for a roughly constant unemployment rate, may reflect post-COVID renormalization."
>
> — Executive Office of the President and Council of Economic Advisers, *Economic Report of the President*, 2024.

Federal Reserve Governor Christopher Waller referenced data from the Job Openings and Labor Turnover Survey and linked it to labor hoarding:

> "The JOLTS data, ..., have been echoing what I have been hearing consistently from my business contacts, which is that firms are holding on to workers but are not backfilling positions or planning to expand hiring."

— Christopher J. Waller, *Cutting Rates in the Face of Conflicting Data*: Remarks at the Council on Foreign Relations, New York, Federal Reserve, October 16, 2025.

Textbook Intuition Behind Labor-Market Narratives The language used in these discussions closely mirrors the intuition of standard textbook models of the labor market. Policymakers rarely invoke a fully specified structural framework when interpreting incoming data, but the narrative terms they use—labor demand, labor supply, and frictions—implicitly rely on a set of basic economic relationships that underlie many formal equilibrium models. These relationships are largely uncontroversial: increases in labor demand tend to raise wages and employment, structural shifts in labor supply affect the size of the labor market, and frictions in matching workers to jobs influence the joint behavior of unemployment and vacancies. Making these implicit assumptions explicit is useful if narrative concepts are to be given empirical content. To illustrate the economic relationships underlying these narratives, we summarize them using a set of simple graphical representations that correspond to familiar textbook environments. Figure 1 presents these relationships in four stylized diagrams that highlight how labor demand, long-run labor supply, short-run labor supply, and matching efficiency affect key labor market outcomes.

An increase in *labor demand* typically leads firms to expand hiring in order to produce more output. To attract additional workers, firms raise wages, which induces more individuals to accept jobs or intensify their search. As a result, employment rises and unemployment declines. In frictional labor markets, firms also post more vacancies to recruit additional workers, so job openings increase alongside employment. These relationships are illustrated in Panel (a) of Figure 1, which shows how a positive shift in labor demand raises wages and employment while increasing vacancies and reducing unemployment.

Narratives involving labor supply often distinguish between long-run and short-run components. *Long-run labor supply* is determined by slow-moving structural forces such as demographics, immigration, education, and retirement patterns. In many textbook representations, this long-run supply is depicted as vertical, reflecting that the size of the labor force is largely fixed in the short run. An outward shift in long-run labor supply expands employment but leaves key labor-market ratios—such as the unemployment and vacancy rates—largely unchanged. Ultimately growing labor supply is accommodated by growing labor demand and wages remain broadly stable.[7] Panel (b) of Figure 1 illustrates this case, in which an increase in long-run labor supply increases employment without materially affecting wages or labor-market tightness.

Short-run labor supply, by contrast, reflects cyclical changes in workers' willingness to participate in the labor market or accept jobs. Participation decisions, job search intensity, and reservation wages can all adjust over the business cycle. In stylized representations, the short-run labor supply curve is often depicted as upward sloping and convex, reflecting that progressively higher wages are required to draw additional workers into employment as labor utilization rises. When the economy approaches its long-run labor supply constraint, further increases in employment require increasingly large wage increases. Panel (c) of Figure 1 illustrates how shifts in short-run labor supply affect both wages and employment as labor market conditions tighten.

[7] See Karahan et al., 2024 who formalize this insight using a firm dynamics model. They show that in the long run, free entry offsets pressures on wages arising from shifts in labor supply.

A third set of narratives focuses on frictions in the process of matching workers to jobs. In search-and-matching models of the labor market, *matching efficiency* summarizes how effectively unemployed workers and posted vacancies are paired to form employment relationships. Changes in matching efficiency shift the relationship between unemployment and vacancies described by the Beveridge curve. An improvement in matching efficiency allows firms and workers to find each other more easily, lowering unemployment and reducing the number of vacancies required to sustain a given level of employment. Panel (d) of Figure 1 illustrates this mechanism using the Beveridge curve and job creation curve framework.

Finally, Panel (e) of Figure 1 summarizes the qualitative co-movements implied by these mechanisms. The table reports how each narrative factor—labor demand, long-run labor supply, short-run labor supply, and matching efficiency—affects key labor market outcomes including employment, unemployment, vacancies, and wages. These patterns represent a set of broadly accepted economic relationships that arise in many textbook models of the labor market. Rather than committing to a particular structural model, we use these uncontroversial restrictions to guide the empirical identification of narrative factors in the econometric framework introduced in Section IV.

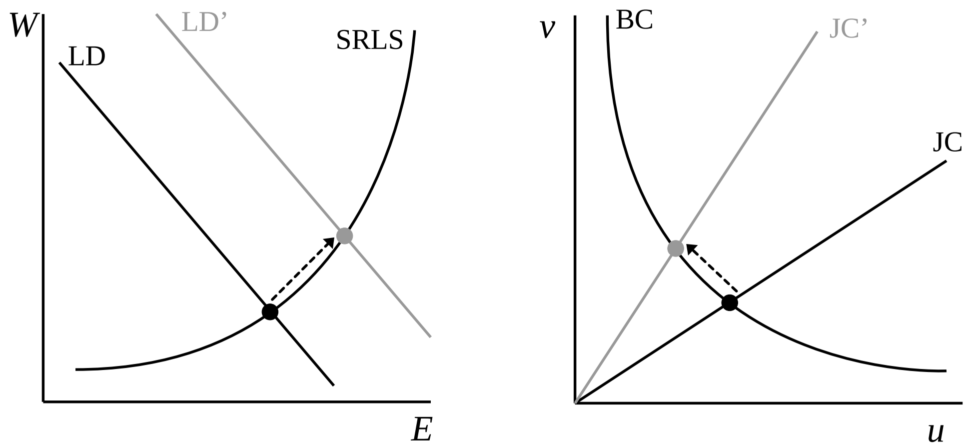
Communication of Common Narratives The textbook intuition discussed above is also reflected in how policymakers communicate about labor market developments. In practice, discussions of labor demand, labor supply, and frictions are often directly linked to observable labor-market indicators such as employment, unemployment, vacancies, and wage growth. To illustrate this connection, we conduct a simple textual analysis of speeches and policy documents to examine how these narrative concepts are used in real-time discussions of labor market conditions.[8]

Our analysis uses speeches and statements by current members of the Federal Reserve Board available through the FRASER archive, supplemented with Economic Reports of the President from 2013 through 2025. These documents capture how policymakers communicate about labor market developments to the public. In total, the corpus contains 502 documents, of which 310 include at least one discussion of labor market conditions.

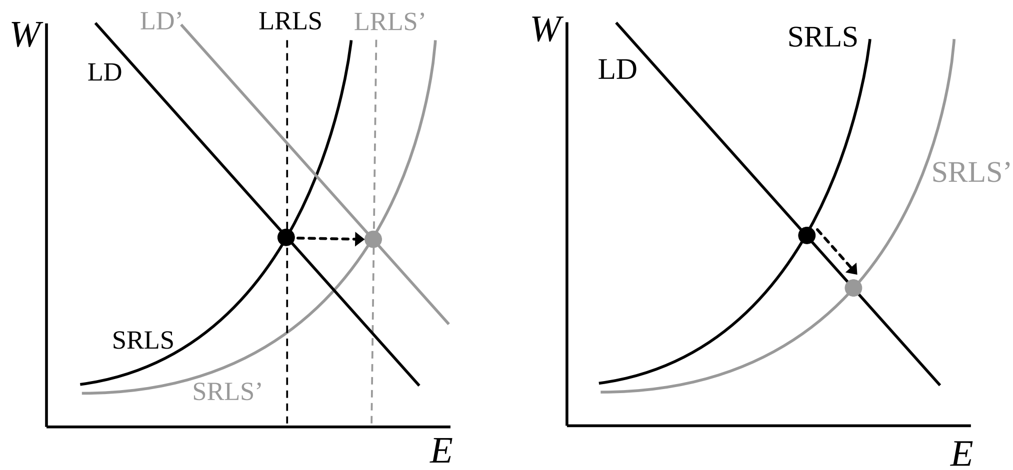
Figure 2 summarizes how references to narrative drivers are associated with mentions of commonly used labor-market indicators. The patterns broadly align with the textbook intuition we discussed. References to labor demand most frequently appear alongside indicators related to employment, hiring, and vacancies. Discussions of long-run labor supply are typically associated with participation, population growth, and immigration. Mentions of matching frictions are concentrated around indicators such as unemployment and vacancies, which are central to standard measures of matching efficiency. Finally, references to short-run labor supply frequently appear together with indicators related to employment, unemployment, and wage growth.

These patterns should be interpreted as illustrative rather than definitive. The purpose of the exercise is not to identify causal relationships but to document how policymakers use narrative language when discussing labor-market data. The results reinforce the idea that the textbook relationships discussed above are

[8] Appendix A describes the construction of the text corpus and the keyword-based procedure used to identify references to narrative drivers and labor-market indicators in policy communications.

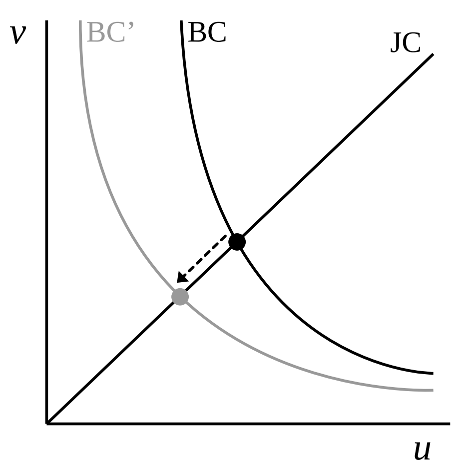


(a) Labor Demand



(b) Long-Run Labor Supply

(c) Short-Run Labor Supply



(d) Matching Efficiency

	E	u	v	W
(a) LD	+	-	+	+
(b) LRLS	+	0	0	0
(c) SRLS	+	~	~	-
(d) ME	~	-	-	~

(e) Sign restrictions

Figure 1: Textbook Illustrations of Labor-Market Narratives and the Implied Sign Restrictions

deeply embedded in real-time policy discussions. Rather than relying on a fully specified structural model, policymakers interpret incoming labor-market data through a small set of widely shared narrative concepts that link observable indicators to underlying economic forces.

Figure 2: Narrative Drivers and Associated Labor-Market Indicators in Policy Communications

Note: These charts plot the number of instances in which terms linked to each narrative driver were mentioned shortly before or after terms linked to different labor-market indicators, listed on the x-axis.
Source: Federal Reserve officials' speeches and 2013-2025 Economic Reports of the President, accessed through FRASER; Authors' calculations.

II. Interpretation of Headline Indicators

Although policymakers increasingly draw on a wide range of labor-market indicators, three measures continue to play a central role in real-time assessments of labor market conditions: payroll employment, E_t^{CES}, the unemployment rate, u_t, and the Labor Force Participation Rate (LFPR), LFPR_t. Payroll employment provides the most visible measure of job creation, the unemployment rate summarizes the balance between job seekers and available jobs, and the labor-force participation rate captures movements in workers' attachment to the labor market. These indicators are routinely discussed in policy communications and media commentary as separate signals about the state of the labor market.

In practice, however, these indicators are mechanically linked through a simple accounting relationship (Hobijn & Şahin, 2023). The percent change in payroll employment can be written as

$$\Delta \log E_t^{\text{CES}} \approx \underbrace{\Delta \log\left(\frac{E_t^{\text{CES}}}{E_t^{\text{Adj}}}\right)}_{\substack{\text{Survey}\\ \text{difference}}} + \underbrace{\Delta \log\left(\frac{E_t^{\text{Adj}}}{E_t^{\text{CPS}}}\right)}_{\substack{\text{Scope}\\ \text{difference}}} - \underbrace{\Delta u_t}_{\substack{\text{Change in}\\ \text{unemployment}\\ \text{rate}}} + \underbrace{\Delta \log \text{LFPR}_t}_{\substack{\text{Change in}\\ \text{participation}\\ \text{rate}}} + \underbrace{\Delta \log P_t}_{\substack{\text{Population}\\ \text{growth}}} . \tag{1}$$

The decomposition in (1) builds on the relationship between employment, unemployment, participation, and population.[9] Household employment can be written as $E_t^{\text{CPS}} = (1 - u_t)\,\text{LFPR}_t\, P_t$, so changes in employment reflect movements in unemployment, participation, and population. Payroll employment in the establishment survey, E_t^{CES}, differs from the household measure because the two surveys cover different employment concepts and are based on separate surveys. To separate differences in employment concepts from differences arising from the surveys themselves, we denote the payroll-adjusted household concept, published by the Bureau of Labor Statistics (BLS), by E_t^{Adj}. The scope-difference term in (1) captures differences in coverage between payroll jobs and household employment, while the survey-difference term reflects discrepancies arising from the distinct sampling and measurement procedures of the two surveys.

The identity in Equation (1) provides a framework for decomposing payroll growth into different survey components and wedges arising from survey and scope differences. [10] Figure 3 displays this decomposition for the 12-month average monthly change in payrolls, showing how the total (the black line) reflects the shifting contributions of unemployment (red), participation (gold), and population growth (olive), as well as the survey and scope reconciliations (cyan and blue).

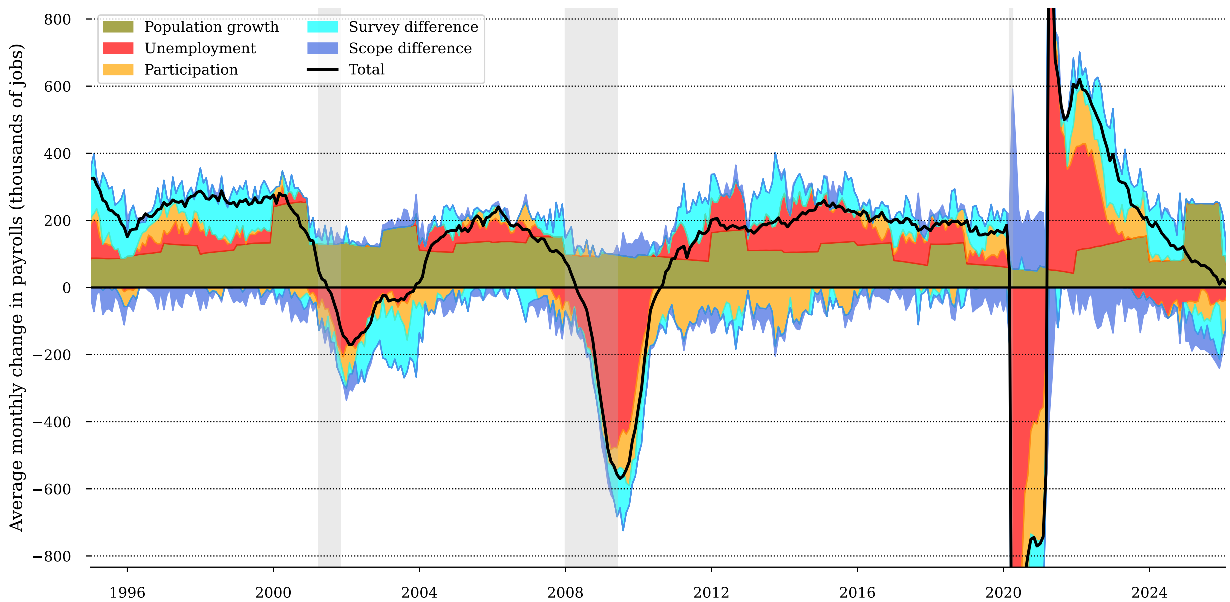
Figure 3 shows that the unemployment margin is the key driver of cyclical fluctuations in payroll growth while the contribution of the labor force participation rate is smaller and tends to lag unemployment movements. Scope differences typically do not contribute much to payroll growth while survey differences tend to be interpreted as more informative by policymakers.

Payroll rule of thumb On a month-to-month basis this simple accounting identity is useful because it allows the calculation of the impact of changes in the unemployment and participation rate, as well as population growth, on nonfarm payrolls using a simple rule of thumb. Table 1 lists this rule for February 2026. The accounting identity implies that a one-tenth percentage point increase in the unemployment rate results in a one-tenth percentage point decline in payrolls, which in February 2026 amounted to 158 thousand jobs. Similar rules for the LFPR and population growth are also listed in the table.

[9] Appendix B contains the derivation of equation (1). The relevant population measure, P_t, in this case is the civilian noninstitutional population 16 years and older.

[10] Equation (1) is closely related to Okun's Law, which links changes in the unemployment rate to output growth (Okun, 1963). Both frameworks use movements in unemployment as a cyclical signal, but they operate in different spaces: Okun's Law requires an estimate of potential output or a stable natural rate of unemployment, while equation (1) is a pure labor market accounting identity that requires neither. Okun's Law also requires taking a stand on what part of unemployment is cyclically demand-determined and what part reflects longer-run trends in the natural rate. For a recent treatment of these issues in the context of maximum employment, see Foote et al. (2025).

Figure 3: Payroll growth decomposed



Note: 12-month change in nonfarm payrolls and its components from equation (1).
Source: BLS and authors' calculations.

Table 1: Payroll growth accounting rules of thumb

Change in household survey measure	Nonfarm payroll jobs
0.1 pp increase in the unemployment rate	-158 thousand
0.1 pp decline in the LFPR	-255 thousand
0.1 pp decline in the population	-158 thousand

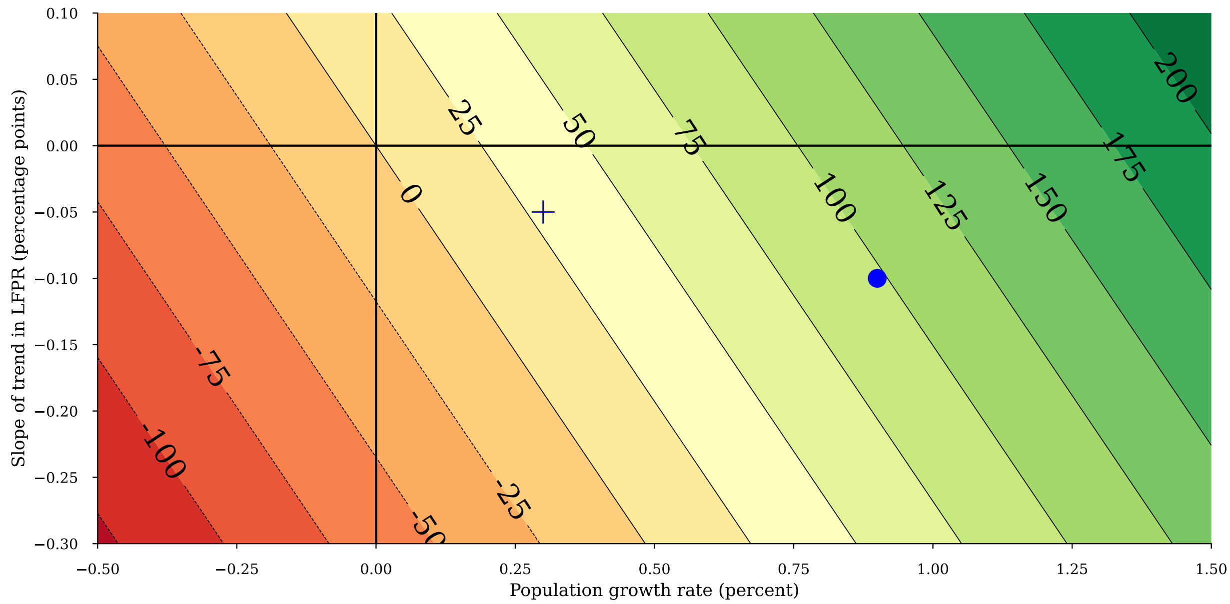
Source: BLS and authors' calculations. Based on data for February 2026.

One common interpretation of the components of the decomposition is that they correspond directly to narrative drivers: unemployment movements are attributed to labor demand, participation movements to labor supply (with cyclical changes reflecting short-run labor supply and trends reflecting long-run labor supply), population growth to long-run labor supply, and the survey and scope differences largely to measurement error.

Trend payroll growth Under this interpretation, trend payroll growth can be viewed as the component driven by long-run labor supply—namely the trend in the LFPR and population growth. Equation (1) then implies that trend payroll growth equals the sum of the growth rate of the LFPR and population growth.[11]

[11]This assumes that the scope and survey differences remain constant.

Figure 4: Breakeven payroll growth



Note: This chart shows the level of monthly payroll growth required to maintain a constant unemployment rate for a given (annual) population growth rate and labor force participation rate trend. For this calculation, the employment level and labor force participation rate are from February 2026. The circle marks the CBO projections for population growth and LFPR for 2026, while the cross marks the long-run CBO forecasts.
Source: BLS, CBO, and authors' calculations.

This corresponds to the *breakeven* level of payroll growth required to keep the unemployment rate constant, given trend participation and population growth.[12]

Figure 4 illustrates this relationship by plotting breakeven payroll growth for a grid of combinations of population growth and the annual change in the trend participation rate. The circle and cross in the figure correspond to the Congressional Budget Office's short- and long-run projections, respectively, for population growth and the participation trend from its February 2026 forecast.[13] The figure also shows that a 0.25 percentage point increase in population growth raises breakeven payroll growth by roughly 30 thousand jobs per month, while a 10 basis point decline in the trend LFPR lowers it by about 20 thousand jobs per month.

Survey Difference Although convenient for thinking about trend payroll growth, the simple interpretation of equation (1) mischaracterizes several components of the decomposition. One example concerns the interpretation of the survey difference. It should not be viewed as pure measurement error due to sampling

[12] The Atlanta Federal Reserve's Jobs Calculator performs similar calculations (https://www.atlantafed.org/research-and-data/data/jobs-calculator).

[13] The CBO's February 2026 baseline forecast "BLS Through 2025 plus CBO projection" predicts the LFPR to decline from 62.4% to 62.3% between 2026 and 2027, with an average annual decline of 0.05 percentage points through 2036. The CBO's January 2026 Demographic Outlook report projects 0.9% growth in the civilian noninstitutionalized population in 2026 and an average annual growth of 0.3% through 2056.

differences between the surveys. Often, real-time survey differences are resolved after revisions to payroll employment and population estimates.

Payroll employment in the Current Employment Statistics (CES) is revised in the two months following the initial release and again during the annual benchmark revision, when the series is aligned with administrative employment counts from the Quarterly Census of Employment and Wages (QCEW). By contrast, CPS employment is not revised.[14] Instead, the household survey incorporates updated population controls each January, reflecting new estimates of the civilian noninstitutional population.

The effect of the annual adjustments of population estimates is evident in Figure 3 from the discrete jumps in the contribution of population growth to payroll growth. The figure also shows that episodes of strong payroll growth accompanied by sizable survey differences are frequently followed by upward revisions to measured population growth, such as during the late 1990s and the 2022–2023 period. This pattern suggests that population increases not yet captured in the household survey were already reflected in payroll employment. In other words, unmeasured population growth in the CPS temporarily creates a wedge between employment measured in the establishment and household surveys.

Figure 5 illustrates this relationship by plotting the month-over-month change in the population estimate from each annual revision against the average survey difference in the preceding year. The two series exhibit a pronounced positive correlation (approximately 0.5). Periods in which survey differences accumulate while population adjustments remain small or negative—such as 1997–1999 or 2022–2024—are eventually resolved by large population revisions, as in 2000 and 2025.

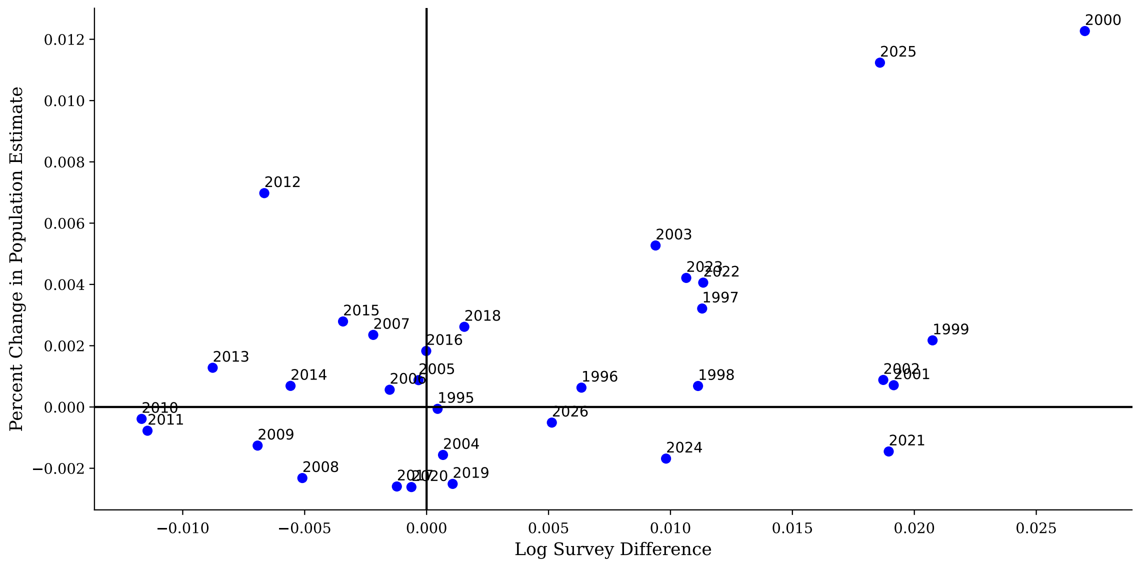
Ambiguity of Narrative Drivers of Headline Indicators The main issue with the common interpretation of the decomposition in equation (1) is not related to the survey difference, however. It is the simplifying assumption that the unemployment rate maps into labor demand and the participation rate and population growth represent labor supply.

For example, the tendency to equate movements in the unemployment rate with shifts in labor demand while holding labor supply fixed often leads to misleading conclusions. Since the unemployment rate and labor force participation rate are jointly determined by the underlying flows between three states of the labor market, they are tightly linked to each other. Using labor-market flows data—tracking transitions between employment, unemployment, and nonparticipation—helps distinguish between reentry, job finding, and labor-force exit. A useful example is the stylized fact that labor force participation tends to rise only with a delay during economic expansions. Using flow data, Hobijn and Şahin (2022) show that this pattern does not reflect delayed re-entry of sidelined or discouraged workers. Instead, it is driven by declining exits from the labor force as workers become more attached to the labor force. This increased attachment is associated with lower job-loss rates and improved job-finding prospects and primarily reflects strengthening labor demand, rather than an expansion in potential labor supply.

While flow-based decompositions represent an important step forward, they only provide a partial solution. Rather than implicitly assigning labor supply to participation and labor demand to unemployment, this

[14] The BLS does periodically update seasonal adjustment factors for Current Population Survey (CPS) labor-market series. These updates can lead to small revisions in previously published seasonally adjusted estimates.

Figure 5: Survey Difference vs Subsequent Population Adjustments



Note: Percent change in CPS population estimates are taken from the annual January adjustments, while the survey difference is the average of the survey difference term from (1) in the preceding 12 months.
Source: BLS and authors' calculations.

approach allows us to shift those assignments to labor-market flows. Some flows are interpreted as reflecting labor supply such as labor force entry while others are assumed to capture labor demand, such as job-finding rates. But as in the example of participation rate's cyclical behavior, these flows themselves are also affected by the underlying drivers and alternative narratives can often rationalize the same flow patterns.

This limitation is not specific to flow data, but reflects a more general feature of labor-market measurement. The data imperfections emphasized throughout this section, such as different concepts of employment, scope and survey differences and revisions, are unavoidable sources of ambiguity, especially in real-time labor-market analysis. The objective of the next section is to develop a framework to extract economically meaningful factors from rich labor-market data.

III. An Interface for Interpreting Labor-Market Indicators

As we have discussed in the context of headline indicators, labor market outcomes reflect the interaction of many forces operating simultaneously, and no single theoretical model—or empirical statistic—can fully capture that complexity. Yet real-time policy analysis requires timely judgments, communicated in a language that allows participants with different views of underlying mechanisms to engage in a shared discussion. Our approach provides an empirical interface between this policy language and the high-dimensional labor-market data used to assess current conditions.

Constructing this interface starts from a general-equilibrium view of the labor market. A wide range of modern macroeconomic models imply that labor market outcomes—wages, vacancies, hiring, separations, participation—are jointly determined by a small number, K, of latent forces that evolve over time. However, in reality we face a high-dimensional and evolving vector of observed data, $\boldsymbol{y}_t$, that no single model can fully accommodate. Our method uses the first K principal components of this data, $\boldsymbol{v}_t$, to summarize the latent drivers of the observed outcomes. Principal components capture cross-sectional covariation in the data while remaining agnostic about the underlying dynamic structure. This flexibility is deliberate: the same principal components can arise from many different dynamic processes, allowing our framework to accommodate diverse structural interpretations without prejudging which is correct.[15] The interface we introduce is a mapping between these components and a vector of narrative drivers, $\boldsymbol{f}_t$.

In particular, the mapping we propose is to think of the narrative drivers as linear combinations of the principal components that summarize the underlying state vector,

$$\boldsymbol{f}_t = \boldsymbol{R}\boldsymbol{v}_t, \tag{2}$$

where $\boldsymbol{R}$ is a rotation matrix that organizes the latent state into components aligned with policy-relevant narratives.[16] This transformation does not introduce new information or impose a particular structural model; it simply provides a relabeling of the same underlying dynamics.

The choice of rotation is necessarily tied to the narrative concepts we consider. Different sets of narrative drivers imply different definitions of $\boldsymbol{f}_t$, and therefore different rotations of the underlying state vector. The rotation matrix $\boldsymbol{R}$ is pinned down by economically motivated identifying restrictions on how the narrative forces $\boldsymbol{f}_t$ relate to observed data $\boldsymbol{y}_t$—that is, how particular indicators load on specific narrative concepts. In this sense, $\boldsymbol{R}$ organizes latent equilibrium dynamics into policy-relevant narratives using assumptions about measurement and interpretation, not specific assumptions about the underlying general-equilibrium structure.

To connect the narrative mapping to observable data, we introduce the measurement equation for the vector of labor-market indicators $\boldsymbol{y}_t$:

$$\boldsymbol{y}_t = \boldsymbol{\Lambda}\boldsymbol{v}_t + \boldsymbol{\varepsilon}_t, \tag{3}$$

where $\boldsymbol{\Lambda}$ is the matrix of factor loadings and $\boldsymbol{\varepsilon}_t$ collects indicator-specific components (including measurement error and idiosyncratic movements). Using the rotation in (2), equation (3) can be rewritten as a measurement equation in terms of the narrative factors:

$$\boldsymbol{y}_t = \boldsymbol{\Gamma}\boldsymbol{f}_t + \boldsymbol{\varepsilon}_t, \text{ where } \boldsymbol{\Gamma} = \boldsymbol{\Lambda}\boldsymbol{R}^{-1} \tag{4}$$

[15] In the spirit of our approach, Shapiro and Watson (1988) identify the role of supply and demand factors in business cycles using a statistical model, identified using minimal and plausible identifying restrictions that are not tied to any specific structural model of the economy. Their key identifying assumption is that "supply shocks" are the only source of business cycle fluctuations that have a long-run impact on the economy, consistent with neoclassical macroeconomic theory.

[16] We assume that $\boldsymbol{R}$ is non-singular so that the mapping between $\boldsymbol{v}_t$ and $\boldsymbol{f}_t$ is invertible. This assumption is made for expositional convenience rather than as a substantive restriction. Because our conceptual argument does not take a stance on the dimension, scale, or dynamics of $\boldsymbol{v}_t$, the interpretation of the narrative factors does not hinge on exact invertibility.

such that $\boldsymbol{\Gamma}$ is the matrix of loadings that maps each narrative driver into the observable indicators. This representation highlights the role of narrative drivers as an interface between theory and data: different theoretical models may imply different dynamics for $\boldsymbol{v}_t$, yet map into a shared set of narrative drivers $\boldsymbol{f}_t$ that structure interpretation of the observed indicators.

What gives content to the narrative factors $\boldsymbol{f}_t$ are the identifying assumptions imposed on the measurement equation (4). These assumptions formalize the types of interpretive judgments that routinely underlie discussions of labor-market indicators. In particular, they specify which elements of $\boldsymbol{y}_t$ are taken to provide the most direct empirical representation of a given narrative concept, which indicators are assumed to carry little or no direct information about certain drivers, and how remaining indicators are expected to co-move with the underlying forces. Together, these assumptions define the scale and directional interpretation of each narrative driver, thereby disciplining the mapping from observed data to economically meaningful narratives without imposing structure on the dynamics of the latent state.

These narrative concepts do not have natural units of measurement, so we use the common convention often applied with Principal Component Analysis (PCA) to express them in standard deviations from their mean, such that the sample mean and variance of f_t are normalized to have mean zero and variance one. This normalizes the scale of the narrative factors.

Equation (4) is a static factor model. Additional requirements for exact identification in this type of model, beyond scale normalization, have been laid out in several papers. The one with the exposition closest to what we use here is Bai and Ng (2013).[17] The standard approach involves a "triangular" pattern of exclusion restrictions, corresponding to zeroes in Γ that imply that certain indicators do not respond to particular factors. These restrictions must be sufficiently rich to prevent the factors from being observationally equivalent under rotation.

The types of exclusion restrictions implied by policymakers' language fall short of what is required for exact identification. This is not accidental. Policy discussions typically avoid committing to a specific structural model of the labor market so that participants with different views of the underlying mechanisms can engage in a shared conversation. As a result, the narrative language used by policymakers imposes only a limited set of restrictions on how different labor market outcomes respond to underlying forces.

Because the narrative language used by policymakers imposes far fewer restrictions on factor loadings than are required for exact identification, it generally does not pin down a unique rotation of the principal components. Instead, these narrative assumptions define a set of admissible rotations that are consistent with the way policymakers interpret labor-market dynamics. We refer to this set as the *narrative feasible set*. Operationally, understanding what terms such as labor demand, long-run and short-run labor supply, and matching efficiency mean in the data therefore requires characterizing this set and determining which empirical patterns are robust across all narrative-consistent interpretations.

The narrative feasible set consists of all rotations of the principal components that satisfy the sign and exclusion restrictions implied by the narrative language. The implied paths of the narrative factors associated with this set can be traced out by simulation. Formally, let the *narrative feasible set* be defined as the

[17] See also Stock and Watson (2002c), Bai and Ng (2002), and Freyaldenhoven (2025).

collection of rotation matrices $\boldsymbol{R}$ such that the corresponding narrative loading matrix $\boldsymbol{\Gamma} = \boldsymbol{\Lambda}\boldsymbol{R}^{-1}$ satisfies

$$\mathcal{R}_{\text{NFS}} = \left\{ \boldsymbol{R} \in \mathbb{R}^{K\times K} : \boldsymbol{H}\,\text{vec}(\boldsymbol{\Gamma}) = \boldsymbol{H}\,\text{vec}\Big(\boldsymbol{\Lambda}\boldsymbol{R}^{-1}\Big) \geq \boldsymbol{0} \right\}. \tag{5}$$

Here, $\boldsymbol{H}$ is a known selection and sign matrix that encodes the narrative restrictions on the factor loadings. Each row of $\boldsymbol{H}$ corresponds to a specific narrative assumption—such as the requirement that a given indicator load positively, negatively, or (approximately) not at all on a particular narrative factor—and the inequality is interpreted elementwise. Rather than selecting a single element of $\mathcal{R}_{\text{NFS}}$, our analysis focuses on mapping this set and summarizing the distribution of narrative outcomes it implies.

It is important to clarify how this form of narrative identification differs from instrumental-variable approaches that are central to much of applied microeconometric work. Instrumental variables are designed to isolate causal effects by exploiting variation that is plausibly orthogonal to unobserved determinants of the outcome. By contrast, the identifying restrictions employed here operate entirely within the measurement equation and draw exclusively on information already contained in the labor-market data system. They are intended to discipline interpretation and labeling of latent forces, not to support causal claims or recover structural parameters.

Our approach is closely related to the literature on sign-restricted vector autoregressions, which characterizes sets of admissible models by sampling rotations consistent with qualitative restrictions (see, for example, Rubio-Ramírez et al. (2010) and Baumeister and Hamilton (2015)). The key difference is conceptual rather than computational. In that literature, rotations are applied to the covariance matrix of reduced-form VAR innovations, and the object of interest is a set of structural shocks.[18] In contrast, we apply rotations to the factor-loading space of a principal-components representation, and the object of interest is a set of admissible narrative interpretations of common movements in labor-market indicators. Our procedure, therefore, does not seek to identify shocks or impose orthogonality or independence assumptions on underlying economic forces, but instead characterizes the range of narrative decompositions consistent with minimal measurement-based restrictions.[19]

From the perspective of applied macroeconometrics, these identifying restrictions also differ from approaches that emphasize the identification of structural shocks. In the vector autoregressive model tradition associated with Sims (1980), identification is typically achieved by imposing restrictions on dynamic responses — such as timing assumptions, orthogonality conditions, or long-run restrictions — that allow innovations to be interpreted as distinct economic shocks. Similarly, Bayesian extensions of this approach rely on prior distributions over model parameters or latent processes to discipline inference about underlying forces. In these frameworks, identification is fundamentally concerned with isolating sources of exogenous

[18] In the vector autoregressive model tradition associated with Sims (1980), identification is typically achieved by imposing restrictions on dynamic responses—such as timing assumptions, orthogonality conditions, or long-run restrictions—that allow innovations to be interpreted as distinct economic shocks.

[19] Examples of papers that use methodologies similar to our approach are Korobilis (2022) and Brave et al. (2019). The former also applies sign restrictions to the factor loadings of a static factor model, while the latter targets the rotation of the principal components from a large panel of monthly time series to maximize their correlation with the business cycle component of quarterly real GDP growth.

variation and tracing their dynamic effects through the system.

By contrast, the identifying assumptions in our framework are not designed to recover structural shocks or to assign causal interpretations to innovations. Instead, they discipline how latent variation is organized and interpreted through the measurement equation in terms of policy-relevant narratives. There is a long tradition in applied macroeconometrics of using precisely such narrative information to construct exogenous shock measures and trace their propagation through the economy. For example, Romer and Romer (2010) and Romer and Romer (2016) identify monetary and fiscal policy shocks by reading historical records to isolate policy changes undertaken for reasons unrelated to current economic conditions. Gorodnichenko and Shapiro (2007) exploit narrative-like information, in the form of unexpected movements in high-frequency indicators relative to professional forecasts, as a source of exogenous variation in a related spirit. Mertens and Ravn (2013) extend this logic by using narratively identified tax liability changes as proxy variables, i.e. external instruments, that correlate with latent structural shocks in an SVAR, thereby supporting causal claims about fiscal policy transmission. In all of these cases, narrative information or data surprises serve as a vehicle for identifying exogenous shocks and quantifying their dynamic causal effects.

Our use of narrative concepts is fundamentally different in both purpose and execution. We do not use narratives to construct shock measures or to support causal inference. Instead, narratives discipline how observed indicators are related to latent factors — they inform the measurement equation, not the shock identification scheme. The result is a framework for organizing and interpreting co-movement in labor-market data in terms that are legible to practitioners, rather than a framework for estimating the effects of exogenous policy interventions. In that sense, our approach is more aligned with the early work on business cycle accounting with factor models due to Sargent and Sims (1977) and, more recently, the logic of Confirmatory Factor Analysis (CFA), e.g. Brown (2015), which is widely used in psychology, sociology, and related fields.[20] The objective of our framework differs fundamentally from that of CFA. Whereas CFA is typically used to test the internal consistency of a theoretical measurement model or to assess the validity of hypothesized constructs, our goal is not to adjudicate among competing theories of the labor market. Instead, we seek to formalize the judgmental assumptions already embedded in policy discussions and to include them within a disciplined static factor model framework.

III.A. Mapping the Narrative Feasible Set

Intuitively, our procedure addresses the following question: given what we believe about how labor-market indicators relate to narrative concepts, which is captured by the restrictions $\boldsymbol{H}$, what are all the reasonable ways those narratives could move together over time? Rather than selecting a single answer, our goal is to characterize the full range of narrative interpretations that are consistent with the data and with the limited assumptions embedded in policy discussions. Specifically, our goal is to map the content of the narrative

[20] In those disciplines, the objects of interest—such as psychological traits, attitudes, or social constructs—are not directly observable and do not admit a single canonical empirical proxy. Identification therefore relies on explicit assumptions about how latent constructs map into multiple observed measures. In CFA, this is achieved by specifying which observed variables are taken to measure which latent traits, fixing scales through normalization, and ruling out certain loadings altogether. These assumptions are not inferred from the data alone; they reflect conceptual judgments about measurement and interpretation.

feasible set $\mathcal{R}_{\text{NFS}}$.

To address this question, we adopt a sampling-based approach that systematically explores alternative ways of combining the underlying statistical components into possible elements of the narrative feasible set.[21] Each candidate interpretation respects the same normalization and uses the same information in the data, but differs in how the narrative forces are allowed to co-move. In this sense, the procedure does not introduce additional structure; it simply makes explicit the interpretive freedom that remains once the narrative assumptions are imposed.

We generate and analyze this collection of admissible narrative interpretations in two steps. First, we sample a wide range of possible correlation patterns among the narrative drivers. This step determines how strongly the narratives are allowed to move together or independently, without privileging any particular pattern ex ante. All narratives are normalized to have unit variance, so differences across interpretations reflect co-movement rather than arbitrary differences in scale.

Second, for each such correlation structure, we apply a random re-orientation that ensures no particular narrative direction is favored. This step guarantees that we explore the full space of admissible interpretations rather than concentrating on a small subset driven by the ordering of variables or by arbitrary starting values. Importantly, these re-orientations preserve the correlation structure and the normalization of the narratives.

Combining these two steps yields a large collection of candidate narrative mappings, each of which implies a distinct but equally admissible interpretation of labor-market dynamics. In practice, we generate hundreds of millions of such candidate interpretations and retain only those that satisfy the narrative restrictions described above. This procedure allows us to characterize the distribution of narrative outcomes, such as their central tendencies, dispersion, and co-movement, rather than focusing on a single point estimate.

From a computational perspective, this approach is straightforward and well suited for real-time analysis. Generating and evaluating a large number of candidate interpretations is highly parallelizable and can be efficiently implemented on modern graphics processing units. In our implementation, drawing and screening a quarter billion candidate narrative representations takes on the order of a few hours on standard GPU hardware, and substantially less on frontier systems. As computational capabilities continue to improve, the cost of exploring the narrative feasible set will continue to decline.

IV. Implementing the Interface

Real-time labor-market analysis draws on a wide and growing range of high-frequency indicators, covering employment, vacancies, hiring, separations, participation, labor market flows, and wages. Together they provide a rich but noisy view of labor market conditions. This breadth of information provides the cross-sectional variation needed to extract common movements and to discipline interpretation through restrictions on how different indicators relate to narrative concepts.

Principal components analysis is well suited to this task because it directly addresses several of the key data imperfections that complicate real-time labor-market assessment. Many commonly used indicators are conceptually ambiguous, in the sense that they reflect multiple underlying forces at once. At the same time, we

[21] Technical details can be found in Appendix C.

observe multiple measures of similar or closely related concepts, often produced by different government and private sources. Finally, labor-market data are subject to missing observations, jagged edges, and revisions that make reliance on any single series problematic. PCA absorbs these features naturally by emphasizing common covariation across indicators while weighting down idiosyncratic noise and measurement error.

More fundamentally, the objective of PCA, namely dimension reduction, is closely aligned with how labor market conditions are assessed in real time. Policymakers synthesize information from dozens of indicators into the small number of underlying narratives that are the focus of our analysis. Our use of PCA formalizes this process and provides a statistical foundation for distilling a limited set of latent forces from various indicators, before organizing those forces into policy-relevant narratives through restrictions.

The purpose of this section is to make explicit how the narrative language used in policy discussions can be translated into constraints on a static factor model representation of the data, as defined in equation (4). We show how the implicit assumptions illustrated in Figure 1 can be expressed as inequality and exclusion restrictions on the factor loadings. These restrictions discipline how latent variation is organized and labeled, while leaving the underlying statistical extraction of common movements unchanged.

IV.A. Choice of Labor-Market Indicators

The implementation of our estimation procedure depends on the set of labor-market indicators available and included in the observed data vector $\boldsymbol{y}_t$. Since we have already identified the restrictions that define the key narratives in Section 1, we base our restrictions on measures of the unemployment rate, the job openings rate, population growth, labor force participation and participation flows, and wage or compensation growth. These indicators provide the primary empirical channels through which labor demand, long-run labor supply, matching efficiency, and short-run labor supply are identified. Additional labor-market measures are useful to the extent that their covariation with these core series helps pin down the principal components that summarize common movements in the data. The choice of which indicators to include is therefore not inconsequential. Panels that over-represent highly correlated variables or rely on redundant disaggregations of aggregate series can give rise to so-called "weak" factors when estimated by principal components that are difficult to interpret (see e.g., Chudik et al. (2011)). With this concern in mind, we focus as much as possible on national-level indicators, using demographic disaggregation only for the unemployment rate. For indicators that are not available at the national level, we rely on industry-, demographic-, or group-specific measures only where necessary to extend historical coverage or capture otherwise unobservable forces.

Against this backdrop, the most commonly used benchmark dataset for large-scale macroeconomic factor model analysis is the Federal Reserve Economic Data Monthly Database (FRED-MD), developed by McCracken and Ng (2016). FRED-MD provides a broad and carefully curated collection of monthly U.S. macroeconomic indicators and has become a standard reference point for empirical work using factor models. Our dataset spans most of the labor-market indicators included in FRED-MD, such as payroll employment, unemployment rates, hours worked, job openings, quits, and aggregate wage measures, ensuring close comparability with this benchmark.

At the same time, we extend beyond the scope of FRED-MD in ways that are directly motivated by our identification restrictions. Because job openings play a central role in distinguishing labor demand from matching inefficiencies, we supplement the JOLTS job openings series with the composite help-wanted index constructed by Barnichon (2010). To anchor the long-run labor supply narrative, we use the harmonized non-institutional population series developed by Coglianese et al. (2025). To better implement the restrictions based on wages, we include survey-based measures of wage adjustment. Most importantly, we use the NFIB series on the fraction of firms raising compensation which provides a long-running proxy for composition-adjusted wage pressures extending back to the late 1960s.

In addition, we incorporate several series that are not part of FRED-MD in order to better capture cyclical covariation in labor market outcomes over long samples and across different regimes. First, we include historical labor turnover measures for manufacturing that provide information on quits and layoffs prior to the start of the Job Openings and Labor Turnover Survey (JOLTS) in 2001. These series extend back several decades and allow the factor structure to reflect labor-market dynamics during earlier recessions and recoveries. Second, we incorporate estimates of matching efficiency and mismatch derived from standard matching-function frameworks. These measures provide direct proxies for changes in labor-market frictions that affect the joint behavior of unemployment and vacancies, without requiring a structural interpretation of the underlying source of those shifts. Finally, we include multiple vintages of nonfarm payroll employment levels, which allow us to study how benchmark revisions and other measurement updates relate to the narrative factors identified in our framework.

Beyond the choice of indicators, we apply a number of data transformations designed to align the observed series more closely with the narrative drivers implied by our economic restrictions. Rather than using levels of the unemployment rate and the job openings rate, we work with their logarithms. This choice reflects the approximately log-linear relationship between unemployment and vacancies embodied in the Beveridge curve and facilitates the distinction between movements along the curve and shifts of the curve itself. The latter reflects changes in matching efficiency.

We also decompose labor-market flows across the participation margin in a way that differs from the standard six-flow decomposition commonly used in the literature (UE, UN, EU, EN, NU, NE, e.g. Blanchard & Diamond, 1990). For our purposes, it is more informative to separately track the share of nonparticipants flowing into the labor force and the share of the labor force flowing into nonparticipation, as these flows more directly capture movements in effective labor supply. The composition of these transitions between employment and unemployment is captured in additional variables.[22] We also use the recently constructed job-to-job transition rate series in Fujita et al. (2024).

Finally, for non-stationary variables exhibiting trend behavior, we use 12-month growth rates or 12-month percentage-point changes. These transformations reduce sensitivity to high-frequency noise in monthly data and align more closely with the horizon over which policymakers typically assess changes in labor market conditions. After transformation, all series are normalized to have zero mean and unit variance to ensure comparability across indicators. We use an outlier filter similar to that used in Stock and Watson (2002c),

[22]The flow data from June 1967 to December 1975 were tabulated by Joe Ritter and made available by Hoyt Bleakley obtained from Robert Shimer's website.

setting observations that exceed eight interquartile ranges in absolute value to missing. In addition, we treat the period from February 2020 through June 2021 as missing. Not doing so materially affects the estimated factor loadings $\mathbf{\Lambda}$ and, in turn, the implied narrative feasible set.

Taken together, these choices yield a monthly dataset spanning January 1960 through February 2026 that contains 94 labor-market indicators. The long sample allows us to study narrative dynamics across multiple business cycles, structural changes in the labor market, and different institutional regimes, while the rich set of indicators provides the cross-sectional variation needed to extract common movements and to discipline interpretation. Missing observations arising from data availability, revisions, and the treatment of the pandemic period are handled naturally within the principal components framework and do not require balanced panels.[23]

IV.B. Narrative Space: Constraints on the Factor Loadings

We organize the empirical analysis around the four narrative drivers that we have introduced above: *labor demand*, *long-run labor supply*, *short-run labor supply*, and *matching efficiency*. In addition to these four narratives, we allow for a fifth residual narrative factor, which we label the *kitchen sink*. This narrative is designed to capture systematic co-movements in labor-market indicators that are present in the data but are not well explained by the four primary narratives. Conceptually, it absorbs the component of common variation in the leading principal components that cannot be credibly or transparently mapped into factors under the narrative restrictions imposed here.[24]

Table 2 summarizes the full set of identifying restrictions used in the baseline implementation. Each column corresponds to a narrative factor, and each row lists an indicator for which a sign or approximate-zero restriction is imposed. The final column reports the residual *kitchen-sink* narrative, which is left unrestricted by construction. In total, we impose 24 qualitative restrictions, reflecting the widely held interpretive conventions about labor demand, labor supply, the labor wedge, and matching efficiency discussed in the previous section. The approximate zeros are implemented as *soft* restrictions: rather than being imposed exactly, they are approximated by selecting the 2 percent of sampled rotations that satisfy the sign restrictions and deviate least from these zeros.[25]

The restrictions in Table 2 operationalize the relationships illustrated in Figure 1. In this implementation, the unemployment rate (U3) serves as the empirical counterpart of u, and nonfarm payroll employment (CES) as our measure of E. The composite Help-Wanted Index and the job openings rate proxy for vacancies, v, while the harmonized civilian noninstitutional population anchors long-run labor supply, $LRLS$. Compensation (ECI), compensation per hour (P&C), and the share of small businesses reporting higher compensation

[23] The details of the data are described in Appendix E.

[24] The purpose of the kitchen sink narrative is not to introduce an additional interpretable economic mechanism, but rather to discipline interpretation of the four core narratives. By explicitly accounting for residual co-movement, we avoid forcing all variation in the data into a small set of named narratives. This allows us to assess how much of the common variation attributed to the leading principal components is robustly captured by the policy-relevant narratives, and how much remains outside their scope. In this sense, the kitchen sink provides a diagnostic for the completeness of the narrative mapping, rather than a fifth substantive driver of labor-market dynamics.

[25] See Appendix C for details of the sampling procedure.

(NFIB) proxy for wages, W. Finally, the labor-force participation rate (LFPR) and labor-force flows provide indicators for shifts in the short-run labor supply curve, $SRLS$.

Table 2: Narrative Restriction Matrix

Indicator	Labor demand	LR labor supply	SR labor supply	Matching efficiency	Kitchen sink
Compensation (ECI)	+		-		
Compensation per hour (P&C)	+		-		
Composite Help-Wanted Index (Barnichon)	+			-	
EPOP ratio (CPS)		≈ 0			
Harmonized civilian noninstitutional population (FRBoG)	≈ 0	+	≈ 0	≈ 0	≈ 0
Job openings rate (JOLTS)	+			-	
LF inflow rate (CPS)			+		
LF outflow rate (CPS)			-		
LFPR (CPS)		≈ 0	+		
Nonfarm payroll employment - current value (CES)		+			+
Small business share raising compensation (NFIB)	+		-		
Unemployment rate (U3) (CPS)	-	≈ 0		-	

Note: Columns represent narrative factors with restrictions indicated by '+' (Positive), '-' (Negative), or '$\approx$ 0' (Approximately zero). The total number of identifying restrictions is 25. Restriction on payrolls and kitchen sink is for sign determination of kitchen sink.

V. Results

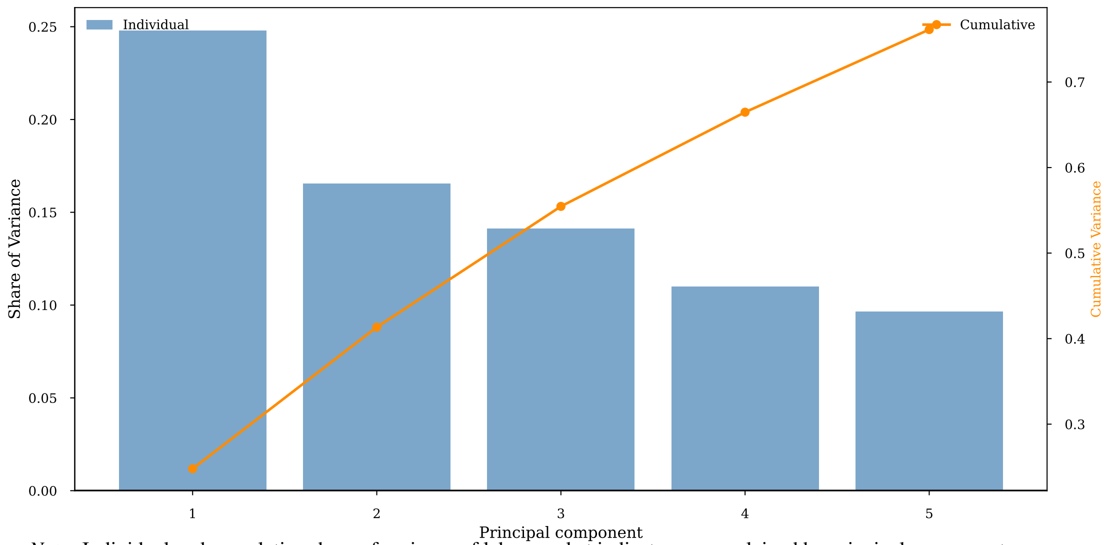
This section presents the empirical results of the narrative framework we have developed. We begin by describing the principal components that summarize common movements in labor-market indicators, and then show how these components can be organized into policy-relevant narrative factors. We conclude by characterizing the resulting narrative feasible set and its implications for real-time interpretation of labor market conditions.

V.A. Principal Components

We begin by briefly describing the statistical principal components that form the basis for the narrative analysis. Let $\boldsymbol{v}_t = (v_{1t}, \ldots, v_{Kt})'$ denote the first $K = 5$ principal components extracted from the standardized labor-market data vector $\boldsymbol{y}_t$. These components summarize the dominant patterns of co-movement across the more than ninety labor-market indicators included in our dataset.

The scree plot in Figure 6 shows that the first five principal components explain 76.7 percent of the total variation in the data. By construction, therefore, narrative factors we obtain as rotations of these components also account for more than three quarters of the variation in the underlying labor-market indicators. This high share of explained variation reflects the strong common component in labor-market dynamics and underscores that a relatively small number of latent forces are sufficient to capture the bulk of aggregate movements observed across employment, vacancies, wages, participation, flows, and other indicators.

Figure 6: Share of variance explained by principal components

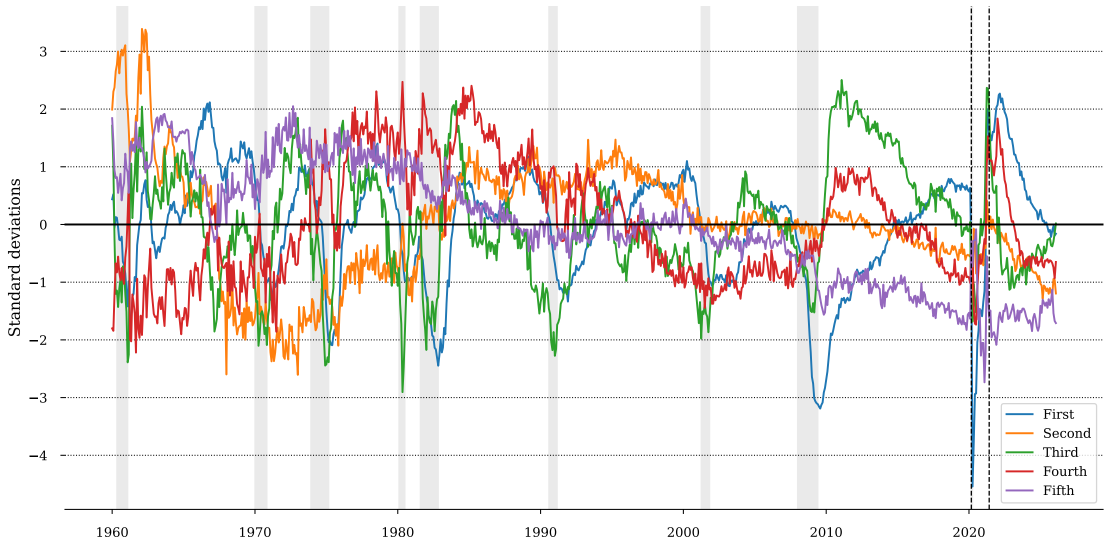


Note: Individual and cumulative share of variance of labor-market indicators, $\boldsymbol{y}_t$ explained by principal components, $\boldsymbol{v}_t$.
Source: Authors' calculations.

Figure 7 shows the time series of the first five components. Several components display clear cyclical patterns. However, none of the principal components can be readily interpreted as corresponding to a single policy-relevant narrative. This lack of direct interpretability is not a shortcoming of principal components analysis; rather, it reflects its purpose. PCA is designed to maximize explained variance, not to recover economically labeled factors. As a result, the principal components provide a statistically efficient summary of common movements in the data, but they do not, on their own, resolve how those movements should be organized into narrative concepts used in policy discussions.[26]

[26]PCA is a well-established method for summarizing co-movement across labor-market indicators (Chung et al., 2014; Gilchrist & Hobijn, 2021) and serves as the foundation for the KC Fed's Labor Market Conditions Indicators (Hakkio & Willis, 2014).

Figure 7: First 5 principal components of data



Note: Monthly data, seasonally adjusted, elements of vector of principal components, $\boldsymbol{v}_t$.
Source: Authors' calculations.

V.B. Narrative Feasible Set

Figure 8 presents the estimated narrative factors obtained by rotating the principal components subject to a minimal set of sign and exclusion restrictions. A striking feature of the figure is how tightly the narrative paths are pinned down despite the deliberately limited nature of these restrictions. Each narrative factor exhibits time-series properties that closely align with its economic interpretation. Labor demand and short-run labor supply are highly cyclical, with pronounced movements around business-cycle turning points. In contrast, long-run labor supply and matching efficiency display more persistent, low-frequency movements that reflect structural and demographic forces. This separation between cyclical and medium- to long-run dynamics emerges naturally from the data, rather than being imposed by construction.

The labor demand factor is strongly procyclical and displays the well-known asymmetry observed in many labor-market indicators, particularly the unemployment rate. Declines in labor demand during downturns are typically rapid, while recoveries tend to be more gradual. This asymmetry is especially evident during the jobless recoveries following the 1991–92 and 2001 recessions, as well as during the sharp contraction and unusually slow recovery after the Great Recession. By contrast, the recovery from the COVID-19 recession was exceptionally rapid: our estimates indicate that by the summer of 2021, labor demand had already surpassed its pre-pandemic level.

The long-run labor supply factor closely tracks long-run movements in the working-age population and captures the pronounced increase in population growth during the 1970s and 1980s as the Baby Boom cohorts started to enter the labor force, as well as subsequent accelerations in the late 1990s and again in the 2020s associated with immigration. Consistent with its interpretation, this factor plays a limited role in explaining high-frequency cyclical fluctuations but accounts for important shifts in the labor market's longer-run capacity.

Our short-run labor supply factor exhibits pronounced cyclical variation. In particular, it tends to decline during recessions, rise sharply around the end of recessions after the unemployment rate peaks, and then gradually decline again during the subsequent expansion. This pattern reflects an important feature of our framework: the narrative factors are not required to be orthogonal in an economic sense. Instead, they capture distinct dimensions of variation in the data that may move together over the business cycle. As a result, the short-run labor supply factor captures periods in which wage growth is unusually strong or weak relative to movements in labor demand.[27]

The economic interpretation of the cyclical behavior of the short-run labor supply is closely related to the composition of the labor force. As emphasized by Hobijn and Şahin (2022), at the end of recessions, the composition of the labor force shifts toward unemployed workers, who tend to have lower reservation wages than employed workers. This makes hiring easier without putting strong upward pressure on wages. Put differently, the short-run labor supply curve is relatively flat in the earlier phase of expansions, as illustrated in our stylized diagram. As the labor market recovers, flows from unemployment to employment and nonparticipation increase, putting downward pressure on unemployment and reducing the pool of readily employable workers. As a result, hiring increasingly requires attracting workers with higher reservation wages, making the effective supply of labor more inelastic and leading to stronger wage growth.[28]

We illustrate how our methodology captures this mechanism in Figure 9 :contentReference[oaicite:0]index=0. Our linear factor model provides a local approximation to a nonlinear, convex short-run labor supply curve. As a result, movements along that curve—toward regions where labor supply is more or less elastic—are reflected in changes in the estimated short-run labor supply factor. This implies that our measure captures both shifts in the position of the short-run labor supply curve and variation in its local elasticity. Accordingly, it is best interpreted as an "effective" short-run labor supply concept that summarizes how both the availability of workers and their responsiveness to labor demand evolve over the business cycle.

The matching efficiency factor traces the medium-run evolution of the Beveridge curve documented in the literature (e.g. Barlevy et al., 2024; Elsby et al., 2015). The outward shifts of the Beveridge curve during the 1970s and 1980s appear as sustained declines in estimated matching efficiency, as does the post–Great Recession period. The factor also captures the sharp outward shift and subsequent inward movement of the Beveridge curve following the COVID-19 shock.[29]

Finally, the kitchen sink factor absorbs residual common variation in labor-market indicators that is not captured by the four primary narratives. Even though we treat it as a residual, an examination of the factor loadings reveals a highly interpretable role: it isolates movements in labor quantities that are not associated with commensurate changes in wages or compensation. The factor exhibits strong positive loadings on non-

[27]Galí (2011) emphasizes that in New Keynesian models with wage rigidities, short-run labor supply shocks are observationally equivalent to wage markup shocks.

[28]This interpretation is consistent with Moscarini and Postel-Vinay (2023), who show that early job-to-job transitions in expansions primarily reallocate workers to better matches, while later transitions tend to be more inflationary.

[29]The movements in the matching efficiency narrative factor closely follow shifts in the historical Beveridge curve illustrated by Hobijn and Şahin (2025)

farm payrolls (CES) (0.64) and aggregate weekly hours (0.63), while remaining almost entirely decoupled from price signals, with near-zero loadings on Average Hourly Earnings (0.01) and Compensation per Hour (0.01).[30]

[30]The complete set of factor loadings is reported in Table D.2 in Appendix D.

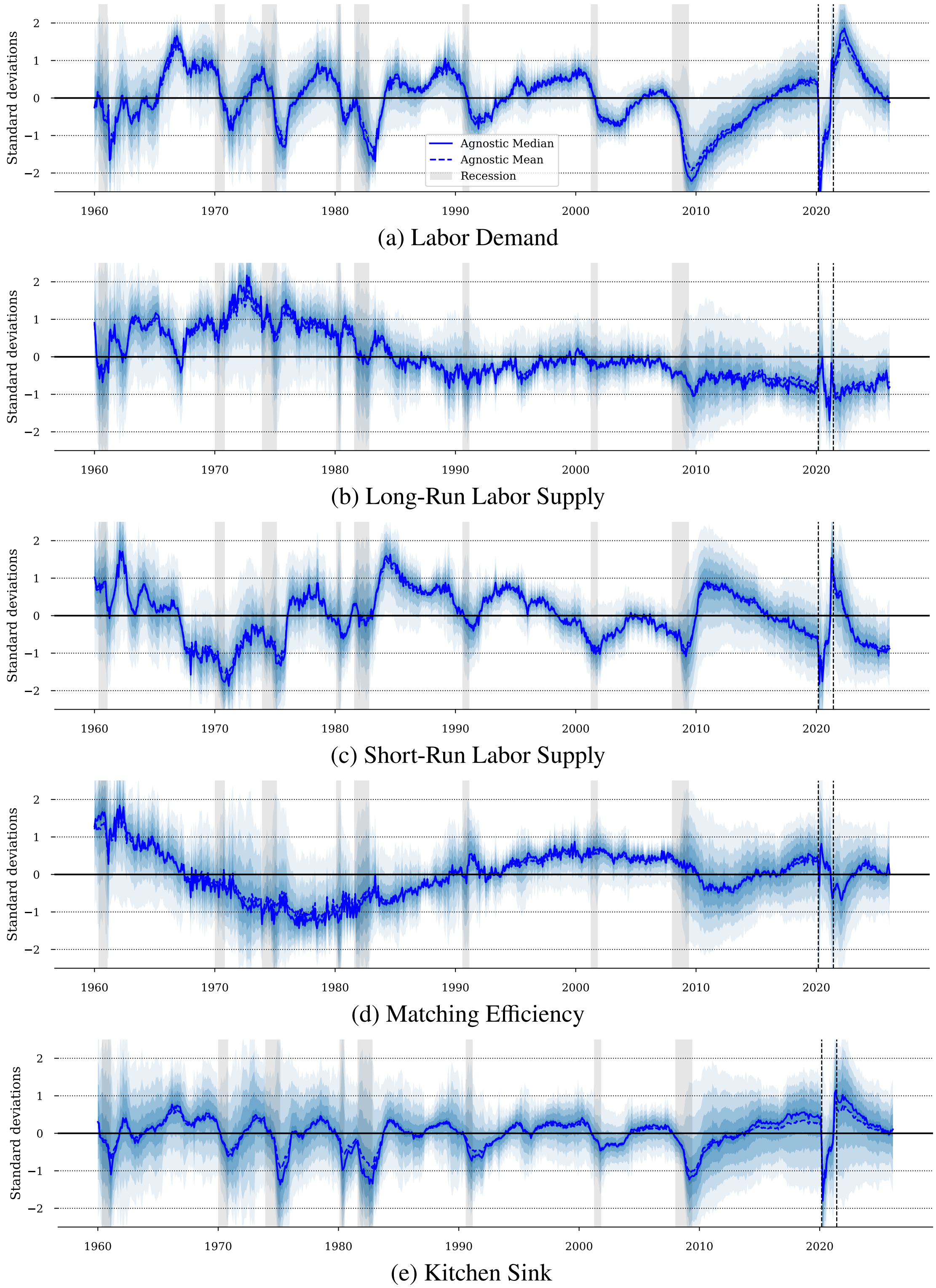


Figure 8: Narrative Feasible Set for the Narrative Factors

Note: This figure displays a *gradient density cloud* representing the set of structural paths that satisfy the agnostic narrative restrictions. The gradient is constructed by calculating percentiles across the distribution of all accepted draws at each point in time. The darkest blue region corresponds to the 45th–55th percentile range, with lighter shades indicating broader intervals out to the 5th–95th percentile envelope. The solid dark blue line denotes the agnostic median (50th percentile), and the dashed blue line indicates the agnostic mean. All paths are standardized. Shaded gray bars indicate NBER-dated recessions. Dashed lines depict COVID-19 period for which data was not used to estimate factor loadings.
Source: Authors' calculations.

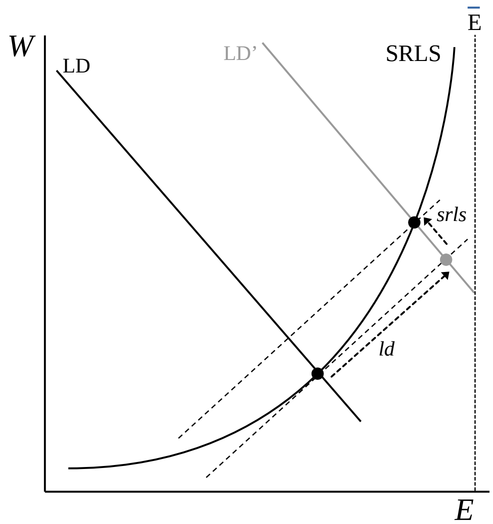


Figure 9: Labor demand and the short-run labor supply

Note: The linear model that we estimate interprets the decline in the short-run labor supply elasticity as labor demand increases as a decline in the short-run labor supply. It does so through a triangulation of the convex short-run labor supply curve.

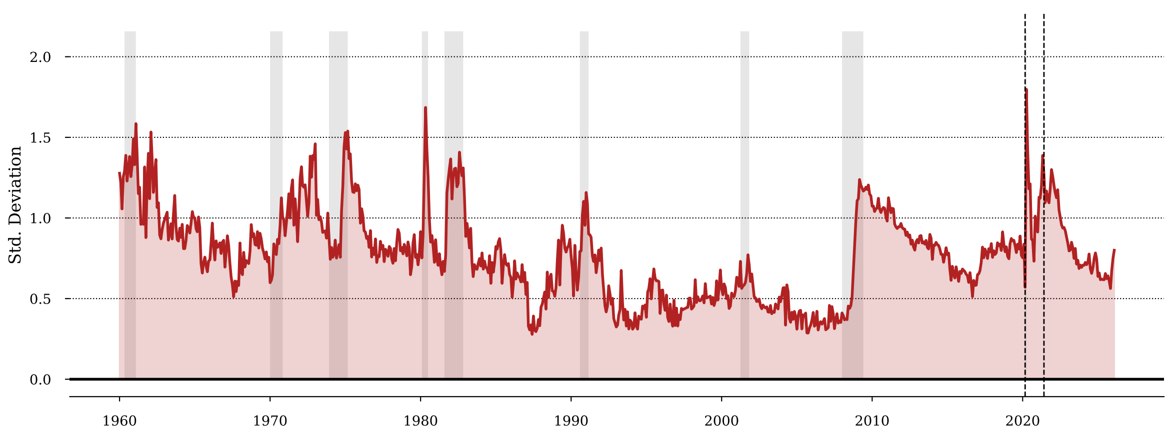


Figure 10: Aggregate Identification Uncertainty (Average Narrative Entropy)

Note: This figure plots the *Average Identification Uncertainty*, calculated as the mean cross-sectional standard deviation across all narrative factors. At each point in time, the value represents the average dispersion of the structural paths that satisfy the narrative restrictions. A higher value indicates a period of greater identification uncertainty (entropy), where the narrative signs are less restrictive in narrowing the set of consistent narrative factors. Shaded gray bars indicate NBER-dated recessions. Dashed lines depict COVID-19 period for which data was not used to estimate factor loadings. The increase in uncertainty in the last month of the sample reflects incomplete availability of data for February 2026 in our dataset.
Source: Authors' calculations.

Identification uncertainty Figure 10 summarizes narrative identification uncertainty over time, measured as the entropy of the admissible narrative decompositions.[31] Several features of the time series stand out. First, narrative uncertainty was markedly lower during the period commonly referred to as the Great Moderation. This finding is consistent with a large literature documenting reduced macroeconomic volatility, more stable co-movements across aggregates, and improved signal extraction during this period (see, for example, Stock and Watson (2002b) and Bernanke (2004)). In an environment characterized by smaller shocks and more predictable relationships among labor-market indicators, the narrative feasible set implied by our minimal restrictions is correspondingly tighter.

Second, narrative uncertainty rises sharply during economic downturns. Recessions are periods in which multiple labor-market forces move simultaneously—labor demand contracts, matching frictions intensify, participation responds endogenously, and wage adjustment may become constrained. As a result, the same observed movements in unemployment, vacancies, and wages can be rationalized by a wider range of narrative interpretations. The increase in entropy during downturns therefore reflects greater uncertainty about how real-time labor market developments should be interpreted, rather than a breakdown of the underlying statistical framework.

Third, narrative uncertainty declines substantially in the most recent part of the sample and reaches levels almost as low as any point since the Great Recession by 2025. Despite the unusually large shocks associated with the pandemic and its aftermath, the co-movement of labor-market indicators in recent years aligns closely with a relatively narrow set of narrative interpretations.

Beyond these broad patterns, the entropy measure reveals a notable asymmetry between expansions and contractions. Narrative uncertainty tends to fall gradually during expansions but rises abruptly during recessions. This asymmetry suggests that uncertainty about labor market conditions rises quickly when conditions deteriorate, while clarity about underlying forces returns more gradually as expansions unfold. This pattern mirrors well-documented asymmetries in macroeconomic volatility and forecasting performance over the business cycle.

Importantly, movements in narrative uncertainty are not mechanically driven by changes in the number or strength of identifying restrictions. Changes in entropy therefore reflect shifts in the empirical content of the data—how tightly the observed co-movements constrain admissible narrative decompositions—rather than changes in judgmental assumptions. In this sense, the entropy measure provides a quantitative summary of how informative the labor-market data are for narrative interpretation at different points in time.

Taken together, these patterns suggest that periods of heightened narrative uncertainty coincide with moments when policymakers face the greatest challenges in interpreting labor market conditions, while periods of low entropy correspond to environments in which incoming data provide clearer guidance for real-time assessment.

[31] The figure here plots the average across narrative factors. Figure D.2 in the appendix depicts the identification uncertainty for each of the narrative factors separately and shows that the movements in uncertainty are highly correlated across factors over time.

V.C. Importance of Different Narrative Factors and Indicators

Decomposition of Indictators in Contributions of Narrative factors Figure 11 shows the historical decomposition of the log of the unemployment rate into the importance of each of the narrative factors. It is constructed as the average of

$$\ln u_t = \lambda_u' \boldsymbol{R}^{-1} \boldsymbol{f}_t + \varepsilon_{u,t} \tag{6}$$

across all narrative factors, $\boldsymbol{f}_t$, and their associated rotations, $\boldsymbol{R}$, drawn from the narrative feasible set. Here λ_u' is the row of loadings from $\boldsymbol{\Lambda}$ associated with the log of the unemployment rate, $\varepsilon_{u,t}$ is the idiosyncratic error for the log of the unemployment rate in month t, and $\ln u_t$ is demeaned and standardized to have unit variance. The resulting paths represent the contribution of each factor to the observed fluctuations in the unemployment rate.

In line with the classic observation from Beveridge (1944), the figure illustrates that a large part of the unemployment rate's cyclical variation is driven by the labor demand factor (blue shaded area). The short-run labor supply plays a secondary role pushing down the unemployment rate later in expansions as the labor force inflow rate declines and outflows increase. This finding is consistent with Elsby et al. (2015), who show that flows between unemployment and nonparticipation amplify the contribution of unemployment–employment flows to fluctuations in the unemployment rate. The decomposition reveals a surprisingly small role for matching efficiency and long-run labor supply in explaining historical unemployment rate fluctuations. The kitchen sink provides some contribution especially at peak and through unemployment rate observations. This is consistent with the kitchen sink capturing the impact of wage rigidities on unemployment, where during recessions employment levels decline more than suggested by the deceleration in wage growth.

Figure 11 provides the time-series basis for decomposing fluctuations in the unemployment rate into the contributions of the different narrative factors. The decomposition shows that labor demand accounts for roughly 40 percent of the variation in the unemployment rate over our sample. The same exercise can be carried out for all indicators in our dataset.[32]

Figure 12 summarizes these decompositions across indicators. Each panel displays a histogram of the share of variance explained by one narrative factor across the full set of labor-market indicators. The headline indicators—payroll growth, the employment-to-population ratio (EPOP), the unemployment rate, and the LFPR—are highlighted with vertical lines. Two results stand out. First, labor demand and short-run labor supply account for the largest share of variation in the data. Together, these narratives explain most of the co-movement across the broad set of labor-market indicators in our sample. In contrast, long-run labor supply and matching efficiency explain a substantially smaller share of overall variation.

Indicator Weights and Narrative Contributions To better understand how the narrative factors are constructed from the underlying data, we examine the relative importance of each indicator in determining the factors. Each narrative factor is a weighted average of the observed labor-market indicators, where the weights reflect how informative each series is about that factor. Intuitively, indicators that co-move more strongly with a given narrative factor receive higher weight, while noisier or less directly related indicators

[32] Table D.1 in the Appendix reports the variance decomposition for all indicators.

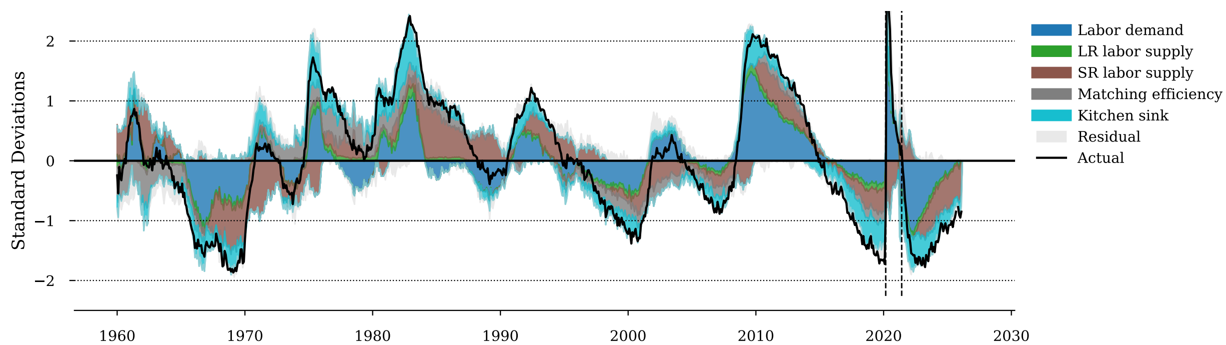


Figure 11: Historical Decomposition of the Unemployment Rate (U3)

Note: This figure plots the contribution of the five narrative factors to the evolution of log of the unemployment rate (U3) (measured in standard deviations from its mean). *Source:* Authors' calculations.

receive lower weight.[33]

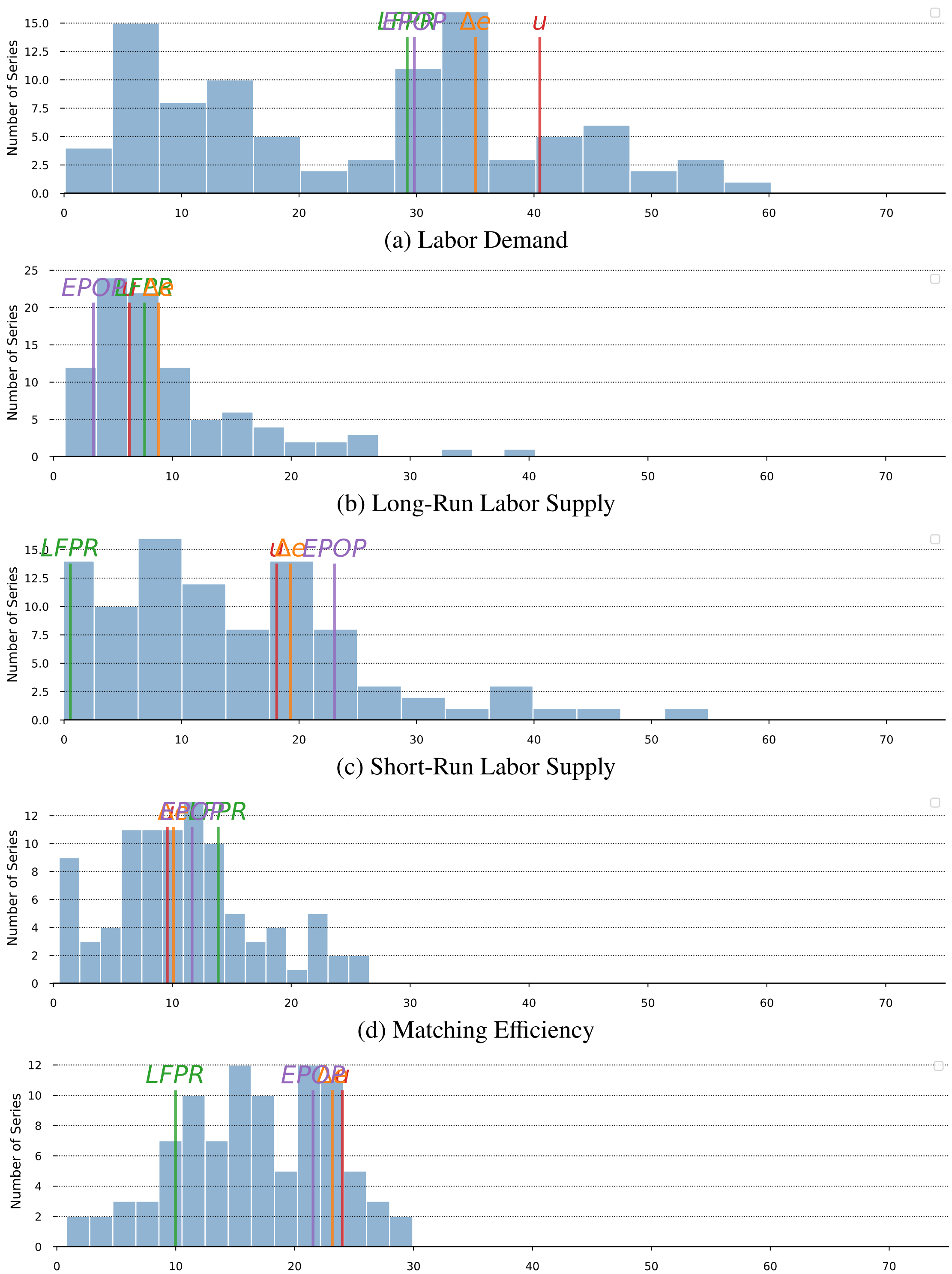
Figure 13 summarizes these weights for each narrative factor. Each panel ranks the 94 indicators from most to least important based on their average absolute contribution to the factor. The solid line shows the median weight across admissible rotations in the narrative feasible set, while the shaded region reflects the dispersion across those rotations.

Several features stand out. First, no narrative factor is dominated by a small set of indicators. Instead, all factors load positively on a broad cross-section of labor-market series, with weights that decline gradually across the ranking. Even the most important indicators account for only a small fraction of the total weight, while a long tail of indicators continues to contribute non-negligibly. This diffuse pattern is not incidental. It reflects the presence of a well-defined covariance structure across U.S. labor-market indicators. Because many series co-move systematically, the common variation can be extracted from a wide cross-section of data, which is precisely what principal components are designed to do. The fact that a broad set of indicators contributes to each factor therefore provides direct empirical support for our use of PCA to summarize labor-market dynamics.

Second, while the headline indicators, payroll growth (ΔE), the unemployment rate (u), the employment-to-population ratio (EPOP), and the labor-force participation rate (LFPR), do contribute to all narrative factors, they are generally not those that get the most weight. As indicated by the labeled arrows in Figure 13, these series typically fall well below the top-ranked indicators in terms of weight. This reflects the fact that, although headline indicators are useful summaries, they themselves aggregate multiple underlying forces and therefore do not isolate any single narrative dimension.

Finally, a number of indicators emerge as consistently important across multiple narrative factors. These include the job openings, layoffs, hires, and quits rates from JOLTS, the probability of losing a job from the Michigan Survey, small business indicators from the NFIB, and measures related to staffing and temporary

[33] These weights play a role analogous to Kalman gains in state-space models: they determine how much each observed series contributes to updating the estimate of a latent factor, with more informative signals receiving larger weights.



(a) Labor Demand

(b) Long-Run Labor Supply

(c) Short-Run Labor Supply

(d) Matching Efficiency

(e) Kitchen Sink

Figure 12: Share of Variance of Indicators Accounted For

Note: Each histogram in this figure plots the distribution of the share of the variance of the indicators that is accounted for by the narrative factor. This share is the mean across all sampled feasible narratives. Details of these variance decompositions are reported in Table D.1. The headline numbers of the unemployment rate, u, LFPR, $LFPR$, EPOP ratio, $EPOP$, and nonfarm payroll growth, Δe, are shown separately in each panel.
Source: Authors' calculations.

help employment. The prominence of these series reflects their central role in capturing key margins of adjustment in the labor market, such as hiring, separations, compensation, and labor-force transitions. At the same time, their influence across multiple factors underscores that individual indicators rarely map cleanly into a single narrative concept, reinforcing the need for a multivariate approach.

Overall, the distribution of weights highlights a central feature of our framework. Namely that narrative factors are not constructed from a small set of canonical indicators, but instead summarize pervasive co-movement across a large and diverse set of labor-market series.

VI. Payroll Growth and Revisions Revisited

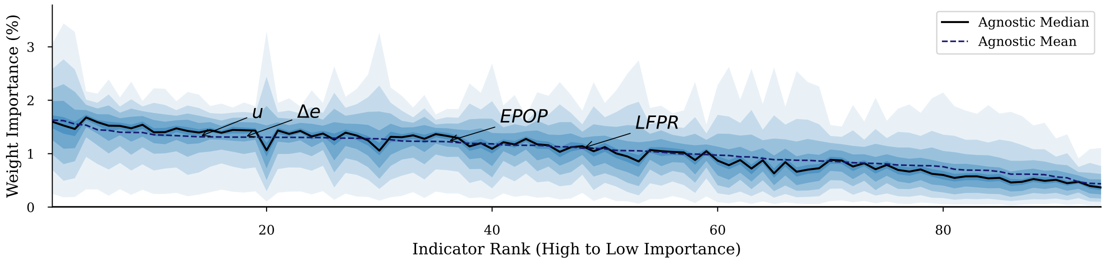
Payroll Growth Decomposition In Section 2 we discussed how equation (1) provides a useful framework to link the headline numbers from the Employment Situation report and to translate changes in the unemployment rate, the LFPR, and population growth into nonfarm payroll jobs. But we cautioned against interpreting these components mechanically as: (*i*) Payroll growth is overall strength of the labor market, (*ii*) the unemployment rate is labor demand, and (*iii*) the participation and population growth rates are labor supply. Our narrative framework allows us to determine which factors are important for each of the components of (1). We show this in Figure 14.

What might be most surprising is Panel 14b, especially when compared to Figure 11. Panel 14b shows that minus the 12-month change in the unemployment rate is largely determined by other factors not by labor demand. The change in the unemployment rate is not included directly among our indicators; instead, the log level of the unemployment rate is. By definition, $-\Delta u_t \approx \Delta \ln EPOP_t - \Delta LFPR_t$. We use this identity to derive the implied factor loadings for $-\Delta u_t$ from the ones for the log changes in the EPOP ratio and LFPR. What this reveals turns out to be very useful for interpreting labor market fluctuations: Where the log level of the unemployment rate is largely determined by labor demand, the change is accounted for by non-demand factors especially by short-run labor supply. It reflects that changes in the unemployment rate move the labor market to different parts of the convex short-run labor supply curve.

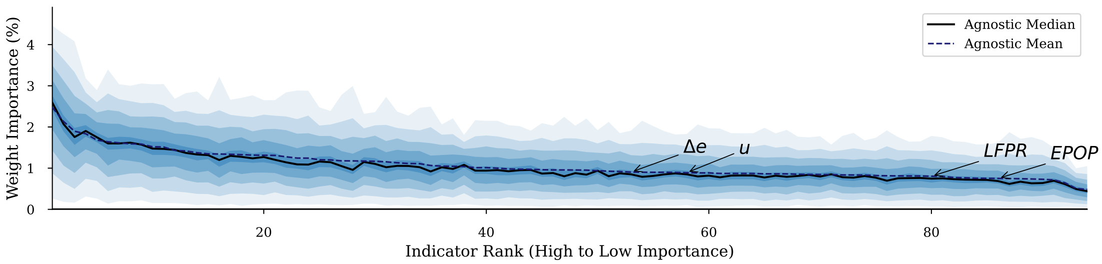
Panel 14c of Figure 14 provides another cautionary tale for the simple interpretation of the components of payroll growth. It shows that interpreting changes in the LFPR as indicative of changes in labor supply is not correct. The largest contributor to changes in the LFPR is actually labor demand, rather than long-run and short-run labor supply. This result is not new. Hobijn and Şahin (2022) use a flow decomposition of changes in the LFPR to show that what is important is the participation cycle, i.e. the part of changes in the LFPR accounted for by flows between unemployment and employment (even though they do not cross the participation margin). This is because unemployment makes workers more likely to subsequently drop out of the labor force.[34]

The final panel of Figure 14 shows that the main driver of population growth is labor supply, which is by construction (see Table 2). What is probably most notable from this panel is that periods with high or low unexplained population growth, which is captured by the residual in the panel, also tend to coincide with

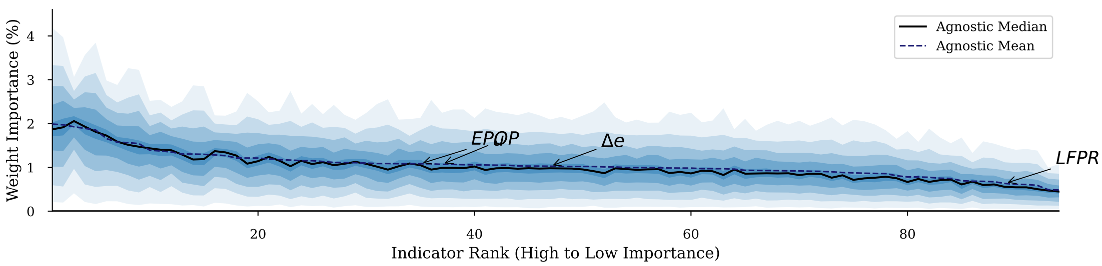
[34] Real-time updates of the part of the 12-month change in the LFPR that is accounted for by the participation cycle can be found on www.LaborMarketUpdate.net (Hobijn & Şahin, 2025).



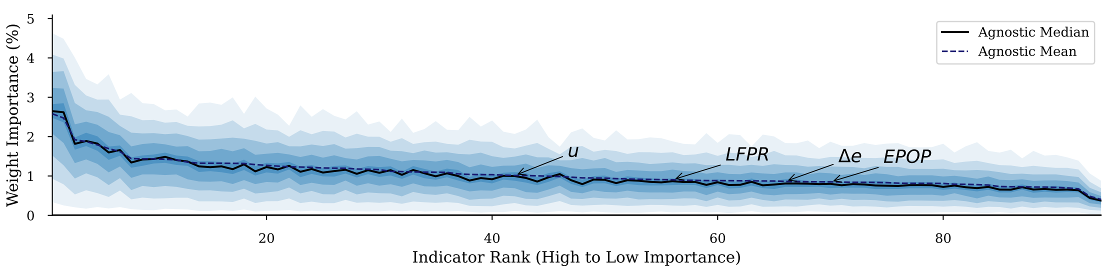
(a) Labor Demand



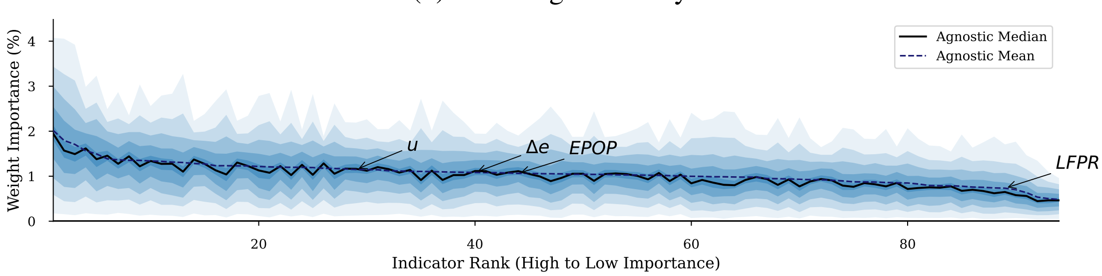
(b) Long-Run Labor Supply



(c) Short-Run Labor Supply



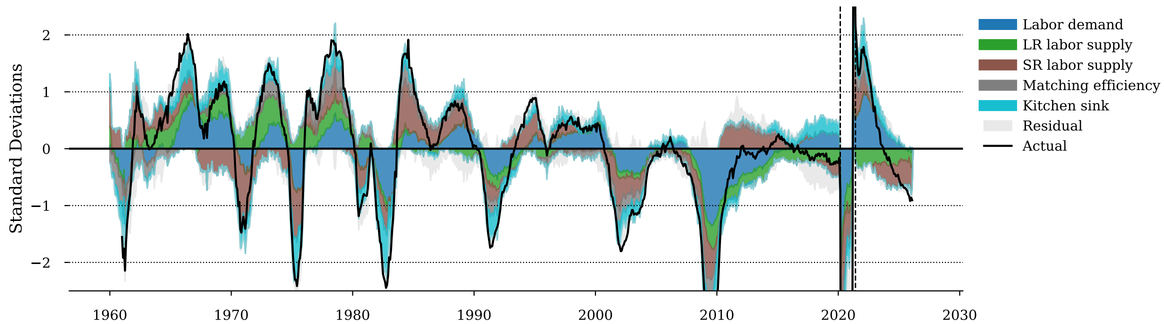
(d) Matching Efficiency



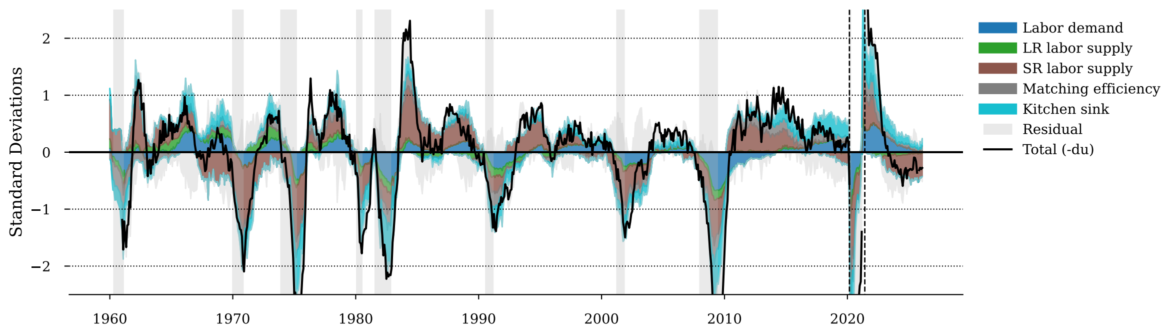
(e) Kitchen Sink

Figure 13: Distribution of relative weights for each narrative factor

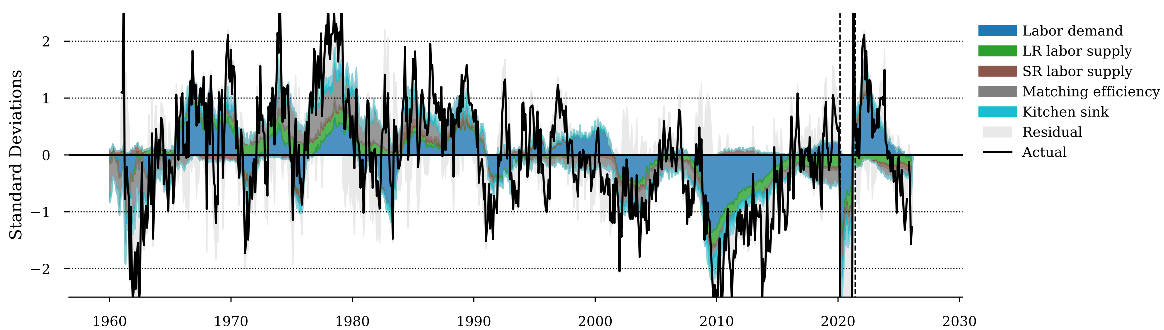
Note: This figure displays the distribution of the absolute weights mapping the 94 labor-market indicators to the identified narrative factor. Indicators are ranked along the x-axis from highest to lowest mean weight. The gradient cloud represents the range of weights across the narrative feasible set, which consists of all rotations satisfying the sign and exclusion restrictions. Specific headline indicators—the unemployment rate (u), labor force participation rate ($LFPR$), nonfarm payroll employment (Δe), and the employment-to-population ratio ($EPOP$)—are annotated with arrows at their respective mean ranks.
Source: Authors' calculations.



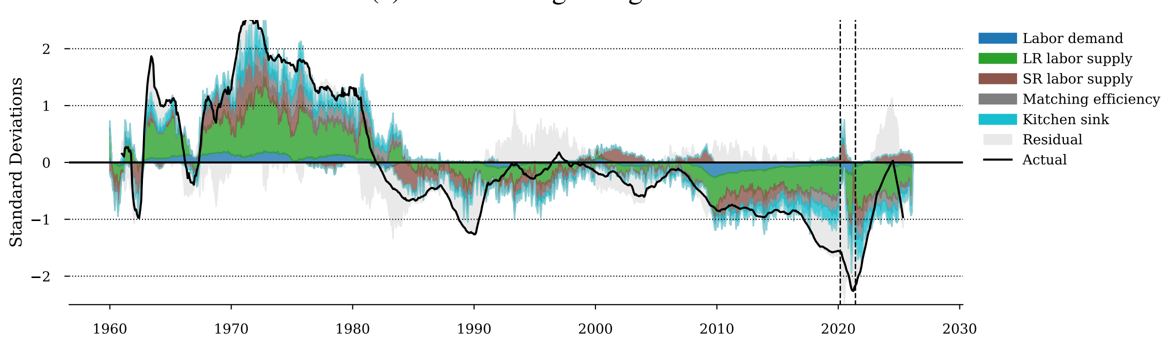
(a) 12-month log change in payroll employment



(b) Minus 12-month change in unemployment rate



(c) 12-month log change in the LFPR



(d) 12-month log change in the harmonized civilian non-institutionalized population

Figure 14: Importance of Narrative Factors for Payroll Decomposition, equation (1)

Note: Historical time series decomposed based on (4) mean across all sampled feasible narratives. All time series are transformed to have mean zero and unit standard deviation. Decomposition of change in the unemployment rate done using $\Delta lnEPOP_t \approx -\Delta u_t + \Delta lnLFPR_t$. All series are standardized to have mean zero and unit standard deviation.
Source: Authors' calculations.

periods of higher or lower residual payroll growth not captured by the five principal components we consider. This is especially apparent in the 2010's, 2020's, and to a less extent, the 1990's. This suggests that what our narrative factors do not capture is the part of population growth that is not correlated with any of the other indicators in our dataset.

Payroll Revisions Revisited Our approach can incorporate data revisions directly through the inclusion of multiple vintages of the same series. Treating revisions as additional noisy measurements allows the factors to absorb information contained in the revision process itself. To give an example, consider Figure 15. It decomposes the difference between the post-benchmark estimate of nonfarm payroll employment growth and the first-released estimate into the portion that covaries with our narrative factors and a residual. The black line shows the total revision (post-benchmark minus first release, both z-transformed to have mean zero and unit standard deviation), while the colored stacked areas show the part of that revision that is aligned with the narrative factors through their estimated co-movement with the broader labor-market data. The light-gray band is the residual component—the part of the revision that is not explained by any of the narratives.

Two findings stand out. First, payroll revisions (as a share of total payrolls) have tended to be smaller in recent decades than in earlier parts of the sample. In the figure, this appears as a clear decline in the magnitude of the total revision series over time: large swings are much more common in the 1960s and 1970s than in the post-1990 period, and the recent years feature comparatively modest revisions. This pattern is consistent with the view that the payroll data system has become more stable over time, so that subsequent benchmark updates typically involve smaller adjustments.

Second, when revisions are sizable, they are only weakly connected to the cyclical narrative forces that organize the rest of the labor-market data. The stacked narrative contributions are generally small relative to the total revision, with the residual component accounting for most of the movement in the revision series. This implies that large payroll revisions primarily reflect measurement and benchmarking issues that are specific to the payroll survey and its reconciliation process, rather than systematic re-interpretations of underlying labor market conditions associated with labor demand, labor supply, and matching efficiency. In other words, our narrative framework can help quantify when revisions align with broader labor-market co-movement, but it also makes clear that most revision variation is orthogonal to the core narratives that drive labor-market fluctuations.

This result may seem counterintuitive. It is well known that revisions to the *level* of payroll employment are highly cyclical, with benchmark revisions typically raising employment in expansions and lowering it in downturns. However, our analysis focuses on *growth rates*, comparing month-over-month changes across data vintages rather than levels. Once expressed in growth rates, much of the cyclical structure in revisions is differenced out, and the remaining variation is considerably less systematic over the business cycle. As a result, revisions to payroll *growth* exhibit only limited co-movement with the narrative factors, which is precisely what is reflected in Figure 15.

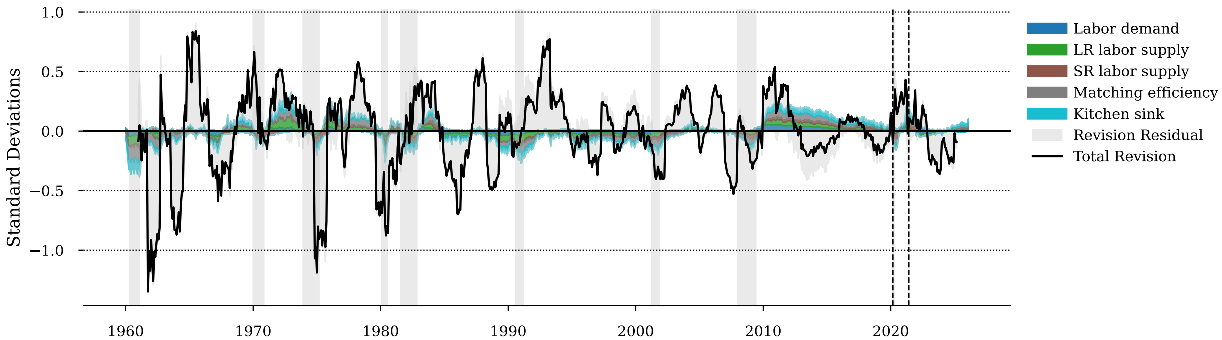


Figure 15: Payroll growth revisions

Note: Payroll revision is difference between normalized (z-transformed) post-benchmark and first release 12-month payroll growth.
Source: Authors' calculations.

VII. Post-Pandemic Labor Market

In this section, we focus on the post-pandemic labor market and use our estimates of the narrative factors to analyze this specific historical episode. The COVID-19 pandemic was accompanied by a sharp deterioration of economic activity and was a big disruption to the labor market. The unemployment rate which stood at 3.5% in February 2020 jumped to 14.8% in April 2020 following widespread lockdowns. The recovery from the pandemic was unusually brisk with the unemployment rate standing at 5.4% in July 2021 which was partially attributable to a record number of workers put on temporary layoffs. In this section, we focus on the time period starting with July 2021 and provide a discussion of subsequent labor market developments light of our analysis.

Figure 16 reproduces our narrative factors for the post-pandemic labor market to highlight their joint evolution. The COVID-19 pandemic marked a sharp departure from the pattern of persistently slow recoveries observed after the 1990–91, 2001, and 2007–09 recessions. Instead, the economy experienced a brisk recovery in 2021–22, which we associate with strong labor demand and initially an increase in short-run labor supply. At the same time, matching efficiency remained low, a pattern often attributed to the Great Resignation, likely reflecting change in workers' preferences for remote work and the erosion of real wages which triggered a wave of reallocation in the labor market.

Beginning in mid-2022, labor demand started to decline which in magnitude was similar to recessions but unfolding more gradually. This decline in labor demand was also accompanied by a decline in short-run labor supply. We interpret this combination—recession-like declines in labor demand without a sharp increase in unemployment rate—as a distinguishing feature of a soft landing relative to a recession.

In Figure 16, we show the decomposition of key labor-market indicators into the importance of each of the narrative factors for the July 2021 to February 2026 period. Short-run labor supply initially puts upward pressure on the unemployment rate (Panel a) but by mid 2022 it starts to reduce payroll growth at the same time keeping unemployment from rising as labor demand moderates. Put differently, our framework reconciles the evolution of low payroll growth (Panel b) with the subdued increase in the unemployment rate from 3.4% in April 2023 to 4.4% February 2026 by a decline in labor supply. This in turn affects wage

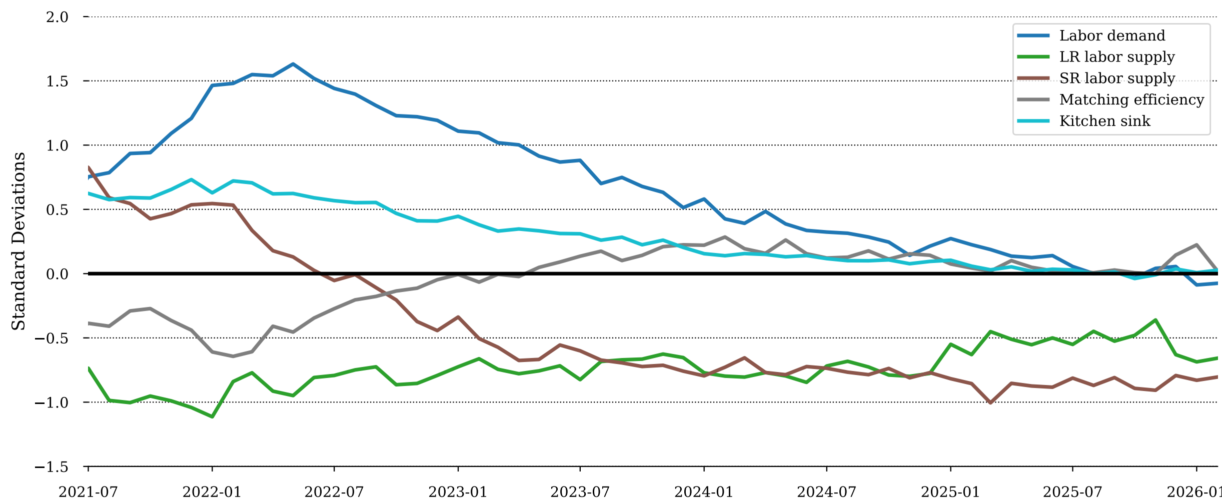


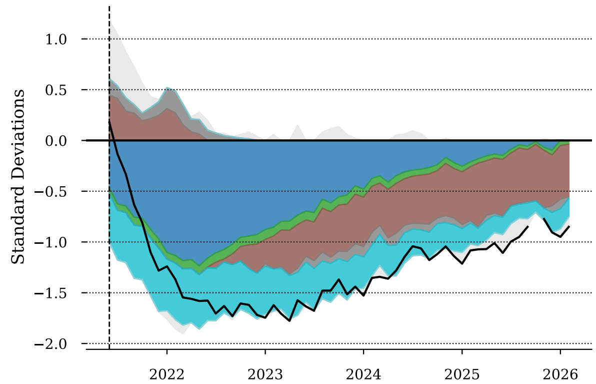
Figure 16: Narrative factor means since the COVID episode

Note: Average structural paths from the Narrative Feasible Set for July 2021 onwards; standardized units.
Source: Authors' calculations.

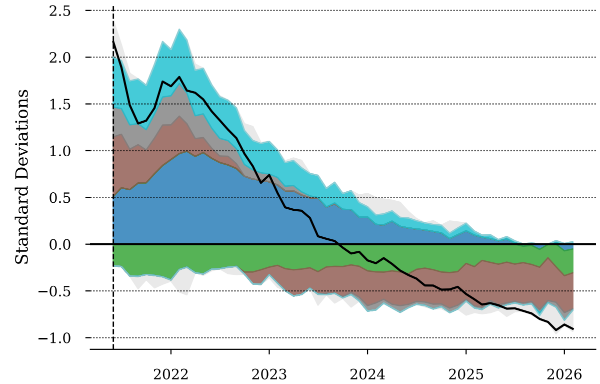
growth with upward pressure on average hourly earnings starting in 2023 (Panel c). There is a large residual for average hourly wages in the 2021-2022 period which coincides with large composition effects as well as high inflationary period.

A distinctive feature of the post-pandemic period was the stark rise in quits often referred to as the Great Resignation and the associated sharp increase in vacancies. While the rise in vacancies was cited as evidence of unusually tight labor market, several studies, including Bagga et al., 2025, Afrouzi et al., 2026, Pilossoph and Ryngaert, 2024 and Guerreiro et al., 2024 challenged this conclusion by arguing that rising inflation and the emergence of remote work were important factors that amplified the effect of relatively fast recovery in labor demand. While our framework does not use any information about these developments, it does show that labor demand accounts for about half of the rise in job openings (Panel d) and quits (Panel e). In addition, part of the increase in job openings is due to declining matching efficiency in the 2021-2022 period and later the decline in short-run labor supply which reduces job-filling rates thereby increasing the stock of vacancies—a channel emphasized by Bagga et al., 2025. Another important takeaway is the disconnect between hires and labor demand. While hires (Panel f) partially reflect employment growth, the hires rate in the economy is tightly linked to turnover which triggers replacement hires.

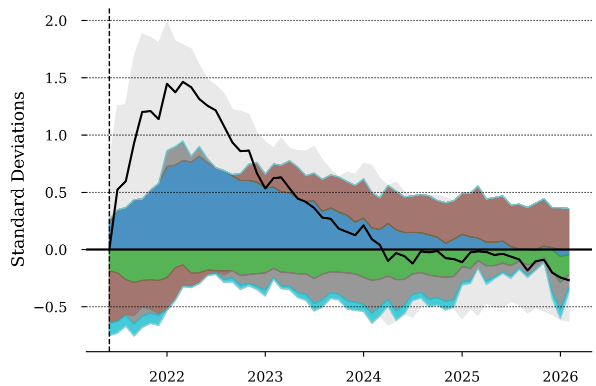
As of February 2026, analysis points to an unusual configuration of labor market conditions. Labor demand has declined to levels that, in past episodes, would typically be associated with the onset of a recession. At the same time, short-run labor supply remains exceptionally low for this stage of the business cycle. This combination helps explain the seemingly contradictory labor market developments: households report increasing difficulty in finding jobs, while firms, particularly small businesses, continue to report challenges in filling vacancies. In our framework, these observations are not inconsistent but instead reflect the joint effect of subdued labor demand and a limited effective supply of workers.



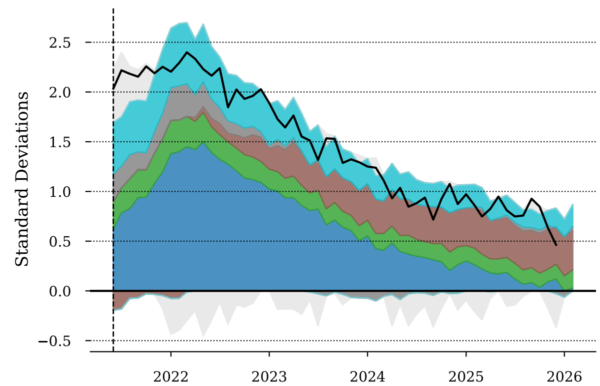
(a) Unemployment rate (U3)



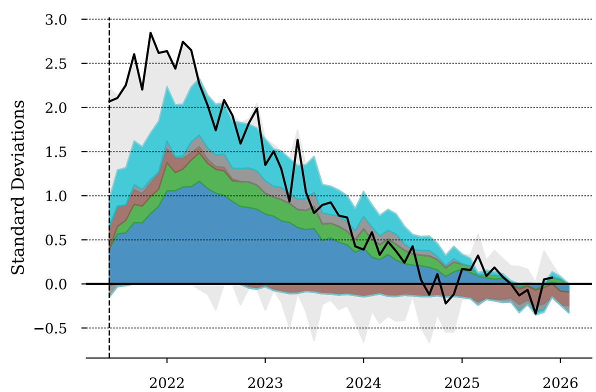
(b) Payroll employment growth



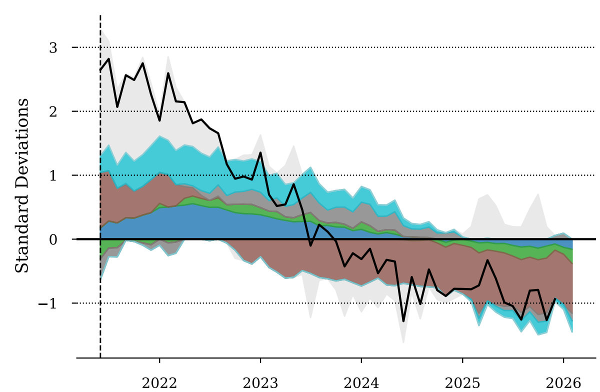
(c) Average hourly earnings



(d) Job openings rate



(e) Quits rate



(f) Hires rate

Figure 17: Post-COVID decompositions of labor-market indicators

Source: Authors' calculations.

VIII. Concluding Remarks

In this paper, we use a rich set of labor-market indicators spanning 1960 to 2026 to estimate four narrative factors that together account for roughly three-quarters of the variation in labor-market indicators. These factors—labor demand, long-run labor supply, short-run labor supply, and matching efficiency—are chosen to reflect the narrative language commonly used by policymakers and are identified using restrictions that follow directly from standard textbook models of the labor market. Our methodology first reduces the variation in close to hundred labor-market indicators to four principal components and then maps these components into the four narrative factors by considering economically meaningful rotations.

An important advantage of our narrative factor framework is that it directly addresses several data imperfections that complicate real-time assessment of labor market conditions. First, the narrative factors eliminate much of the conceptual ambiguity inherent in individual indicators. Single series—such as the unemployment rate, vacancies, or wage growth—often reflect multiple underlying forces at once. By contrast, the narrative factors aggregate information across indicators in a way that is explicitly disciplined by economically meaningful sign and exclusion restrictions, yielding interpretable measures that map directly into policy-relevant concepts.

Second, the principal-components backbone of the framework allows the narrative factors to be estimated even when key indicators are temporarily unavailable. Because the factors are inferred from the full cross section of labor-market data and their historical covariance structure, missing observations in individual series, such as gaps in unemployment or job openings data, do not prevent estimation. Instead, the available indicators provide information about the latent narratives through their established co-movement with the missing series. This feature is particularly valuable in real time, when publication delays or data disruptions can otherwise obscure assessment.

Third, the framework naturally accommodates the presence of multiple measures of the same or closely related concepts. Rather than requiring the analyst to select a single preferred indicator, PCA aggregates across overlapping measures, while the narrative loadings reveal the extent of their conceptual similarity through common loading patterns. In this way, the narrative factors make explicit which indicators provide redundant information and which contribute distinct signals, turning conceptual overlap into an empirical feature rather than a source of confusion.

Finally, our analysis relies on a set of uncontroversial economic restrictions to identify key narrative factors that are both empirically disciplined and easy to communicate. At the same time, the results highlight important areas where structural general equilibrium models should place greater emphasis. In particular, the strong interaction we document between short-run labor supply and labor demand points to the need for models that incorporate an operative labor supply margin within a three-state labor market framework with search and matching frictions.[35]

We see two natural next steps for our analysis. First, expanding the framework to incorporate non-labor-market variables could provide a richer view of labor market dynamics. This would be particularly

[35] While this literature is growing—with contributions such as Krusell et al., 2017, Cairó et al., 2021, Graves et al., 2023, and Qiu, 2023—most models still rely on a two-state abstraction.

useful since the co-movement between some macroeconomic measures and labor-market indicators have shifted over time. For example, the Okun's law relationship has shifted as the cyclicality of productivity has weakened, altering how output fluctuations translate into labor market dynamics. Second, extending the framework to a fully real-time setting would make it even more useful for policy analysis though this would substantially increase the complexity of the signal extraction problem, as it would require dealing with data revisions, publication lags, and changing relationships across indicators in real time.

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Making Sense of Labor Market Indicators Amid Data Imperfections

Appendix

ABSTRACT This appendix describes details about data series used, explains the sampling method for the narrative rotations that we apply, provides derivations of some of the expressions in the main text, and includes additional results and details about results.

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A Textual Analysis of Policy Communications

This appendix describes the procedure used to construct the textual analysis summarized in Figure 1. The goal of the exercise is descriptive: to examine how policymakers link narrative labor market concepts to observable indicators when discussing labor market conditions.

A.1 Document Collection

The text corpus consists of speeches and official statements by current members of the Federal Reserve Board available through the FRASER archive maintained by the Federal Reserve Bank of St. Louis. The earliest documents in the archive date back to 2013. These speeches range from conference remarks and economic outlook presentations to prepared statements delivered at public events. To supplement these sources, we also include the Economic Reports of the President for the years 2013–2025. In total, the combined dataset contains 502 documents.

A.2 Identification of Narrative Drivers

To identify references to narrative drivers, we apply a set of regular expression searches to the raw text of the documents. Each narrative concept is associated with a small set of keywords. For example, references to labor demand are identified using terms such as “demand,” while discussions of matching frictions are identified using expressions such as “mismatch,” “matching,” or “search friction.” These searches extract sentences containing potential references to each narrative concept.

A.3 Identification of Labor Market Indicators

We then examine the extracted sentences for references to commonly used labor market indicators, including unemployment, vacancies, wage growth, participation, population growth, and hiring. To improve coverage, the search procedure includes common variations of these terms (for example, “job growth” and “job gains,” or “vacancy” and “vacancies”) as well as simple filters designed to reduce false matches.

A.4 Interpretation

The resulting counts measure how frequently narrative drivers and labor market indicators appear in close textual proximity. Because many policy discussions reference multiple drivers simultaneously—for example, discussing labor demand and labor supply in the same paragraph—individual indicators may appear in association with more than one narrative concept. For this reason, the analysis is intended only to illustrate broad patterns in policy communication rather than provide a precise mapping between narrative concepts and individual indicators.

B Mathematical derivations

Derivation of equation (1): Start with the accounting identity

$$\log E_t^{\text{CES}} = \log\left(\frac{E_t^{\text{CES}}}{E_t^{\text{Adj}}}\right) + \log\left(\frac{E_t^{\text{Adj}}}{E_t^{\text{CPS}}}\right) + \log E_t^{\text{CPS}}. \tag{B.1}$$

Taking first differences yields

$$\Delta \log E_t^{\text{CES}} = \Delta \log\left(\frac{E_t^{\text{CES}}}{E_t^{\text{Adj}}}\right) + \Delta \log\left(\frac{E_t^{\text{Adj}}}{E_t^{\text{CPS}}}\right) + \Delta \log E_t^{\text{CPS}}. \tag{B.2}$$

We refer to the first term as the *survey difference* and the second as the *scope difference*. By CPS definitions,

$$E_t^{\text{CPS}} \; = \; (1 - u_t)\, \text{LFPR}_t \, P_t. \tag{B.3}$$

Taking logs and differences gives the *exact* log identity

$$\Delta \log E_t^{\text{CPS}} = \Delta \log(1 - u_t) + \Delta \log \text{LFPR}_t + \Delta \log P_t. \tag{B.4}$$

Substituting (B.4) into (B.2) yields the exact decomposition

$$\Delta \log E_t^{\text{CES}} = \underbrace{\Delta \log\left(\frac{E_t^{\text{CES}}}{E_t^{\text{Adj}}}\right)}_{\text{survey difference}} + \underbrace{\Delta \log\left(\frac{E_t^{\text{Adj}}}{E_t^{\text{CPS}}}\right)}_{\text{scope difference}} + \Delta \log(1 - u_t) + \Delta \log \text{LFPR}_t + \Delta \log P_t. \tag{B.5}$$

For small changes in u_t, the first term in (B.4) satisfies

$$\Delta \log(1 - u_t) = \log(1 - u_t) - \log(1 - u_{t-1}) \approx -\frac{\Delta u_t}{1 - \bar{u}_t}, \tag{B.6}$$

where $\bar{u}_t$ is a point between u_t and u_{t-1} (by the mean value theorem). When u moves modestly and is not too close to one, researchers often use the even simpler approximation $\Delta \log(1 - u_t) \approx -\Delta u_t$. Using (B.6) (or the $-\Delta u_t$ shorthand) gives the practical five-term decomposition:

$$\Delta \log E_t^{\text{CES}} \approx \underbrace{\Delta \log\left(\frac{E_t^{\text{CES}}}{E_t^{\text{Adj}}}\right)}_{\text{(1) survey difference}} + \underbrace{\Delta \log\left(\frac{E_t^{\text{Adj}}}{E_t^{\text{CPS}}}\right)}_{\text{(2) scope difference}} - \Delta u_t + \underbrace{\Delta \log \text{LFPR}_t}_{(4)} + \underbrace{\Delta \log P_t}_{(5)}. \tag{B.7}$$

Equation (B.7) is the version reported in the main text; (B.5) provides the exact counterpart.

C Sampling the Narrative Rotations

To map the statistical principal components $\boldsymbol{v}_t$ into economically interpretable narrative factors, we define a linear transformation

$$\boldsymbol{f}_t = \boldsymbol{R}\boldsymbol{v}_t,$$

where $\boldsymbol{f}_t \in \mathbb{R}^K$ denotes the vector of narrative factors. In the oblique framework, $\boldsymbol{R} \in \mathbb{R}^{K\times K}$ is a nonsingular, generally non-orthogonal transformation, allowing the narrative factors to be contemporaneously correlated.

Rather than sampling $\boldsymbol{R}$ directly, we work with its inverse $\boldsymbol{W} = \boldsymbol{R}^{-1}$, which rotates the loading space. Given the principal-components loading matrix $\boldsymbol{\Lambda}$, the implied narrative loadings are

$$\boldsymbol{\Gamma} = \boldsymbol{\Lambda}\boldsymbol{W}.$$

Crucially, the reconstruction of the observed data is invariant to the choice of $\boldsymbol{W}$. Specifically,

$$\boldsymbol{y}_t = \boldsymbol{\Lambda}\boldsymbol{f}_t + \boldsymbol{\epsilon}_t = (\boldsymbol{\Lambda}\boldsymbol{W})(\boldsymbol{W}^{-1}\boldsymbol{v}_t) + \boldsymbol{\epsilon}_t = \boldsymbol{\Lambda}\boldsymbol{v}_t + \boldsymbol{\epsilon}_t, \tag{C.1}$$

so that alternative narrative rotations preserve the statistical fit of the underlying principal-components representation.

Each candidate rotation matrix $\boldsymbol{W}$ is constructed as

$$\boldsymbol{W} = \boldsymbol{Q}\boldsymbol{L}_c^{-1}, \tag{C.2}$$

where $\boldsymbol{Q}$ is orthogonal and $\boldsymbol{L}_c$ is a lower-triangular Cholesky factor. The sampling procedure consists of three stages.

1. Correlation structure and unit-variance normalization. We draw a Cholesky factor $\boldsymbol{L}_c$ from an Lewandowski-Kurowicka-Joe (LKJ) distribution with shape parameter $\eta = 1$. This distribution has full support over correlation matrices and does not privilege any particular pattern of comovement ex ante. By construction,

$$\operatorname{diag}(\boldsymbol{L}_c\boldsymbol{L}_c^\top) = \mathbf{1},$$

which ensures that each narrative factor $f_{j,t}$ has unit variance. This normalization fixes scale and allows comparisons across narrative interpretations to reflect differences in comovement rather than arbitrary rescaling. The implied covariance matrix of the narrative factors is

$$\operatorname{Var}(\boldsymbol{f}_t) = (\boldsymbol{W}^\top\boldsymbol{W})^{-1} = \boldsymbol{L}_c\boldsymbol{L}_c^\top.$$

2. Uniform orientation. Conditional on a given correlation structure, we apply a random orthogonal re-orientation to ensure uniform exploration of the admissible rotation space. Specifically, we draw a matrix

$\boldsymbol{Z} \in \mathbb{R}^{K \times K}$ with independent standard normal entries, $Z_{ij} \sim \mathcal{N}(0, 1)$.

$$\boldsymbol{Z} = \boldsymbol{Q}\boldsymbol{R}_{\mathrm{qr}}, \tag{C.3}$$

and adjusting signs so that the diagonal elements of $\boldsymbol{R}_{\mathrm{qr}}$ are positive. This step removes any dependence on variable ordering or on a particular Cholesky factorization.

3. Rejection sampling under narrative restrictions. Narrative assumptions are expressed as inequality restrictions on the implied loading matrix,

$$\boldsymbol{H}\,\mathrm{vec}(\boldsymbol{\Gamma}) = \boldsymbol{H}\,\mathrm{vec}(\boldsymbol{\Lambda W}) \geq \boldsymbol{0}. \tag{C.4}$$

We reject all candidate rotations that violate these restrictions. Exact zero restrictions are imposed as soft constraints: among each block of 100,000 candidate draws that satisfy the inequality restrictions, we retain the 2% with the smallest ℓ_2 distance from the zero constraints. This procedure enforces approximate exclusion while preserving a broad set of admissible narrative interpretations.

D Additional results

The results in this section provide a deeper look into the robustness and interpretability of the narrative factors. Figure D.2 presents the *Identification Uncertainty*, or narrative entropy, for each of the five factors: Labor Demand, Labor Supply, Labor Wedge, Matching Efficiency, and the Kitchen Sink. This metric captures the average dispersion among the set of structural paths that satisfy our narrative restrictions at any given point in time. Higher values on the y-axis indicate periods where the narrative sign restrictions are less informative, allowing for a broader range of consistent structural interpretations, whereas lower values suggest the narrative constraints more tightly pin down the factor's path.

Figure D.3 shows the means for the narrative factors in the narrative feasible set for our baseline and four alternative specifications. The "BLS data only"specification is the one where we only include the 64 indicators published by the Bureau of Labor Statistics (BLS) or ones based on BLS data, including the those derived from Current Population Survey (CPS) microdata. The results for this specification are very similar to our baseline. But there are some periods where they diverge. This is mainly because our identifying restrictions include constraints on the factor loadings for the diffusion index for the share of small businesses that have increased wages over the past three months, published by the National Federation of Independent Businesses (NFIB). This indicator is useful for identification because it is a proxy for composition-adjusted cyclical wage increases. The 64 indicators in this specification get very close to the baseline specification, suggesting that the cross-sectional dimension in the baseline is larger than needed for identification of the narrative factors. "No data on match efficiency/mismatch" excludes measured matching efficiency and mismatch indicators, which depend on assumed elasticities of the matching function. The results excluding these two measures are virtually indistinguishable from our baseline. Hence, the assumptions made to construct these indicators had no material impact on our results.

The final two specifications include two different subsamples of the data. The first, “Post-2007 data,” only includes data from 2008 onwards. This sample includes only the Great Recession, since we do not use data from the Covid period for estimation of the Principal Component Analysis (PCA). This sample also has a relatively small time dimension compared to the number of indicators that we include. That makes the estimation of the covariance structure that is at the heart of the PCA relatively unreliable. The result is that, apart from the labor demand factor, the other factors are very different than in the baseline. The second, “Post-1993 data,” only includes data from 1994 onwards. Though, in this case the time dimension is much longer than the previous specification, this sample still only contains two recessions. It also has a hard time identifying the medium-run fluctuations in population growth and matching efficiency that are central to the baseline results because it does not yield data for the ’70s and ’80s when these fluctuations occurred.

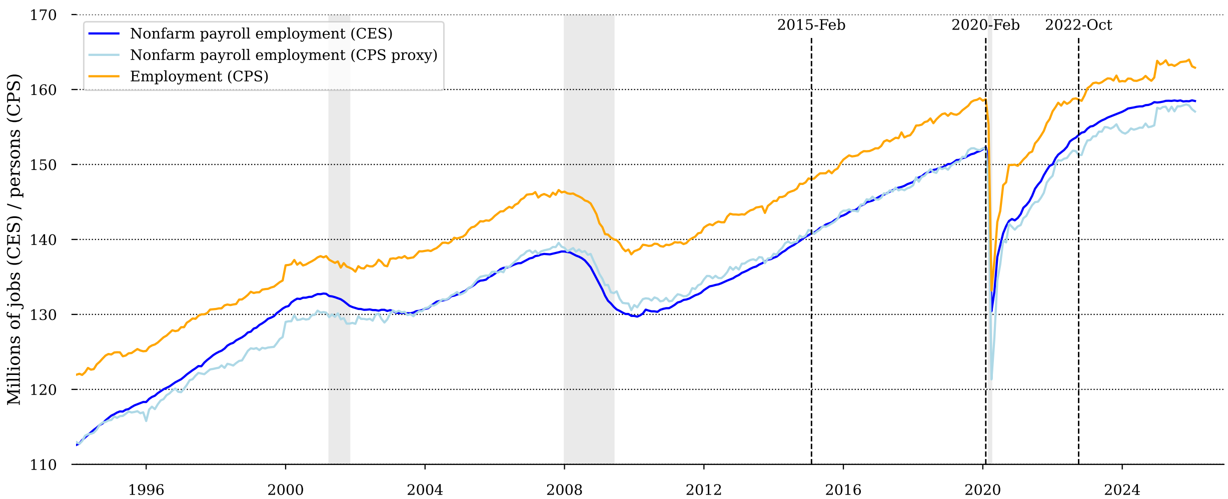
Figure D.4 displays the posterior distribution of correlations between the identified factors across all valid narrative rotations. To provide a benchmark for these results, the figure includes the LKJ prior distribution ($\eta = 1$) as a red dashed line, representing the agnostic starting point of our sampling procedure. The deviation of the blue shaded posterior from this prior illustrates how the narrative restrictions—rather than our initial assumptions—force specific patterns of co-movement between economic drivers to satisfy the observed data.

Figure D.5 quantifies structural labor market dynamics by estimating a VAR(1) for the estimated narrative factors in the narrative feasible set. To account for model and identification uncertainty, we utilize an ensemble identification approach. For each valid rotation matrix R in our ensemble, we examine the full set of recursive (Cholesky) orderings of the latent factors. We impose a structural hierarchy where *Labor Demand* is ordered first (most exogenous) and the *Kitchen Sink* factor is ordered last (most endogenous). The intermediate factors —*Long-Run Labor Supply*, *Short-Run Labor Supply*, and *Matching Efficiency*— are allowed to enter the recursive chain in all possible permutations.

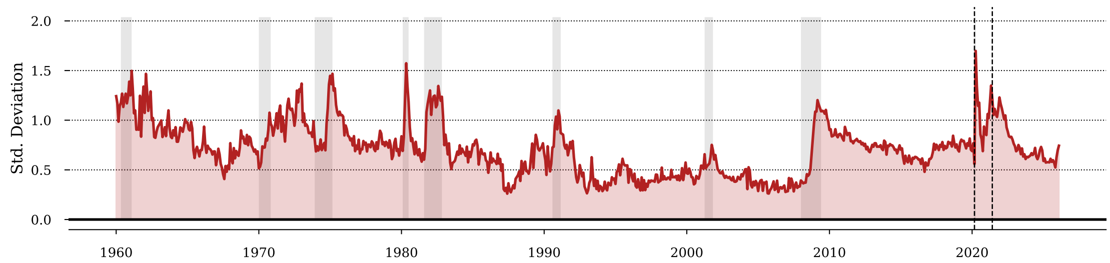
A candidate structural path is only accepted if the resulting impact matrix satisfies our narrative sign restrictions on the observed variables. The structural impulse response functions (IRFs) are then constructed by projecting these identified structural shocks back into the variable space using the factor loading matrix Λ and the corresponding rotation R. The distribution of the accepted impulse response functions is shown in Figure D.5.

Finally, Table D.1 provides a detailed *Identified Variance Decomposition* for the full suite of 94 macro-labor indicators. For each indicator, the table reports the percentage of its total variation attributed to each of the five narrative factors and a remaining residual component. This allows for a granular assessment of which economic forces drive specific indicators. For instance, the decomposition reveals the extent to which ”Job Openings” are driven by Labor Demand versus Matching Efficiency, or how much ”Average Hourly Earnings” are influenced by Labor Supply shifts.

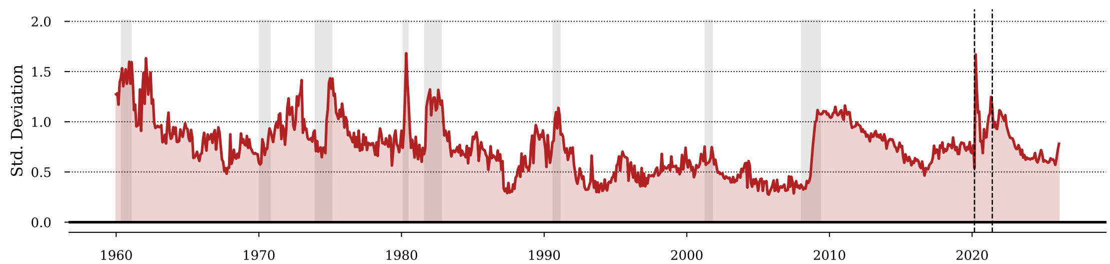
Figure D.1: Three measures of employment



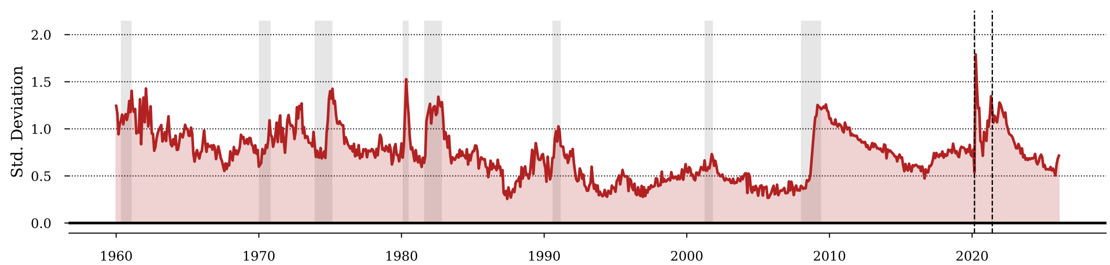
Note: Three employment concepts. Nonfarm payroll employment from the Current Employment Statistics, nonfarm payroll employment proxy based on data from CPS, and broad employment measure from CPS. Monthly observations; seasonally adjusted.
Source: BLS and authors' calculations.



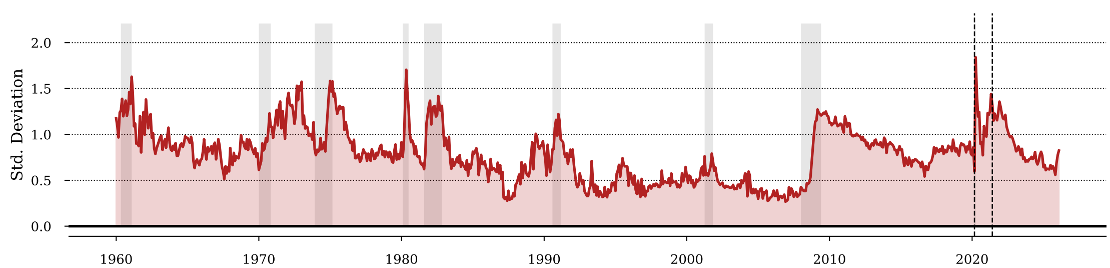
(a) Labor Demand



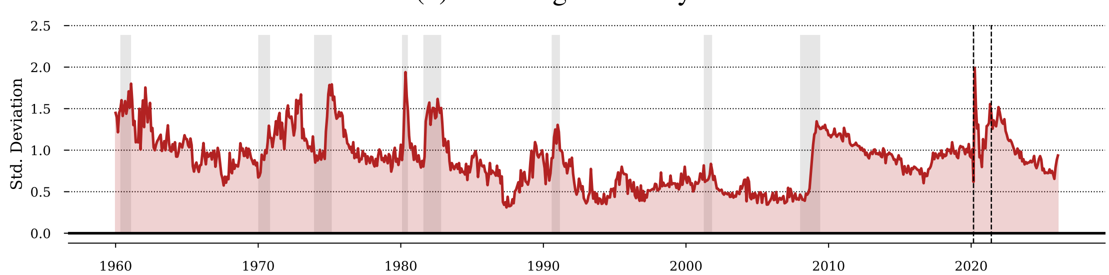
(b) Long-Run Labor Supply



(c) Short-Run Labor Supply



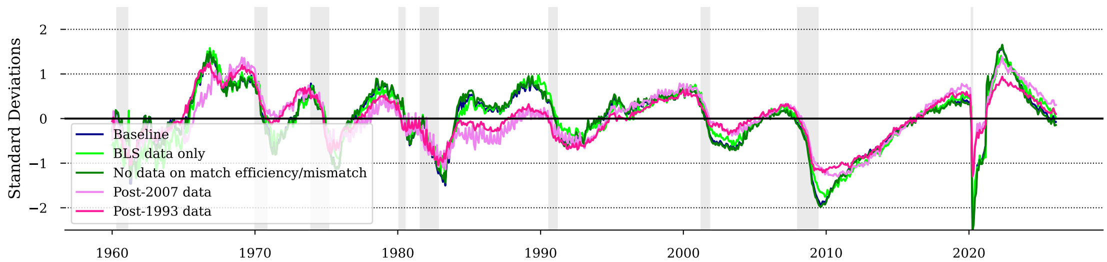
(d) Matching Efficiency



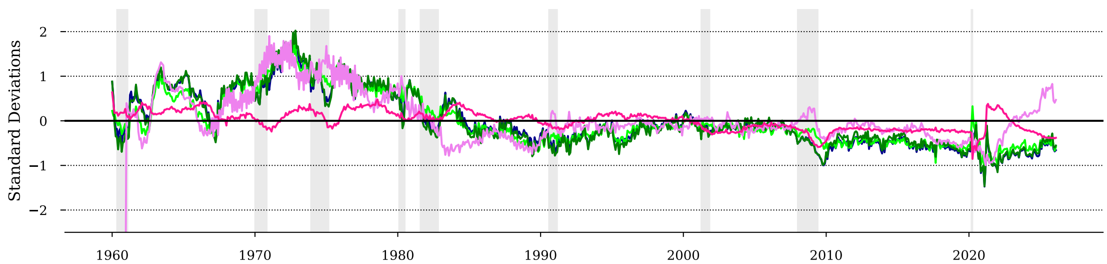
(e) Kitchen Sink

Figure D.2: Identification Uncertainty (Narrative Entropy)

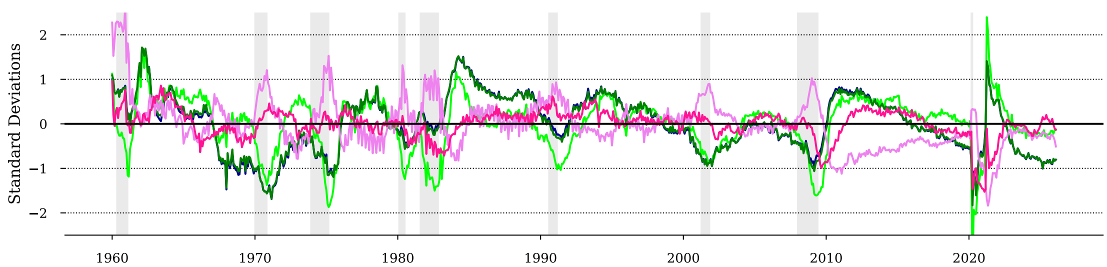
Note: This figure plots the *Identification Uncertainty* for each narrative factor. At each point in time, the value represents the average dispersion of the structural paths that satisfy the narrative restrictions. A higher value indicates a period of greater identification uncertainty (entropy), where the narrative signs are less restrictive in narrowing the set of consistent structural models. Shaded gray bars indicate NBER-dated recessions.
Source: Authors' calculations.



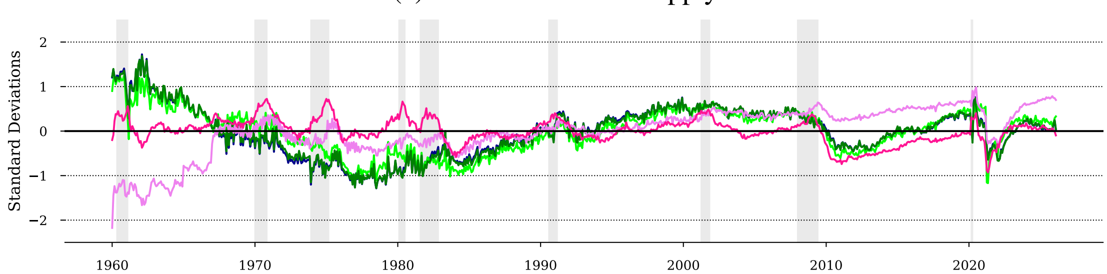
(a) Labor Demand



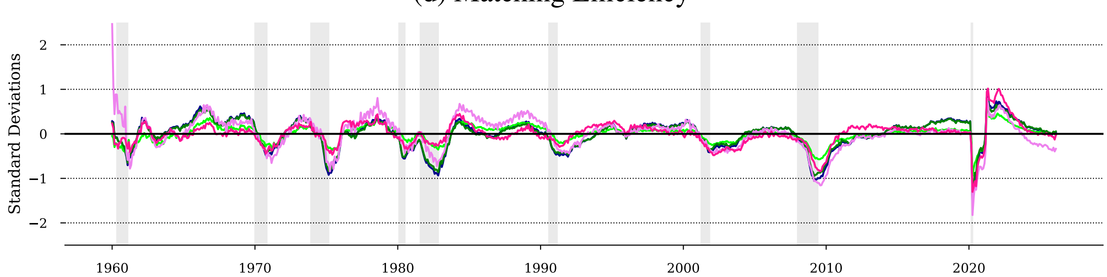
(b) Long-Run Labor Supply



(c) Short-Run Labor Supply



(d) Matching Efficiency



(e) Kitchen Sink

Figure D.3: Comparison of means of narrative factors across five specifications

Note: This figure plots the means for each narrative factor for the baseline specification in the main text and four alternative specifications. “BLS data only”: includes only the 64 indicators published by the BLS or derived from them or the underlying CPS microdata, “No data on match efficiency/mismatch”: Excludes measured matching efficiency and mismatch indicators, which depend on assumed elasticities of the matching function, “Post-2007 data”: Only includes data from Jan-2008 onwards, “Post-1993 data”: Only includes data from Jan-1994 onwards.
Source: Authors’ calculations.

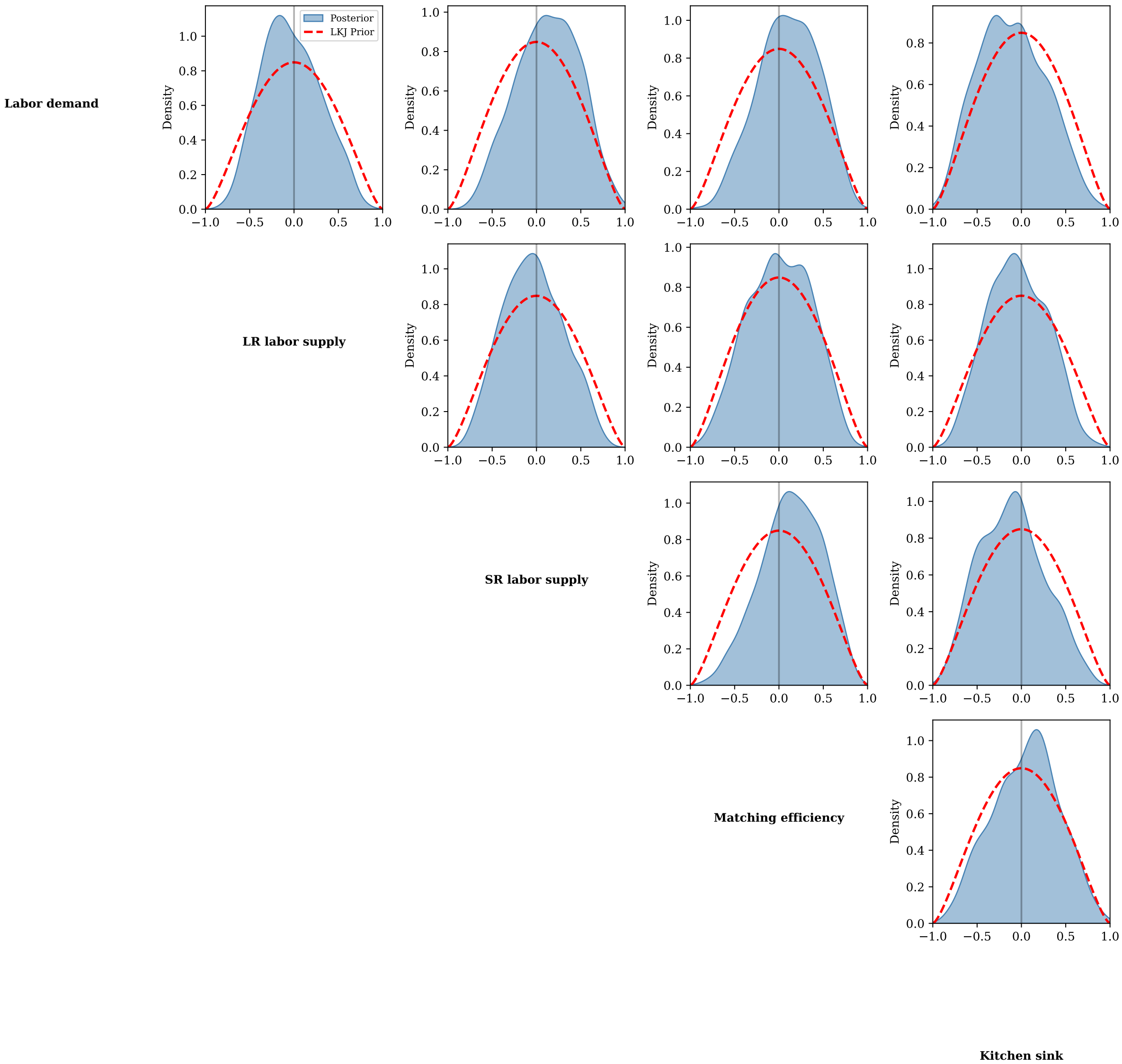


Figure D.4: Payroll growth revisions

Note: Distribution of correlations across factors across draws in the Narrative feasible set. The red dashed lines are the distribution of the correlations we sampled from using the LKJ distribution.
Source: Authors' calculations.

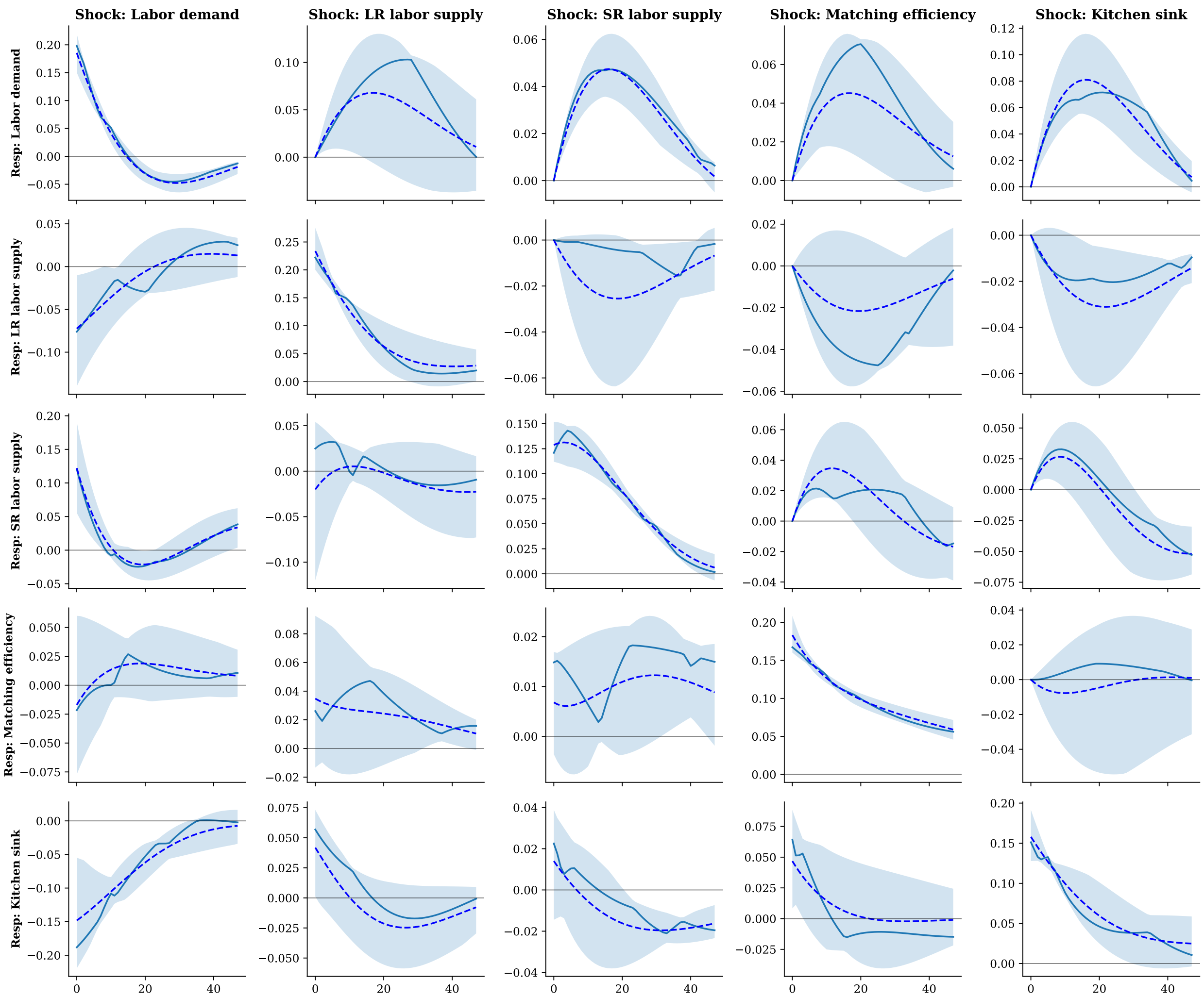


Figure D.5: Structural impulse response functions

Note: We still need an explanatory note here.
Source: Authors' calculations.

Table D.1: Identified Variance Decomposition (Percentage of Total Variation)

Indicator	Labor demand	LR labor supply	SR labor supply	Matching efficiency	Kitchen sink	Residual
Actual birth-death contribution (CES)	46.0	2.7	8.4	8.2	25.6	9.1
Aggregate Weekly Hours (CES)	19.7	6.4	32.4	11.2	23.0	7.3
Announced hiring (CGC)	15.3	3.7	3.4	8.5	7.3	61.9
Announced job cuts (CGC)	9.1	2.7	26.1	10.2	9.4	42.6
Attrition rate (Revelio)	20.5	4.6	39.4	14.9	14.6	6.0
Average hourly earnings	12.8	19.4	10.5	23.6	11.0	22.8
Average weekly hours – all employees (CES)	12.1	10.6	18.7	7.4	12.6	38.5
Average weekly hours – prod and non-sup (CES)	8.5	4.9	22.9	9.6	11.1	43.0
Average weekly wage (QCEW)	7.4	11.6	0.1	13.0	6.0	61.9
Broad unemployment rate (U6) (CPS)	51.5	5.5	19.5	4.1	18.0	1.5
Compensation (ECI)	31.0	6.3	1.3	5.8	13.3	42.4
Compensation per hour (P&C)	12.4	20.0	7.4	21.9	11.7	26.7
Composite Help-Wanted Index (Barnichon)	37.2	10.1	3.4	13.4	16.9	19.0
Covered payroll employment (QCEW)	29.3	6.0	21.6	12.0	19.7	11.3
EE flow rate (FRB Phi)	8.7	18.7	4.4	22.8	20.8	24.7
EPOP ratio (CPS)	29.8	3.4	23.0	11.7	21.5	10.6
EU flow rate (CPS)	26.1	10.8	17.2	11.0	27.3	7.6
Employment (Revelio)	33.5	8.7	18.8	13.7	17.5	7.8
Estimated match efficiency (Cobb-Douglas) (LMU)	5.3	3.5	4.3	3.8	4.4	78.8
Expectations about unemployment rate change (Umich)	6.0	4.5	20.5	9.3	12.6	47.0
Harmonized civilian noninstitutional population (FRBoG)	6.7	40.5	11.5	13.4	14.3	13.6
Hires rate (JOLTS)	25.1	10.0	1.6	18.7	29.9	14.7
Hiring rate (Revelio)	19.8	4.5	40.4	14.8	14.5	5.9
Hourly earnings at small businesses (Paychex)	47.9	12.4	-0.2	14.0	16.9	9.1
Hours worked nonfarm business sector (P&C)	17.7	6.9	32.8	12.6	20.7	9.3
Imputed birth-death contribution (CES)	30.0	14.4	6.3	12.7	15.9	20.7
Initial claims (DOLETA)	33.4	8.1	15.0	6.2	25.9	11.3
Job Openings (Revelio)	32.2	7.7	19.7	15.1	16.1	9.2
Job openings (Indeed)	28.8	6.0	29.1	16.3	15.1	4.7
Job openings (Lightcast)	15.9	3.0	8.0	14.8	6.1	52.3
Job openings rate (JOLTS)	60.2	7.0	5.1	3.7	20.6	3.4
Job quality index (SUNY Buffalo)	4.8	1.4	2.3	0.5	2.8	88.3
LF inflow rate (CPS)	16.1	8.4	19.3	4.9	9.0	42.2

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Table D.1: Identified Variance Decomposition (Percentage of Total Variation)

Indicator	Labor demand	LR labor supply	SR labor supply	Matching efficiency	Kitchen sink	Residual
LF outflow rate (CPS)	4.6	26.8	1.2	26.6	14.5	26.3
LFPR (CPS)	29.2	7.7	0.5	13.9	10.0	38.7
Labor market differential (jobs gap)	6.3	5.4	12.8	12.1	16.3	47.2
Labor shortage (NFIB)	53.9	3.9	8.4	0.9	20.4	12.5
Layoffs rate (JOLTS)	44.2	8.8	2.2	12.0	18.8	14.0
Long-term unemployment share (27 weeks or more) (CPS)	28.9	25.5	10.2	12.6	15.7	7.1
Manufacturing Employment Index (ISM)	10.2	14.8	14.4	14.3	21.8	24.5
Manufacturing hires rate (historical) (LMU+JOLTS)	35.1	9.5	5.6	4.0	16.9	28.9
Manufacturing layoffs rate (historical) (LMU+JOLTS)	14.8	15.5	8.0	18.5	25.3	17.9
Manufacturing quits rate (historical) (LMU+JOLTS)	42.0	15.7	6.5	6.5	14.3	15.1
Median duration of unemployment (CPS)	32.2	22.5	7.3	10.8	15.3	11.8
Median usual weekly earnings (CPS)	19.8	8.0	6.5	17.9	10.6	37.2
Mismatch (LMU)	33.3	4.3	7.7	7.1	26.3	21.2
Multiple job holders (CPS)	8.9	19.4	3.6	24.0	19.3	24.7
New Hires Quality (Upjohn)	7.5	12.7	13.4	8.4	13.6	44.3
Non-employment index (FRB Ric)	52.7	4.1	21.1	1.5	18.8	1.8
Nonfarm payroll employment (ADP)	16.0	5.1	22.8	12.8	10.8	32.4
Nonfarm payroll employment (CPS proxy)	35.0	3.6	14.3	7.8	23.9	15.3
Nonfarm payroll employment - current value (CES)	35.0	8.8	19.3	10.1	23.2	3.6
Nonfarm payroll employment - first release (CES)	35.6	7.8	17.6	8.2	21.5	9.2
Nonfarm payroll employment - post benchmark (CES)	35.3	8.7	18.9	10.1	23.4	3.6
Nonfarm payroll employment - second release (CES)	35.2	7.9	18.0	8.3	21.6	9.1
Nonfarm payroll employment - third release (CES)	35.0	7.9	18.0	8.3	21.5	9.3
Noninstitutionalized population	5.9	34.3	9.0	11.6	11.4	27.8
Part-time for economic reasons (CPS)	33.1	6.8	24.0	6.0	16.9	13.2
Participation Cycle (LMU)	33.6	3.1	10.7	6.7	23.4	22.5
Plans to increase employment (NFIB)	30.8	5.1	7.1	10.6	25.7	20.6
Positions not able to fill (NFIB)	44.3	7.6	13.9	2.0	23.2	9.0
Posted wages (Indeed)	0.1	5.5	43.8	21.2	9.5	19.9
Prevalence of zero wage changes (LMU)	12.5	9.9	22.5	22.7	11.9	20.4

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Table D.1: Identified Variance Decomposition (Percentage of Total Variation)

Indicator	Labor demand	LR labor supply	SR labor supply	Matching efficiency	Kitchen sink	Residual
Private households wage and salary workers (CPS)	18.1	10.6	6.6	15.1	8.5	41.2
Probability of losing job (Umich)	12.8	4.9	6.2	7.0	12.0	57.1
Quits rate (JOLTS)	50.2	8.7	-0.7	9.0	26.2	6.6
Salaries (Revelio)	0.6	2.1	1.0	1.3	0.8	94.1
Self employed (unincorporated) (CPS)	8.0	23.3	18.2	18.0	17.6	14.9
Services Employment Index (ISM)	11.3	8.7	16.3	11.0	22.8	29.9
Share of LF U job losers (CPS)	46.5	6.0	13.5	5.5	23.2	5.4
Share of LF inflows to E (CPS)	43.0	4.7	24.2	0.9	15.9	11.2
Share of LF outflows from E (CPS)	44.1	4.8	26.1	1.4	15.1	8.5
Share of labor force U Job leavers (CPS)	6.4	18.8	10.7	24.9	18.6	20.6
Share of laid off on temporary layoff (CPS)	23.2	14.2	13.8	10.3	11.1	27.4
Small Business Employment (Intuit)	2.6	3.0	36.7	12.0	7.6	38.0
Small business job growth (Paychex)	35.0	11.2	1.5	16.5	13.9	21.8
Small business share raising compensation (NFIB)	55.6	4.7	8.8	1.5	21.6	7.8
Staffing Index (ASA)	30.2	3.7	13.1	9.7	28.8	14.5
Temporary help employment (CES)	5.5	3.6	54.9	6.7	12.2	17.1
Temporary layoff outflow rate	25.0	6.1	5.4	3.2	10.3	50.0
UE flow rate (CPS)	40.9	14.6	10.3	6.8	17.6	9.9
Unemployment Rate - 20 Yrs. & Over, Women (CPS)	35.3	8.4	17.3	12.5	23.5	3.0
Unemployment Rate - Black or African American (CPS)	30.3	10.4	25.3	8.7	21.7	3.5
Unemployment Rate - Hispanic or Latino (CPS)	30.9	10.5	21.6	7.5	22.7	6.7
Unemployment inflow rate (s) (LMU)	8.8	26.7	9.3	22.7	24.6	7.8
Unemployment outflow rate (f) (LMU)	39.3	18.4	8.4	6.4	15.2	12.3
Unemployment rate (U3) (CPS)	40.5	6.4	18.1	9.6	24.0	1.4
WARN Act notices (FRB Cleveland)	13.3	9.8	15.9	22.1	16.7	22.1
Wage growth of job changers (ATL Fed)	44.5	12.1	-1.2	12.5	20.6	11.5
Wage growth of job stayers (ADP)	5.2	2.5	39.5	16.2	9.6	27.0
Wage growth of job stayers (ATL Fed)	36.6	11.5	8.8	13.6	17.0	12.5
Wage growth of job switchers (ADP)	6.7	1.0	13.7	10.8	5.0	62.9
Wages of new hires (Upjohn)	1.3	4.1	0.7	1.7	2.8	89.4
Workers with unpaid absences (CPS)	6.8	11.8	-0.6	8.8	10.3	62.9

Table D.2: Mean Factor Loadings

Indicator	Labor demand	LR labor supply	SR labor supply	Matching efficiency	Kitchen sink
Actual birth-death contribution (CES)	0.56	0.19	0.47	-0.29	0.56
Aggregate Weekly Hours (CES)	0.28	0.36	0.81	-0.20	0.63
Announced hiring (CGC)	0.43	-0.06	0.14	-0.69	0.23
Announced job cuts (CGC)	-0.22	0.16	-0.88	0.44	-0.42
Attrition rate (Revelio)	0.31	-0.03	0.86	-0.36	0.38
Average hourly earnings	0.52	0.31	-0.49	-0.59	0.01
Average weekly hours – all employees (CES)	-0.35	0.56	0.57	0.31	0.39
Average weekly hours – prod and non-sup (CES)	-0.40	0.21	0.76	0.16	0.30
Average weekly wage (QCEW)	0.34	0.33	-0.07	-0.43	0.10
Broad unemployment rate (U6) (CPS)	-0.83	-0.21	0.74	-0.23	-0.26
Compensation (ECI)	0.55	-0.18	-0.09	0.20	0.17
Compensation per hour (P&C)	0.45	0.36	-0.31	-0.47	0.01
Composite Help-Wanted Index (Barnichon)	0.82	0.27	-0.05	-0.43	0.46
Covered payroll employment (QCEW)	0.52	0.34	0.65	-0.38	0.63
EE flow rate (FRB Phi)	0.02	-0.09	0.85	0.60	0.20
EPOP ratio (CPS)	0.52	0.20	0.63	-0.41	0.61
EU flow rate (CPS)	-0.56	0.11	0.56	-0.21	-0.26
Employment (Revelio)	0.56	-0.03	0.57	-0.25	0.32
Estimated match efficiency (Cobb-Douglas) (LMU)	0.28	-0.10	-0.30	0.00	-0.10
Expectations about unemployment rate change (Umich)	-0.22	0.19	0.75	0.08	0.38
Harmonized civilian noninstitutional population (FRBoG)	0.10	0.65	-0.27	-0.13	-0.01
Hires rate (JOLTS)	0.34	-0.16	1.00	0.83	0.57
Hiring rate (Revelio)	0.30	-0.04	0.88	-0.36	0.38
Hourly earnings at small businesses (Paychex)	1.05	-0.10	-0.25	-0.47	0.15
Hours worked nonfarm business sector (P&C)	0.26	0.34	0.82	-0.33	0.61
Imputed birth-death contribution (CES)	0.51	-0.52	-0.25	0.29	-0.08
Initial claims (DOLETA)	-0.66	-0.02	0.49	-0.03	-0.34
Job Openings (Revelio)	0.54	-0.01	0.58	-0.39	0.32
Job openings (Indeed)	0.48	-0.00	0.69	-0.45	0.34
Job openings (Lightcast)	0.43	0.12	0.27	-0.76	0.20

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Table D.2: Mean Factor Loadings

Indicator	Labor demand	LR labor supply	SR labor supply	Matching efficiency	Kitchen sink
Job openings rate (JOLTS)	0.86	-0.09	-0.42	-0.48	0.28
Job quality index (SUNY Buffalo)	0.24	0.18	-0.23	0.05	0.14
LF inflow rate (CPS)	-0.64	0.38	0.88	0.53	0.05
LF outflow rate (CPS)	0.04	0.42	-0.09	-0.59	0.00
LFPR (CPS)	0.67	0.20	0.10	-0.49	0.30
Labor market differential (jobs gap)	-0.00	-0.36	-0.56	-0.45	-0.44
Labor shortage (NFIB)	0.89	0.07	-0.44	-0.17	0.38
Layoffs rate (JOLTS)	-0.76	-0.08	0.60	0.85	-0.24
Long-term unemployment share (27 weeks or more) (CPS)	-0.65	-0.43	0.34	-0.07	-0.13
Manufacturing Employment Index (ISM)	-0.06	0.34	0.44	-0.03	0.41
Manufacturing hires rate (historical) (LMU+JOLTS)	0.63	0.29	-0.14	-0.10	0.40
Manufacturing layoffs rate (historical) (LMU+JOLTS)	-0.22	0.07	-0.00	0.28	-0.29
Manufacturing quits rate (historical) (LMU+JOLTS)	0.73	0.36	-0.23	-0.18	0.35
Median duration of unemployment (CPS)	-0.66	-0.41	0.21	-0.11	-0.20
Median usual weekly earnings (CPS)	0.69	0.04	-0.57	-0.67	-0.06
Mismatch (LMU)	-0.52	-0.39	0.13	0.10	-0.50
Multiple job holders (CPS)	0.05	0.09	0.46	0.65	0.14
New Hires Quality (Upjohn)	-0.20	0.68	0.44	0.19	0.44
Non-employment index (FRB Ric)	-0.85	-0.25	0.80	-0.15	-0.29
Nonfarm payroll employment (ADP)	0.46	-0.15	1.08	-0.58	0.47
Nonfarm payroll employment (CPS proxy)	0.55	0.26	0.55	-0.15	0.64
Nonfarm payroll employment - current value (CES)	0.58	0.38	0.57	-0.34	0.64
Nonfarm payroll employment - first release (CES)	0.60	0.35	0.55	-0.28	0.61
Nonfarm payroll employment - post benchmark (CES)	0.58	0.37	0.57	-0.34	0.63
Nonfarm payroll employment - second release (CES)	0.59	0.35	0.56	-0.28	0.61
Nonfarm payroll employment - third release (CES)	0.59	0.36	0.56	-0.29	0.61
Noninstitutionalized population	0.14	0.60	-0.25	-0.16	0.03
Part-time for economic reasons (CPS)	-0.71	-0.17	0.70	-0.34	-0.23
Participation Cycle (LMU)	0.59	0.05	0.37	-0.09	0.54

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Table D.2: Mean Factor Loadings

Indicator	Labor demand	LR labor supply	SR labor supply	Matching efficiency	Kitchen sink
Plans to increase employment (NFIB)	0.58	0.11	-0.12	0.34	0.44
Positions not able to fill (NFIB)	0.86	-0.12	-0.64	-0.06	0.30
Posted wages (Indeed)	-0.43	-0.11	1.03	-0.78	0.28
Prevalence of zero wage changes (LMU)	-0.30	-0.10	0.70	-0.73	0.11
Private households wage and salary workers (CPS)	-0.64	0.01	1.17	1.16	0.17
Probability of losing job (Umich)	-0.27	0.32	-0.89	-0.17	-0.35
Quits rate (JOLTS)	0.68	-0.23	0.23	0.25	0.39
Salaries (Revelio)	-0.26	-0.26	0.37	0.15	0.01
Self employed (unincorporated) (CPS)	-0.13	0.40	0.56	0.37	0.14
Services Employment Index (ISM)	0.08	0.64	0.41	0.15	0.60
Share of LF U job losers (CPS)	-0.81	-0.14	0.45	-0.24	-0.36
Share of LF inflows to E (CPS)	0.86	0.06	-0.76	0.06	0.23
Share of LF outflows from E (CPS)	0.88	0.06	-0.79	0.11	0.20
Share of labor force U Job leavers (CPS)	-0.05	0.32	0.47	-0.55	-0.00
Share of laid off on temporary layoff (CPS)	0.61	0.24	-0.49	-0.04	0.02
Small Business Employment (Intuit)	-0.43	-0.01	1.37	-0.69	0.45
Small business job growth (Paychex)	-0.95	0.28	-0.14	1.00	-0.21
Small business share raising compensation (NFIB)	0.94	0.01	-0.49	-0.03	0.37
Staffing Index (ASA)	0.38	0.08	0.75	0.31	0.60
Temporary help employment (CES)	-0.15	0.30	1.42	0.03	0.62
Temporary layoff outflow rate	0.62	-0.23	-0.43	0.12	0.11
UE flow rate (CPS)	0.75	0.38	-0.29	0.29	0.33
Unemployment Rate - 20 Yrs. & Over, Women (CPS)	-0.71	0.13	0.66	-0.44	-0.22
Unemployment Rate - Black or African American (CPS)	-0.71	0.20	0.87	-0.27	-0.14
Unemployment Rate - Hispanic or Latino (CPS)	-0.70	0.19	0.79	-0.21	-0.17
Unemployment inflow rate (s) (LMU)	-0.03	0.41	0.36	-0.40	-0.06
Unemployment outflow rate (f) (LMU)	0.76	0.42	-0.31	0.09	0.29
Unemployment rate (U3) (CPS)	-0.77	-0.00	0.63	-0.38	-0.28
WARN Act notices (FRB Cleveland)	-0.31	0.11	-0.44	0.70	-0.36
Wage growth of job changers (ATL Fed)	0.67	-0.30	0.04	0.14	0.16

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Table D.2: Mean Factor Loadings

Indicator	Labor demand	LR labor supply	SR labor supply	Matching efficiency	Kitchen sink
Wage growth of job stayers (ADP)	-0.02	-0.07	0.98	-0.61	0.38
Wage growth of job stayers (ATL Fed)	0.62	-0.27	-0.36	0.20	-0.02
Wage growth of job switchers (ADP)	0.16	0.13	0.50	-0.64	0.29
Wages of new hires (Upjohn)	0.00	-0.40	0.06	-0.00	-0.17
Workers with unpaid absences (CPS)	0.15	-0.75	0.84	0.13	0.02

E Data details

We use a dataset of 94 macro-labor time series. Most of them are monthly and only a few quarterly. The sample covers the period from January 1960 to February 2026. Data are sourced from ADP, American Staffing Association, Atlanta Fed, Barnichon, Bureau of Labor Statistics, Challenger, Gray & Christmas, Cleveland Fed, Conference Board, Department of Labor Employment and Training Administration, Federal Reserve Bank of Philadelphia, Federal Reserve Bank of Richmond, Federal Reserve Board of Governors, Indeed, Institute for Supply Management, Intuit, LaborMarketUpdate.net, Lightcast, National Federation of Independent Businesses, Paychex, Revelio Labs, Self, University of Buffalo, University of Michigan, and Upjohn Institute and retrieved via ALFRED, Barnichon, BoG, FRED, Haver, LMU, LMU/JOLTS, Revelio, Self, and UMICH. Detailed transformation and sample metadata for each series are provided in Table E.1 below. More details about the data, as well as retrieval code, can be found in the replication files distributed with this article. For some series the mnemonic for the numerator is listed.The ratio is constructed from the ratio of that numerator and the appropriate denominator.

Table E.1: Dataset Overview and Variable Transformations

Label	Transf.	Start	End	Distributor	Code
Actual birth-death contribution (CES)	$y_{i,t}$	2009/03	2025/03	Self	actualbirthdeaths
Aggregate Weekly Hours (CES)	$100 \times \Delta_{12} \ln y_{i,t}$	1965/01	2026/02	FRED	AWHI
Announced hiring (CGC)	$100 \times \ln y_{i,t}$	2004/05	2026/02	Haver	CGCHTO@SURVEYS
Announced job cuts (CGC)	$100 \times \ln y_{i,t}$	1989/03	2026/02	Haver	CGCTO@SURVEYS
Attrition rate (Revelio)	$y_{i,t}$	2021/01	2026/02	Revelio	Web download
Average hourly earnings	$100 \times \Delta_{12} \ln y_{i,t}$	1965/01	2026/02	FRED	AHETPI
Average weekly hours – all employees (CES)	$100 \times \Delta_{12} \ln y_{i,t}$	2007/03	2026/02	FRED	AWHAETP
Average weekly hours – prod and non-sup (CES)	$100 \times \Delta_{12} \ln y_{i,t}$	1965/01	2026/02	FRED	AWHNONAG
Average weekly wage (QCEW)	$100 \times \Delta_{12} \ln y_{i,t}$	1976/01	2025/04	Haver	WW0TZ0@CEW
Broad unemployment rate (U6) (CPS)	$\ln y_{i,t}$	1994/01	2026/02	FRED	U6RATE
Compensation (ECI)	$100 \times \Delta_{12} \ln y_{i,t}$	2002/01	2025/10	FRED	ECICOM
Compensation per hour (P&C)	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2025/10	FRED	COMPNFB
Composite Help-Wanted Index (Barnichon)	$\ln y_{i,t}$	1960/01	2000/11	Barnichon	CHWI
Covered payroll employment (QCEW)	$100 \times \Delta_{12} \ln y_{i,t}$	1976/01	2025/06	Haver	EM0TZ0@CEW
EE flow rate (FRB Phi)	$y_{i,t}$	1995/10	2026/01	FRED	FMPSA
EPOP ratio (CPS)	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2026/02	FRED	CE16OV
EU flow rate (CPS)	$y_{i,t}$	1967/06	2026/02	FRED	LNS17400000
Employment (Revelio)	$100 \times \Delta_{12} \ln y_{i,t}$	2022/01	2026/02	Revelio	Web download
Estimated match efficiency (Cobb-Douglas) (LMU)	$100 \times \Delta_{12} y_{i,t}$	1961/02	2025/12	Self	matchefficiency
Expectations about unemployment rate change (Umich)	$100 \times \ln y_{i,t}$	1978/01	2026/02	UMICH	S30
Harmonized civilian noninstitutional population (FR-BoG)	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2025/05	BoG	pn16
Hires rate (JOLTS)	$y_{i,t}$	2000/12	2025/12	FRED	JTSHIL
Hiring rate (Revelio)	$y_{i,t}$	2021/01	2026/02	Revelio	Web download
Hourly earnings at small businesses (Paychex)	$100 \times \Delta_{12} \ln y_{i,t}$	2015/01	2026/02	Haver	LPXHE@USECON

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Table E.1: Dataset Overview and Variable Transformations

Label	Transf.	Start	End	Distributor	Code
Hours worked nonfarm business sector (P&C)	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2025/10	FRED	HOANBS
Imputed birth-death contribution (CES)	$y_{i,t}$	2004/12	2026/02	Self	imputedbirthdeaths
Initial claims (DOLETA)	$100 \times \ln y_{i,t}$	1967/01	2026/02	FRED	ICSA
Job Openings (Revelio)	$y_{i,t}$	2022/01	2026/02	Revelio	Web download
Job openings (Indeed)	$y_{i,t}$	2020/02	2026/02	FRED	IHLIDXUS
Job openings (Lightcast)	$y_{i,t}$	2020/01	2026/02	Haver	USBG@WEEKLY
Job openings rate (JOLTS)	$\ln y_{i,t}$	2000/12	2025/12	FRED	JTSJOL
Job quality index (SUNY Buffalo)	$100 \times \Delta_{12} \ln y_{i,t}$	1991/01	2025/12	Haver	JQI@USECON
LF inflow rate (CPS)	$y_{i,t}$	1967/06	2026/02	FRED	LNS17900000
LF outflow rate (CPS)	$y_{i,t}$	1967/06	2026/02	FRED	LNS17800000
LFPR (CPS)	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2026/02	FRED	CLF16OV
Labor market differential (jobs gap)	$y_{i,t}$	1967/02	2026/02	Haver	EFJN@CBDB
Labor shortage (NFIB)	$y_{i,t}$	1993/04	2026/02	Haver	NFIB21@SURVEYS
Layoffs rate (JOLTS)	$y_{i,t}$	2000/12	2025/12	FRED	JTSLDL
Long-term unemployment share (27 weeks or more) (CPS)	$y_{i,t}$	1960/01	2026/02	FRED	LNS13025703
Manufacturing Employment Index (ISM)	$y_{i,t}$	1960/01	2026/02	Haver	NAPMEI@USECON
Manufacturing hires rate (historical) (LMU+JOLTS)	$y_{i,t}$	1960/01	2025/12	LMU/JOLTS	historicallts
Manufacturing layoffs rate (historical) (LMU+JOLTS)	$y_{i,t}$	1960/01	2025/12	LMU/JOLTS	historicallts
Manufacturing quits rate (historical) (LMU+JOLTS)	$y_{i,t}$	1960/01	2025/12	LMU/JOLTS	historicallts
Median duration of unemployment (CPS)	$y_{i,t}$	1967/07	2026/02	FRED	UEMPMED
Median usual weekly earnings (CPS)	$100 \times \Delta_{12} \ln y_{i,t}$	1980/01	2025/07	FRED	LES1252881500Q
Mismatch (LMU)	$\ln y_{i,t}$	2001/02	2025/12	LMU	mismatch
Multiple job holders (CPS)	$y_{i,t}$	1994/01	2026/02	FRED	LNS12026619
New Hires Quality (Upjohn)	$100 \times \Delta_{12} \ln y_{i,t}$	2002/01	2026/01	Haver	NHQLV@USECON
Non-employment index (FRB Ric)	$y_{i,t}$	1994/01	2026/01	FRED	NEIM156SFRBRIC

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Table E.1: Dataset Overview and Variable Transformations

Label	Transf.	Start	End	Distributor	Code
Nonfarm payroll employment (ADP)	$100 \times \Delta_{12} \ln y_{i,t}$	2011/01	2026/02	Haver	LAXEPA@USECON
Nonfarm payroll employment (CPS proxy)	$100 \times \Delta_{12} \ln y_{i,t}$	1995/01	2026/02	Haver	LERSPCA@USECON
Nonfarm payroll employment - current value (CES)	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2026/02	FRED	PAYEMS
Nonfarm payroll employment - first release (CES)	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2026/02	ALFRED	PAYEMS
Nonfarm payroll employment - post benchmark (CES)	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2025/03	ALFRED	PAYEMS
Nonfarm payroll employment - second release (CES)	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2026/01	ALFRED	PAYEMS
Nonfarm payroll employment - third release (CES)	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2025/12	ALFRED	PAYEMS
Noninstitutionalized population	$100 \times \Delta_{12} \ln y_{i,t}$	1961/01	2026/02	FRED	CNP16OV
Part-time for economic reasons (CPS)	$y_{i,t}$	1960/01	2026/02	FRED	LNS12032194
Participation Cycle (LMU)	$y_{i,t}$	1978/12	2026/02	LMU	participationcycle12monthchange
Plans to increase employment (NFIB)	$y_{i,t}$	1973/10	2026/02	Haver	NFIB1@SURVEYS
Positions not able to fill (NFIB)	$y_{i,t}$	1973/10	2026/02	Haver	NFIB2@SURVEYS
Posted wages (Indeed)	$100 \times \Delta_{12} \ln y_{i,t}$	2020/01	2026/01	Haver	LIWTY@USECON
Prevalence of zero wage changes (LMU)	$y_{i,t}$	1986/10	2026/01	LMU	prevalenceofzerowagechanges
Private households wage and salary workers (CPS)	$y_{i,t}$	2000/01	2026/02	FRED	LNU02032190
Probability of losing job (Umich)	$y_{i,t}$	1997/12	2026/02	UMICH	S17
Quits rate (JOLTS)	$y_{i,t}$	2000/12	2025/12	FRED	JTSQUL
Salaries (Revelio)	$100 \times \Delta_{12} \ln y_{i,t}$	2023/01	2026/02	Revelio	Web download
Self employed (unincorporated) (CPS)	$y_{i,t}$	1960/01	2026/02	FRED	LNS12032192
Services Employment Index (ISM)	$y_{i,t}$	1997/07	2026/02	Haver	NMFEI@USECON
Share of LF U job losers (CPS)	$y_{i,t}$	1967/01	2026/02	FRED	LNS13025699
Share of LF inflows to E (CPS)	$y_{i,t}$	1967/06	2026/02	FRED	LNS17200000
Share of LF outflows from E (CPS)	$y_{i,t}$	1967/06	2026/02	FRED	LNS17600000
Share of labor force U Job leavers (CPS)	$y_{i,t}$	1967/01	2026/02	FRED	LNS13023705
Share of laid off on temporary layoff (CPS)	$y_{i,t}$	1967/01	2026/02	FRED	LNS13023653
Small Business Employment (Intuit)	$100 \times \Delta_{12} \ln y_{i,t}$	2016/01	2026/01	Haver	LINTA@USECON

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Table E.1: Dataset Overview and Variable Transformations

Label	Transf.	Start	End	Distributor	Code
Small business job growth (Paychex)	$100 \times \Delta_{12} \ln y_{i,t}$	2015/01	2026/02	Haver	LPXJ@USECON
Small business share raising compensation (NFIB)	$y_{i,t}$	1984/04	2026/02	Haver	NFIB19@SURVEYS
Staffing Index (ASA)	$100 \times \ln y_{i,t}$	2006/06	2026/02	Haver	ASASI@SURVEYS
Temporary help employment (CES)	$100 \times \Delta_{12} \ln y_{i,t}$	1991/01	2026/02	FRED	TEMPHELPS
Temporary layoff outflow rate	$y_{i,t}$	1978/12	2026/01	LMU	unemploymentoutflowratebyreason
UE flow rate (CPS)	$y_{i,t}$	1967/06	2026/02	FRED	LNS17100000
Unemployment Rate - 20 Yrs. & Over, Women (CPS)	$\ln y_{i,t}$	1960/01	2026/02	FRED	LNS14000026
Unemployment Rate - Black or African American (CPS)	$\ln y_{i,t}$	1972/01	2026/02	FRED	LNS14000006
Unemployment Rate - Hispanic or Latino (CPS)	$\ln y_{i,t}$	1973/03	2026/02	FRED	LNS14000009
Unemployment inflow rate (s) (LMU)	$y_{i,t}$	1960/02	2026/01	LMU	2stateinflowrate
Unemployment outflow rate (f) (LMU)	$y_{i,t}$	1960/02	2026/01	LMU	2stateoutflowrate
Unemployment rate (U3) (CPS)	$\ln y_{i,t}$	1960/01	2026/02	FRED	UNEMPLOY
WARN Act notices (FRB Cleveland)	$100 \times \ln y_{i,t}$	1996/07	2026/01	Haver	WARNW@USECON
Wage growth of job changers (ATL Fed)	$y_{i,t}$	1997/03	2026/01	FRED	FRBATLWGT3MMAUMHWGJMJSW
Wage growth of job stayers (ADP)	$100 \times \Delta_{12} \ln y_{i,t}$	2021/10	2026/02	Haver	LPAYJS@USECON
Wage growth of job stayers (ATL Fed)	$y_{i,t}$	1997/03	2026/01	FRED	FRBATLWGT3MMAUMHWGJMJST
Wage growth of job switchers (ADP)	$100 \times \Delta_{12} \ln y_{i,t}$	2021/10	2026/02	Haver	LPAYJC@USECON
Wages of new hires (Upjohn)	$100 \times \Delta_{12} \ln y_{i,t}$	2002/01	2026/01	Haver	NHQLE@USECON
Workers with unpaid absences (CPS)	$y_{i,t}$	2000/01	2026/02	Haver	ENMXWUA@EMPL