

Expanding the Frontier of Economic Measurement: Weekly Regional Employment Statistics.

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Abstract: Big data offers potentially enormous benefits for improving economic measurement. We use microdata from a major U.S. payroll processor to construct weekly indexes of private-sector employment at the national, state, and county levels. Because the processor's client base changes over time, we measure week-to-week growth among matched continuing employers and chain those growth rates into continuous indexes. Validating the series against the Quarterly Census of Employment and Wages (QCEW), we find that the payroll measures track official employment well, but that their errors relative to final QCEW growth are wider than those from initial Current Employment Statistics (CES) at the state level. We demonstrate the value of the weekly series by studying an event affecting local markets. Applying it to Hurricane Helene, we show that county-level employment losses in Asheville and Tampa are visible within weeks of landfall, well before they appear in monthly or quarterly official statistics, and at a geographic scale and frequency finer than published survey estimates.

Keywords: Big data, regional employment, economic measurement

JEL Codes: E01, E24, R11

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1. Introduction

Economic shocks do not wait for statistical release calendars. A hurricane can interrupt local activity overnight, a bridge closure can alter commuting and commerce the next day, and a major employer can expand, contract, or shut down between one month and the next. Even recurring economic activity can turn on relatively narrow windows: tourism in some areas may peak in a single week in the summer. Yet many of the most reliable economic statistics are observed at a monthly or quarterly frequency and released with substantial lags. By the time conventional data establish that local employment changed, much of the response may already have occurred.

In the absence of timely official statistics, researchers, policymakers, businesses, and journalists often turn to other signals. Initial unemployment claims, credit-card transactions, job postings, mobility measures, online prices, private payroll records, and other sources can provide information much closer to the time and place at which economic activity occurs. Such measures became especially prominent during the COVID-19 pandemic, when rapidly changing conditions created an unusual demand for information on economic activity in close to real time ([Chetty et al., 2023](#); [Vavra, 2021](#); [Cajner et al., 2020](#)). More generally, transaction data, online prices, and payroll records have demonstrated the potential for private-sector data to provide economic measures at frequencies and geographic scales that are difficult to obtain from traditional collection systems ([Cavallo and Rigobon, 2016](#); [Cajner et al., 2018](#); [Dunn et al., 2026](#)).

In this paper, we use payroll microdata maintained by a major U.S. payroll processor to construct weekly indexes of private-sector employment at the national, state, county, and metropolitan-area levels. The approach extends the regional-employment framework developed by [Dunn et al. \(2026\)](#) from monthly to weekly frequency. Weekly payroll employment measures have previously been constructed at the national level by [Cajner et al. \(2023\)](#); our contribution is to produce corresponding measures at the state, metropolitan-area, and county levels and to evaluate what this additional geographic resolution reveals.

Because the payroll processor's client population changes over time, raw payroll totals cannot be interpreted directly as employment growth. We instead adapt the matched-sample logic of official payroll employment statistics, measuring week-to-week employment growth among

employers observed in both periods and requiring continuing employers also to have been present four weeks earlier.² We then chain these matched weekly growth rates to construct continuous employment indexes.

The statistics will be updated weekly and published through the Opportunity Insights Economic Tracker.³

The growing use of alternative data for economic research and measurement reflects a broader transformation in the economic data environment. A growing share of economic activity now passes through digital systems, generating large quantities of data as a routine byproduct of transactions and business operations. At the same time, advances in storage, computing, data engineering, and machine learning have made it possible to process these data at scales that were previously impractical (Varian, 2014; Einav and Levin, 2014; Abraham et al., 2021). The result is a substantial expansion in the feasible resolution of economic measurement. In principle, researchers can increasingly place a microscope over a particular place or episode and ask not simply whether economic activity changed, but when it changed and where the adjustment was concentrated.

The features of such data that provide value, however, also distinguish them from official statistics. Private and administrative data are generally created to carry out transactions or operate programs, not to measure a fixed statistical population. Their coverage may be selective, their composition may change, and the underlying systems that generate them may evolve. A payroll processor may not have any clients in certain industries; a payments platform can change market share; an online marketplace can change its product mix. An observed change in a large dataset therefore need not correspond one-for-one with a change in the economy (Abraham, 2022; Dunn et al., 2026). Greater volume and computational sophistication do not eliminate the problems of statistical definition, representativeness, and comparability.

These limitations make the official statistical system more, not less, important as alternative data become more widely used. The official statistics provide a stable foundation for the growth of alternative data to enhance and provide new insights not possible from official statistics alone. Surveys, censuses, and administrative records provide definitions of populations and

²The additional four-week requirement helps ensure that an employer transitioning between payroll processors over several weeks is not mistakenly classified as a rapidly growing business.

³<https://tracktherecovery.org/>

economic concepts, stable benchmarks against which new measures can be evaluated, and consistency across geography and over time. New data sources provide a different set of strengths: timeliness, frequency, and granular detail. The useful model is therefore not one in which private big data replace official statistics, but one in which the two are connected. Official statistics provide the frame; alternative data can provide the microscope ([Abraham, 2022](#); [Ehrlich et al., 2022](#)).

This complementarity also guides how we use the weekly employment measures in this paper. Our first objective is to evaluate whether the payroll indexes provide credible measures of employment by comparing them with the Quarterly Census of Employment and Wages (QCEW), which provides a near-census benchmark for covered employment. We also compare the performance of our weekly series with the monthly Current Employment Statistics (CES), which is an official employment survey that is more timely than the QCEW available on a monthly basis. These comparisons establish the relationship between the higher-frequency payroll measures and an official statistical universe, and they identify the geographic scales at which sampling variation becomes important. Our second objective is to ask what additional information becomes available once employment can be observed weekly. We examine localized employment disruptions due to Hurricane Helene to determine more precisely when employment responses occurred and how quickly they developed or reversed.

Our results show both the promise and the limits of these weekly payroll measures. At the national level, the payroll index tracks QCEW employment closely and captures major turning points substantially earlier. At the state level, the series performs especially well when employment movements are large, although its errors relative to final QCEW growth are wider than those of initial CES estimates, particularly outside periods dominated by large common shocks. These findings reflect similar findings of [Dunn et al. \(2026\)](#) based on monthly payroll data. The value of the weekly data is clearest at finer geographic and temporal scales. In the Hurricane Helene application, the payroll series identifies sharp county-level employment losses within weeks of landfall and reveals the beginning of the recovery well before comparable official county statistics become available. At the same time, differences in the measured recovery illustrate the limitations of the continuing-employer design, which does not reflect businesses that remain closed weeks after the event. This finding reinforces the role of the weekly measures as a complement to, rather than a substitute for, official statistics.

The contribution of the weekly measures is therefore not simply greater timeliness. Their

principal value is additional resolution. Official monthly and quarterly statistics provide the stable frame within which the economic significance of changes can be understood; payroll data allow us to look inside those intervals. The combination provides a way to exploit the rapidly changing data and computational environment without abandoning the population concepts, validation, and continuity that give economic statistics their meaning.

The remainder of the paper proceeds as follows. Section 2 describes the payroll data, the CES, and the QCEW benchmark. Section 3 describes construction of the weekly employment indexes. Section 4 evaluates the resulting series against official employment statistics. Section 5 uses the weekly measures to examine the timing of discrete local employment shocks. The final sections discuss the advantages and limitations of high-frequency local employment measurement and concludes.

2. Data

2.1. Private Payroll Data

The payroll data used in this paper come from a U.S. payroll processor that provides payroll services primarily to small- and medium-sized businesses. In the course of processing payroll, the company collects detailed information on employers, employees, pay periods, hours, and compensation. The resulting microdata cover more than 5 percent of U.S. private-sector employment and provide a substantially more granular view of employment activity than is typically available in published statistics.

An important advantage of payroll-processing data is that the underlying records are generated continuously as part of normal business operations. This makes it possible to construct employment measures at relatively high frequency and at detailed geographic levels, rather than being tied to a fixed survey collection and publication schedule. The weekly employment indices developed in this paper use this timely information to measure employment at national, state, county, and metropolitan-area levels. All microdata remain within the payroll processor's secure environment, and the data used in this analysis are aggregated and anonymized before leaving that environment.

Related private-sector data have increasingly been used to supplement traditional economic statistics, particularly when latency and granularity are important. [Chetty et al. \(2023\)](#), for example, used high-frequency private-sector data to track economic activity during the COVID-19 pandemic. [Cajner et al. \(2020\)](#) used payroll data from the largest payroll processor in the country, ADP, to track weekly national employment changes during the pandemic. [Dunn et al. \(2026\)](#) use the same payroll-processor data used in this paper, to construct more timely and geographically detailed measures of regional employment. The present paper directly extends work of [Dunn et al. \(2026\)](#) and more broadly builds on this line of work by moving the regional employment measurement to a weekly frequency.

The flexibility of the payroll data comes with an important limitation. The data are a convenience sample rather than a probability sample of U.S. employers, and their composition reflects the business model and customer base of the payroll processor. Coverage is weighted toward small- and medium-sized businesses and varies across industries and geographies. In addition, the client population changes over time as businesses enter and leave the processor's customer base. Raw employment totals from the payroll system therefore cannot be interpreted directly as changes in aggregate employment.

This feature of the data motivates the construction of the weekly indices described in Section 3. Rather than treating changes in the payroll processor's client population as economic change, we measure employment growth using matched samples of continuing employers and then chain those growth rates through time. The official statistics described below provide an external benchmark against which the resulting measures can be evaluated.

2.2. BLS Data

2.2.1. Quarterly Census of Employment and Wages (QCEW)

The Quarterly Census of Employment and Wages (QCEW), produced by the Bureau of Labor Statistics (BLS), provides one of the most comprehensive measures of employment and wages in the United States. The program is based primarily on mandatory unemployment-insurance reporting by employers to state workforce agencies, which compile and verify the records before transmitting them to BLS. As a result, QCEW covers nearly the full universe of employment subject to state and federal unemployment-insurance programs and provides

detailed information on employment, total wages, establishments, industry, and geography.

This near-census coverage makes QCEW particularly valuable as a benchmark. Unlike a sample survey, QCEW measures employment across a very large share of the employer universe and is available at detailed geographic and industry levels, including counties. The Current Employment Statistics program described below is benchmarked annually to QCEW employment totals.

The principal limitation associated with this breadth and detail of information is latency⁴. QCEW estimates become available only after a substantial processing and publication lag, generally several months after the reference quarter. QCEW therefore provides an especially useful picture of where employment ultimately stood, but considerably less information about economic conditions in real time. This tradeoff makes it particularly useful for the purposes of this paper: QCEW provides a detailed official-statistics benchmark against which the higher-frequency payroll measures can be evaluated, while the weekly payroll data provide information about developments that occur between QCEW observations and before QCEW estimates become available.

BLS publishes QCEW data at multiple levels of industry detail. For the applications considered here, we focus on broad sectors corresponding to the high-level groupings shown in Table 1. Unless otherwise noted, the QCEW data used in this paper are the most recently available vintage at the time of the analysis and therefore incorporate subsequent revisions to previously published observations.

2.2.2. Current Employment Statistics (CES)

The Current Employment Statistics (CES) program represents a monthly establishment survey conducted by BLS and is designed to provide highly timely measures of payroll employment, hours, and earnings by industry. National estimates are generally released shortly after the end of the reference month, with state and metropolitan-area estimates following later in the month. This makes CES one of the principal sources used by policymakers, businesses, and researchers to monitor current labor-market conditions.

⁴There are limitations to the use of QCEW as a time series and the data may contain breaks representing noneconomic changes. CES addresses these breaks during the benchmarking process.

Table 1. QCEW Supersector Codes

Code	Supersector
1011	Natural Resources and Mining
1012	Construction
1013	Manufacturing
1021	Trade, Transportation, and Utilities
1022	Information
1023	Financial Activities
1024	Professional and Business Services
1025	Education and Health Services
1026	Leisure and Hospitality
1027	Other Services
1028	Public Administration
1029	Unclassified

CES is based on a large sample of establishments rather than the near-universe administrative records underlying QCEW. The sampling design disproportionately includes larger establishments, with sample weights used to produce estimates representative of the broader employer population.⁵ The program provides national, state, and metropolitan-area estimates, but does not generally provide the county-level employment statistics available from QCEW. CES therefore offers substantially greater timeliness than QCEW, but at a lower level of geographic detail and with additional sampling uncertainty.

CES estimates are revised as additional survey responses and benchmark information become available. Initial estimates are followed by routine revisions, and the series are subsequently benchmarked to QCEW employment counts⁶. This feature makes CES especially useful for studying the relationship between timeliness and later information: early releases provide a real-time view of employment conditions, while subsequent vintages incorporate additional information unavailable at the time of the initial estimate.

For portions of the analysis that examine real-time measurement, we retain the historical vintages of CES estimates rather than relying only on the latest revised series. This allows us to evaluate the information that would actually have been available to a user at a given point in time. The distinction is important for the broader motivation of this paper. A statistic

⁵See the BLS CES technical documentation at <https://www.bls.gov/web/empst/cestn.htm#tb1>.

⁶CES relies on additional benchmark sources, primarily County Business Patterns and the Railroad Retirement Board, to account for the 3 percent of nonfarm payroll employment not covered by unemployment insurance. See: <https://www.bls.gov/opub/hom/ces/calculation.htm#noncovered-employment>.

may eventually provide an accurate account of employment conditions while still leaving policymakers and researchers with relatively little information during the period in which an economic shock is unfolding.

Response rates to establishment surveys have also declined in recent years, increasing the importance of understanding how timely survey estimates perform as information accumulates.⁷ The comparison between CES, QCEW, and the payroll-based measures therefore provides three distinct perspectives on employment measurement: a timely official survey, a comprehensive but delayed administrative benchmark, and a high-frequency private-sector data source.

3. Construction of the Weekly Employment Indices

3.1. Employment Determination

We construct weekly employment measures from payroll records using a reference-week convention designed to parallel the reference-period concept used in official payroll employment statistics. Each reference week is identified by its week ending date which is a Saturday. An employee is counted as employed in a given week when the payroll records contain qualifying positive pay and positive hours for a pay period that includes that Saturday.

The employment determination uses forms of compensation that provide evidence that the employee was attached to the employer during the reference week. These include regular pay, overtime, vacation and holiday pay, sick leave, piecework, and tips. Irregular supplemental payments that do not reliably indicate current employment are excluded from the employment determination. Payments are converted to weekly equivalents so that observations are comparable across weekly, biweekly, semimonthly, and monthly payroll schedules, and negative payment corrections are netted against the payments they revise.⁸

⁷BLS reports establishment-survey response rates at <https://www.bls.gov/osmr/response-rates/>.

⁸For example, consider an hourly employee on a biweekly payroll whose check for a period shows \$1,600 of regular pay for 80 hours, \$150 of overtime for 5 hours, and a \$2,000 quarterly bonus. For the employment determination, the bonus is excluded and the regular and overtime pay are scaled by 7/14 to a weekly equivalent of \$875 for 42.5 hours. If the employer later determines that 4 of the 80 regular hours were reported in error, the adjustment carries the original pay period dates and enters the same reference week as a payment of -\$80 for -4 hours, and it is summed with the original payment, netting out the hours recorded in error. After netting, the employee's regular pay for the week is \$1,520 for 76 hours, or \$760 for 38 hours on

Payroll records do not always contain complete hours information. Where possible, missing hours are resolved using information within the employee's own payroll records. Salaried employees with missing hours are assigned 40 hours per week, while hourly employees with missing hours may have hours recovered using an observed employee-specific wage rate. Employees whose hours cannot be determined or imputed are not counted as employed. Employment is therefore determined from payroll payments rather than from employer-reported hiring or termination dates.

3.2. Continuing Employers and the Matched Sample

A challenge in constructing employment statistics from a payroll processor is that the client population is not fixed. Employers can enter or leave the payroll system because of changes in the processor's market share (e.g., through business combinations) or in individual firms' payroll decisions. Changes in raw payroll totals would therefore combine changes in employment with changes in the composition of the processor's client base.

We address this problem using a matched-employer design related to the matched-sample methodology used in the Current Employment Statistics program. For each reference week, we classify an employer as a *continuing unit* if it has positive employment in the current week, the immediately preceding week, and the week four weeks earlier. The current- and prior-week requirement ensures that each week-to-week employment comparison is made using the same employers. The additional four-week lookback screens out employers that appear only intermittently in the weekly data, and importantly removes those employers that may be transitioning slowly to a new payroll provider.⁹

Employers present in the previous week but absent in the current week are classified as exits, while other currently observed employers that do not satisfy the continuing-unit definition are classified as entries. Neither entries nor exits contribute directly to the published growth indexes, as we cannot tell if the entries or exits are due to actual firm entry or exit or whether they are due to firms changing payroll processors. Consequently, the resulting series measure employment growth among continuing employers rather than changes in total employment

a weekly basis, and the employee is counted as employed. Had the entire check been voided without a reissue, net regular pay and hours would be zero and the employee would not be counted as employed in that period.

⁹For example, an employer may move half of the employees to a new provider in one week, and the other half in the following week. We do not want to mistakenly infer the growth rate in the second week as the true growth rate in employment.

arising from entry to or exit from the payroll processor’s client population.

This distinction is important for interpretation. The indices are not representative of employment levels and do not attempt to reproduce net employment changes arising from firm births and deaths. Instead, they provide a consistent measure of employment growth within an evolving matched sample of employers.

3.3. Weekly Growth and Chaining

For geographic unit g and reference week t , let C_{gt} denote the set of continuing employers used in the comparison of weeks $t - 1$ and t . We define the weekly employment growth factor as

$$G_{gt} = \frac{\sum_{i \in C_{gt}} E_{igt}}{\sum_{i \in C_{gt}} E_{ig,t-1}}, \quad (1)$$

where E_{igt} denotes employment at employer i . Because employment is summed before the ratio is calculated, employers contribute to aggregate growth in proportion to their employment.

The weekly growth factors are chained over time to create our index I_{gt} ,

$$I_{gt} = I_{g,t-1} G_{gt}, \quad (2)$$

and each resulting series is normalized to the week ending January 7, 2023. Published values are expressed as net growth relative to that base week, so that a value of 0.05 represents employment 5 percent above the base-week index value.

Chaining is important because the matched employer set can change from one weekly comparison to the next. The same calendar week’s employment may appear in two adjacent extracts—once as the current period and once as the prior period—but the continuing-employer sets underlying those two extracts need not be identical. We do not splice those

overlapping employment levels together. Instead, each extract contributes only its internally matched current-to-prior growth factor. The chain therefore allows the sample defining growth to evolve from week to week without treating changes in sample composition as employment growth.

At detailed geographic or industry levels, some series may have weeks with too few continuing employers to form a valid growth link or may encounter zero denominators. These problems become more relevant as the geographic and industry cells become smaller and are an important consideration in interpreting the most detailed series.

A similar methodology has been applied in prior work both at the weekly and monthly level by [Cajner et al. \(2018, 2023\)](#); [Dunn et al. \(2026\)](#) and is also related to the monthly chaining of employment estimates applied in CES. CES supplements the chaining methodology with a net birth-death model, which generates another important methodological difference to our estimates.

3.4. Geographic and Industry Series

We construct employment indexes at four geographic levels: national, state, county, and metropolitan area. State estimates cover the 50 states and the District of Columbia. County estimates are identified using five-digit county FIPS codes. Metropolitan-area estimates aggregate counties into the metropolitan definitions used for the published series.

Within each geography, the same matched-sample and chaining procedure is applied separately to total employment and to selected subgroups. The published data include total employment; four broad industry groups corresponding to CES supersectors (trade, transportation, and utilities; professional and business services; education and health services; and leisure and hospitality); and four wage groups defined by the employee's hourly wage relative to an hourly-equivalent federal poverty guideline (below 100 percent, 100 to 150 percent, 150 to 250 percent, and above 250 percent). Each subgroup series is normalized independently to its own value in the base week. The specific details for how these hourly wage groups are determined follows the methodology applied in [Chetty et al. \(2023\)](#).

The analysis in this paper focuses primarily on total employment. We use industry detail

selectively where the economic mechanism associated with a particular event implies a clear industry exposure and where the underlying local sample is sufficiently large. The wage-group measures are part of the published weekly data but are not central to the applications considered here.

3.5. Seasonal Adjustment and Revisions

Weekly payroll employment contains both substantial recurring seasonal variation, particularly around major holidays when payroll timing can shift measured employment between adjacent weeks, and end-of-year sample churn that can temporarily distort measured employment. We therefore produce both unadjusted and seasonally adjusted versions of each published series.

Seasonal adjustment is performed separately for each subgroup series using a robust STL decomposition with a 52-week seasonal period. The procedure estimates a smoothly evolving weekly seasonal component while reducing the influence of unusually large observations on the estimated seasonal pattern. Only complete annual cycles are used to estimate the seasonal factors. For the current incomplete partial year, seasonal factors are applied from the matching periods of the most recent complete year. Residual volatility around the winter holidays, where payroll timing and sample churn distort the series, is treated with an additional smoothing step that replaces the seasonally adjusted values in those weeks with a centered 12-week rolling median of the seasonally adjusted values to reduce the impact of residual volatility not corrected for by the seasonality adjustment alone.

Weekly observations are also subject to revision for the first two weeks after they become available as payroll information continues to arrive after the reference period. Under the weekly processing schedule, a reference week first becomes eligible for processing approximately two weeks after it ends, allowing the payrolls covering it to be run, and is then reprocessed in each of the following two weekly runs as the remaining payrolls and any corrections are processed. Each week therefore passes through three successive versions, and the published build uses the most recent available version. Periodically, we rebuild the full history, which incorporates the small share of payrolls processed more than four weeks after a reference week; the series analyzed in this paper is such a rebuild, so all but its most recent weeks are final full collections of observations.¹⁰

¹⁰Dunn et al. (2026) examine data based on these weekly revisions and find that monthly estimates change little three weeks after the reference period.

The appropriate version of the series depends on the empirical application. The event study and seasonal-pattern applications use adjusted or unadjusted measures according to the question being studied, with the objective of separating event-related movements or recurring seasonal timing from ordinary calendar variation.

4. Validation Against Official Employment Statistics

4.1. National Comparison

Figure 1 compares the national weekly payroll index with monthly QCEW employment over 2016–2026. Both series are seasonally adjusted and expressed as percent changes from the week ending January 7, 2023. The two measures track one another relatively closely across the full period. They rise together over the pre-pandemic expansion, fall sharply and simultaneously in the spring of 2020, and recover along similar paths through 2021 and 2022. The correlation between monthly changes in the two series is 0.94 over the full sample and 0.57 excluding 2020. At the national level, the payroll data clearly contain information about aggregate employment conditions, and they contain it several months before the corresponding QCEW observation becomes available.

The series nonetheless differ in ways that follow from their construction. Over the pre-pandemic period the payroll index shows somewhat slower cumulative growth than QCEW. This is consistent with the matched-employer design described in Section 3.2 because the Payroll index measures growth only among continuing employers, it excludes the contribution of firm entry net of exit, which is typically positive. Some observed discrepancy is also consistent with the composition of the payroll processor’s client base, which is not representative of overall employment. The data is weighted toward small and medium-sized businesses and more toward some industries than others. The payroll measure should therefore be read as employment growth within an evolving matched sample of employers, not as an estimate of a representative level or growth of national employment.

The pandemic period illustrates both the value and the limits of this interpretation. The payroll index falls more steeply than QCEW in April 2020 and recovers more quickly over the following months. The deeper trough is what one would expect from a sample tilted

toward smaller employers and toward sectors such as leisure and hospitality, where the 2020 contraction was concentrated. The episode also shows that the weekly series identifies the turning point well before the QCEW observation for the second quarter of 2020 was published. Figure 1 does not resolve whether the difference in amplitude reflects genuine differences in the exposure of the payroll processor’s clients or the mechanics of the matched-sample design, and this distinction matters more for events measured at fine geographic scales, where the underlying samples are smaller.

Figure A1 shows the same comparison without seasonal adjustment. The payroll series exhibits substantially larger recurring within-year variation than the monthly QCEW series, reflecting both genuine seasonal employment patterns and the sensitivity of weekly measurement to payroll timing around holidays.¹¹ The amplitude of this variation motivates the seasonal-adjustment procedure described in Section 3.5 and indicates that unadjusted weekly movements should be interpreted cautiously, especially without reference to the corresponding week in prior years.

Taken together, these comparisons support a specific reading of the national series. The payroll index is not a substitute for QCEW.¹² The payroll series is, however, informative about the direction, timing, and approximate magnitude of national employment changes, and it delivers that information at weekly frequency and with a lag of weeks rather than months. This is the same complementarity exploited in Dunn et al. (2026), where payroll-based measures are blended with official statistics rather than used in isolation.

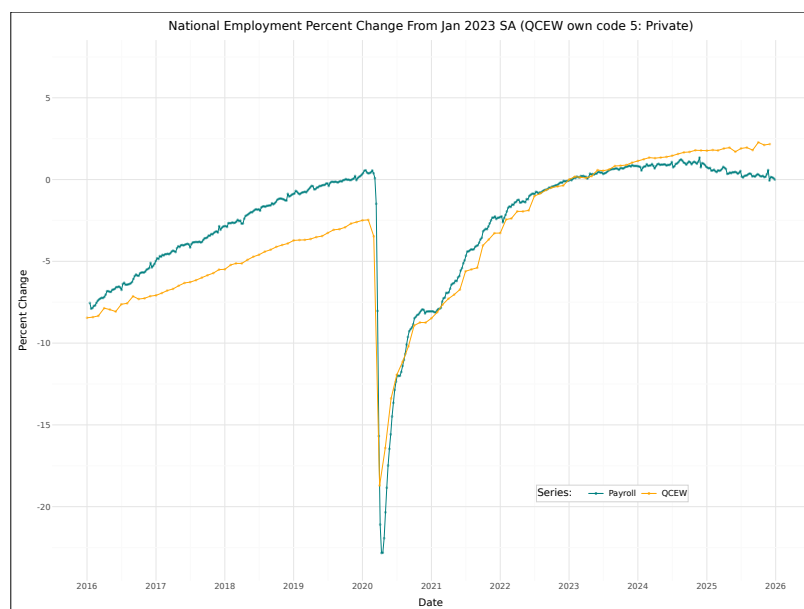
4.2. State Comparisons

Figure 2 reports state-level correlations between year-over-year growth in the payroll indexes and in QCEW employment for leisure and hospitality, the sector with the largest and most geographically varied employment movements over this period. Panel A begins in January 2020 and therefore includes the pandemic; Panel B is restricted to observations from January 2023 forward.

¹¹The key national measure of employment is from the CES. We find that final national CES estimate is very close to the national QCEW employment estimate reported here.

¹²It is not drawn from a probability sample, it does not measure a fixed employment universe, and its growth concept differs from that of official statistics

Figure 1. National Trends in Employment QCEW Private Monthly Estimates and Payroll Data Weekly Estimates (Seasonally Adjusted)



Note. This figure shows weekly seasonally adjusted Payroll series and monthly QCEW private sector trends over the period from 2016 to 2026.

The contrast between the panels is the key point to highlight. Including the pandemic, correlations are strongly positive and similar across areas, with the median state correlation is 0.93, and 42 states exceed 0.75. The payroll data reproduce the timing and relative magnitude of the 2020 drop in employment and recovery in nearly every state, indicating that the payroll indicator recovers a large common shock that matches well with official estimates. However, restricting attention to 2023 onward, the median correlation falls to 0.67, and while most states remain positive, a few turn negative. Some attenuation is also mechanical: once the pandemic is excluded, the common variation in economic movement captured in the two series is far smaller relative to the idiosyncratic variation in each. Similar patterns appear in [Dunn et al. \(2021\)](#) based on spending estimates and [Dunn et al. \(2026\)](#).

Figures [A2](#) through [A4](#) repeat the exercise for trade, transportation, and utilities; professional and business services; and education and health services. The same qualitative pattern holds in each.

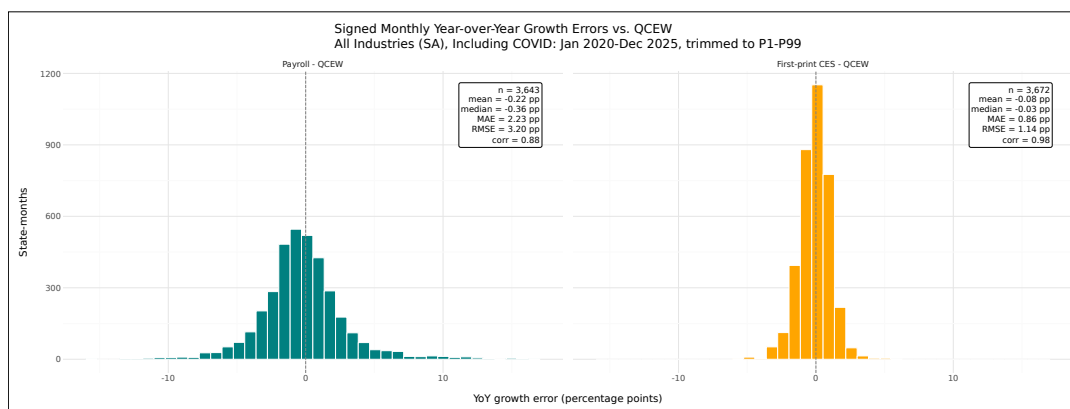
The payroll data generate an imperfect signal, but the trade-off is the availability of more timely information. This trade-off is not unique to private data. It parallels the existing relationship between the CES survey, which is timely but subject to sampling error, and the more complete QCEW data observed with a lag of several months. To quantify it, we compute year-over-year state-level growth from the initial CES estimate and from the payroll series as first published, and measure each against year-over-year growth in the final QCEW estimate. Both errors are therefore constructed the same way, from the information a user would actually have had at the time.

Combining across industries, these errors are reported in Figure [3](#). The top panel covers the 2020 period forward, with payroll errors on the left and first-estimate CES errors on the right. While the payroll data are more timely, the errors produced by this series are considerably wider than those from CES, highlighting the relative accuracy of the less-timely survey. The payroll errors are also centered slightly below zero, the direction implied by the matched-employer design of Section 3.2, since the indexes measure growth only among continuing employers and therefore omit the contribution of net entry. The bottom panel shows the same comparison for the post-COVID period, where the pattern is similar. We also report these estimates by industry in the appendix Figure [A5](#) where the patterns are the same, but the histogram of errors are, not surprisingly, wider for both CES and payroll data as the sample sizes for these subgroups are smaller.

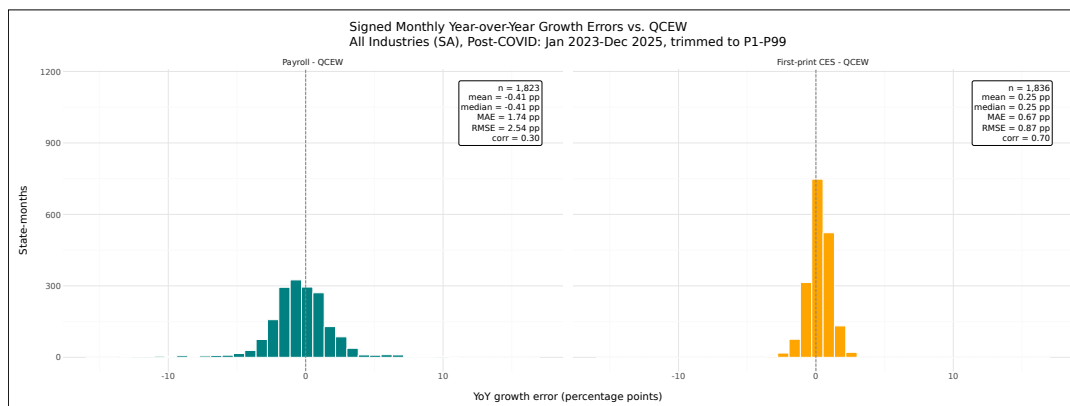
Note. This figure shows year-over-year correlations between the QCEW monthly data and payroll data series. The top figure includes the 2020-Covid period and the bottom figure shows estimates post- January 2023. The figure shows strong positive correlation for the Covid period, demonstrating the capabilities of the data to capture major events. The bottom post-Covid correlations also tends to show positive correlations, but they are much weaker.

Figure 3. State Level Year-over-Year Growth Correlations Between QCEW and Payroll Data: Aggregate

A. Including COVID, 2020 On



B. Post-COVID, 2023 On



Note. This figure shows the distribution of signed errors in monthly year-over-year state employment growth, measured in percentage points relative to year-over-year growth in QCEW private-sector employment. Left panels show the payroll index minus QCEW; right panels show the first-published CES total private estimate minus QCEW, with CES growth computed within the vintage that first published each month. All series are seasonally adjusted. The corresponding distributions by industry are reported in Appendix Figure A5. .

These results highlight the conditions under which the weekly series is most useful. Specifically, the payroll indexes are informative about employment movements that are large relative to the sampling variation in the underlying payroll matched sample. The data tends to be less informative when the underlying economic shock is small, especially when looking at small geographic areas or industries. For this reason, we do not treat the indexes as a representative measure of local employment. Instead, they should either be blended with national estimates as in [Dunn et al. \(2026\)](#) or used in studying events where the signal to noise ratio is larger, such as in the case of disasters. Section 5 applies the series to examine particular events that have large effects on local markets.

5. Applications of Weekly Local Employment Data

5.1. Timing of Discrete Local Employment Shocks

Hurricane Helene made landfall in Florida's Big Bend region on September 26, 2024 and moved inland through Georgia and into the southern Appalachians. Its economic effects were geographically uneven in a way that makes it useful for this exercise. The most severe disruption occurred not near landfall but in western North Carolina, where extreme rainfall produced catastrophic flooding, destroyed road and water infrastructure, and interrupted business activity for an extended period. Along the Florida Gulf coast, the storm passed offshore and produced substantial storm surge without the sustained infrastructure loss experienced inland.

We examine two counties. Buncombe County, North Carolina, which contains the city of Asheville and was among the most severely affected areas in the region. Its economy is heavily oriented toward tourism, and the storm arrived immediately before the autumn peak season. Pinellas County, Florida, is part of the Tampa MSA and experienced coastal flooding of a different character and duration. In both cases we use the leisure and hospitality series, where the exposure is most direct and the local sample is relatively large. Both counties experienced employment movements far outside the range of ordinary local variation, suggesting that they are useful test cases for this type of analysis.

Figure 4 shows Buncombe County. Panel A presents the information available as of the vintage

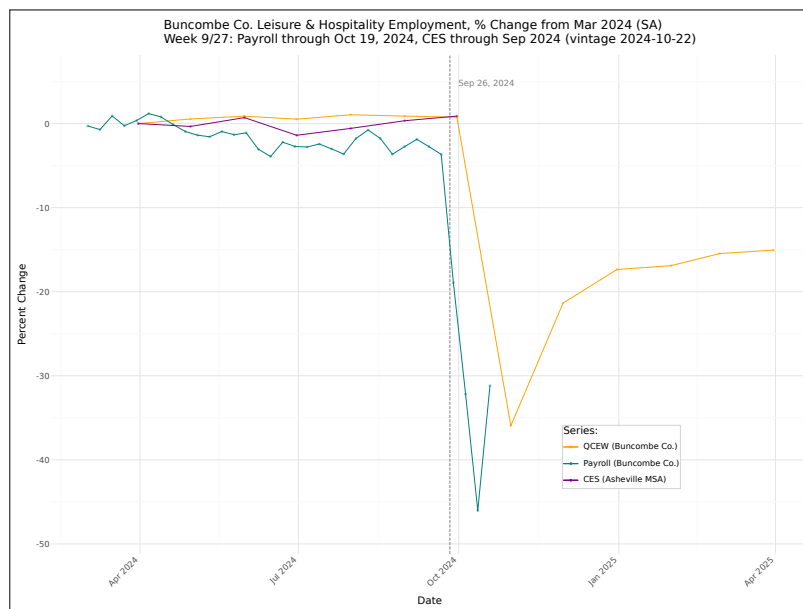
of October 22, 2024, with payroll data through October 19, 2024 and CES estimates for the Asheville MSA through September. The payroll series falls by approximately 42 percentage points within two weeks of the storm and has already begun to recover by the end of the available data. The CES estimate for September 2024, published a month after the reference month and covering a period that ends four days after landfall, shows essentially no movement. QCEW observations for the third and fourth quarters of 2024 were not yet available. At this vintage, the payroll data are the only source that identifies both the magnitude of the disruption and the beginning of the recovery.

Panel B of Figure 4 presents the same county as of March 2025, with payroll data through February 22, 2025 and CES through January 2025. The full time period is now visible in all three series: a sharp contraction beginning the week of September 28, 2024, a trough within two weeks, and a partial recovery over the subsequent months. The later official statistics confirm the direction and approximate scale of the event, but they do not recover its timing. The monthly CES estimates do not capture the primary affected county of Buncombe, but instead capture the broader Asheville MSA area covering three counties: Buncombe, Henderson, and Madison. As both Henderson and Madison were less affected by Helene, the affect of the storm for Buncombe reflected in the Asheville MSA is muted, relative to what is observed in the payroll series that can more accurately identify the most affected county. Official county level estimates for Buncombe county only come several months later from the QCEW, which are shown in orange. We see here that the monthly dip down for QCEW is much closer in magnitude to the initial payroll data series estimate. However, due to QCEW frequency being monthly, rather than weekly, the high frequency dip down and recovery observed in the payroll data is not as clearly observed. This picture makes clear the advantages of the more timely and granular data for understanding events, such as the employment effects of Helena.

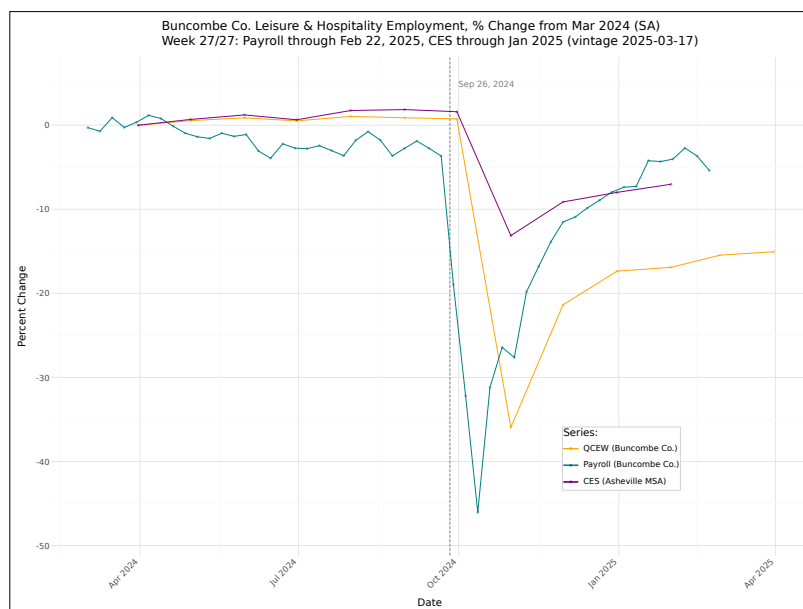
Figure 5 shows the Helena event for Pinellas County and follows a similar pattern. The figure shows a sharp decline immediately after the storm, visible in the payroll data weeks before it appears in official statistics, followed by recovery. Two differences are notable. The contraction is smaller, at roughly 20 percent compared to the approximately 40 percent decline in Buncombe, consistent with the more limited nature of the disruption in the Tampa area. Similar to the Buncombe event, we see that the CES estimate, which covers the entire Tampa MSA, also shows more muted effects. Again, a likely reason is that the Tampa MSA includes Pinellas county but also several counties that were less affected by this event,

Figure 4. Hurricane Helene: Leisure and Hospitality Employment, Buncombe County (Asheville MSA): Leisure and Hospitality Sector

A. Nine weeks after the event



B. 27 weeks after the event



Note. This figure shows employment estimated by different series as available on a given date, expressed as percent change from March 2024, six months before Hurricane Helene made landfall. The teal line is the weekly payroll index for leisure and hospitality employment in Buncombe County, truncated at the last week that would have been observable at that vintage. The purple line is the CES leisure and hospitality estimate for the Asheville MSA (Buncombe, Henderson, and Madison Counties) as published in that vintage. The orange line is monthly QCEW private leisure and hospitality employment for Buncombe County as eventually published, shown in full in both panels for reference. Panel A uses the CES vintage of October 22 2024, with payroll data through the week ending October 19 2024 and CES through September 2024. Panel B uses the vintage of March 17 2025, with payroll data through February 22 2025 and CES through January 2025. All series are seasonally adjusted.

including Hernando, Hillsborough, and Pasco counties. Similarly, the official estimates from QCEW that reflect solely Pinellas county do not come until several months later, and they show a magnitude more in line with the payroll series estimates.

One important note is that in both areas studied as part of this event, the recovery observed in the payroll series appears more complete than that observed in the CES and QCEW series. A likely reason for this is due to the payroll series not capturing business exits or businesses that continue to be closed during the recovery period, while QCEW, which is a more complete Census of employment, will capture these net changes from entry and exit. This highlights an important limitation of the chained payroll series. The weekly series is therefore better suited to identifying the onset and initial trajectory of a disruption than to measuring the extent of eventual recovery, and it does not displace the need for comprehensive official statistics after the event.

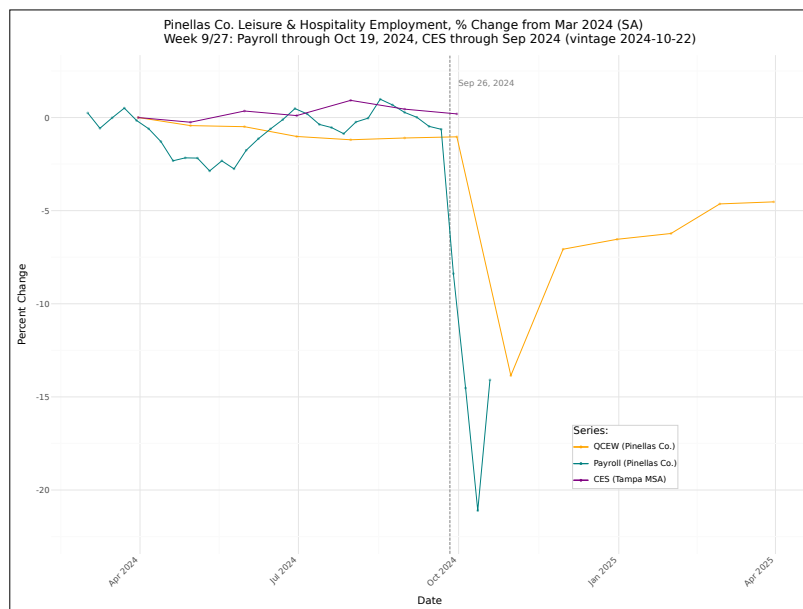
6. Discussion

The results in this paper point to a particular role for high-frequency private-sector data in economic measurement. The weekly payroll indices are not uniformly more accurate than existing official statistics. At the state level, first-published CES estimates have substantially narrower errors relative to final QCEW employment growth than the payroll series, particularly outside periods dominated by very large common shocks. The payroll data instead provide a different combination of attributes: weekly frequency, short publication latency, and geographic detail extending to the county level.

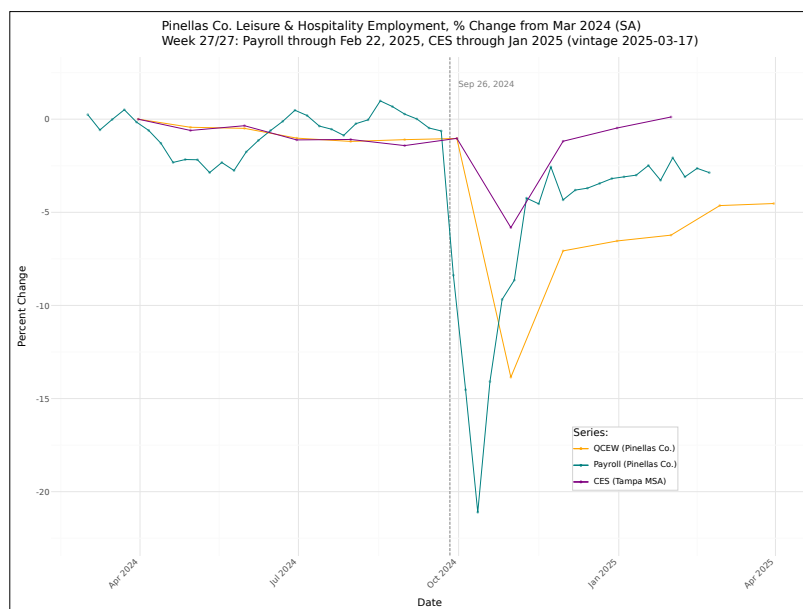
This distinction helps characterize when the weekly series are most informative. The payroll indices perform best when the underlying economic movement is large relative to variation in the matched payroll sample. The COVID-19 collapse is visible clearly across states, and the Hurricane Helene application shows that large local disruptions can be identified at weekly frequency and at a geographic scale finer than that available from timely official employment estimates. When economic movements are smaller, particularly within narrow industries or small geographic areas, idiosyncratic variation in the underlying client sample becomes increasingly important. The additional resolution provided by the payroll data therefore comes with a corresponding signal-to-noise tradeoff.

Figure 5. Hurricane Helene: Leisure and Hospitality Employment, Pinellas County (Tampa MSA): Leisure and Hospitality Sector

A. Nine weeks after the event



B. 27 weeks after the event



Note. This figure shows employment estimated by different series as available on a given date, expressed as percent change from March 2024, six months before Hurricane Helene made landfall. The teal line is the weekly payroll index for leisure and hospitality employment in Pinellas County, truncated at the last week that would have been observable at that vintage. The purple line is the CES leisure and hospitality estimate for the Tampa-St. Petersburg-Clearwater MSA (Hernando, Hillsborough, Pasco, and Pinellas Counties) as published in that vintage. The orange line is monthly QCEW private leisure and hospitality employment for Pinellas County as eventually published, shown in full in both panels for reference. Panel A uses the CES vintage of October 22, 2024, with payroll data through the week ending October 19, 2024 and CES through September, 2024. Panel B uses the vintage of March 17, 2025, with payroll data through February 22, 2025 and CES through January, 2025. All series are seasonally adjusted.

The construction of the indices creates a second important limitation. By design, weekly growth is measured among continuing employers. This prevents changes in the payroll processor's customer base from being interpreted mechanically as changes in employment, but it also means that the indices do not capture the full extensive margin of local employment change. Firms that close for an extended period or disappear from the matched sample cease to contribute to subsequent growth links. This feature is visible in the Hurricane Helene results, where employment in the payroll series appears to recover more fully than in later CES and QCEW estimates. The weekly indices are therefore better suited to identifying the onset, timing, and initial trajectory of a disruption than to measuring the eventual level of employment after business entry and exit have become important.

These limitations reinforce the broader motivation for combining alternative and official data. QCEW provides broad universe coverage and detailed geography, but only after a substantial lag. CES provides considerably more timely official estimates and performs well as a measure of state employment, but it is available at lower frequency and does not provide county employment estimates. The payroll series add another point on this frontier: still greater frequency and geographic resolution, but with a less representative underlying sample and greater sampling variation. No single source dominates along every dimension.

For this reason, payroll measures should generally be interpreted as complements to official statistics rather than as substitutes. One possible use is as an early indicator of large localized disruptions, with subsequent CES and QCEW releases providing confirmation and a more complete account of the eventual employment response. Another is to use the weekly series to resolve the timing of changes that are already apparent in lower-frequency official data. This distinction is important. The value of weekly measurement need not rest on producing a superior estimate of the monthly or quarterly employment level. It can instead arise from revealing what occurs within those reference periods.

The same logic extends beyond discrete shocks. Economic activity often has recurring seasonal patterns that occur on a finer calendar than monthly statistics can reveal. Weekly measures can potentially distinguish whether otherwise similar counties reach seasonal employment peaks in different weeks within the same month. This type of application uses high-frequency data not primarily to obtain an earlier estimate, but to recover temporal structure that is lost through aggregation.

More generally, the results illustrate a useful division of labor between new data sources and the official statistical system. Large private datasets and modern computing make it increasingly feasible to observe economic activity at high frequency and fine geographic resolution. Official surveys, censuses, and administrative records remain essential for defining the statistical universe, providing representative benchmarks, and maintaining consistency across time and place. The strongest use of the new data environment may therefore come from connecting these sources rather than asking either to perform all of the functions of the other.

7. Conclusion

This paper develops weekly indices of private-sector employment from payroll-processing microdata at the national, state, metropolitan-area, and county levels. The indexes are constructed from matched samples of continuing employers and chained over time, allowing weekly employment growth to be measured without inadvertently incorporating changes in the payroll processor's client population.

Comparison with official employment statistics shows both the promise and the limits of the resulting measures. The payroll indices capture large aggregate and regional employment movements and provide information at substantially higher frequency and lower latency than QCEW. At the same time, their errors relative to final QCEW growth are wider than those of initial CES estimates at the state level, and performance deteriorates as the underlying economic signal becomes small relative to variation in the payroll sample. The series should therefore be interpreted as a high-frequency indicator rather than a replacement for representative official employment statistics.

The Hurricane Helene application illustrates where the additional resolution is most useful. In both Buncombe County, North Carolina, and Pinellas County, Florida, the payroll data identify sharp employment contractions within weeks of the storm and reveal the beginning of the recovery before comparable official county-level statistics become available. The later official estimates broadly confirm the disruption, but their monthly frequency and broader geographic coverage provide less information about precisely when the changes occurred. At the same time, differences in the measured recovery highlight the consequences of the

continuing-employer design and the continued importance of comprehensive official statistics for measuring the longer-run employment response.

The contribution of the weekly series is therefore not simply that they arrive sooner. Their principal value is that they allow economic activity to be examined at a temporal and geographic scale closer to the scale at which many economic events actually occur. Used together, official statistics and high-frequency private data can provide both the stable frame needed for economic measurement and the finer-grained view needed to understand what happens within conventional statistical intervals.

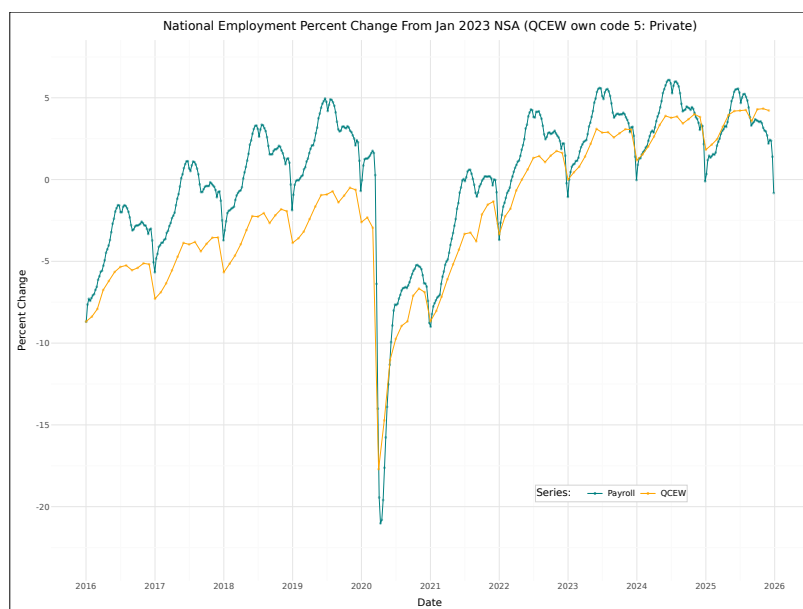
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Figure A1. National Trends in Employment QCEW Private Monthly Estimates and Payroll Data Weekly Estimates (Not Seasonally Adjusted)

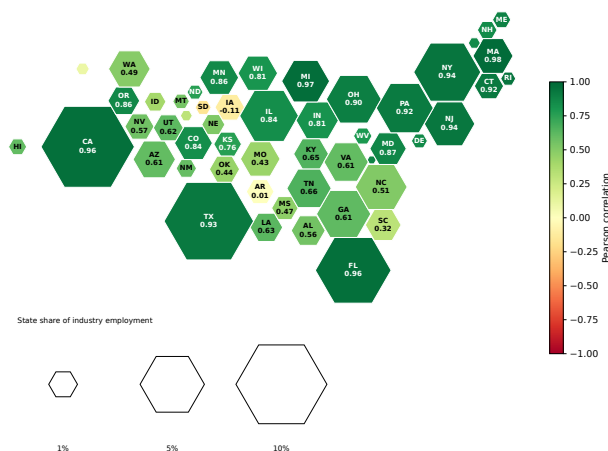


Note. This figure shows weekly non seasonally adjusted Payroll series and monthly QCEW private sector trends over the period from 2016 to 2026.

Figure A2. State Level Year-over-Year Growth Correlations Between QCEW and Payroll Data: Trade, Transport, and Utilities

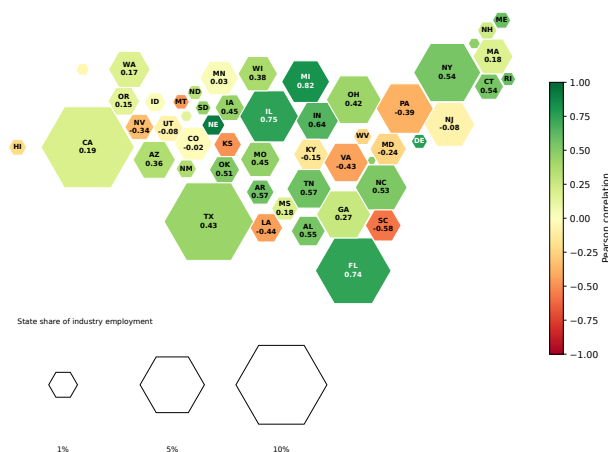
A. Including COVID, 2020 On

Payroll vs. QCEW Monthly Year-over-Year Growth Correlations
Trade, Transportation, and Utilities (SA), Including COVID: Jan 2020-Dec 2025
Hexagon area proportional to state share of Trade, Transportation, and Utilities QCEW employment, Dec 2025



B. Post-COVID, 2023 On

Payroll vs. QCEW Monthly Year-over-Year Growth Correlations
Trade, Transportation, and Utilities (SA), Post-COVID: Jan 2023-Dec 2025
Hexagon area proportional to state share of Trade, Transportation, and Utilities QCEW employment, Dec 2025



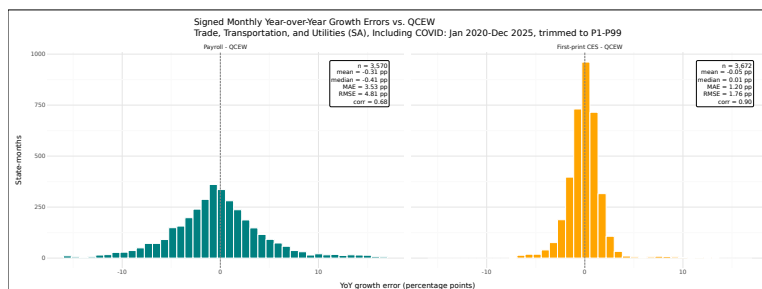
Note. This figure shows year-over-year correlations between the QCEW monthly data and payroll data series. The top figure includes the 2020-Covid period and the bottom figure shows estimates post- January 2023. The figure shows strong positive correlation for the Covid period, demonstrating the capabilities of the data to capture major events. The bottom post-Covid correlations also tends to show positive correlations, but they are much weaker..

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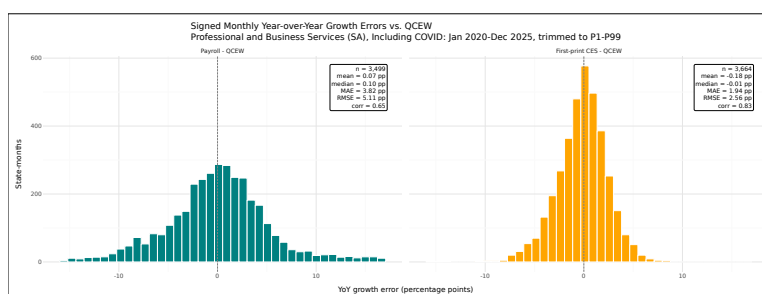
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Figure A5. State Level Year-over-Year Histogram Plots of Errors: By Industry Including COVID, 2020 Onwards

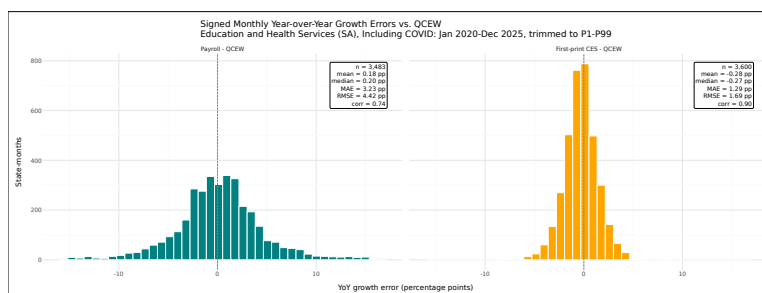
A. Trade, Transportation and Utilities



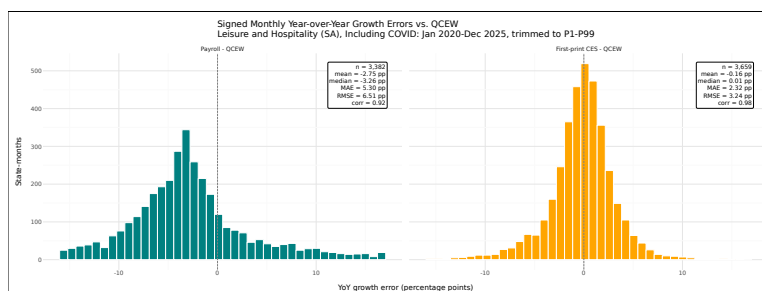
B. Professional and Business Services



C. Education and Health Services



D. Leisure and Hospitality



Note. Each panel repeats the comparison in Figure 3 for one industry supersector group. The panels show the distribution of signed errors in monthly year-over-year state employment growth, measured in percentage points relative to year-over-year growth in QCEW private-sector employment for the same industry supersector. Within each panel, the left histogram shows the payroll index minus QCEW and the right histogram shows the first-published CES estimate minus QCEW, with CES growth computed within the vintage that first published each month. All series are seasonally adjusted.