Building Labor Market Statistics with Administrative Labor Market Data

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Abstract

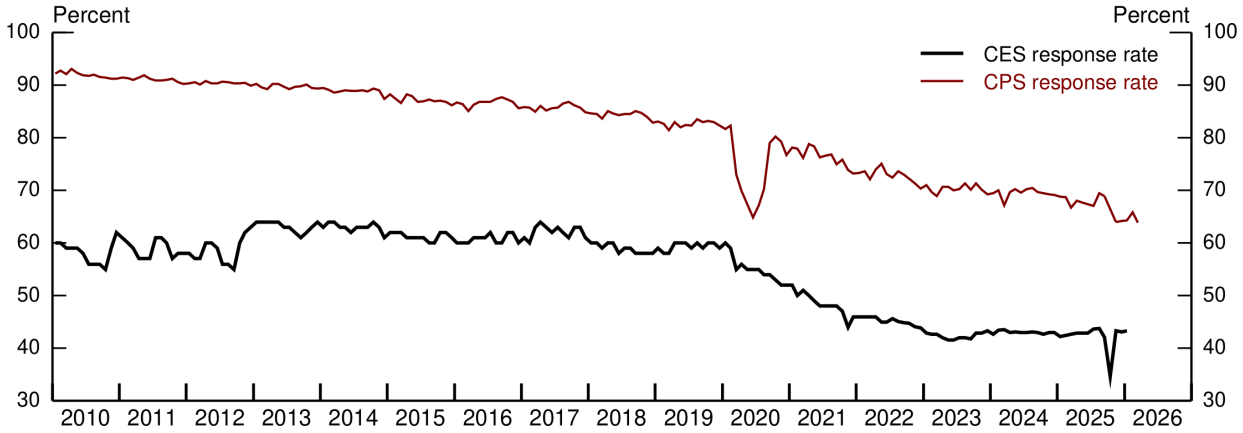
This paper provides a blueprint for building labor market statistics with administrative labor market data. We start by reviewing the official labor market statistics, including a discussion of their challenges, most notably falling survey response rates. Then we review and evaluate existing employment statistics based on administrative private labor market data, including ADP, Paychex, UKG, Gusto, Intuit, and Revelio. The main part of the paper provides a discussion of challenges in constructing labor market statistics from payroll provider data, based on our decade-long experience of working with these data. We propose practical solutions for dealing with issues such as accounting for different payroll frequencies, seasonal adjustment challenges, adjusting for potential sample selection issues, and making adjustments for unobserved business births and death. We conclude with a summary of lessons learned.

*The analysis and conclusions set forth here are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors.

1 Introduction

Official employment statistics in the United States have traditionally been generated through sample-based surveys, such as the Current Employment Statistics (CES) survey or the Current Population Survey (CPS). However, in recent years these statistical products have suffered from declining response rates as shown in Figure 1, which in turn can potentially lead to the selection bias from non-response when non-respondents differ systematically from respondents. Moreover, the CES survey has been subject to relatively large benchmark revisions in recent years as discussed in Decker (2026).

Figure 1: CES and CPS Response Rate



At the same time, several new sources of administrative labor market data have become available in recent years. Most notably, private companies processing payrolls have readily available data that one could use to construct labor market statistics. In this paper, we summarize lessons we learned in using one such dataset from a large U.S. payroll provider to construct real-time labor market statistics, in particular measures of employment and compensation growth. We also review other, similar attempts by other researchers.

We show that in order to build real-time statistics with private administrative labor market data, one needs to deal with several challenges, including accounting for different payroll frequencies, seasonal adjustment challenges, adjusting for potential sample selection issues and making adjustments for unobserved business births and deaths. After discussing solutions to deal with each of those problems, we show that indeed one can construct reliable labor market statistics, with accuracy similar to those observed in official statistics. Our results provide a blueprint to build modern labor market statistics in the 21st century.

2 Official Labor Market Statistics

In the U.S., the most important source of timely labor market statistics is the employment situation release, published monthly by the BLS.[1] The employment situation release contains information from two separate surveys: CPS, a survey of households, and CES, a survey of business establishments.

The household survey is drawn using a stratified probability sample based on the most recent decennial census and subsequent updates to the U.S. housing unit address list. The survey contains roughly 60,000 eligible housing units each month, with the response rates declining and currently hovering around 65 percent.[2] In the end, this translates into about 40,000 employed individuals in each monthly survey. The CPS employment concept counts individuals as employed if they worked for pay during the reference week (typically the week including the 12th day of a month), and also if they were temporarily absent from a job. Importantly, the CPS measures the number of employed persons, not jobs. For tracking monthly movements, CPS employment is relatively noisy and the estimate of the monthly change in CPS employment has a 90-percent confidence interval of +/- 650,000. In addition to employment, the CPS also provides detailed information on individual labor market status, hours worked, and earnings, including a monthly measure of usual weekly earnings for wage and salary workers.

The establishment survey is drawn using a stratified probability sample based on the employer records from the unemployment insurance system. The survey contains about 120,000 businesses and government agencies each month, representing approximately 630,000 establishments.[3] In terms of employment, the CES sample includes about 26 percent of all nonfarm payroll employees, with large variation across industries, ranging from 9 percent in construction to 63 percent for government. The response rates for CES survey have been declining in recent years as well and currently hover around 40 percent. The CES measures employment using a payroll concept according to which individuals are counted as employed if they receive pay for any part of the pay period including the 12th day of the month. Unlike the CPS, the CES counts jobs rather than employees. CES employment estimates are substantially more precise that CPS estimates; the estimate of the monthly

[1] Another important timely labor market data in the U.S. include initial and continued claims for unemployment insurance, published weekly by the Department of Labor. However, given that less than half of unemployed file for unemployment insurance and given that the share who file varies cyclically, these data provide an incomplete view of the developments in the labor market.

[2] The CPS uses a 4-8-4 rotation pattern, where a sampled household is interviewed for four consecutive months, then leaves the sample for eight months, and then returns for four additional months before permanently exiting.

[3] The universe of unemployment insurance tax accounts consists of roughly 12.1 million establishments.

change in CES employment has a 90-percent confidence interval of +/- 122,000. In addition to employment, the CES also provides detailed information on hours worked and earnings for payroll employees in the nonfarm sector.

In addition to near-real-time monthly estimates from CPS and CES, the BLS also publishes employment and compensation data in their Quarterly Census of Employment and Wages (QCEW), which is based on near-census of employment based on unemployment insurance tax records, covering about 95 percent of U.S. jobs. These data typically have a lag of about 5-6 months and are used to benchmark CES data annually (each March).

Economists have traditionally relied on official monthly labor market statistics for several good reasons. First, CPS and CES are based on carefully designed random probability samples, aiming to achieve appropriate representativeness of the population they intend to measure. Second, CPS and especially CES have relatively large samples; in some states, responding to CES survey is mandatory. Third, CPS and CES statistics are constructed following established statistical methodologies and procedures that are consistent over time and are clearly described in associated documentation. Fourth, CPS and CES data have long histories which renders them suitable for time-series analysis.

However, official labor market statistics also face some limitations and tradeoffs. Most importantly, official labor market statistics are subject to measurement error due to factors such as sampling error, nonresponse, reporting errors, and imperfect seasonal adjustment. With declining response rates, the benefits of random probability samples are vanishing and measurement issues can arise due to the selection bias when non-respondents differs systematically from respondents. While some of the measurement issues could potentially be improved with larger samples, increasing the sample size is very costly. Additionally, in the case of CES measuring the employment contribution from business births and deaths has been a long standing challenge, and imperfect measurement from this component often contributes notably to the benchmark revision. In the case of CPS, the BLS has to come up with assumptions for the population growth and those assumptions can be imprecise, especially when large changes in net immigration occur, as has been the case in recent years.

3 Payroll Employment Data

A viable alternative to measuring employment with surveys is to instead rely on data by payroll service providers. We list below major payroll providers in the U.S., which are already using their data to construct employment statistics and/or have had their data used for the purposed of academic research. We compile the information about those payroll providers from publicly available 10-Ks and other public reports, company websites, and web searches.

1. **Automatic Data Processing, Inc. (ADP)** is a payroll and human resources services provider. For the fiscal year ending on June 30, 2025, ADP served 26 million workers and was responsible for the payrolls for 1 out of every 6 workers in the U.S. (1 out of every 5 workers in the private sector), making them the largest payroll provider in the country. The company publishes a regular payroll employment statistic, the National Employment Report.

2. **Paychex** was founded as a payroll service provider but now includes human resource and benefits outsourcing. For the fiscal year ending on May 31, 2025, Paychex had approximately 800,000 clients across the U.S. and parts of Europe; some of these clients may be non-payroll clients. The company claims to pay 1 out of every 11 workers in the US. The company also releases its Small Business Employment Watch, which draws on data from approximately 350,000 clients to estimate unemployment and wages among small businesses each month.

3. **UKG** is a multinational technology company and the result of a merger between Ultimate Software and Kronos Incorporated. As of August 2025, UKG serves about 6.2 million employees in the United States, or roughly 1 out of 20 private employees. UKG also releases a monthly measure of employment in its Workplace Activity Report.

4. **Gusto** provides payroll and human resource services for about 400,000 small businesses and publishes a monthly small business employment indicator that is focused on firms with fewer than 50 employees. It is unclear how many employees are covered by Gusto's 400,000 clients. We can construct a rough guess by assuming that all Gusto firms have fewer than 100 employees and, subject to that ceiling, a size distribution similar to the U.S. private sector, which would suggest an average firm size of 8 employees for a total headcount of around 3 million.

5. **Homebase** provides time clock and payroll services for small businesses (largely in customer-facing industries) and publishes occasional reports based on their data. Homebase data cover about 100,000 businesses with about 2 million hourly employees. Homebase data have been used in many academic papers.

6. **Intuit** offers a number of payroll products both online and through its QuickBooks application, targeted toward small businesses. Intuit's payroll services serve at least 1 million employees from more than 250,000 small businesses. The company publishes the monthly Small Business Index, which is regularly benchmarked to the BLS Business Employment Dynamics.

3.1 Evaluating Existing Employment Statistics based on Payroll Provider Data

In this subsection, we provide an evaluation of existing employment statistics published by payroll providers, as well as the employment measure constructed by Revelio and some temporary help companies. [To be completed...]

4 ADP-FRB Employment Statistics

In this section we provide a discussion of challenges in constructing labor market statistics from payroll provider data, based on our decade-long experience of working with these data. We propose practical solutions for dealing with issues such as accounting for different payroll frequencies, seasonal adjustment, adjusting for potential sample selection issues, and making adjustments for unobserved business births and death. The discussion here builds on our existing research, including Cajner et al. (2018, 2020*a*,*b*, 2022, 2023).

4.1 Description of ADP Microdata

ADP (Automatic Data Processing, Inc.) is one of the largest payroll providers in the U.S., processing payrolls for approximately 26 million U.S. workers, which is roughly 20 percent of total U.S. private sector employment. The ADP microdata are organized at the level of Payroll Account Controls (PACs), which can correspond to the establishment or firm level. Each PAC has a record for the end of every pay period containing the date payroll was processed, employment information for the pay period, and time-invariant characteristics such as anonymized identifiers, NAICS industry codes, and geographic location. A distinctive feature of the ADP data is that they include two employment concepts: "active employees", which encompasses all individuals in the payroll system regardless of whether they received pay during a given period, and "paid employees", which includes only those issued paychecks during the pay period. The data are available at weekly frequency since July 2009, providing a substantially higher-frequency window into labor market dynamics than traditional monthly surveys.

The ADP data offer several advantages for measuring aggregate labor market activity. First, these data are very timely, with information for a pay period typically available within a week of the pay period's end, enabling near-real-time analysis of employment trends. Second, because ADP captures payroll information throughout the entire month rather than just the reference week containing the 12th (as in the BLS CES and CPS data), the data can better capture month-long employment dynamics and are less susceptible to temporary

distortions during specific weeks. Third, the sample is broadly representative of the US economy across industries, firm sizes, and geography, though with modest overrepresentation in manufacturing and large businesses; these compositional differences can be addressed through reweighting using Quarterly Census of Employment and Wages (QCEW) data. However, the data also present challenges: selection into ADP's client base may introduce biases, true establishment births and deaths cannot be directly observed (as changes in ADP's client roster may reflect contract decisions rather than genuine economic entry and exit), and the panel structure requires careful handling of pay frequency heterogeneity across businesses.

4.2 Brief Overview of Methodology behind ADP-FRB

Next, we provide a quick overview of methodology behind the construction of ADP-FRB series. In the following subsection, we will discuss in detail specific methodological challenges.

To construct aggregate ADP-FRB employment indexes, we first calculate weekly employment growth rates for continuing establishments (i.e., those appearing in consecutive weeks), which allows us to abstract from changes in ADP's client base. Each establishment's growth rate is calculated using a standard formula. The establishment-level growth rates are then aggregated using a two-stage weighting scheme: first by each establishment's employment level, and second by cell-specific weights that adjust for the representativeness of ADP's sample. Specifically, we construct weights at the intersection of six establishment size classes (1-19, 20-49, 50-99, 100-299, 300-499, and 500+ employees) and two-digit NAICS industries using employment shares from the BLS Quarterly Census of Employment and Wages (QCEW), effectively reweighting ADP data to match the size-industry distribution of the U.S. economy.

Cumulating these weighted weekly growth rates produces a weekly employment index in levels, which we then subject to two key adjustments. First, we benchmark the series annually to QCEW employment levels each March, using a procedure analogous to the CES methodology: we set the ADP-FRB March level equal to the QCEW March level, then linearly "wedge back" the adjustment to the previous March benchmark, ensuring that year-over-year changes align with the comprehensive QCEW counts while preserving the higher-frequency variation captured in the ADP data. We also apply a forward benchmark correction (similar to the CES birth-death model) that uses a historical regression of past benchmark misses to project an adjustment factor for periods beyond the most recent benchmark.

Second, we seasonally adjust the data using the Cleveland and Scott (2007) methodology

for the weekly series, which combines locally weighted regressions on trigonometric functions with fixed-effect controls for major holidays. The final monthly ADP-FRB series can be constructed in two different ways. First, we can average the weekly index levels within each month (weighting by the number of days each week contributes to that month), producing a measure that captures employment dynamics throughout the entire month rather than just the reference week containing the 12th as in CES. Second, we also produce monthly series by using the week containing the 12th, which are in turn directly comparable to the CES statistics.

4.3 Challenge 1: Pay Frequency Heterogeneity

The heterogeneity in pay frequencies across ADP clients creates fundamental challenges for constructing weekly employment measures. About 22 percent of businesses issue paychecks weekly, 46 percent biweekly, 21 percent semimonthly, and 11 percent monthly. This heterogeneity means that in any given week, only a subset of businesses report new payroll information; specifically, weekly payers plus approximately half of biweekly payers (those whose pay cycles align with that particular week). For businesses with longer pay frequencies, one must impute employment during non-reporting weeks by assuming it remains constant at the level observed in the most recent payroll event, then updating these estimates when the next payroll is processed. This creates a real-time estimation problem: initial weekly employment estimates are based primarily on weekly and biweekly payers and must be revised as semimonthly and monthly payers report, typically within two to four weeks. To address this, ADP-FRB methodology implements a real-time adjustment procedure that uses historical relationships between preliminary "first print" estimates and final values (once all businesses have reported) to forecast the likely revisions, though this forecasting component performed less reliably during the COVID-19 crisis when employment changes were unprecedented in magnitude and speed.

Beyond pay frequency heterogeneity, the fundamental challenge is that payroll data measure employment over pay periods rather than at specific points in time. In turn, this often requires interpolation and in our work we experimented with two alternative approaches. In the end, our preferred method was stepwise interpolation: we assigned each Saturday the employment level from the pay period containing that date, creating a series that remains constant within pay periods but can jump discretely at pay period boundaries. This approach exactly matches true employment if—as human resource practices suggest—most hires and separations are timed to coincide with pay period starts and ends, and it aligns conceptually with the CES methodology of measuring employment for the pay period including a

reference date. The alternative, linear interpolation, assumes employment evolves smoothly along a linear path between consecutive pay dates, which has the advantage of producing less volatile series but rests on the less realistic assumption of continuous within-period adjustment. Importantly, neither method can produce fully real-time estimates: stepwise interpolation requires waiting until the end of a pay period to observe its employment level, while linear interpolation requires data from both the preceding and following pay dates. This inherent lag means that measured employment changes may be shifted by one to two weeks relative to when actual hirings and separations occurred, though in practice this timing ambiguity matters less for understanding month-to-month trends than for pinpointing the exact week of labor market turning points.

4.4 Challenge 2: Weighting and Representativeness

Constructing nationally representative employment estimates from ADP microdata requires careful weighting to correct for compositional differences between ADP's client base and the broader U.S. economy. The ADP sample modestly overrepresents manufacturing and large businesses while underweighting construction and exhibiting higher coverage in the Northeast region. We face several fundamental decisions in designing our weighting scheme: which dimensions to include (industry, size, geography), what level of granularity to use within each dimension, and whether to treat ADP payroll units (PACs) as firms or establishments when mapping to official statistics. Our baseline approach employs a two-dimensional weighting scheme using two-digit NAICS industry codes crossed with six establishment size classes (1-19, 20-49, 50-99, 100-299, 300-499, and 500+ employees). For each cell, we calculate the weight as the ratio of target population employment in that cell. In our baseline approach we treat PACs as establishments and use QCEW, but we also experimented with treating PACs as firms and use Statistics of U.S. Businesses (SUSB) data as our alternative benchmark (the choice between these approaches affects the estimated magnitude of employment changes, especially for small businesses, but produces similar overall trends).

An important decision in our weighting methodology was to exclude geography as a weighting dimension, despite some regional variation in ADP coverage. Including state or regional cells would dramatically increase the number of weighting cells, in turn creating severe small cell size problems that would undermine the stability and reliability of our estimates. In particular, when industry-by-size-by-geography cells contain very few ADP businesses, the weighted growth rates become extremely volatile and sensitive to idiosyncratic shocks at individual businesses, since our weighting formula amplifies the influence of underrepresented cells to match population shares. A single large employment change

at one of the few ADP businesses in a sparsely populated cell could generate wildly implausible swings in the aggregate index. Moreover, approximately 10-20 percent of ADP PACs have missing or unreliable industry codes, and for these observations we must assume the industry is missing-at-random conditional on size; adding geography to this imputation problem would compound the uncertainty. We therefore prioritize the industry-by-size structure, which captures the most economically meaningful heterogeneity in employment dynamics while maintaining sufficient cell sizes to ensure stable estimates. This pragmatic choice sacrifices some geographic precision but produces a more robust national employment measure, and importantly, our industry-by-size reweighting successfully eliminates most of the bias that would otherwise arise from ADP's compositional differences relative to the U.S. economy. In short, when deciding the weighting scheme, one needs to make decisions that balance representativeness and precision, and in our experience the industry-by-size reweighting best addresses this tradeoff.

4.5 Challenge 3: Outlier Detection

Constructing aggregate employment indexes from establishment-level microdata requires careful treatment of outliers, as extreme growth rates at individual establishments can arise from both genuine economic events and data quality issues. Large swings in PAC-level employment may occur due to processing errors, payroll corrections for past mistakes (such as paying workers for incorrect hours), or the timing of bonus payments to subsets of workers; none of these reflect true changes in employment. Such spurious events are particularly problematic in the paid employment series. To address this, we apply a symmetric rule-of-thumb filter based on the Davis, Haltiwanger and Schuh (1996) growth rate measure, which treats positive and negative changes symmetrically. Specifically, we drop observations where weekly DHS growth rates exceed 1.8 or fall below -1.8, thresholds that correspond roughly to a 100-worker establishment losing 95 employees or a 5-worker establishment gaining 95 employees in a single pay period (such large changes more likely reflect data anomalies than actual employment dynamics).

4.6 Challenge 4: Seasonal Adjustment

Seasonally adjusting weekly employment data presents substantial challenges compared to traditional monthly series. Unlike monthly data, weekly observations are not exactly periodic—the first Saturday of any year can fall anywhere from January 1st through January 6th, creating a misalignment between the calendar and the measurement frequency. This non-periodicity complicates standard seasonal adjustment approaches. Additionally, weekly

data exhibit complex seasonal patterns driven by both slow-moving annual cycles (such as summer hiring in leisure and hospitality) and sharp discrete events tied to specific holidays. Holiday effects are particularly intricate: employment patterns shift not only during holiday weeks themselves (Thanksgiving, Memorial Day, Labor Day, New Year's, Christmas, and July 4th) but also in the weeks immediately preceding major holidays as businesses adjust staffing levels. The pandemic introduced a further complication, as the extreme employment swings in 2020-2021 tended to distort estimated seasonal factors.

To address these challenges, the ADP-FRB weekly series employs a two-component approach based on Cleveland and Scott (2007), the same methodology the BLS uses to seasonally adjust weekly unemployment insurance claims. The procedure combines locally weighted regressions applied to trigonometric functions—which flexibly capture slow-moving, smoothly evolving seasonal patterns—with fixed coefficient regressions that explicitly control for holiday effects and their leading indicators. This framework allows seasonal factors to evolve gradually over time while ensuring that discrete holiday-related patterns are consistently identified. For the COVID-19 period, we adopted a special treatment: data after February 2020 were excluded from seasonal factor estimation to prevent the unprecedented pandemic-driven swings from distorting the underlying seasonal patterns, though this approach necessarily meant that the factors did not capture any genuine shifts in seasonality that may have occurred during or after the pandemic. The monthly ADP-FRB series are seasonally adjusted using the Census Bureau's X-13 ARIMA-SEATS program, which is better suited to the monthly frequency and allows for direct comparison with official BLS statistics.

4.7 Challenge 5: Payroll Employment Concept, Active vs. Paid

The ADP payroll microdata provide two distinct measures of employment that capture different aspects of the employment relationship. Active employment includes all individuals who maintain an active record in a business's payroll system during a given pay period, regardless of whether they received compensation, encompassing not only workers who were paid but also those on unpaid leave, workers with zero hours, and temporarily furloughed employees who remain attached to their employer. Paid employment, by contrast, counts only those individuals who actually received a paycheck during the pay period, including regular wages and salaries as well as bonus payments and payroll corrections.

In typical economic conditions, we prefer active employment for our headline ADP-FRB series for several reasons: it is substantially less volatile than paid employment (which fluctuates due to the timing of bonuses, payroll corrections, and other irregular payments), its seasonal patterns more closely mirror those in the QCEW benchmark data, and it has his-

torically demonstrated superior performance in forecasting official BLS employment statistics. Conceptually, active employment aligns more closely with the household survey (CPS) notion of employment, measuring labor market attachment rather than simply payment receipt, while paid employment corresponds more directly to the establishment survey (CES) concept.

The extraordinary circumstances of the COVID-19 pandemic, however, revealed a critical limitation of active employment and necessitated a temporary methodological shift. During the initial months of the pandemic, temporary layoffs—in which workers were separated from payroll but employers intended to recall them—soared to nearly 80 percent of all job losses. Because many employers kept these temporarily furloughed workers in their payroll systems (listed as active but unpaid), the active employment measure failed to capture the full magnitude of the labor market collapse. We therefore pivoted to emphasizing paid employment from March 2020 through September 2021, as it better reflected the reality that millions of workers had lost their paychecks even if they technically remained attached to their employers. By mid-2021, as the share of temporary layoffs returned to its pre-pandemic level of approximately 14 percent and the gaps between paid and active employment losses converged, we reverted to active employment as our primary measure. This experience demonstrates that the optimal employment concept depends on the specific labor market dynamics at play: active employment better captures permanent employment relationships and changes in labor demand during normal times, while paid employment provides a more accurate real-time picture during periods dominated by temporary separations and widespread furloughs.

4.8 Challenge 6: Birth-Death Adjustment and Bias Correction

A fundamental challenge in constructing employment statistics from the ADP microdata is that we cannot directly observe genuine establishment births and deaths, as changes in ADP's client roster may reflect business decisions about payroll processing rather than actual economic entry and exit. When a new PAC appears in the ADP data, it could represent a true business startup, an existing firm newly contracting with ADP, or a seasonal business reopening; similarly, when a PAC disappears, it could indicate genuine business closure, acquisition by another firm, a switch to a competing payroll provider, or a decision to bring payroll processing in-house. Beyond this birth-death ambiguity, the ADP sample may suffer from the selection bias, because businesses choosing external payroll processing may systematically differ from those handling payroll internally, with potential variations by firm size, age, and industry. For instance, very small startups may lack the resources

for external payroll services, while extremely large corporations may prefer internal systems, and the returns to outsourcing likely vary across industries. These selection issues could bias employment estimates in ways that are difficult to predict or directly measure, though we expect such biases to evolve slowly over time rather than shifting dramatically from month to month.

To address both the unmeasured birth-death component and potential slow-moving sample selection biases, we implement a forward benchmark correction analogous to the CES birth-death model but broader in scope. This procedure annual benchmark revisions to identify systematic discrepancies between raw ADP-FRB estimates and "true" employment (the latter is effectively determined by QCEW). We then estimate a historical regression of these benchmark misses on their lagged values, using the estimated relationship to project a constant correction factor for periods beyond the most recent benchmark. For example, following the most recent March benchmark, we add a constant adjustment to each subsequent week based on the prediction from our regression model of how much ADP-FRB is likely to diverge from "true" employment. Between 2005 and 2020, this approach reduced our root-mean-squared benchmark miss from 625,000 jobs to 427,000 jobs, demonstrating substantial improvement in accuracy. The success of this relatively simple correction suggests that the combined effects of unmeasured birth-death dynamics and sample selection biases are reasonably stable and at least to a certain extent predictable over time.

4.9 Evaluating the Performance of ADP-FRB

This subsection will provide an evaluation of the performance of ADP-FRB series, including comparing annual benchmark revisions for CES, ADP-FRB, and ADP-NER. [To be completed.]

5 Conclusions

Lessons learned and summary conclusions. [To be completed.]

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