FULCRUM

US Employment: Breakevens, Benchmarking and Blindspots*

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US employment is a key indicator for financial markets and monetary policy, yet frequent and sizeable revisions make real-time assessment difficult. In this paper we develop a comprehensive framework for interpreting and nowcasting US labour market conditions, building on factor-model approaches to economic activity. We make three distinct contributions. Our first contribution is the construction of a real-time employment vintage database. We harmonise the three principal US employment sources and link them to a wide range of auxiliary indicators. The database preserves revision histories and enables a consistent comparison of vintages across surveys. Our second contribution is a factor-based model designed to handle revision uncertainty explicitly, while incorporating information from indicators spanning labour demand, labour supply, and slower-moving structural forces such as migration. The model delivers conditional projections of payrolls and the breakeven rate, and treats short- and long-horizon revisions in a consistent manner. Our third contribution is a set of empirical applications: estimating the US employment breakeven rate, automatic annual benchmarking, and addressing data blindspots. We estimate the current US employment breakeven at just under 100k jobs per month; expect roughly half of the initial QCEW benchmark revision to persist in the final data; and show that the recent federal government shutdown did not prevent reliable inference, owing to the availability of private-sector indicators. Based on initial vintages, we estimate a modest further softening in labour market conditions for the remainder of the year, with the US unemployment rate rising to 4.5% and flat payroll growth, in the initial vintages, and closer to 30k after benchmarking.

1. Introduction

US employment is a critical indicator for both financial markets and policymakers, yet it suffers from well-documented shortcomings, including frequent, substantial, and persistent revisions (Aruoba, 2008). As a result, no single indicator provides a reliable or timely measure of underlying labour market conditions. Although previous research has examined labour market news and data revisions separately, a comprehensive framework that unifies the two remains underdeveloped.

This paper addresses that gap by proposing a comprehensive framework for understanding and nowcasting US labour market conditions. Building on established approaches to activity nowcasting using factor models (Antolín-Díaz et al., 2017, 2024), we adapt and extend these methods to employment, providing a coherent structure for inter-

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preting labour market developments in real time. The framework is particularly relevant in the current policy environment, characterised by the Federal Open Market Committee's renewed focus on the full-employment side of its mandate, reduced reliability of official data releases, and the recent US federal government shutdown, which delayed both data collection and dissemination. Together, these factors underscore the importance of a systematic, model-based approach to monitoring US employment in real-time.

Three challenges motivate our approach. Firstly, measurement error is pervasive, as the primary survey-based indicators, including non-farm payrolls and the household survey, are subject to substantial and systematic revisions. To address this, we explicitly incorporate revision uncertainty in a tractable manner, allowing uncertainty to rise naturally for earlier data vintages. This facilitates the extraction of underlying measures of labour market conditions which are robust to short-term noise statistical noise and measurement error.

Second, the abundance of available labour market indicators makes inference difficult. Our framework integrates a broad range of indicators that inform both labour demand and supply, allowing the informational weights to adjust flexibly as new data arrive. This enables the model to isolate trend and cyclical components in employment while balancing the trade-off between timeliness and precision.

Third, structural forces, most notably migration, affect the level of employment but evolve more slowly than the cycle. We extend the framework to incorporate these factors, allowing for conditional forecasting exercises in which alternative assumptions about migration or other structural drivers imply different paths for employment and the breakeven rate.

The framework jointly models short-horizon (monthly) and long-horizon (annual) revisions, ensuring a consistent treatment of uncertainty over time and across surveys. It also accommodates periods when official reports are unavailable, but related private-sector indicators are observable, such as during government shutdowns, allowing labour market assessments to remain up to date. As a result, real-time updates can be produced immediately following new releases, yielding a continuously updated assessment of labour market conditions.

Our contributions are threefold. First, we construct a real-time employment vintage database, harmonising the three principal US employment sources, the Current Employment Statistics (CES), the Current Population Survey (CPS) and the Quarterly Census of Employment and Wages (QCEW). We link these to a broad set of auxiliary indicators. This includes harmonising definitions through time and preserving full revision histories, allowing consistent vintage comparison across surveys.

Second, we develop a factor-based model that treats revision uncertainty explicitly and pools information from indicators spanning labour demand, labour supply, and structural drivers such as migration. We implement a two-factor structure in which employment is decomposed into a slow-moving structural trend and a cyclical component. The model produces conditional projections of payrolls and the breakeven rate, and treats short- and long-horizon revisions in a consistent way.

Third, we present three applications: estimation of the US employment *breakeven rate*; automatic annual *benchmarking*; and addressing data *blindspots*. We define the current US employment breakeven as a natural corollary of the modelling environment and, after accounting for the slowdown in net migration between 2024 and 2025, estimate this is currently running just under 100k jobs per month. This breakeven level is consistent with alternative estimates and the evolution of the unemployment rate and other cyclical conditions this year. We find that roughly half of the initial QCEW benchmark gap is expected to persist in the final data, substantially less suggested by early benchmark models

Berger and Phillips (1993). Finally, we show that the recent federal government shutdown did not impair real-time inference, owing to the availability of private-sector indicators. Based on initial vintages, we estimate a modest further softening in labour market conditions for the remainder of the year, with the US unemployment rate rising to 4.5% and flat payroll growth, in initial vintages, and around 40k per month after benchmarking. Together, these applications demonstrate the framework's ability to deliver timely and internally consistent assessments of US employment, even in the absence of official data.

1.1. Related Literature

The literature directly addressing the joint treatment of US employment surveys and their measurement properties remains relatively limited. A number of studies have examined the statistical relationships across employment indicators, often at the state level, or have compared the Current Employment Statistics (CES) and Current Population Survey (CPS) measures of employment. Earlier work, for instance, explores discrepancies between the CES and CPS during cyclical turning points, such as the post-2001 recovery (Wu, 2004). Other contributions include labour market quantities within broader factor models of economic activity Antolín-Díaz et al. (2017, 2024). More recent work has also used private sector employment data to augment official statistics (Cajner et al., 2022, 2018) and shown that this can assist with early detection of turning points, particularly when incorporating higher-frequency weekly data (Cajner et al., 2023).

The closest contribution is Goto et al. (2023), who combine CES and CPS data to estimate an underlying employment factor. However, their approach places minimal weight on the CPS and assumes that all measurement errors are non-stochastic white noise. This contrasts with empirical evidence showing that revision processes in both surveys are serially correlated and themselves informative. Moreover, Goto et al. (2023) do not incorporate the long-run co-integrating relationship between the CES and the Quarterly Census of Employment and Wages (QCEW), which arises from the annual benchmarking procedure. Our framework instead models these revision dynamics and long-run linkages directly, allowing us to extract a more accurate measure of underlying employment.

We also build on the literature on data revision models (e.g., Berger and Phillips, 1993, 1994a,b; Brave et al., 2021) and from studies examining breakeven concepts and equilibrium labour market conditions (e.g., Bick, 2025; Bidder et al., 2016; Gregory and Bick, 2025; Petrosky-Nadeau and Stewart, 2024). Together, these strands of research inform our approach but have not been previously unified within a single framework for nowcasting quantities in the US labour market.

2. Data and Revisions

This section describes the data used in the construction of our US labour market nowcast. We use three primary sources of employment information: the Quarterly Census of Employment and Wages (QCEW), the Current Employment Statistics (CES) survey, and the Current Population Survey (CPS).

The QCEW is a comprehensive administrative dataset providing near-universal coverage of US establishments, encompassing approximately 10 million work sites. It serves as the benchmark for employment levels and is widely regarded as the most accurate measure of total employment. By contrast, the CES and CPS are survey-based measures released as part of the monthly employment report. The CES samples around 666,000 work sites (approximately 144,000 firms) to estimate payroll employment, while the CPS surveys roughly 60,000 households to capture individual labour force status.

As shown in Figure 1, the three employment series share a common long-term trend, consistent with co-integration across datasets (panel a), and trace the evolution of aggregate US employment over time. The discrepancies between series, or wedges (shown in panel b), reflect both sampling variability and conceptual differences in measurement.[1] The QCEW and CES measure employment at the establishment level, whereas the CPS captures the labour force status of individuals. Although the magnitude of these wedges has varied over time, they have tended to persist, partly due to definitional differences. For example the CES covers nonfarm payrolls while the QCEW includes all employment. The CES is periodically benchmarked to administrative data from the QCEW, whereas the QCEW itself is not subject to benchmarking revisions.

Across all three datasets, short-term volatility at the monthly frequency is substantial (Figure 1, panels c and d). The QCEW and CPS display the highest volatility, with standard deviations of monthly changes exceeding their mean, while the CES is comparatively more stable but still notably noisy. As a result, empirical analyses typically focus on medium-term changes, over 3- or 12-month horizons, to abstract from high-frequency fluctuations. Smoothing over these intervals yields considerably greater stability.

Revisions to the survey-based measures are large and systematic (Table 1). The CES, in particular, is typically revised upward, with final monthly change in non-farm payroll employment increasing by an average of roughly 17,000 relative to the initial vintage. These revision patterns underscore the importance of accounting for data uncertainty when interpreting short-term movements in employment.

Finally, survey response rates have declined markedly over the past two decades, with a particularly sharp deterioration since the Covid-19 pandemic (Figure 1, panel e). In the most recent data, response rates for the CES have fallen from around 60% to roughly 45%. Over the same period the CPS response rates have fallen from around 90% to roughly 70%. The CPS continues to achieve the higher level of participation among the two, while the CES has experienced the steepest and most persistent decline, with little evidence of recovery. For comparison, the UK's Labour Force Survey has faced similar challenges, with response rates dropping sharply in recent years despite renewed efforts to restore coverage (Lievesley, 2024). In the US context, the sustained decline in response rates has drawn increasing scrutiny (US Bureau of Labor Statistics, 2023), given its implications for data reliability, benchmark revisions, and the interpretation of near-term labour market developments.

The following subsections discuss each dataset in turn, highlighting their specific properties, sources of revision, and implications for modelling US labour market dynamics.

2.1. QCEW

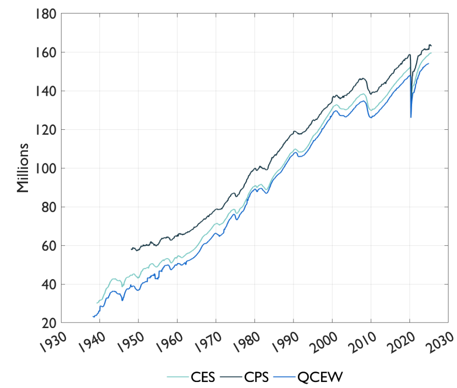
The Quarterly Census of Employment and Wages (QCEW) provides a comprehensive administrative measure of US employment and wages. Its origins date to the Social Security Act of 1935, which established the requirement for employers covered by unemployment insurance (UI) programs to report employment and wage data to state agencies. Earlier iterations of the series were published under the titles "Quarterly Employment and Wages" (QEW) and "ES–202". The QCEW thus constitutes the most detailed source of establishment-level employment information available for the United States, covering the universe of employers subject to UI taxation.

Historical QCEW data are available from the Bureau of Labor Statistics (BLS) and Haver Analytics until 1994 and were extended backward using archival information contained in annual BLS reports on unemployment insurance coverage. The differing vintages are displayed in Figure 2. The resulting series provides a consistent measure of employment from the 1930s to the present. Several

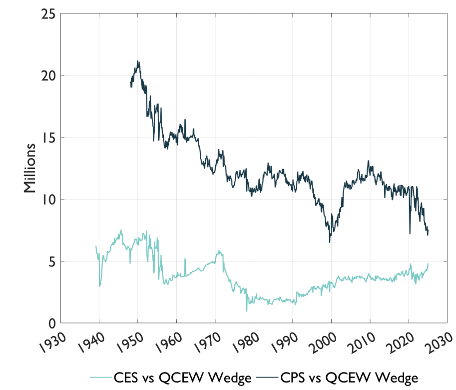
[1] We do not discuss the private-sector employment series produced by Automatic Data Processing (ADP) here. In that case, the wedge relative to other measures is larger, primarily due to the exclusion of government employees.

Figure 1: US Employment

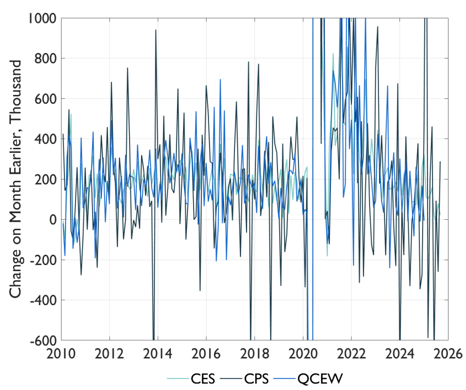
(a) US Employment Level



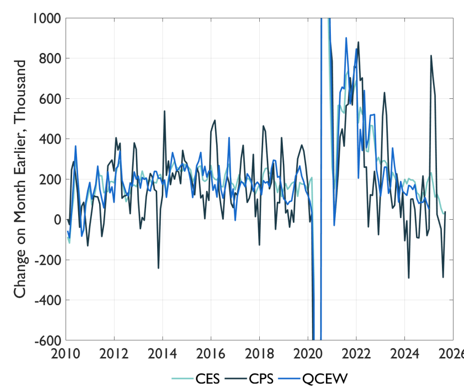
(b) US Employment Survey Wedge



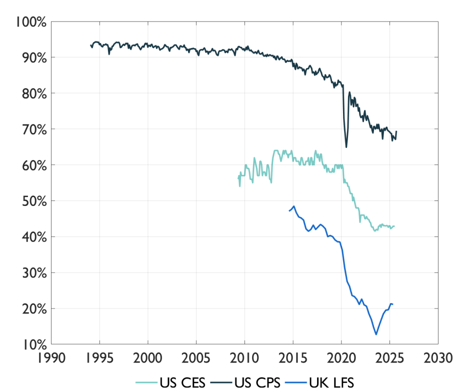
(c) 1 Month Change



(d) 3 Month Change



(e) Employment Survey Response Rates



Sources and Notes: Fulcrum Asset Management LLP, BLS and Haver Analytics. Figure shows level and change in US employment according to alternative measures. QCEW uses the definitional adjustments as discussed in the main text. CPS and CES are unadjusted data. December 11, 2025.

Table 1: CES and CPS Summary Statistics

	Establishment Survey (CES)					Household Survey (CPS)		
A. By Vintage	$\Delta E_{t,1}^{CES}$ Initial	$\Delta E_{t,2}^{CES}$ Second	$\Delta E_{t,3}^{CES}$ Third	$\Delta E_{t,b1}^{CES}$ Benchmark	$\Delta E_{t,L}^{CES}$ Latest	$\Delta E_{t,1}^{CPS}$ Initial	$\Delta E_{t,b1}^{CES}$ Benchmark	$\Delta E_{t,L}^{CES}$ Latest
Mean	120	125	136	137	139	125	125	131
Std. Dev.	190	197	202	196	196	350	316	304
Normalised	0.63	0.63	0.68	0.70	0.71	0.36	0.40	0.43
B. By Time Period	1 Month	3 Months	12 Months			1 Month	3 Months	12 Months
Mean	140	139	139			133	133	132
Std. Dev.	198	173	151			304	191	135
Normalised	0.71	0.81	0.92			0.44	0.70	0.98

Sources and Notes: Fulcrum Asset Management LLP. Table shows average monthly change in employment, in thousands, across alternative vintages (in panel A) and time period (in panel B) as published by the BEA. In panel A changes are single month. In panel B the latest vintages are used. Data from February 1961 until December 2019. Std. Dev. is the standard deviation while normalised values take the ratio of the average to the standard deviation. December 11, 2025.

major expansions in UI coverage, implemented in January 1956, January 1972, and January 1978, introduce discontinuities in the level of employment recorded in the administrative data. To address these, the series was normalised around these dates as well as the end of these quarters to remove mechanical increases in coverage which may enter directly or only as firms report at the quarter-end. This process ensures a consistent definition of employment across the historical sample.

To enhance comparability with the CES survey of non-farm payrolls, agricultural employment was excluded from the reconstructed QCEW series, while logging employment was retained, consistent with the CES definition. In addition, because the available administrative data are not seasonally adjusted, the series was seasonally adjusted prior to analysis to mitigate the influence of regular intra-annual variation. The final series is shown as a **thick black** line in Figure 2.

Although the formal benchmarking of the CES to the QCEW began in 1982, the QCEW and its predecessors were used in a more limited, sector-specific benchmark process as early as the 1940s. Consequently, while the extended series provides valuable historical context, it should be interpreted with caution prior to the institutionalisation of the benchmarking process in the 1980s.

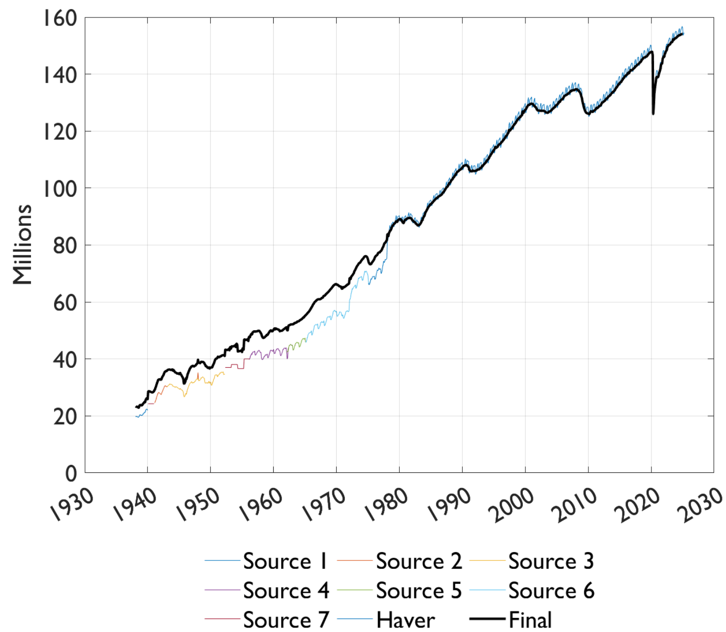
2.2. CES

The Current Employment Statistics (CES) program is a monthly survey of businesses that measures employment, hours, and earning and is commonly referred to as non-farm payrolls. It is the most widely cited indicator of US employment and, consequently, we will align employment definitions to be consistent with the CES.

CES data are subject to multiple rounds of revision. This process, and our notation, are outlined in Figure 3. In the months immediately following each release, $t+2$, $t+3$, revisions primarily reflect the incorporation of late survey responses. Establishments are permitted to submit their reports for up to three months after the initial collection period, so the first three vintages of any given release, denoted $E_{t,1}^{\text{CES}}$, $E_{t,2}^{\text{CES}}$ and $E_{t,3}^{\text{CES}}$ respectively, successively incorporate additional firm-level information as it becomes available. These short-term revisions therefore capture improvements in survey completeness rather than methodological changes.

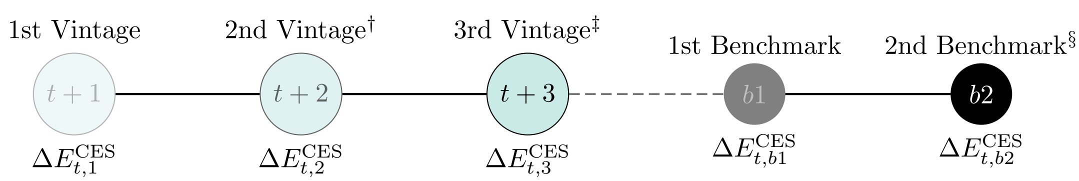
In addition to these near-term updates, the CES undergoes an annual benchmarking process designed to align survey-based estimates with the more comprehensive administrative data from the QCEW. This we denote as $E_{t,b1}^{\text{CES}}$ and $E_{t,b2}^{\text{CES}}$. This benchmarking exercise typically occurs each February, alongside the release of the January Employment Situation

Figure 2: QCEW Vintages



Sources and Notes: Fulcrum Asset Management LLP. Figure shows vintages of the QCEW data, backspliced to provide a consistent series (shown in the **thick black** line) after seasonally adjusting and accounting for adjustments in the Unemployment Insurance coverage. Historical QCEW source data are taken from archival publications. Sources 2 to 7 are taken from various successive quarterly volumes of Employment and Wages between 1950 and 1975 (US Bureau of Labor Statistics, 1950, 1952, 1963, 1972, 1974, 1975), retrieved from the University of Michigan digital repository. Source 1 is taken from the corresponding US Employment Service publication which pre-dated the BLS (US Employment Service, 1938). December 11, 2025.

Figure 3: Notation and Current Employment Statistics Revisions Process



Sources and Notes: Fulcrum Asset Management LLP. Figure shows a graphical representation of the vintage structure in the Current Employment Statistics Survey. t denotes the reference date. †First revision. ‡Second revision. §Non-seasonally adjusted data in January, February and March do not undergo a second benchmark revision. Text within circles represents the release dates. December 11, 2025.

Report, and revises the level of employment in the March vintage of the previous year. The procedure ensures that the CES remains consistent with the universe of employment covered by unemployment insurance records, though it can result in substantial revisions to previously published estimates. During the summer the BLS announces a preliminary estimate for the scale of this benchmarking revision.

The maturity of any given CES vintage therefore depends on the time elapsed since the initial release. The first vintage is published one month after the reference period, followed by second and third vintages over the subsequent two months as additional responses are incorporated. Only after the annual benchmarking are the data considered final for that year.

The revision process can also be illustrated graphically using data vintage matrices. Figure 4 depicts how successive CES vintages evolve over time. This Figure should be read horizontally, from left to right. Fixing a particular reference period date on the y-axis, each monthly release of CES data is typically revised twice in the following two months as additional survey responses are incorporated. Moving horizontally this is depicted in the diagram as a movement from the light teal dots to the **darker teal** dots, as in Figure 3. Subsequently, and potentially after a significant delay, the series remains unchanged until the next annual benchmarking exercise, at which point broader adjustments are applied to align the data with administrative sources. This is depicted in the Figure as the **grey** dots (for the first benchmarking) and **black** dots (for the second benchmarking). In contrast, the CPS does not undergo interim revisions. Instead, all benchmark revisions to the CPS are implemented simultaneously, with adjustments to the level of employment introduced in a single month as part of the annual revision cycle.

The revision process can also be illustrated using data vintage matrices. Figure 4 traces the evolution of successive CES releases over time. The figure is read horizontally. For any given reference month on the y-axis, each initial CES estimate is typically revised twice over the following two releases as additional survey returns are incorporated. Horizontally, this corresponds to the movement from the light teal to the **darker teal** dots (consistent wit the movement in Figure 3). Thereafter, the employment estimate generally remains unchanged until the next annual benchmarking exercise, when broader adjustments are made to reconcile the survey with administrative records. In the figure, these benchmark updates appear as the grey (first benchmark) and **black** (second benchmark) dots. In contrast, the CPS does not receive interim revisions. All benchmark adjustments are implemented at once, with level shifts introduced in a single month as part of the annual revision cycle.

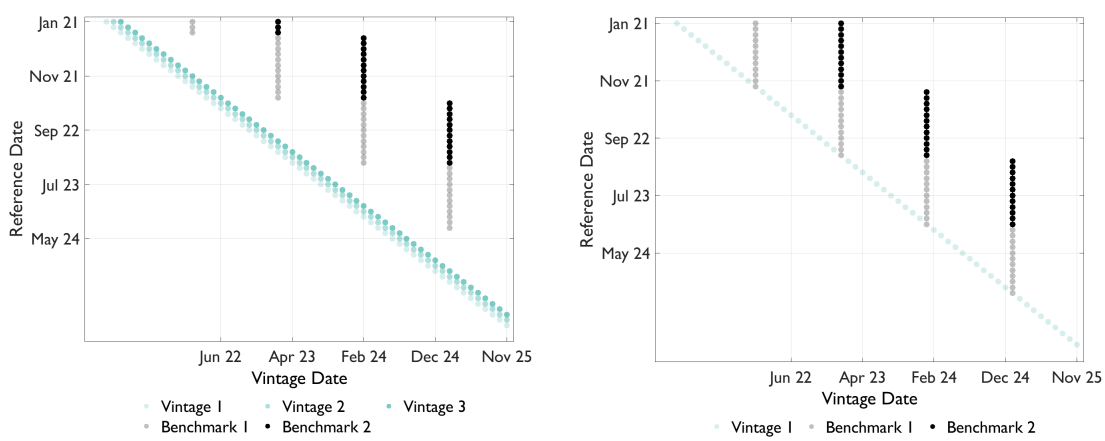
This release structure is analytically useful because it imposes a natural hierarchy on the precision of the data. Early vintages of the CES contain greater measurement error, as they rely on incomplete survey responses, whereas subsequent vintages incorporate additional information and therefore exhibit reduced noise. The benchmarked data, produced after reconciliation with unemployment insurance records, provide the most accurate representation of underlying employment and serve as the closest available approximation to the true level of non-farm payroll employment.

2.2.1 The Benchmarking Process

Each February, the BLS benchmarks the CES employment level to the QCEW and other auxiliary administrative sources. The benchmarking is performed in non-seasonally adjusted (NSA) so that the benchmarked CES March level coincides with the corresponding QCEW level on a consistent definition. The resulting difference between the March QCEW level and the pre-benchmarked CES March sample estimates is then distributed linearly across the preceding eleven months using a "wedge-back" procedure (US Bureau of Labor Statistics, 2025).

Figure 4: CES and CPS Vintage Matricies

(a) CES (b) CPS



Sources and Notes: Fulcrum Asset Management LLP, Haver Analytics. Figure shows example matrix of data vintages, highlighting the locations of data revisions used in the text. This figure is read horizontally. For any given reference month on the y-axis, the light teal dots denote the initial CES estimates, which are typically revised twice over the subsequent two releases as additional survey responses are incorporated, moving to the **darker teal** dots. Also see Figure 3. Thereafter, estimates generally remain unchanged until the annual benchmarking exercise, at which point broader adjustments are introduced to reconcile the survey with administrative records. These benchmark updates are shown as **grey** (first benchmark) and **black** (second benchmark) dots. By contrast, the CPS does not receive interim revisions (shown in panel (b) as all benchmark adjustments are implemented simultaneously, with the level shift applied in a single month. December 11, 2025.

Formally, if $E_{s,3}^{\text{NSA,CES}}$ denotes the initially published latest (typically third) monthly vintage of the NSA CES level for March of year s and $E_{s}^{\text{NSA,QCEW}}$ represents the NSA QCEW level for the same March, then the benchmark difference may be defined as:

$$w_s \equiv E_{s}^{\text{NSA,QCEW}} - E_{s,3}^{\text{NSA,CES}} \tag{1}$$

This wedge reflects the difference between the pre-benchmark CES level and the benchmark-consistent QCEW level.

The benchmark wedge, w_s is then distributed linearly across the preceding eleven months using the "wedge-back" procedure by adding a linear fraction to each month. The adjustment to the NSA CES level for month $s-k$, with $k = 0, 1, \ldots, 11$ is:

$$E_{s-k,b}^{\text{NSA,CES}} - E_{s-k,3}^{\text{NSA,CES}} = \frac{12-k}{12} w_s \tag{2}$$

This ensures the March level, corresponding to $k = 0$, is fully aligned, and the sum of the level adjustments over the twelve months is qeual to the size of the wedge itself:

$$\sum_{k=0}^{11} \tfrac{12-k}{12} w_s = w_s \tag{3}$$

This adjustment smooths the level shift introduced by benchmarking, effectively spreading one-twelfth of the total revision over each of the prior eleven months.

As focus will often be on the change in employment, it is useful to express the corresponding adjustment to the change in CES employment as:

$$\Delta E_{s-k,b1}^{\text{NSA, CES}} = \Delta E_{s-k,3}^{\text{NSA, CES}} + \tfrac{1}{12} w_{s-k}, \tag{4}$$

where Δ denotes a one period, monthly, change.

This process introduces a predictable mechanical pattern of serial correlation in measurement error, as revisions in one month are mechanically linked to revisions in adjacent months with a deterministic backward propagation. Accounting for this feature is essential when modelling underlying employment, as it allows more accurate inference about the true level of payroll employment. The NSA growth rates of months after the benchmarking date are left unaffected although seasonal factors are also simultaneously re-estimated over a five-year window.

2.3. CPS

The final principal employment series is the Current Population Survey (CPS), commonly referred to as the household survey. Unlike the establishment-based CES, the CPS is revised only once per year, when updated population controls are introduced following decennial or intercensal adjustments. Each February, these revised controls are incorporated into the January estimates, with the entire level change applied to that month (Di Natale, 2003). Consequently, monthly CPS estimates, including the unemployment rate, remain unrevised for the remainder of the year. This situation is displayed in Figure 4, panel b.

To ensure definitional comparability and harmonisation with the CES, the CPS requires several adjustments. Specifically, we remove agricultural workers, the unincorporated self-employed, unpaid family workers, and those on unpaid leave, while adding multiple jobholders. This aligns the CPS concept of employed persons with the CES concept of jobs. The BLS Research Series on Household Employment provides a smoothed, seasonally adjusted version of this adjusted CPS series, eliminating the discrete January level shifts associated with the annual population updates. Coglianese et al. (2025) provide an alternative method of smoothing these changes.

The BLS Research Series begins in January 1994, coinciding with the availability of data on multiple job holders. For earlier years, we follow BLS guidance in using the household survey measure of non-agricultural wage and salary employment as the closest proxy. This yields a consistent historical series, allowing for direct comparison across the

CPS, CES, and QCEW. The adjustment method originally developed by the BLS (Di Natale, 2003), though discontinued, continues to be implemented in the Haver Analytics database.

2.4. Remaining Data

In addition to the consistently defined measures of employment, we incorporate several auxiliary indicators intended to capture the cyclical dynamics of US labour market activity. These include the employment subcomponents of the Institute for Supply Management (ISM) surveys, key elements from the Job Openings and Labor Turnover Survey (JOLTS) such as the quits rate and vacancy rate, and initial claims for unemployment insurance, aggregated to a monthly frequency. We gather real-time vintages from ALFRED whenever available.

The initial claims data are further adjusted to address reporting gaps associated with recent federal government shutdowns. In the most recent weeks of the sample, not all states have reported claims data. Following the Haver Analytics methodology, we employ a bottom-up estimate that aggregates reported states and imputes values for non-reporting states by assuming constant levels relative to the latest available data. This adjustment ensures that the series remains timely and internally consistent even during temporary disruptions.

In addition, payroll employment data from the private sector firm Automatic Data Processing (ADP) is used to inform both the trend and cyclical components of employment. We extend this series back to 2001, beyond the commonly available post-2010 vintages, by incorporating historical vintages obtained from ALFRED.

3. Stylised Facts

3.1. Stylised Fact 1: CES Revisions Are Typically Upward

Revisions to employment data are generally positive, particularly for the CES series, as shown in Figure 5, panel a. On average, the monthly change in non-farm payrolls is revised upward by between 15,000 and 20,000 relative to the initial release. This difference is both economically and statistically significant over the full sample. These upward revisions primarily reflect the incorporation of late survey responses and the effects of annual benchmarking. Since 2019, the magnitude of these revisions has moderated somewhat, although benchmark adjustments continue to produce large positive level shifts. By contrast, the household survey (CPS) exhibits no systematic bias, shown in panel b, with mean changes across vintages statistically indistinguishable from zero.

3.2. Stylised Fact 2: No Distinct Monthly Pattern

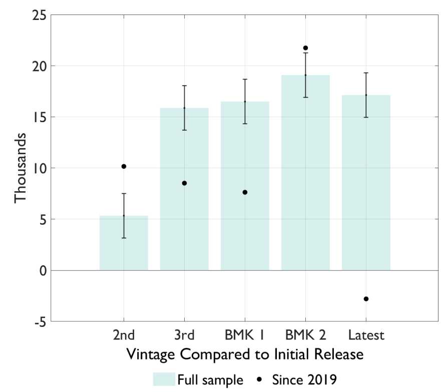
Contrary to common perception, revisions do not exhibit a consistent monthly pattern, as no single month is systematically associated with stronger or weaker employment reports of meaningful statistical significance. Across the twelve calendar months, average revisions fluctuate around zero, with most confidence intervals encompassing the null, as shown in Figure 5, panels c and d. A modest tendency toward downward revisions in mid-year months is observable but not statistically robust. Overall, the evidence suggests that monthly variation in revisions is largely idiosyncratic rather than seasonal.

3.3. Stylized Fact 3: Serial Correlation in Revisions

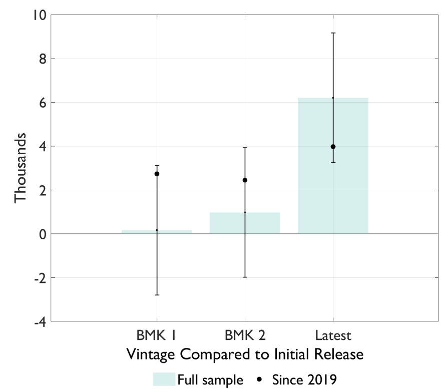
CES employment data revisions exhibit mild serial correlation, as shown in Figure 5, panel e. Positive revisions in a given month are often accompanied by upward revisions to adjacent months within the same data vintage, suggesting that information incorporated in later releases tends to shift several months of data in the same direction.

Figure 5: CES and CPS Revision Statistics

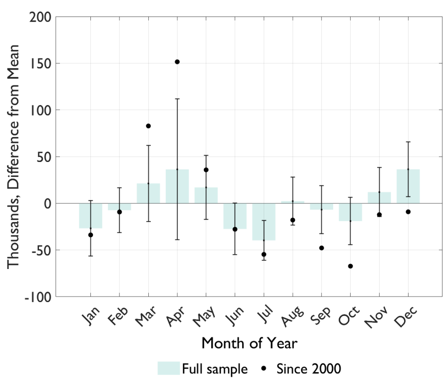
(a) Average Revision to Monthly Change in CES



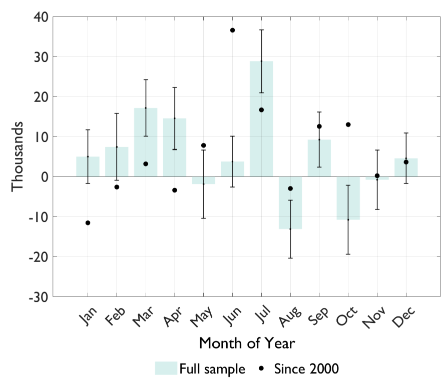
(b) Revisions to Monthly Change in US CPS



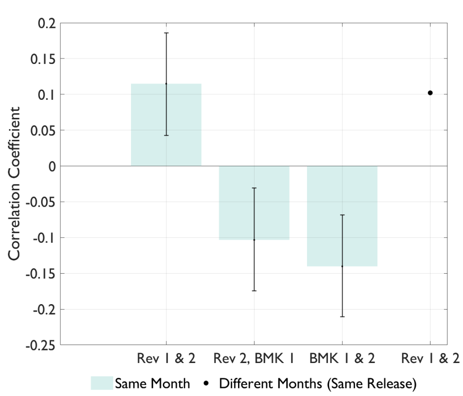
(c) Monthly Average CES Revision



(d) Monthly Average CPS Revision



(e) Correlation Between CES Revisions



Sources and Notes: Fulcrum Asset Management LLP. The bars represent mean changes while the whiskers show 1 standard error. December 11, 2025.

4. Model

To formalise the relationship between our US employment series, we initially define the QCEW as the reference, or "true" series. Given its comprehensive administrative coverage and its use as the target of the CES benchmarking process, it provides the best available approximation to the true level of employment. Conceptually, the QCEW combines a long-run trend in employment with a cyclical component reflecting fluctuations in labour market activity.

The post-benchmark CES series is aligned to the QCEW each year through the benchmarking procedure described in Section 2.2. After this adjustment, the CES can be regarded as a noisy proxy for the QCEW, differing by a time-varying wedge which captures residual discrepancies between the two sources. This wedge, denoted w_t, may reflect definitional differences, incomplete coverage, or other persistent sources of measurement error.

The first-, second-, and third-release vintages of CES employment incorporate additional sampling and non-response errors, denoted $\tilde{\eta}_{t,3}$, $\tilde{\eta}_{t,4}$ and $\tilde{\eta}_{t,5}$ respectively. These idiosyncratic errors are progressively eliminated following sequential data revisions. The CPS, after our adjustments to smooth and align with the CES definition described in Section 2.3, is treated as another noisy measure of the same underlying employment concept with it's own measurement error, $\tilde{\eta}_{t,6}$. This measurement error is assumed to be independent of the CES sampling process but shares the same definitional wedge due to our steps towards data harmonisation. As discussed in section 2, due to the small differences between series as a result of the second CES benchmarking process and revisions in the CPS series these vintage formulations are abstracted from. The model could easily be extended to incorporate these sources of uncertainty.

Finally, the level of payroll employment from the private sector Automatic Data Processing (ADP) services company is also assumed to track the true underlying level of employment. As ADP benchmark their series to ensure consistency with the CES this too is presumed to share a common time-varying wedge, w_t, alongside it's own definitional discrepancy and measurement error, $\tilde{\eta}_{t,7}$.

Together, these relationships imply the following system of observation equations:

$$E_t^{\text{QCEW}} = E_t^{\text{T}} + E_t^{\text{C}}, \tag{5}$$
$$E_{t,B}^{\text{CES}} = E_t^{\text{T}} + E_t^{\text{C}} + w_t, \tag{6}$$
$$E_{t,3}^{\text{CES}} = E_t^{\text{T}} + E_t^{\text{C}} + w_t + \tilde{\eta}_{t,3}, \tag{7}$$
$$E_{t,2}^{\text{CES}} = E_t^{\text{T}} + E_t^{\text{C}} + w_t + \tilde{\eta}_{t,3} + \tilde{\eta}_{t,4}, \tag{8}$$
$$E_{t,1}^{\text{CES}} = E_t^{\text{T}} + E_t^{\text{C}} + w_t + \tilde{\eta}_{t,3} + \tilde{\eta}_{t,4} + \tilde{\eta}_{t,5}, \tag{9}$$
$$E_{t,1}^{\text{CPS}} = E_t^{\text{T}} + E_t^{\text{C}} + w_t + \tilde{\eta}_{t,6}, \tag{10}$$
$$E_{t,1}^{\text{ADP}} = E_t^{\text{T}} + E_t^{\text{C}} + w_t + \tilde{\eta}_{t,7}, \tag{11}$$

where E_t^{T} denotes the unobserved "trend" component of employment, E_t^{C} the unobserved "cyclical" component. w_t denotes the persistent wedge between the level of employment in the CES, CPS and ADP surveys with the QCEW, and $\tilde{\eta}_{t,i}$ represent survey and vintage-specific persistent measurement errors.

To improve identification of the cyclical employment component, we incorporate additional labour market indicators, denoted z_t^i. These include both official variables, such as the monthly unemployment rate, and unofficial data, such as the employment subcomponent of the ISM index. Each of these variables load on the cyclical component according to:

$$z_t^i = a^i + \sum_{j=0}^{k} \lambda_j^i E_{t-j}^{\text{C}} + \eta_t^i. \tag{12}$$

where $k \geq 1$ represents the number of lags in the system.

Together, including these indicators enhances inference about cyclical conditions in employment, independently of longer term structural movements.

The unobserved components evolve according to a standard stochastic processes. The trend level of employment is taken to follow a local-linear trend specification, allowing for smooth but time-varying changes in the level of employment, for instance due to migration or structural shifts.. In contrast, the cyclical component and measurement errors follow autoregressive dynamics. These are described as:

$$E_t^{\text{T}} = \mu_{t-1} + E_{t-1}^{\text{T}} + \epsilon_{t,1}, \tag{13}$$
$$\mu_t = \mu_{t-1} + \epsilon_{t,2}, \tag{14}$$
$$E_t^{\text{C}} = \beta_3 E_{t-1}^{\text{C}} + \epsilon_{t,3}, \tag{15}$$
$$w_t = \alpha_4 + w_{t-1} + \epsilon_{t,4}, \tag{16}$$
$$\tilde{\eta}_{t,j} = \alpha_{j+2} + \beta_{j+2}\tilde{\eta}_{t-1,j} + \epsilon_{t,j+2}, \tag{17}$$

where $\epsilon_{t,i}$ are mutually uncorrelated, mean-zero disturbances with finite variance and $j \in \{3, \cdots, 7\}$. The remaining η_t^i measurement error terms are assumed to be independently and identically distributed errors.

For estimation, the system defined above can be expressed in the compact state–space form commonly used in the Kalman filter framework. Let $\mathbf{Y}_t$ denote the vector of observed variables and $\mathbf{X}_t$ the vector of latent states. The measurement (observation) and transition (state) equations are then given by:

$$\mathbf{Y}_t = \mathbf{A} + \mathbf{H}\mathbf{X}_t + \boldsymbol{\eta}_t, \tag{18}$$
$$\mathbf{X}_t = \mathbf{D} + \mathbf{F}\mathbf{X}_{t-1} + \boldsymbol{\epsilon}_t, \tag{19}$$

where $\boldsymbol{\eta}_t$ and $\boldsymbol{\epsilon}_t$ represent, respectively, the measurement and state disturbances. The corresponding vectors of observables, $\mathbf{Y}_t$, represents an $n \times 1$ vector of data:

$$\mathbf{Y}_t = \begin{bmatrix} E_t^{\text{QCEW}} & E_{t,B}^{\text{CES}} & E_{t,3}^{\text{CES}} & E_{t,2}^{\text{CES}} & E_{t,1}^{\text{CES}} & E_{t,1}^{\text{CPS}} & E_{t,1}^{\text{ADP}} & \mathbf{Z}_t \end{bmatrix}', \tag{20}$$

where an n_z subset, $\mathbf{Z}_t$, are data which load only on the cyclical components:

$$\mathbf{Z}_t = \begin{bmatrix} \text{U3}_t & \cdots & \text{ISM}_t \end{bmatrix}', \tag{21}$$

The unobserved state vector, $\mathbf{X}_t$, is of size $(9+k)\times 1$ and consists of the trend and cycle components as well as the measurement errors, described as:

$$\mathbf{X}_t = \begin{bmatrix} E_t^{\text{T}} & \mu_t & E_t^{\text{C}} & w_t & \tilde{\eta}_{t,3}\cdots\tilde{\eta}_{t,7} & E_{t-1}^{\text{C}}\cdots E_{t-k}^{\text{C}} \end{bmatrix}', \tag{22}$$

The matrices $\mathbf{A}$, $\mathbf{H}$, $\mathbf{D}$, and $\mathbf{F}$ impose the restrictions implied by the observation and state equations. The observation equation intercept vector, $\mathbf{A}$, is of size $n \times 1$, with the first 7 elements restricted to 0, as described to the functional forms described in equations (5) to (11), and the remainder unconstrained representing the a^i components of (12). The state equation intercept vector, $\mathbf{D}$, is of size $(9+k)\times 1$, and restricted to be zero except for positions 4 to 7, reflecting the functional forms described in equations (13) to (17).

The observation equation loading matrix, $\mathbf{H}$, of size $n \times (9+k)$, can be partitioned into the components which incorporate two key blocks: (i) a employment indicators block, of size $(n-n_z)\times(9+k)$ denoted $\mathbf{H}^{\text{ME}}$, which links survey vintages, which is stacked above (ii) a **cyclical influence** block, of size $n_z \times (9+k)$ denoted $\mathbf{H}^{\text{CI}}$, which links auxiliary indicators to the cyclical employment component. These matrices are defined as:

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}^{\text{EI}} \\ \mathbf{H}^{\text{CI}} \end{bmatrix} \tag{23}$$

$$\mathbf{H}^{\text{EI}} = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & \\ 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & \\ 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & \\ 1 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & \mathbf{0}_{n-n_z\times k} \\ 1 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & \\ 1 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & \\ 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & \end{bmatrix} \tag{24}$$

$$\mathbf{H}^{\text{CI}} = \begin{bmatrix} \mathbf{0}_{n_z\times 2} & \boldsymbol{\lambda}^0_{n_z\times 1} & \mathbf{0}_{n_z\times 6} & \boldsymbol{\Lambda}_{n_z\times k}, \end{bmatrix} \tag{25}$$

where $\boldsymbol{\lambda}^0_{n_z \times 1}$ and $\boldsymbol{\Lambda}_{n_z \times k}$ are matrices respectively containing the contemporaneous and lagged λ^i_j entries from equation (12).

Similarly, the state equation loading matrix, $\mathbf{F}$, of size $(9+k) \times (9+k)$, can be partitioned into the components which incorporate three blocks: (i) a **trend definition** block, of size $4 \times (9+k)$ denoted $\mathbf{F}^{\mathrm{TD}}$; (ii) a **measurement error** block, of size $5 \times (9+k)$ denoted $\mathbf{F}^{\mathrm{ME}}$; and (iii) a **cyclical influence** block, of size $k \times (9+k)$ denoted $\mathbf{F}^{\mathrm{CI}}$ where lags of the employment cycle are identified. Again, these matrices defined and stacked respectively as:

$$\mathbf{F} = \begin{bmatrix} \mathbf{F}^{\mathrm{TD}} \\ \mathbf{F}^{\mathrm{ME}} \\ \mathbf{F}^{\mathrm{CI}} \end{bmatrix} \tag{26}$$

$$\mathbf{F}^{\mathrm{TD}} = \begin{bmatrix} \begin{matrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \beta_3 & 0 \\ 0 & 0 & 0 & 1 \end{matrix} & \mathbf{0}_{4\times(5+k)} \end{bmatrix} \tag{27}$$

$$\mathbf{F}^{\mathrm{ME}} = \begin{bmatrix} \mathbf{0}_{5\times 4} & \mathrm{diag}\{\beta_5 \cdots \beta_9\} & \mathbf{0}_{5\times k} \end{bmatrix} \tag{28}$$

$$\mathbf{F}^{\mathrm{CI}} = \begin{bmatrix} \mathbf{0}_{k\times 9} & \mathbf{I}_k \end{bmatrix} \tag{29}$$

Finally, the disturbance term shocks, $\boldsymbol{\eta}_t$ and $\boldsymbol{\epsilon}_t$, of size $n \times 1$ and $(9+k) \times 1$ respectively, and are assumed to follow standard orthogonal processes:

$$\boldsymbol{\eta}_t \overset{\mathrm{iid}}{\sim} N(\mathbf{0}, \mathbf{R}_t), \tag{30}$$

$$\boldsymbol{\epsilon}_t \overset{\mathrm{iid}}{\sim} t(\mathbf{Q}_t), \tag{31}$$

where $\mathbf{R}_t$ and $\mathbf{Q}_t$ denote the covariance matrices of observation and state errors, respectively. In the baseline specification, both are treated as time-invariant but are estimated jointly with the model parameters. The use of a t-distribution for $\boldsymbol{\epsilon}_t$ allows for occasional large innovations. Both matrices $\mathbf{R}_t$ and $\mathbf{Q}_t$ are diagonal. The first $n - n_z$ diagonal elements of $\mathbf{R}_t$ are equal to 0 while the first last k diagonal elements of $\mathbf{Q}_t$ are also equal to 0. There are no fat tails assumed in the first two states.

The estimation algorithm is described in Appendix A.

5. Results

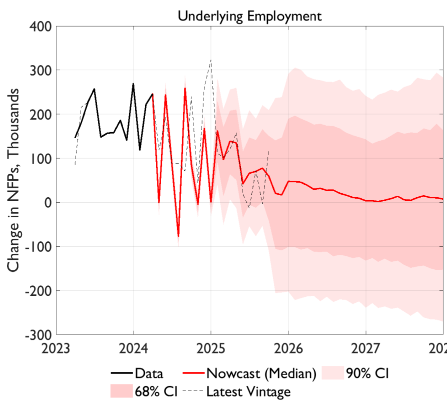
This section reports our main findings. The model extracts a positive but slowing underlying pace of overall US employment growth, as shown in Figure 6. Current single month underlying employment gains, defined as $\Delta E^{\mathrm{CES}}_{t,B}$, are modestly positive after accounting for revisions and the benchmarking process (shown in panel a), while three-month growth shows a similar, attenuated signal (shown in panel b). Uncertainty widens substantially beyond the latest observed release as vintages mature and benchmark adjustments are incorporated. When underlying employment growth is compared to the current vintage, shown as the dashed black lines in 6, panels (a) and (b), the underlying change in employment is slightly above the latest vintage on a 3-month basis, given the historical bias in employment revisions. Looking back over the past year the latest vintage of employment is estimated to have over-estimated employment gains early in 2025 which should be corrected as part of the annual benchmarking process. Prior to this, where a CES benchmarking has already been observed, the latest CES vintage largely coincides with the underlying level of employment as evidenced by the reduction in the credible set.

The model also implies an increase in labour market slack over the coming year as the unemployment rate is projected to move up toward 5%, a path that is above the FOMC's most recent projection for 4.5% by the end of 2025 and 4.4% by the end of 2026. Our projection is shown in 6, panel c, alongside a similar deterioration in broader measure of labour market slack, such as the $U6$ underemployment rate (shown in 6, panel d). This continues the gradual deterioration in measure of labour market slack seen since the Covid-19 rebound in 2022.

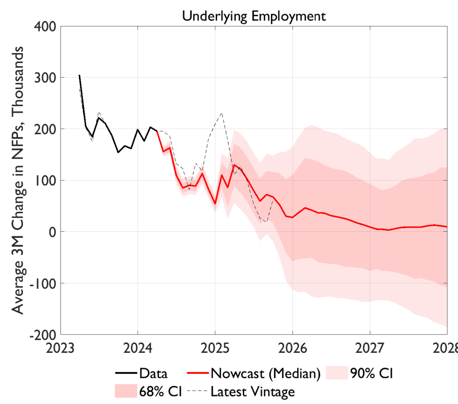
A second exercise decomposes the change in employment into its constituent model components. The results are shown in Figure 7. Panels (a), (c),

Figure 6: Employment and Unemployment Projections

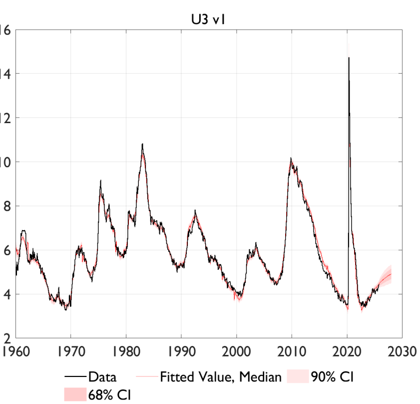
(a) Change in Underlying Employment, $\Delta E^{\text{CES}}_{t,B}$



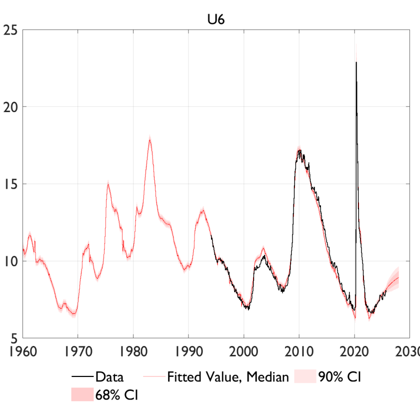
(b) Change in Underlying Employment, $\Delta^3 E^{\text{CES}}_{t,B}$



(c) Unemployment Fitted Value, $U3$



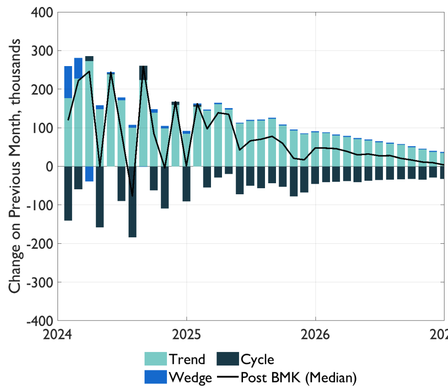
(d) Underemployment Fitted Value, $U6$



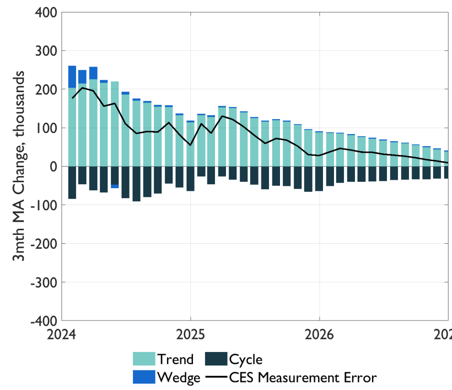
Sources and Notes: Fulcrum Asset Management LLP. Figure plots the median posterior estimates and credible intervals derived from the state-space model. The dotted series in panels (a) and (b) indicate the latest vintage of the data. December 11, 2025.

Figure 7: Employment Decomposition

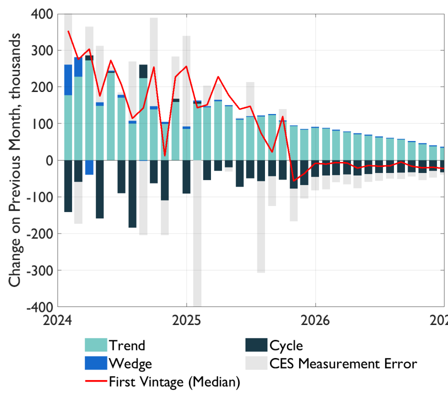
(a) Underlying in Employment, $\Delta E_{t,B}^{\text{CES}}$



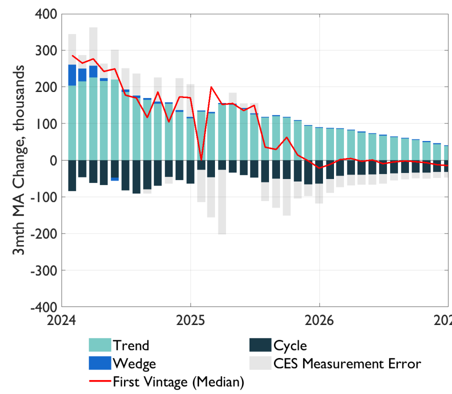
(b) Underlying in Employment, $\Delta^3 E_{t,B}^{\text{CES}}$



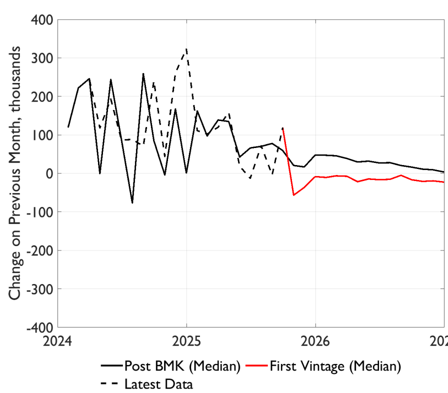
(c) First Vintage of Employment, $\Delta E_{t,1}^{\text{CES}}$



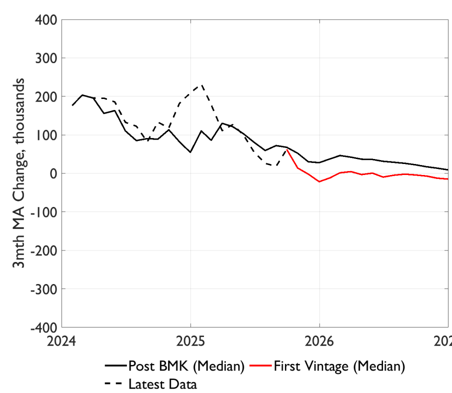
(d) First Vintage of Employment, $\Delta^3 E_{t,1}^{\text{CES}}$



(e) Different Employment Vintages



(f) Different Employment Vintages



Sources and Notes: Fulcrum Asset Management LLP. Figure plots the median posterior estimates and credible intervals derived from the state-space model. The dotted series in panels (a) and (b) indicate the latest vintage of the data. December 11, 2025.

and (e) plot the one month change in CES employment, while panels (b), (d), and (f) plot the three month change. Panels (a) and (b) decompose the median forecasted change in underlying employment into its three principal components: the trend, the cyclical factor, and the measurement wedge between post-benchmark CES and QCEW employment. From the end of 2025 onward, the contribution of the trend component gradually declines, reflecting demographic headwinds. Its contribution falls from roughly 105k today to about 50k by late 2026, shown by the teal bars. The cyclical component remains highly persistent, normalising only slowly from its current contribution of roughly −43k, shown by the **dark blue bars**. By contrast, the wedge component is small on average and expected to play only a limited role over the forecast horizon, shown by the light blue bars. Together, these three elements mechanically sum to the model's estimate of the change in underlying employment, shown by the **solid black** line.

Panels (c) and (d) incorporate measurement error across CES vintages by adding the cumulative CES measurement errors, shown as the grey bars. The mechanical sum of all components in each of these panels now equals the initial vintage of CES employment, shown by the **solid red** line. This alternative decomposition offers a clear interpretation of the monthly 119k initial CES employment gain in September 2025 as, within our framework, most of this increase reflects CES measurement error rather than a change in underlying trend or cyclical conditions.

Finally, panels (e) and (f) highlight that the underlying employment measure is systematically above the initial CES vintage over the projection period, consistent with the historical upward revision bias discussed in section 2. The gap between the underlying series (the **solid black** line) and the initial vintage (the **solid red** line) illustrates this pattern. By the end of 2026, our model anticipates that final benchmarked payrolls will show monthly gains of roughly 15k, with initial estimates expected to come in slightly below that level and possibly even negative.

The broader results of the state-space model are presented in Figure 8, which summarises the estimated paths of the three key unobserved states and their associated error variances. Panels (a) to (c) respectively display the level of trend employment, the change in the trend employment level and the cyclical component of employment. Several points are worth noting.

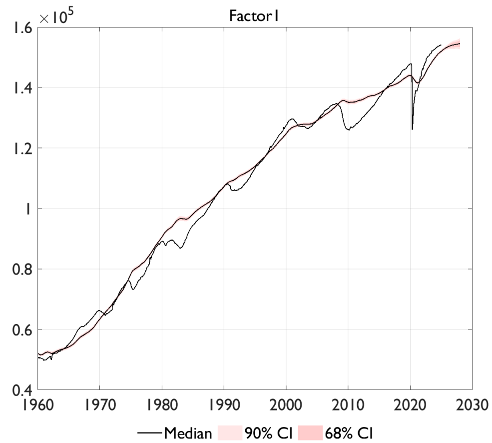
Panel (a) depicts the estimated underlying trend level of US employment, which closely tracks the QCEW benchmark series over the sample period. Panel (b) shows the month-to-month change in this trend, indicating a clear moderation in recent months as the pace of trend employment growth has declined well below 100k per month as the 2023/24 migration boost has faded. The variances of both the level and trend states are treated as non-stochastic.

The difference between the observed employment level and the estimated trend in panel (a) defines the cyclical component of employment, shown in panel (c). The cyclical factor remains mildly positive, suggesting that employment is still running somewhat above trend, but is now close to neutral (≈ 0). This gradual fading of cyclical support is weighing on monthly job gains, consistent with the decomposition of underlying employment growth, shown previously in Figure 6, panel (e). The variance of this cyclical component displays fat-tailed behaviour, with large volatility spikes around major economic events such as the Covid-19 pandemic, the Global Financial Crisis, and the early 1980s recession.

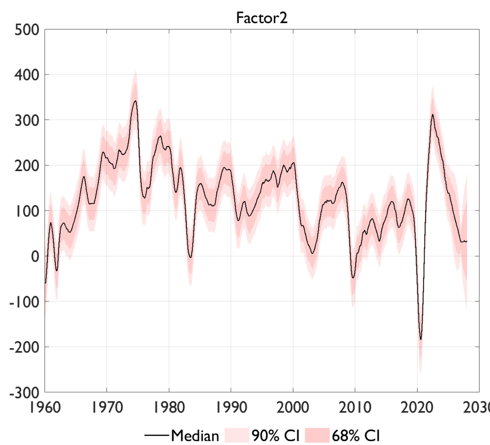
The remaining latent states capture various definitional wedges and measurement error processes, including between the benchmarked CES and QCEW employment levels and within the CES series (between the benchmark and earlier vintages). The variance of these CES wedges similarly display episodes

Figure 8: Model Estimates

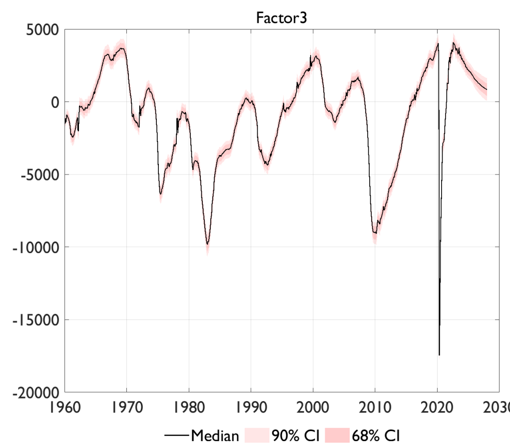
(a) Employment Trend



(b) Δ Employment Trend



(c) Cycle



Sources and Notes: Fulcrum Asset Management LLP. December 11, 2025.

of elevated volatility.

Overall, the unobserved state estimates suggest that the underlying trend in employment has slowed, the cyclical component has nearly normalised, and measurement errors, particularly during periods of macroeconomic stress, remain an important source of volatility in the employment data.

We estimate the model using Bayesian methods. Posterior estimates of the key model parameters are displayed in Table 2, alongside the corresponding priors. We estimate the state variables using the Kalman filter.

6. Applications

In this section, we consider three practical applications of the framework developed above. The first application explores how the model can be used to infer the *breakeven* rate of employment change, that is, the rate of job growth consistent with a stable unemployment rate, directly from the estimated components. The second application evaluates the model's performance in tracking and updating benchmark revisions to CES employment, comparing its behaviour to the canonical framework of Berger and Phillips (1993). The final application examines the use of the model to produce an *unofficial* employment report, for example, during a US government shutdown or other circumstances in which official data releases are delayed, but alternative model indicators remain available.

6.1. Breakeven

In this subsection, we compare our model estimates to the concept of the breakeven rate of employment growth. This measure has received renewed attention recently,[2] with most estimates now placing the breakeven rate between 0k and 50k (Bick, 2025; Cheremukhin, 2025; Edelberg et al., 2025; Mercan, 2025; Mericle and Rindels, 2025; Reinhart, 2025), as both supply and demand have fallen in tandem (Bengali et al., 2025). This range of breakeven estimates is consistent with the methodology used by the St. Louis Federal Reserve (Bick, 2025) and reflects a substantial decline from estimates earlier in the year (Gregory and Bick, 2025; Petrosky-Nadeau and Stewart, 2024).

The breakeven rate of employment growth is defined as the short-term change in employment required to keep the unemployment rate constant. It can be derived directly from basic labour force identities. The total labour force, L_t, is given as the sum of the employed, E_t, and the unemployed, U_t:

$$L_t \equiv E_t + U_t. \tag{32}$$

The unemployment rate is defined as $u_t \equiv \frac{U_t}{L_t}$. Taking first differences, the monthly change in the unemployment rate can be expressed as:

$$\Delta u_t = \frac{U_t}{L_t} - \frac{U_{t-1}}{L_{t-1}} = \left[1 - \frac{E_t}{L_t}\right] - \left[1 - \frac{E_{t-1}}{L_{t-1}}\right] \tag{33}$$

$$= \frac{E_{t-1}}{L_{t-1}} - \frac{E_t}{L_t}. \tag{34}$$

Setting $\Delta u_t = 0$ implies that the unemployment rate is constant, which allows us to define the ex-post monthly breakeven level of employment, E_t^{BE}, as:

$$\Delta u_t = 0, \tag{35}$$

$$\Rightarrow \quad E_t^{\text{BE}} \equiv \frac{L_t}{L_{t-1}} E_{t-1}, \tag{36}$$

$$\Rightarrow \quad E_t^{\text{BE}} = (1 + g_t) E_{t-1}, \tag{37}$$

where $g_t \equiv \frac{L_t}{L_{t-1}} - 1$ is the net labour force growth rate. Therefore, for the unemployment rate to remain constant, the level of employment (and equivalently unemployment) must grow at the same rate as the labour force, g_t. The breakeven rate of employment growth thus provides a useful threshold for

[2] For instance, Chair Powell discussed this at the September 2025 FOMC press conference, noting: "It's clearly come way down... You could say it's somewhere between 0 and 50k and you'd be right, or wrong." (Powell, 2025)

Table 2: Prior and Posterior Estimates

	Prior		Posterior		
	Parameter 1	Parameter 2	5th	50th	95th
a_8	5.85	0.52	5.08	5.34	5.61
a_9	49.8	2.27	49.8	50.0	50.3
a_{10}	2.01	0.22	1.97	2.07	2.16
a_{11}	11.2	2.89	12.1	12.8	13.5
a_{12}	351	43.1	311	326	342
a_{13}	0.12	1.00	0.10	0.18	0.26
a_{14}	9.99	1.37	9.21	9.65	10.1
a_{15}	1.35	0.28	1.25	1.34	1.44
a_{16}	62844	19931	64571	66007	67482
a_{17}	4565	608	4025	4212	4404
a_{18}	57.8	5.76	57.7	58.0	58.3
a_{19}	-4.87	9.36	0.25	3.60	6.83
λ_8^0	-0.64	0.13	-0.58	-0.51	-0.44
λ_9^0	3.55	0.56	2.08	2.17	2.26
λ_{10}^0	0.07	0.04	0.05	0.08	0.12
λ_{11}^0	1.25	0.62	1.81	1.89	1.97
λ_{12}^0	-0.10	0.01	-0.17	-0.17	-0.17
λ_{13}^0	1.46	0.25	1.35	1.42	1.50
λ_{14}^0	-0.81	0.26	-0.85	-0.77	-0.69
λ_{15}^0	-0.10	0.05	-0.23	-0.19	-0.14
λ_{16}^0	-15.8	3.89	-27.2	-26.9	-26.6
λ_{17}^0	-0.38	0.15	-0.32	-0.31	-0.30
λ_{18}^0	3.01	1.13	4.38	4.47	4.57
λ_{19}^0	0.01	0.00	0.00	0.00	0.00
α_4	-0.24	0.50	2.35	2.52	2.69
α_5	-3.76	0.50	-2.78	-1.87	-0.95
α_6	-14.1	0.50	-13.9	-13.7	-13.5
α_7	-19.7	0.50	-19.3	-18.9	-18.6
α_8	46.9	0.50	38.4	39.7	40.9
α_9	-8450	0.50	-1374	-1248	-1093
β_3	0.92	0.02	0.97	0.97	0.98
β_5	0.92	0.50	0.92	0.92	0.92
β_6	0.01	0.50	0.01	0.01	0.01
β_7	0.04	0.50	0.04	0.04	0.04
β_8	0.94	0.50	0.95	0.95	0.95
β_9	0.63	0.50	0.94	0.95	0.95

Sources and Notes: Fulcrum Asset Management LLP. Table shows prior and posterior estimates for the specified parameters. Prior parameter 1 is the mean of the normal distribution while prior parameter 2 is the standard deviation of the normal distribution. Posterior estimates represent 5th, 50th and 95th percentile of the model posterior estimates. Due to small values entries for λ_i^0 for $i \in \{8, 9, 10, 11, 13, 14, 15, 18\}$ have been multiplied by 1000. December 11, 2025.

assessing whether observed job gains are sufficient to prevent an increase in unemployment.

Following Gregory and Bick (2025), the change in the breakeven level of employment can be expressed in terms of population dynamics. Start from the identity defining the breakeven employment level. Using the definitions of $g_t \equiv \frac{\Delta L_t}{L_{t-1}}$ and $\frac{E_{t-1}}{L_{t-1}} = 1 - u_{t-1}$ we can rewrite (37) as:

$$E_t^{\mathrm{BE}} = (1 + g_t)E_{t-1}, \quad (38)$$

$$E_t^{\mathrm{BE}} - E_{t-1} = g_t E_{t-1}, \quad (39)$$

$$\Delta E_t^{\mathrm{BE}} = \Delta L_t \frac{E_{t-1}}{L_{t-1}}, \quad (40)$$

$$\Delta E_t^{\mathrm{BE}} = \Delta L_t (1 - u_{t-1}), \quad (41)$$

Next, rearranging the definition of the labour force participation rate, PR_t, the level of labour force may be written as $L_t = PR_t \cdot Pop_t$, where Pop_t is the chosen population base, usually the CPS civilian non-institutional population. First differencing gives:

$$\Delta L_t = PR_t \Delta Pop_t + Pop_{t-1} \Delta PR_t. \quad (42)$$

Combining (41) and (42) yields an exact expression for the change in the breakeven level of employment:

$$\Delta E_t^{\mathrm{BE}} = \big(PR_t \Delta Pop_t + Pop_{t-1} \Delta PR_t\big)(1 - u_{t-1}). \quad (43)$$

Finally, two assumptions are used to adjust the exact expressions. Firstly, monthly changes in the labour force participation rates as neglected, given that these are typically small and noisy. This assumption implies $Pop_{t-1}\,\Delta PR_t \approx 0$ and the exact expression in (43) simplifies to:

$$\Delta E_t^{\mathrm{BE}} = PR_t \Delta Pop_t (1 - u_{t-1}). \quad (44)$$

Finally, Gregory and Bick (2025) adjust the timing convention by replacing the beginning-of-period employment share $1 - u_{t-1}$ by the contemporaneous share $1 - u_t$, to give:

$$\Delta E_t^{\mathrm{BE}} = PR_t \Delta Pop_t (1 - u_t). \quad (45)$$

A wedge can be introduced to match the CES employment concept of jobs.

According to this measure of the employment breakeven rate, using the latest labour force participation and unemployment rates from the CPS together with population projections from the CBO, the breakeven level of employment growth has declined sharply from over 200k per month in 2024 to below 50k by the end of 2025. This is shown in Figure 9, panel (a). The main driver of this decline is the reversal in net migration. In 2024, net migration added around 175k per month to the breakeven, but this contribution is projected to fall to around 17k per month by the end of 2025, and to decline further through 2026. In contrast, the contribution from natural population change (births minus deaths) has remained comparatively stable and modest, implying that nearly all of the recent fall in the breakeven rate stems from the normalisation of migration flows.

In Figure 9, panel (b), the impact of recent revisions to the CBO's population estimates are shown. These revisions lower the overall pace of population growth, particularly from late 2025 into 2026, and consequently shift the timing of the peak in breakeven employment growth earlier while reducing its level at the end of 2025. Overall, slower population expansion translates directly into a lower breakeven rate of employment growth, as described in equation (45), consistent with the ongoing demographic drag on labour supply.

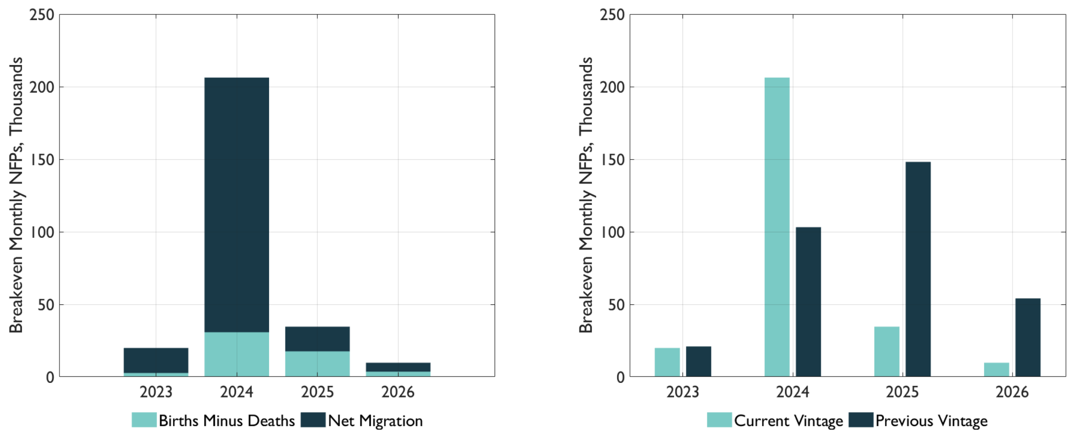
We can link this concept of the employment breakeven directly to our model framework described in section 4. In the state–space representation, cyclical conditions influence the unemployment rate, $\mathrm{U3}_t$, according to:

$$\mathrm{U3}_t = a_7 + \lambda_{7,1} E_t^{\mathrm{C}} + \lambda_{7,2} E_{t-1}^{\mathrm{C}} + \eta_{t,7}, \quad (46)$$

Figure 9: US Employment Breakeven Estimates

(a) Year-End Break Evens

(b) Benchmark CES Vintage



Sources and Notes: Fulcrum Asset Management LLP. December 11, 2025.

where E_t^{C} represents the cyclical component of employment, $\lambda_{7,1}$ and $\lambda_{7,2}$ capture the contemporaneous and lagged effects of the cycle on the unemployment rate, and $\eta_{t,7}$ is an idiosyncratic error term.

Taking expectations conditional on time t, forecasted changes in the unemployment rate depend on forecasted changes in the cyclical component:

$$\mathbb{E}_t[\Delta \mathrm{U3}_{t+1}] = \lambda_{7,1}\mathbb{E}_t[\Delta E_{t+1}^{\mathrm{C}}] + \lambda_{7,2}\mathbb{E}_t[\Delta E_t^{\mathrm{C}}] + \mathbb{E}_t[\Delta \eta_{t+1,7}]. \tag{47}$$

Therefore, within the model, the breakeven concept, defined as the rate of employment growth consistent with no change in the unemployment rate, corresponds to the condition:

$$\mathbb{E}_t[\Delta \mathrm{U3}_{t+1}] = 0. \tag{48}$$

That is, the unemployment rate is expected to remain constant when cyclical conditions are expected to exert no net effect on employment. Expressing this in terms of the employment cycle gives:

$$0 = \lambda_{7,1}\,\mathbb{E}_t[\Delta E_{t+1}^{\mathrm{C}}] + \lambda_{7,2}\,\mathbb{E}_t[\Delta E_t^{\mathrm{C}}] + \mathbb{E}_t[\Delta \eta_{t+1,7}]. \tag{49}$$

Given the cyclical state equation, (15), which takes a random-walk form, the breakeven condition implies that the expected cyclical component must be stable with:

$$\mathbb{E}_t[E_t^{\mathrm{C}}] = \mathbb{E}_t[E_{t-1}^{\mathrm{C}}] = 0. \tag{50}$$

Intuitively, when the employment cycle exerts no upward or downward pressure on job growth, the model predicts no systematic change in the unemployment rate, an internal definition of the breakeven rate consistent with the labour-force, based measure derived earlier.

The breakeven change in employment, when expressed in terms of the post-benchmark vintage of the CES employment concept, can therefore be written as:

$$\Delta E^{\text{BE}}_{t+1,B} = \mathbb{E}_t\left[\Delta E^{\text{T}}_{t+1} + \Delta w_{t+1}\right], \tag{51}$$

where $\Delta E^{\text{T}}_{t+1}$ denotes the expected change in the underlying trend component of employment, and Δw_{t+1} represents the expected change in the QCEW–CES wedge.

This expression shows that, within the model, the breakeven rate of employment growth corresponds to the expected change in employment that arises purely from structural (trend) forces and definitional adjustments between the CES and QCEW measures. In other words, when cyclical influences are neutral ($\mathbb{E}_t[\Delta E^{\text{C}}_{t+1}] = 0$), maintaining a constant unemployment rate requires employment to evolve only through its trend and measurement–wedge components. This is akin to the concept of the breakeven rate moving solely in response to population dynamics, as discussed earlier.

Finally, given current population growth estimates, discussed above, and their implications for the employment breakeven, we perform a conditional forecasting exercise in which the model is disciplined by externally imposed conditions on the future trend in employment growth. In the model $\mathbb{E}_t[\Delta E^{\text{T}}_{t+1}] = \mathbb{E}_t[\mu_{t+1}]$, where μ_t denotes the change in the trend component of employment. Population projections, discussed above, imply that by the end of 2026, the breakeven rate of employment growth should be approximately 30k per month. To incorporate this information, we augment the state-space system with an additional pseudo-observation that links the change in the trend component, μ_t, to this externally provided breakeven path.

Formally, we impose that the expected value of the trend in December 2026 equals 30k, but we introduce this as a soft constraint rather than a fixed equality. Specifically, the imposed observation is treated as being observed with uncertainty, such that:

$$\mu_{Dec2026} \sim \mathcal{N}(30\text{k},\, 15\text{k}^2), \tag{52}$$

allowing the model to deviate from the target within a plausible range (approximately between 0k and 60k). This conditioning approach allows the forecast to remain consistent with current demographic trends which then anchor the long-run trajectory of employment growth, but preserve flexibility in the short-run dynamics of the state-space model.

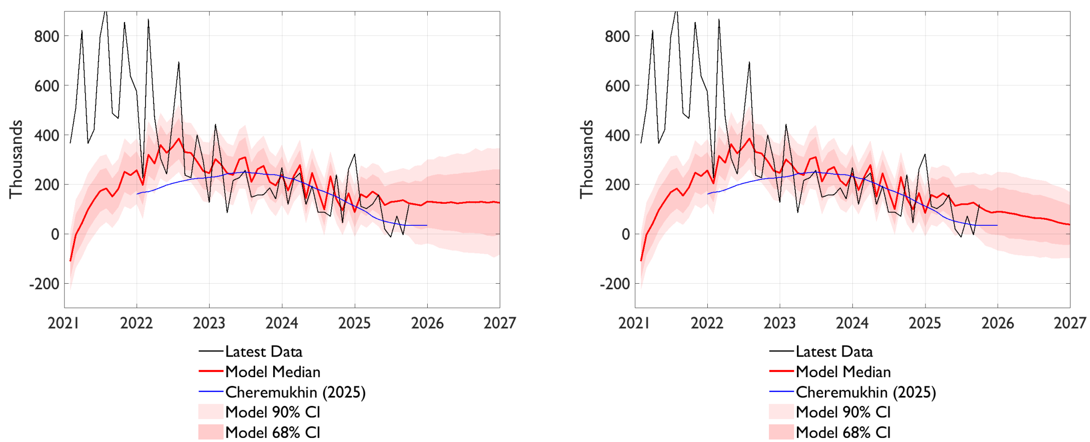
The impact of this exercise on the model's breakeven estimates is illustrated in Figure 10, which presents the estimated changes in the CES employment breakeven. Panel (a) displays the unconditional model estimates, while panel (b) shows the corresponding conditional estimates. Imposing the conditioning assumption lowers the estimated breakeven rate of employment growth, bringing it closer to external benchmarks, such as those reported by Cheremukhin (2025).

The effects of this conditional forecasting assumption are summarized in Table 3. Imposing the breakeven constraint lowers the projected monthly change in employment from an average of around 85k to approximately 50k by the end of the year. The conditioning assumption also affects earlier periods because the trend component, μ_t, is jointly estimated over the full sample, constraining its endpoint influences its inferred historical (smoothed) path. As a result, the estimated underlying monthly change in employment for previous months is also revised downward once the benchmarked CES payroll data become available.

In terms of implied three-month changes in nonfarm payrolls, the conditioning exercise reduces projected gains by similar amounts over the near-term forecast. The overall impact on the unemployment rate and the broader U6 underemployment measure, however, is minimal. For these variables the conditional forecasts differ by less than one tenth of a percentage point. This is, perhaps, expected as the

Figure 10: US Employment Breakeven Estimates

(a) Unconditional (b) Conditional



Sources and Notes: Fulcrum Asset Management LLP and Cheremukhin (2025). Figure shows the latest vintage of one-month changes in CES employment alongside estiamtes of the employment breakeven. December 11, 2025.

Table 3: Median CES Forecasts with Differing Conditions

	1 Month Change (NFPs)			3 Month Change (NFPs)			U3 Unemployment Rate		
	Latest	Unconditional	Conditional	Latest	Unconditional	Conditional	Latest	Unconditional	Conditional
31-May-2025	19	52	49	99	120	116	4.2	4.3	4.3
30-Jun-2025	-13	75	69	55	97	92	4.1	4.4	4.4
31-Jul-2025	79	78	74	28	68	65	4.2	4.4	4.4
31-Aug-2025	22	116	97	29	89	80	4.3	4.4	4.4
30-Sep-2025		91	56		93	74		4.5	4.4
31-Oct-2025		76	51		91	67		4.5	4.5
30-Nov-2025		99	68		85	57		4.5	4.5

Sources and Notes: Fulcrum Asset Management LLP. Table shows impact of conditional foreacasting on the underlying (after benchmarking) change in employment according to the CES survey. December 11, 2025.

conditioning directly targets the trend component of employment growth rather than its cyclical component, though indirect effects will arise across all unobserved states.

6.2. Benchmarking: Automatic Annual Revisions

A further application of the model relates to the annual benchmark revision process. Data from the QCEW are released with a lag and are incorporated into the CES with an additional delay, as discussed in section 2. Consequently, for a period of time, information about the forthcoming March benchmark is available but not yet reflected in the official CES estimates. Several studies have exploited this feature to recalibrate estimates of the current pace of monthly employment growth.

The canonical early benchmark models of Berger and Phillips (1993, 1994a,b) illustrate how this adjustment can be implemented within a simple framework. In their approach, the early benchmark estimate of employment, denoted EB_t, is defined as:

$$\ln EB_t = \begin{cases} \ln E_t^{\text{CES}}, & \text{if } 0 \le t < i, \\ \ln E_{i-1}^{\text{CES}} + \left(\ln E_t^{\text{QCEW}} - \ln E_{i-1}^{\text{QCEW}}\right), & \text{if } i \le t < j, \\ \ln E_{i-1}^{\text{CES}} + \left(\ln E_{j-1}^{\text{QCEW}} - \ln E_{i-1}^{\text{QCEW}}\right) + \left(\ln E_t^{\text{CES}} - \ln E_{j-1}^{\text{CES}}\right), & \text{if } j \le t, \end{cases}$$

where i denotes the first month following the previous benchmark revision, and j marks the first month for which QCEW data are unavailable.

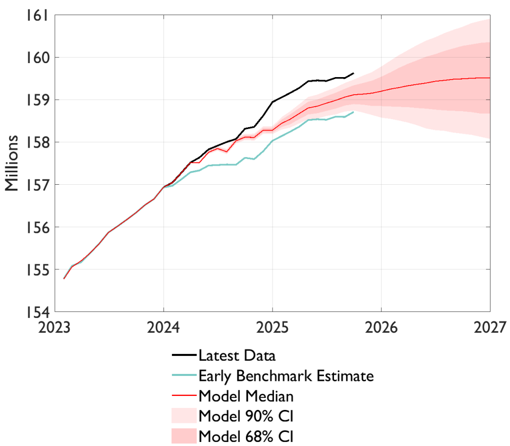
This specification ensures that the benchmarked CES values are used whenever possible. The implied growth rate of non-farm payrolls is therefore updated using QCEW data whenever these are available after a previous benchmark, and extrapolated using CES data once the QCEW series ends. In essence, this approach stitches together the two data sources, QCEW and CES, so that the most recent benchmark information is incorporated as soon as feasible while maintaining continuity in the level of the employment series.

A comparison between the data, the early benchmark model of Berger and Phillips (1993), and our own framework is presented in Figure 11. Panel (a) displays the level impact of the benchmark adjustment, while panel (b) shows its effect on the monthly change in employment. Overall, the early benchmark model implies a notably weaker path for payroll employment, with most of the downward adjustment concentrated in the first quarter of 2025. In contrast, our model generates a more moderate revision. Specifically, the post-benchmark CES employment implied by our framework suggests a smaller adjustment, at around half the magnitude of the Berger model estimate. Although the level of employment in early 2025 is still expected to be revised lower, the decline is less pronounced than would be implied by the purely mechanical growth rate adjustment. This reflects the fact that our model explicitly incorporates the CES to QCEW benchmarking wedge whenever QCEW data are available, allowing the estimated adjustment to evolve smoothly rather than mechanically, which is more consistent with the pattern of available vintages and auxiliary indicators.

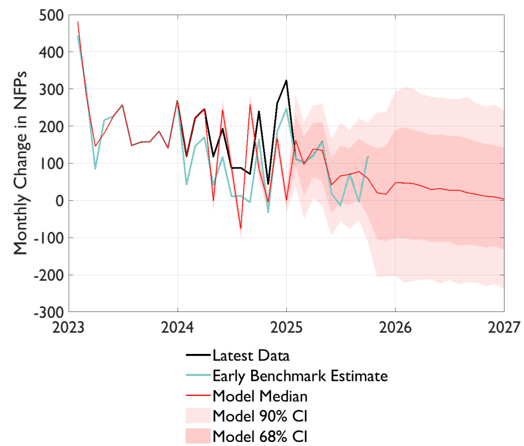
The Bureau of Labor Statistics (BLS) has announced that its preliminary, non–seasonally adjusted benchmark adjustment for March 2025 is expected to reduce the level of employment by approximately -911k. By comparison, the early benchmark estiamtes method suggests a difference of -692k in seasonally adjusted terms, with our framework anticipating a smaller final revision of around -563k. This difference is broadly consistent with patterns observed in recent years, shown in Figure 11, panel (c). In each of the past several benchmark cycles, the initial BLS estimate of the benchmark adjustment has subsequently been revised closer to zero. For example, the initial estimate for the 2024 revision was around -800k while the final revision settled near -600K. This recurring pattern reinforces confidence in our model's more moderate estimate, which lies between the current CES data vintage and the early benchmark projection of Berger and Phillips (1993).

Figure 11: Estimated Benchmarking Impact

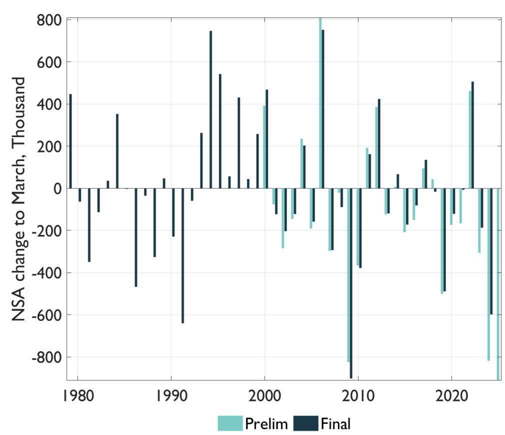
(a) US Employment



(b) Change in US Employment



(c) Official Benchmarking Revisions



Sources and Notes: Fulcrum Asset Management LLP, Haver Analytics, BLS. The chart shows the latest vintages of the Berger and Phillips (1993) early benchmark estimates for non-farm payrolls. The early benchmark model is represented in teal, while the median estimate from the full model is depicted in red. Panel (a) illustrates the level of employment, while panel (b) highlights the three-month change. Panel (c) shows how benchmarking estimates themselves have changed. December 11, 2025.

6.3. Blindspots: Unofficial Employment Report

Model forecasts are generated using the state-space representation defined in equations (18) and (19). As such, our forecasts are based on an incomplete information set available at the time of estimation. In November 2025, this information set included data from the monthly ADP employment report and initial claims releases for both October and November. The model projections are presented in Table 4, which shows that the forecasted increases in underlying employment for the delayed October and November reports were approximately 20k each, after the benchmarking adjustment. These projections imply a modest moderation in labour market conditions, consistent with the unemployment rate edging up toward 4.5% by the end of 2025.

The implications of these employment forecasts for the sequential revisions of the CES are summarised in Table 5. The table shows how successive vintages of the one-month change in CES employment are expected to evolve over the revision cycle. Relative to the latest available data, initial vintages are projected to remain modest, with subsequent revisions typically amounting to gains in the low tens of thousands by the third release. Following the annual benchmarking process, monthly employment gains are anticipated to average around 30k on a three month basis. Overall, the most recent data appear to understate the eventual benchmark-adjusted increase in employment by a considerable margin, given the information contained in other indicators.

7. Conclusion

This paper presents a new framework for analysing US labour market data within a unified state-space structure. The model jointly incorporates multiple data sources and their revision properties, allowing for a coherent interpretation of the labour market. By integrating the QCEW, CES and CPS along with other auxiliary indicators, the framework provides a consistent view of both the trend and cyclical components of employment. Importantly, the model can be estimated and updated rapidly, typically within minutes following the release of an employment report, offering a timely and transparent assessment of underlying labour market conditions.

We demonstrate several useful applications of this framework. First, we show how it can be used to generate unofficial employment estimates during periods when official data releases are delayed, such as during a US government shutdown. Second, we use the model to link structural demographic factors to the concept of the employment breakeven rate, highlighting how recent changes in population growth and migration have sharply reduced the breakeven level of job gains. Finally, we apply the framework to assess the implications of the annual benchmarking process, showing how the model anticipates and refine early benchmark revisions.

Taken together, our results provide a cohesive and internally consistent narrative: the pace of US employment growth has moderated as firms add fewer workers each month. This slowdown primarily reflects a deceleration in labour supply, evidenced by the declining breakeven employment rate, rather than a sharp deterioration in demand. While cyclical support for employment has faded somewhat, there is little indication of imminent labour market dislocation. Overall, the model offers a robust and flexible platform for real-time monitoring of labour market trends and for interpreting new data as it becomes available.

Table 4: Unofficial US Employment Report

	1 Month Change (NFPs)		3 Month Change (NFPs)		U3 Unemployment		U6 Unemployment	
	Data	Underlying	Data	Underlying	Data	Underlying	Data	Underlying
Jun 25	-13	**66**	55	**80**	4.1	**4.4**	7.7	**8.0**
Jul 25	72	**70**	26	**59**	4.2	**4.4**	7.9	**8.1**
Aug 25	-4	**78**	18	**72**	4.3	**4.4**	8.1	**8.1**
Sep 25	119	**59**	62	**68**	4.4	**4.4**	8.0	**8.2**
Oct 25		**21**		**52**		**4.5**		**8.2**
Nov 25		**17**		**30**		**4.5**		**8.3**
Dec 25		**48**		**28**		**4.5**		**8.3**

Sources and Notes: Fulcrum Asset Management LLP. Table shows latest model projections in absence of the US employment report for October. **Black** numbers denote latest official data. **Red** numbers denote model median estimates. For CES non-farm payrolls underlying differs from data due to measurement error and estimated impact of future revisions, for CPS unemployment and underemployment rates differences are attributed to measurement error away from underlying employment cycle. December 11, 2025.

Table 5: Latest Median CES Revision Forecasts

	1 Month Change (NFPs)				
	Latest Data	First Vintage	Second Vintage	Third Vintage	Benchmark
Jun 25	-13	147	14	-13	**66**
Jul 25	72	73	79	72	**70**
Aug 25	-4	22	-4	**23**	**78**
Sep 25	119	119	**77**	**70**	**59**
Oct 25		**-57**	**-28**	**-20**	**21**
Nov 25		**-36**	**-38**	**-22**	**17**
Dec 25		**-8**	**1**	**11**	**48**

Sources and Notes: Fulcrum Asset Management LLP. Table shows latest model projections for sequential CES revisions. **Black** numbers denote observed vintage data. **Red** numbers denote model median forecasts. December 11, 2025.

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A. Estimation Algorithm

The estimation proceeds by iterating between state smoothing and parameter updating steps within a Bayesian state-space framework. Given the observed data $\{\mathbf{Y}_t\}_{t=1}^T$, we initialise the procedure as follows:

1. **Initialization:** Specify initial guesses for the parameters in the system matrices $\mathbf{A}$, $\mathbf{D}$, $\mathbf{F}$, $\mathbf{H}$, $\{\mathbf{Q}_t\}_{t=1}^T$, and $\{\mathbf{R}_t\}_{t=1}^T$, along with an initial condition for the state vector, $\mathbf{X}_0$.

2. **State smoothing:** Conditional on these initial parameter values, obtain the smoothed estimates of the latent states, $\{\mathbf{X}_t\}_{t=1}^T$, using the Durbin–Koopman simulation smoother.

3. **Update state parameters:** Given the smoothed state sequence, update the parameters in the state transition equation, $\mathbf{D}$ and $\mathbf{F}$, using a Gibbs sampling step based on a Bayesian VAR formulation. In this step, $\mathbf{D}$ and $\mathbf{F}$ are drawn conditional on $\{\mathbf{Q}_t\}_{t=1}^T$, with appropriate priors specified for each. In practice, these updates can be performed state-by-state.

4. **Update state covariance:** Conditional on the new draws of $\mathbf{D}$ and $\mathbf{F}$, update $\{\mathbf{Q}_t\}_{t=1}^T$ using an Inverse–Wishart distribution.

5. **Update the measurement parameters:** Given the latest smoothed states, update the measurement parameters $\mathbf{A}$, $\mathbf{H}$, and $\{\mathbf{R}_t\}_{t=1}^T$ following an analogous Gibbs sampling step, with $\{\mathbf{R}_t\}_{t=1}^T$ also drawn from an Inverse–Wishart distribution.

6. **Iteration:** Repeat the above steps $10,000$, discarding the initial $2,000$.

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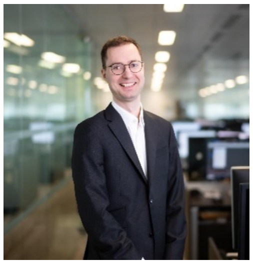
Director, Economics Research



Dan Wales joined Fulcrum as Economics Research Director in 2024. Dan joined Fulcrum from the IMF and before that the Bank of England where he worked as an economist. He graduated from the LSE with a First-Class degree in Econometrics and Mathematical Economics. He has a PhD in economics from Hughes Hall, Cambridge and was a Janeway post-doctoral Research Fellow in Economics at the Cambridge Faculty of Economics and Christ's College.

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