Improving the Accuracy of Economic Measurement with Multiple Data Sources: The Case of Payroll Employment Data

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March 14, 2019

Abstract

This paper combines information from two sources of U.S. private payroll employment to increase the accuracy of real-time measurement of the labor market. The sources are the Current Employment Statistics (CES) from BLS and microdata from the payroll processing firm ADP. We briefly describe the ADP-derived data series, compare it to the BLS data, and present the results of an exercise that benchmarks the data series to an employment census. The CES and the ADP employment data are each derived from roughly equal-sized and mostly non-overlapping samples. We argue that combining CES and ADP data series reduces the measurement error inherent in both data sources. In particular, we infer "true" unobserved payroll employment growth using a state-space model and find that the optimal predictor of the unobserved state puts approximately equal weight on the CES and ADP-derived series. Moreover, the estimated state contains information about future readings of payroll employment.

Keywords: labor market, economic measurement, big data, state-space models.

JEL Classification: J2, J11, C53, C55, C81.

*All authors are at the Federal Reserve Board of Governors. We thank ADP for access to and help with the payroll microdata that underlie the work performed within this paper. In particular, this work would not have been possible without the support of Jan Siegmund, Ahu Yildirmaz, and Sinem Buber. We are grateful for discussions with Katharine Abraham, Erik Hurst, Gray Kimbrough, Alan Krueger, Matthew Shapiro, Mark Zandi, Boragan Aruoba, and seminar participants at the Federal Reserve Board, the Federal Reserve Bank of Cleveland, ESCoE Conference on Economic Measurement, the BLS, NBER CRIW meetings, and the 2018 ASSA meetings. 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

Economists and statisticians are increasingly confronted with new data sources, often produced by private companies as part of their business operations, that may be useful for economic research and measurement. These new data hold promise for advancing economic measurement and understanding, but their use raises many questions. How are new, alternative data different from traditional surveys and censuses? How are we to assess their reliability? How should multiple disparate data sources be synthesized to produce the best possible estimates? We seek to answer these questions in the context of measuring payroll employment. We use data from a private payroll provider to build an index of US payroll employment, similar in spirit to the Current Employment Statistics (CES) survey. While the CES survey is carefully conducted and uses an extremely large sample, it still suffers from significant sampling error and nonresponse. The ADP-derived employment indexes are based on a sample that is roughly the same size as the CES sample, so it is plausible that pooling the information in from ADP with CES would reduce sampling error and increase our understanding of the state of the labor market at a given time.

Previous work using the ADP data by Cajner et al. (2018) describes the construction of weekly and monthly aggregate employment series based on ADP's weekly payroll microdata. Their aggregate series (ADP-FRB) are designed to be an independent signal about labor market conditions rather than solely an attempt to forecast monthly BLS employment figures. However, Cajner et al. (2018) do indeed find the timeliness and frequency of the ADP payroll microdata substantially improves forecast accuracy for both current-month employment and revisions to the BLS CES data.

In this paper we further compare the ADP-FRB index to existing, high-quality government estimates and find that it behaves well. The ADP-FRB index, and state-space estimates derived from it, provide information about future CES estimates in real-time, particularly at the start of the great recession. In addition, we integrate benchmark employment data and compare ADP-FRB benchmark revision the CES benchmark revisions. While the CES and ADP-FRB series are both prone to significant sampling and non-sampling error, the BLS Quarterly Census of Employment and Wages (QCEW) is generally considered the "final word" for annual employment growth due to its comprehensive administrative source data. Consequently, we benchmark the ADP-based series to the QCEW on an *annual* basis. The benchmarking procedure is broadly similar to CES benchmarking and ensures that year-to-year changes are governed by the QCEW, while higher-frequency changes, and the period after the most recent benchmark, are mostly a function of the ADP data.[1]

Existing work on using nontraditional data sources for economic measurement typically take official government data as the source of truth, at all frequencies. For example, the monthly National Employment Report (NER) series published by ADP are constructed with the goal of predicting the fully revised CES data.[2] In this paper we take a different approach by recognizing that both CES and ADP-FRB employment are subject to non-negligible measurement error and use the Kalman filter to extract estimates of unobserved " true" employment growth from observations of both series.

Our baseline model assumes that true U.S. employment growth follows a persistent, latent process, and that both the CES and ADP-FRB estimates are noisy signals of this underlying process. Standard state-space tools allow us to estimate the latent process and the observation error associated with each series. We find that the optimal predictor of the unobserved state, using only contemporaneous information, puts approximately equal weight on the CES and ADP-FRB series. This is not necessarily surprising, as the ADP sample covers roughly the same fraction of private nonfarm U.S. employment as the CES sample (about 20 percent), so the sampling errors ought to be of roughly similar magnitude. We also show that the smoothed state estimate, as constructed in real-time, helps forecast future values of CES. Throughout, we focus on the role of these privately generated data as a complement to existing official statistics. While there is no substitute for official statistics in terms of consis-

[1]Benchmarking illustrates an essential role that government statistics play even when there is significant value in nontraditional data sources.

[2] Mastercard's SpendingPulse, which attempts to forecast U.S. retail sales, is another example.

tency, transparency, and scientific collection methods, official numbers do have limitations that alternative data sources can address.

The paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes the process of creating ADP-based employment indexes and lays out the both the strengths and inherent limitations of measuring nationwide payroll employment with ADP data. In section 4 we compare the ADP-FRB employment estimates to the official benchmarks annually, discuss the role of the birth-death model in the official estimates, present a case study of the importance of alternative employment data during the Great Recession, and show the efficacy of the ADP-FRB estimates in predicting fully-revised CES payroll employment numbers. Section 5 introduces the state-space model that combines the information from both the ADP-FRB and CES-based estimates and provides evidence that the combined state improves our understanding of current and future payroll gains. Section 6 concludes.

2 Related Literature

Ours is not the first paper to make use of ADP payroll data. Several papers study the National Employment Report (NER), ADPs publicly available monthly estimate of U.S. payroll gains constructed jointly with Moody's Analytics. Importantly, NER estimates are derived from a model including not only ADP microdata but also other contemporaneous and lagged indicators of U.S. economic activity. The existing literature finds that the NER moves closely with CES (Phillips and Slijk (2015)) and has some ability to forecast CES, though it does not appear to improve forecasts beyond other known information such as consensus forecasts (Gregory and Zhu (2014), Hatzius et al. (2016)).

As noted above, we do not use the NER but instead focus on the ADP microdata. A number of recent papers explore these data. Cajner et al. (2018) analyze the representativeness of ADP microdata (relative to CES and QCEW) and construct an ADP payroll index that can improve forecasts of CES; we employ that index in the present paper. Ozimek et al.

(2017) use ADP's linked employer-employee microdata to study the negative effect of workforce aging on aggregate productivity growth. Grigsby et al. (2018) study wage rigidity in the same data, finding that the high-frequency microdata can be useful for shedding light on a key business cycle question. Cho (2018) uses ADP microdata to study the employment and wage effects of the 2009 American Recovery and Reinvestment Act.

Our approach in the present paper is different from those above in that we explicitly investigate the usefulness of ADP as a supplement to CES data for tracking the underlying state of the labor market. In this respect, our work is inspired by Aruoba et al. (2016); these authors note difficulties assessing the growth of aggregate output in real time given limitations on the comprehensiveness and timeliness of GDP measures. Two independent measures of GDP exist: the commonly reported expenditure-side approach, and the income-based approach. Both are prone to error arising from various sources. Aruoba et al. (2016) combine the two measures using a state space framework, recovering an underlying state of output growth they label "gross domestic output" (GDO). We follow this general approach with a focus on employment rather than output.

3 Data

This paper is centered around three data sources: ADP microdata, the Current Employment Statistics (CES) survey, and the Quarterly Census of Employment and Wages (QCEW). Before turning to the ADP microdata in Section 3.1, it is useful to briefly lay out the relevant features of the CES and the QCEW.

The CES is the main source of monthly employment information in the U.S. It is published by the BLS a few days after each reference month and is based on a stratified-sample survey of about 500,000 private establishments covering 23 percent of all U.S. private employees.[3] The CES asks each respondent for the count of employees who worked for pay

[3] See https://www.bls.gov/web/empsit/cestn.htm. Note that the CES contains data for total nonfarm payroll employment, but here we focus only on private payroll employment, excluding government employment to be consistent with the reliable scope of ADP.

in the pay period including the 12th of the reference month. Aggregate CES employment growth is a (weighted) average of the growth reported by units that respond for two or more consecutive months, plus a birth-death residual adjustment.

While the CES is a very large survey, it is still based on a sample and subject to sampling and non-sampling error (as discussed further below). In contrast the QCEW, also maintained by the BLS, is a near-census of unemployment insurance-covered employment and serves as the sampling frame for much of the CES as well as the target for the annual benchmark of the CES. The main drawback of the QCEW is that the data are collected quarterly and published with a lag of two quarters. Thus, while the QCEW has negligible sampling error, it is of limited use to real-time decision makers. In addition, the QCEW is subject to various sources of non-sampling error.[4] Nevertheless, we follow CES in using the QCEW for reweighting the ADP microdata and as a benchmark target.

3.1 Structure and Representativeness of the ADP Microdata

ADP provides human capital management services to firms, including payroll processing. Processing payroll for a client firm involves many tasks including maintaining worker records, calculating taxes, and issuing paychecks. The structure of the microdata is determined by the business needs of ADP. ADP maintains records at the level of Payroll Account Controls (PAC), which often correspond to business establishments (but may sometimes correspond to firms) as defined by the Census Bureau and the BLS. Each PAC updates their record at the end of each pay period. The record consists of the date payroll was processed, employment information for the pay period, and many time-invariant PAC characteristics (such as an anonymized PAC identifier, NAICS industry code, zip code, etc.). PAC records include both the number of individuals employed ("active employees") and the number of individuals issued a paycheck in a given pay period ("paid employees"). Active employees include wage earners with no hours in the pay period, workers on unpaid leave, and the

[4] For a detailed analysis of measurement challenges in CES and QCEW, see Groen (2012).

like. Paid employees include any wage or salary workers issued regular paychecks during the pay period as well as those issued bonus checks and payroll corrections. In this paper we focus exclusively on active employment, having found that it generally performs better, though we plan to further investigate the active/paid distinction in the future.[5] The data begin in July 1999.[6]

The files we use are weekly snapshots of individual PAC records, taken every Saturday since July 2009 (snapshots were taken semimonthly between May 2006 and June 2009 and monthly before May 2006). Each snapshot contains the most recent pay date for each PAC, the relevant employment counts, and the other information described above. Since few firms regularly process payroll more than once per week, the weekly snapshots provide a comprehensive history of PAC-level employment dynamics.

Several important differences between ADP payroll microdata and the QCEW and CES data exist in terms of pay frequency, region, establishment size, and industry composition:[7]

- **Pay Frequency:** The composition of businesses by pay frequency in the ADP data is roughly comparable to the population estimates available. In the ADP microdata, PACs reporting biweekly payroll frequency are somewhat more common, and those reporting weekly pay are somewhat less common, than in the official BLS data.

- **Region:** ADP data provide reasonable geographic representation of the country as a whole.

- **Size:** While the ADP data include businesses of all sizes (in terms of employment), ADP PACs generally tend to be larger than U.S. establishments. The ADP PAC size distribution marks a middle ground between the CES sample and the QCEW universe, with relatively more employment in small units compared to the CES sample. No-

[5] One topic for further investigation is exactly *why* active employment performs better than paid employment. It is possible that double counting due to the inclusion of payroll corrections, reimbursements, and bonuses adds noise to paid employment as measured in the ADP data.

[6] When accessing the microdata, we follow a number of procedures to ensure confidentiality. Business names are not present in the data we access.

[7] These composition differences are covered in detail by Cajner et al. (2018), which also provides additional detail on the construction of the indexes covered in section 3.2.

tably, however, ADP has significantly more employment in mid-sized units than does CES, with a distribution that looks reasonably similar to QCEW.

- **Industry Composition:** Compared to both the CES sample and the QCEW universe, the ADP sample modestly overweights manufacturing employment and slightly overweights employment in services. Trade, transportation, and utilities employment is underweighted in the ADP data, while the weight of construction employment in ADP is similar to the CES sample, but both ADP and the CES sample underweight construction employment relative to QCEW.

3.2 Series Construction

The process of transforming the raw data to usable aggregate series is complex. Here we provide a brief, simplified explanation of the process. The interested reader may refer to Cajner et al. (2018) for details.

Each week, we calculate the weighted average growth of employment at PACs appearing in the data for two consecutive weeks. The restriction to "continuers" allows us to abstract from changes in the size of ADP's client base: as long as client turnover is random, the growth rate of continuers will be a valid estimate of aggregate growth (of continuers.) Growth rates are weighted by PAC employment and further weighted for representativeness by size and industry. We use QCEW employment counts by establishment size and two digit NAICS as the target population. Formally, let $w_{j,t}$ be the ratio of QCEW employment in a size-industry cell j to ADP employment in cell j in week t, let $C(j)$ be the set of ADP businesses in cell j, let $e_{i,t}$ be the employment of the i'th business, and let $g_{i,t} = \frac{e_{i,t} - e_{i,t-1}}{e_{i,t-1}}$ be the weekly growth rate of business i.[8] Aggregate growth is estimated as

[8] For weighting we use QCEW employment values as of March each year. While we could allow QCEW values to vary quarterly or monthly, the shares are slow-moving and thus this would not significantly alter the results.

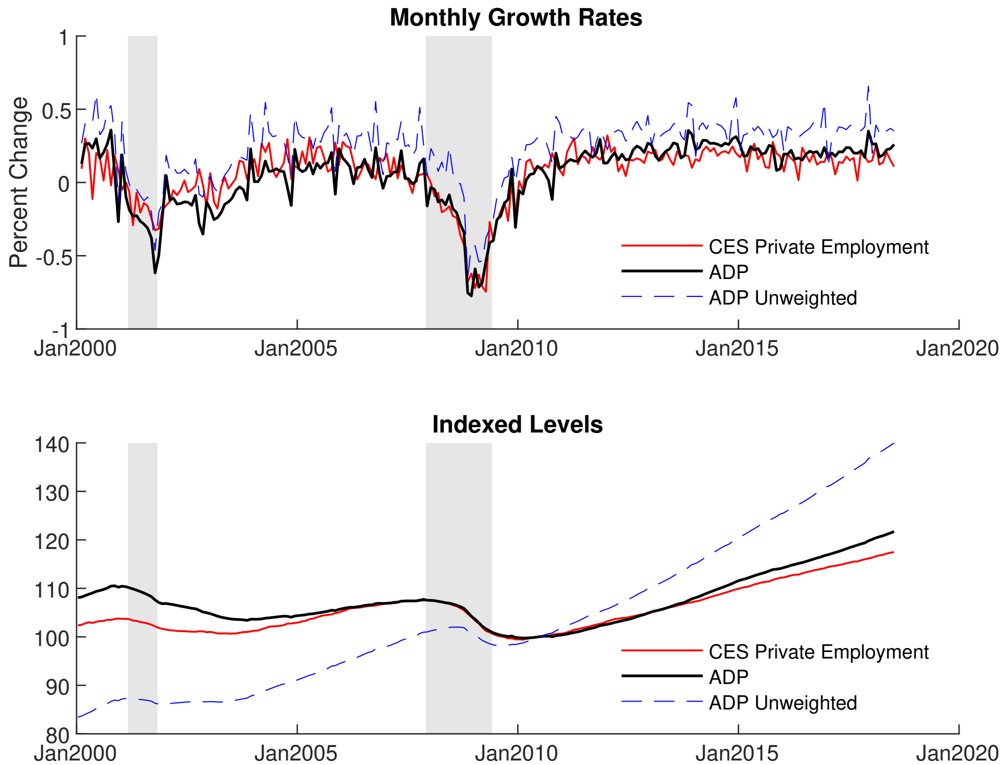
$$g_t = \frac{\sum_{j=1}^{J} w_{j,t-1} \sum_{i \in C(j)} e_{i,t-1} g_{i,t}}{\sum_{j=1}^{J} w_{j,t-1} \sum_{i \in C(j)} e_{i,t-1}} \tag{1}$$

Cumulating the weekly growth rates yields a (non-seasonally adjusted) weekly index level for employment. Our focus in this paper is on monthly estimates. We calculate the monthly index as the average of the weekly index for each month, weighting by days to account for partial weeks in each month.[9] Monthly averaging smooths through the weekly volatility, and the results in Cajner et al. (2018) suggest that averaging improves performance relative to point-in-time methods more similar to the CES. The monthly index is seasonally adjusted using the X-12 algorithm.

Figure 1 displays the seasonally adjusted ADP series (black line) along with the indexed CES estimate (red line). Importantly, the growth rate of the (weighted) ADP series is very similar to the CES and the business-cycle frequency fluctuations are very closely aligned. Moreover, this ADP-FRB series does not incorporate any of the benchmarking discussed below, so nothing forces it to resemble CES. It is also evident that the ADP series is volatile, and much of the month-to-month variation does not appear to be related to the monthly swings in the CES data. We interpret this as evidence that both series are contaminated with measurement error, which can plausibly be attenuated by modeling the series jointly. For reference, Figure 1 also shows the ADP unweighted series, which does not correct the ADP size-industry distribution. Clearly, the unweighted series has a markedly different trend growth rate, though it shares the qualitative business-cycle frequency behavior of the others.[10]

[9] For example, if a calendar week has 4 days in January and 3 days in February, our weighting by days procedure proportionally attributes the weekly employment to both months.

[10] While we do not directly use the weekly ADP series in this paper, we view these high-frequency measurements as a promising topic for future research on, for example, natural disasters. The weekly series are discussed in more detail in Cajner et al. (2018).



Note: Monthly data (current vintage), normalized to 100 in 2010.
Source: ADP, CES, authors' calculations. CES series is benchmarked; ADP-FRB is not.

Figure 1: Index Levels and Growth Rates

3.3 Strengths and Weaknesses of Different Types of Payroll Employment Data

Perhaps the most important issue when analyzing the quality of a dataset is its representativeness. Obviously, the QCEW data have a clear advantage here since these data represent population counts.[11] In contrast, CES and ADP estimates are sample based. As with CES, our ADP samples are adjusted with weights that are meant to make the estimates representative of the U.S., but this does not solve all issues. In the case of ADP, an important sample selection issue exists since only the firms that hire ADP to manage their payrolls show up in the ADP data. In the case of CES, the data are based on a probability sample of establish-

[11]Note, though, that there is a small scope discrepancy between QCEW on the one hand and CES/ADP on the other hand: about 3 percent of jobs that are within scope for CES/ADP estimates are exempt from UI tax law. For more detail, see `https://www.bls.gov/news.release/cewqtr.tn.htm`.

ments, but since the response rates are only about 60 percent (Kratzke, 2013), this introduces a potential sample selection issue as well.

Both the ADP and the CES data are subject to dynamic selection issues related to establishment entry and exit. In the U.S., young firms account for a disproportionate share of employment growth (Haltiwanger et al., 2013); indeed, mean and median net employment growth rates of firms above age five tend to be around zero (Decker et al., 2014). A critical limitation of the CES sample is its lack of coverage of new firms and establishments.[12] In addition, the CES cannot directly measure establishment deaths. The BLS attempts to correct for these shortcomings using a two-step CES birth/death methodology. In the first step, employment losses from business deaths are excluded from the sample in order to offset the missing employment gains from new business births. Thus, dead establishments (i.e., those reporting zero employment) and nonrespondents (suspected dead establishments) are given the same growth rate as the continuing establishments in the CES survey. In the second step, an ARIMA model estimates the birth/death residual: employment at newly formed establishments less employment at exiting establishments. This estimate is added to the estimates from the CES establishment sample to generate the final CES estimate. In many months, the model's contribution to headline employment estimates is sizable.[13] Actual new firms do not affect CES estimates until the sample is rotated.[14]

Even after a benchmark revision the monthly CES data never truly account for the birth and death of establishments. When a benchmark revision occurs, with the January CES re-

[12] The CES sample is redrawn only once a year. See the CES technical notes https://www.bls.gov/web/empsit/cestn.htm.

[13] See a discussion of the model and its recent contributions here: https://www.bls.gov/web/empsit/cesbd.htm. For example, since 2009 the Net Birth/Death adjustment has added a nontrivial average of 800,000 jobs to a particular year's employment gains, or roughly 40 percent.

[14] The sampling frame is based on QCEW source data (state unemployment insurance (UI) records), which lag several months. It might be wondered if the UI records pick up new establishments quickly; this is apparently the case. Employers must file UI taxes if they have paid (cumulatively) $1,500 or more in payroll, so most new employers would appear in the UI records very quickly; see https://oui.doleta.gov/unemploy/pdf/uilawcompar/2018/coverage.pdf. However, note that even after a business birth appears in the UI records, there is also time required for sampling, contacting, and soliciting cooperation from the firm, and verifying the initial data provided. In practice, CES cannot sample and begin to collect data from new firms until they are at least a year old; see https://www.bls.gov/web/empsit/cestn.htm.

lease in a given year, the previous year's March level of the CES data is set to the March level of QCEW employment. The monthly sample-based estimates for the 11 months preceding the March benchmark are revised with the use of a "wedge-back" procedure, where a linear fraction of the benchmark revision is added to the CES level each month.[15] This results in a constant being added to the monthly change in employment each year. So, while the year-to-year change in the post-benchmark CES data will capture the within QCEW-scope dynamics of entry and exit at the annual frequency, the monthly numbers will not.

ADP suffers from a related limitation in that we do not know the age composition of ADP clients, nor do we observe firm or establishment age in the ADP microdata. However, new and young firms may enter the ADP data immediately upon engaging ADP for payroll services. While the number of young firms in ADP data is unknown, any number could be a useful supplement to the CES data in which new firms are entirely absent.

As discussed above, the ADP data consist of weekly snapshots (since July 2009). In contrast, the QCEW and the CES data contain only information for the pay period that includes the 12th day of the month. As a result, the CES and QCEW data cannot measure employment activity over the entire month, which can be especially problematic in the case of temporary distorting events during the reference period. For example, an unusually large weather event (e.g., a hurricane or a snow storm) that reduced employment during the reference period but left the rest of the month unaffected would result in a CES employment report that understates the strength of the labor market throughout the month. In the weekly ADP data we can, in principle, observe both the shock and the recovery. In any case, averaging the level of employment for the month attenuates the impact of such short-lived events.

Finally, the QCEW and the ADP data are both essentially administrative data and thus arguably somewhat less prone to reporting errors and nonresponse, which typically plague survey data such as the CES.

[15] Again, see the CES technical notes.

4 Comparing ADP-FRB to Official Data

4.1 Predicting Annual Benchmarks

We follow the CES in benchmarking the level of our ADP-FRB indexes to the QCEW each year. Our procedure closely follows that of the CES: We iteratively force each March value of ADP-FRB to match the corresponding QCEW value, and we linearly wedge back the pre/post benchmark revision. The wedge reaches zero at the prior (already benchmarked) March. The data are currently benchmarked through March of 2017.

Throughout the paper, we use our monthly ADP index starting in 2007. For the purpose of annual benchmarking, this means we begin annual benchmark comparisons with the 2008 benchmark year, which measures the change in private nonfarm employment from April 2007 through March 2008. In the 10 years starting from 2008, the pre-benchmark ADP-FRB estimates were closer to the eventually published population counts in 4 years, while the pre-benchmark CES estimates were more accurate in 6 years (see Table 1). Overall, the root-mean-squared benchmark revision is 0.49 percent for the ADP-FRB data and 0.36 percent for the BLS CES data from 2008 onwards. Interestingly, the ADP-FRB estimates markedly outperformed the CES estimates during the Great Recession (2008-2010). Specifically, from 2008 to 2010 the ADP-FRB absolute revisions averaged 200 thousand per year, whereas the BLS-CES absolute revisions averaged 490 thousand per year. In contrast, over the past 5 years the pre-benchmark ADP-FRB estimates consistently overpredicted employment growth.

An evaluation of the CES benchmark misses should also take the net birth-death model into account, as the net birth-death adjustment adds roughly 40 percent to a particular year's employment change. As a result, a comparison of the benchmark misses of ADP-FRB series to the CES data is not exactly direct, as the ADP-FRB data would likely only capture a fraction of the contribution of the employment contribution of births. The third row in Table 1 presents the benchmark miss of the CES data without the inclusion of the net birth-death adjustment. That is, the "CES no BD" row reflects the growth to the level of employment

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
ADP-FRB	-173	-451	12	709	283	-230	-1030	-853	-322	-623
CES	-137	-933	-391	229	481	340	105	-259	-151	136
CES No BD	645	-216	-55	561	972	975	874	638	737	1066

Notes: Units: Thousands of jobs. CES revisions are the post-benchmark (QCEW-based) March estimate less the pre-benchmark estimate. ADP-FRB revisions are calculated in a similar fashion. CES no BD are the CES benchmark revisions that would have occurred excluding net birth-death adjustment.
Source: https://www.bls.gov/web/empsit/cesbmart.pdf, authors' calculations.

Table 1: Level differences between private employment benchmarks and estimates

solely due to the sample of businesses for which the CES data is collected.

As can be seen in the table, the benchmark misses excluding the net birth-death adjustment are substantially larger (with a root-mean-squared revision of 0.65 percent on average since 2008). Since 2008, the misses have also been almost always positive, reflecting a positive effect of establishments' births on the level of employment. The negative revisions in 2009 and 2010 point towards autoregressive nature of the birth-death adjustment carrying inertia forward from previous years employment changes. That is, since new business formation falls in recessionary years, the net effect of the birth-death framework overpredicts the actual birth-death contribution to employment growth and thus CES benchmark misses were larger than benchmark misses of CES data with no birth-death adjustment.

We more formally test the performance of ADP-FRB and CES in predicting annual benchmarked employment growth by running the following regressions. The dependent variable is the annual change in employment from March of year $t-1$ to March of year t as known upon the release of the CES benchmark revision in February of year $t+1$. We consider three different independent variables, with each annual observation specified as the econometrician observed them at the time of the CES jobs report for March of year t: (1) annual employment change from March of $t-1$ to March of t as estimated by monthly CES non-seasonally adjusted figures; (2) estimated annual employment change from March of $t-1$ to March of t as estimated by monthly CES non-seasonally adjusted figures in which the contributions of the birth-death model have been removed; and (3) annual employment change from March of $t-1$ to March of t as observed in the ADP-FRB non-seasonally adjusted ("active") employment index. The purpose of the exercise is to evaluate the ability of an analyst to estimate "true" (i.e., benchmarked) employment gains for the past year, observed at the time of the CES March employment report (in early April). At that time, the analyst has in hand CES data for the first release of March of year t (which includes the second release of February of year t and the third release of January of year t and all prior months). The analyst also has in hand the past year's ADP-FRB data, up through the third week of March of year t. That is, we estimate the following:

$$\Delta EMP_t^B = \alpha + \beta \Delta EMP_t^{March} + \varepsilon_t$$

where ΔEMP_t is the change in private nonfarm employment from March of year $t-1$ to March of t, the B superscript indicates the benchmark revision vintage of the series, the *March* superscript indicates the vintage of the series that is released with the March jobs report in year t (where we construct the annual estimate by summing all non-seasonally adjusted monthly estimates through the year), and ΔEMP_t^{March} can be the March vintage of CES, CES without birth-death model contributions, or ADP-FRB ("active") employment.

Table 2 reports results from this annual forecasting exercise. While we believe there is value in reporting this formal test, given the extremely small sample size the results are suggestive at best and should be treated with caution. That said, we find that the best predictor of benchmarked employment growth, according to both adjusted R^2 and RMSE, is the CES series that excludes birth-death model contributions (column 2). That is, the birth-death model does not appear to improve estimates of annual employment growth beyond the inclusion of a simple regression constant (compare columns 1 and 2). The ADP series (column 3) has predictive content but is outperformed by both CES series. However, we do find that adding the ADP series to the CES series that excludes birth-death contributions does improve forecasts (column 5).[16]

[16] In unreported exercises, we find that, unsurprisingly, the results are highly sensitive to the specific time

	(1)	(2)	(3)	(4)	(5)
CES	1.126***			1.104***	
	(0.0316)			(0.142)	
CES excl. Birth-Death		1.154***			0.927***
		(0.0235)			(0.0847)
ADP			0.976***	0.0197	0.199**
			(0.0543)	(0.121)	(0.0818)
Constant	-163.7*	604.5***	-135.1	-163.6*	452.5***
	(76.93)	(75.29)	(172.8)	(82.61)	(79.37)
Observations	10	10	10	10	10
R-squared	0.990	0.994	0.969	0.990	0.995
Adj. R-squared	0.989	0.993	0.965	0.988	0.994
RMSE	299.2	243.3	535.9	319.7	224.2

Notes: Dependent variable is benchmarked annual change in private nonfarm employment, March to March. Years 2008-2017. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors in parentheses.

Table 2: Forecasting Annual Employment Changes

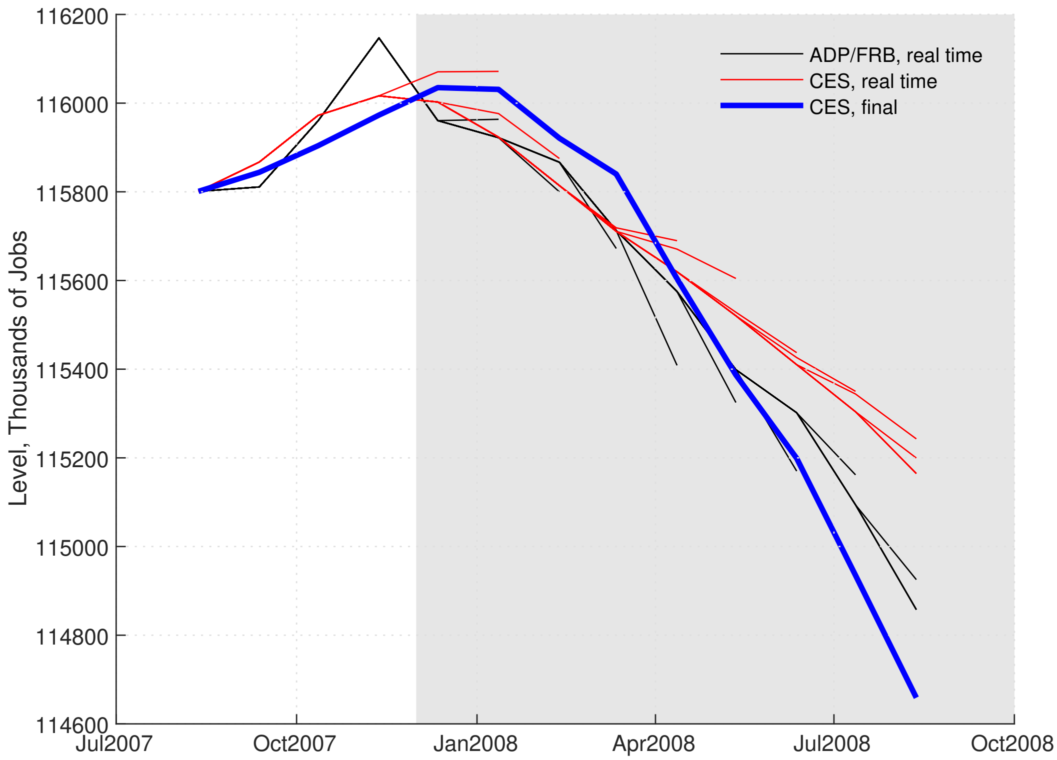
While the regression results on Table 2 are interesting, it is difficult to draw conclusions from such small-sample exercises. Moreover, ADP-FRB data are most valuable to policymakers if they increase our ability to understand recessions in real time; the predictive power of ADP-FRB during periods of steady, modest job growth is much less useful. We illustrate the point with a simple case study from the only recession in our ADP sample. [17]

Consider the beginning of the Great Recession. The NBER recession dating committee identified December 2007 as the business cycle peak, but throughout 2008 economic data sent somewhat mixed signals about the deterioration of labor market conditions. CES data releases from throughout 2008 revised substantially with the 2009 QCEW benchmark.

Figure 2 reports three payroll real time ADP-FRB and CES estimates of the level of employment, along with the final (current vintage) CES estimate. The heavy blue line is the final CES estimate, which shows employment losses of about 1.4 million jobs by August 2008. The red lines show each real-time vintage estimates for 2008: each end point repre-

period included.

[17] ADP began taking snapshots of semimonthly data starting in May 2006.



Note: Monthly data. NBER recession is shaded in gray. Real time lines show each successive vintage as a connected line, with the end point at the first-print value for that month. All series have been normalized to match the current vintage CES estimate in August 2007.
Source: ADP, CES, authors' calculations.

Figure 2: Real Time vs. Current Vintage Estimates

sents a first-print estimate, and the thicker central line represents the estimate after a few monthly revisions (but before the benchmark revision). That is, following the line back from an endpoint in month t, the line reflects the path of employment as it would have been known to observers in month t (including revisions up to that date). The black lines show the same set of real-time estimates for the ADP-FRB index. All the real-time series have been normalized to equal the CES current vintage estimates in August 2008 to remove a level shift due to benchmark revisions.

As is apparent from the figure, in real time the ADP-FRB series was typically more accurate in tracking the true pace of labor market deterioration during the first year of the recession. By August, real time CES estimates showed job losses totaling about 750,000, while ADP-FRB was at approximately 1.0 million job losses (both numbers should be compared to the current vintage estimate of 1.4 million job losses). Better knowledge of this deterioration would have been useful to policymakers as the critical fourth quarter of 2008 approached. In future cyclical downturns, ADP data may again prove useful in previewing the eventual revisions to CES data.

4.2 Predicting Monthly Employment

While annual forecasts of the benchmark revisions are important, the CES is a monthly measure of employment that revises over several releases as both more data and benchmarks become available. This section evaluates the ability of the ADP-FRB employment indexes to improve forecasts of CES data in real time and in conjunction with other real-time indicators. Table 3 reports forecasting models described in Cajner et al. (2018) using real-time ADP indexes and other variables to predict the final print of CES (i.e., after all the revisions). In particular, we estimated the following regression model:

$$\Delta EMP_t^{CES,final} = \alpha + \beta_1 \Delta EMP_t^{ADP,RT5} + \beta_2 \Delta EMP_{t-1}^{CES,RT} + \beta X_t + \omega_t \tag{2}$$

The explanatory variables include current month real-time (as of 5 weeks after the start of the month, which corresponds to the week before or the week of the Employment Situation release) ADP-FRB data, previous month real-time (first print) CES private employment, as well as initial unemployment insurance claims, Michigan Survey unemployment expectations, lagged (previous-month) unemployment rate change, and Bloomberg market CES payroll employment expectations. In addition, $\omega_t = \varepsilon_t + \rho\varepsilon_{t-1}$ is an MA(1) error term.[18]

Cajner et al. (2018) discuss similar results in more detail; here we simply note that the ADP-FRB indexes for active employment make statistically significant contributions to the model and generate modest improvements to forecasting accuracy. Column (1) of table 3

[18] The MA error term corrects for serial correlation in the errors when estimating equations of the change in employment. The results for a similar specification using OLS are qualitatively similar, despite the existence of serial correlation.

	(1)	(2)	(3)	(4)	(5)
ADP-FRB active employment			0.29**	0.39***	0.16**
			(0.11)	(0.11)	(0.07)
Lagged private CES employment	0.82***	-0.13	-0.21	0.51***	
	(0.07)	(0.15)	(0.14)	(0.12)	
Lagged UR change	-156.73**	-45.66	-43.05	-123.09**	
	(61.56)	(52.17)	(46.84)	(58.02)	
Unemployment expectations	39.17***	30.95***	14.08	16.55	15.21
	(11.82)	(11.01)	(12.29)	(12.74)	(10.88)
Initial UI claims	-3.10***	-0.91	-0.79	-2.52***	-0.56
	(0.74)	(0.71)	(0.72)	(0.83)	(0.52)
CES employment expectations		1.15***	0.98***		
		(0.16)	(0.15)		
Private CES employment					0.97***
					(0.07)
UR change					33.12
					(36.03)
Constant	4.87	-17.77*	-24.39**	-7.48	-17.85**
	(9.36)	(10.40)	(11.58)	(10.77)	(8.98)
RMSE	99	84	80	92	58

Notes: Dependent variable is final print of CES private employment. ADP series are real-time vintage, as of 5 weeks after the start of the month (i.e., the week before or week of the Employment Situation release). Unemployment expectations are from the Michigan survey. CES employment expectations are eve-of-release median markets expectations. Lagged private CES employment refers to pre-Employment Situation release. Robust standard errors in parentheses. RSMEs are calculated in-sample. * p<0.10, ** p<0.05, *** p<0.01. Estimation period: 2007m1-2018m9.

Table 3: Forecasting Monthly Employment Changes

reports the baseline forecasting model without the ADP-FRB data or market expectations. Adding market expectations in column (2) improves the forecast notably, as can be seen from the 15,000-job reduction in RMSE. In column (3) we add the ADP-FRB index and find that RMSE declines and the ADP-FRB coefficient is statistically significant; that is, the inclusion of the ADP-FRB index provides further marginal forecasting improvement beyond the inclusion of market expectations, in contrast to Gregory and Zhu (2014) results using ADP NER. In column (4) we report a model including ADP-FRB but omitting market expectations, which reduces RMSE by 7,000 jobs relative to the baseline. Finally, column (5) indicates that even when the first print of CES data is available, the real-time ADP-FRB data provide additional signal about the final or "true" BLS measure of employment change.

The forecasting success of the ADP indexes should not be overstated. The improvement in predictive ability may be statistically significant but is not dramatic. However, we should not expect too much improvement because the sampling variance of the CES estimate is large relative to the RMSE of our forecasts. For example, from 2013 until 2017 (which omits the Great Recession period of large forecast errors), the out-of-sample RMSE for predicting monthly payroll employment using the ADP data (along with other predictors) is 70,700 jobs, whereas the (sampling) standard error of the CES estimate is 65,000.[19] To the extent that sampling error is i.i.d., the sampling error provides a lower bound on the forecasting error for CES estimates. Practically, it should be nearly impossible to reduce the RSME of a forecast below 65,000, and any forecast that achieved better performance would be forecasting sampling error, not actual changes in employment.

The fact that our forecasting errors are already close the 65,000 lower bound, even without the ADP indexes, suggests that the main value of the ADP data may not be in forecasting CES. The data can instead be used to generate estimates that are timelier, higher frequency, and more granular. In addition, the ADP data may be combined with the CES to reduce total measurement error.

On net, the ADP-FRB measure of employment adds value to our understanding of the annual and monthly measures of employment and has some predictive power for benchmark revisions. Importantly, we find that during the large employment declines of the Great Recession, the ADP-FRB employment provided a more accurate measure of the employment declines. With these findings in mind, we now turn to a methodology that combines the information from both the official BLS measures of employment and the ADP-FRB series.

5 State-space model of Employment

Payroll employment growth is one of the most reliable business cycle indicators. Each postwar recession in the U.S. has been characterized by a year-on-year drop in payroll employ-

[19] See https://www.bls.gov/web/empsit/cestn.htm

ment as measured by the BLS in CES, and outside of these recessionary declines, the year-on-year payroll employment growth has always been positive. Thus, if one knew the "true" underlying payroll employment growth, this would help enormously in assessing the state of the economy in real time. In this section, we present results from a state space model to infer the "true" underlying payroll employment growth.[20]

Let ΔEMP_t^U denote the unobserved, "true" change in private payroll employment (in thousands of jobs), which is assumed to follow an AR(1) process:

$$\Delta EMP_t^U = \alpha + \rho \Delta EMP_{t-1}^U + \epsilon_t^U.$$

ΔEMP_t^U is a latent variable for which we have two observable noisy measures, BLS CES (ΔEMP_t^{CES}) and ADP-FRB (ΔEMP_t^{ADP}). Both are monthly changes in thousands of jobs. The observed values of CES and ADP employment gains are a function of the underlying state according to the following measurement equations:

$$\begin{bmatrix} \Delta EMP_t^{ADP} \\ \Delta EMP_t^{CES} \end{bmatrix} = \begin{bmatrix} \beta_{ADP} \\ \beta_{CES} \end{bmatrix} \Delta EMP_t^U + \begin{bmatrix} \epsilon_t^{ADP} \\ \epsilon_t^{CES} \end{bmatrix}.$$

Without loss of generality, we can assume that $\beta_{CES} = 1$. This only normalizes the unobserved state variable to move one-for-one (on average) with CES. We make this assumption in our baseline specification but leave β_{ADP} unrestricted. This is in contrast to Aruoba et al. (2013), who assume that both the observation variables in their paper (GDP and GDI) have unit loadings on the unobserved state variable. While those authors' assumption is justifiable given their use of the two well-understood (and conceptually equivalent) measures of output, given the relatively untested nature of the ADP data we feel it better to let the model choose the loading.

We assume that all shocks are Gaussian, and that ϵ_t^U is orthogonal to the observation errors $(\epsilon_t^{ADP}, \epsilon_t^{CES})$. However, we do allow the observation errors $(\epsilon_t^{ADP}, \epsilon_t^{CES})$ to be con-

[20] Aruoba et al. (2016) use a similar approach to provide a better measure of output.

temporaneously correlated, with variance-covariance matrix Σ:

$$\Sigma = \begin{bmatrix} \sigma^2_{ADP} & \sigma^2_{ADP,CES} \\ \sigma^2_{ADP,CES} & \sigma^2_{CES} \end{bmatrix}.$$

The Kalman filter is a widely used and very flexible framework. It is also particularly well-suited for our application. Both the CES and ADP-FRB estimates can be regarded approximately as sample means, with the samples drawn from the same population. As such, both CES and ADP-FRB are (approximately) truth plus mean-zero sampling error. This sampling error is captured by the Kalman filter in the observation noise terms. A critical assumption for our setup is that this noise is i.i.d. over time. This would be exactly true if CES and ADP-FRB redrew their samples every month, but there is in fact much overlap in the units from one month to the next. This means that any persistence in idiosyncratic establishment-level growth can propagate to persistence in the sampling error. Fortunately, the available evidence suggests that there is very low, or even negative, persistence in short-run establishment growth (see Cooper et al. (2015)), which in turn implies nearly i.i.d. sampling error and justify the Kalman filter.

5.1 Characterization of the State

The estimates for the model above are collected in the first column of Table 4 (the models are estimated on the data from 2006m5 to 2018m8). Interestingly, the estimate of β_{ADP} is precisely estimated and not statistically different from unity. Somewhat surprisingly, the covariance of the observation errors $\sigma^2_{ADP,CES}$ is negative, though it is not statistically different from zero. Specification 2 further generalizes the model, allowing for the ADP observation equation to have its own intercept α_{ADP}. This makes little difference, and the point estimates are essentially unchanged from the baseline. Specification 3 imposes a unit factor loading in the ADP equation and a diagonal Σ. Again, these alterations do not significantly change the point estimates, though the variances of the observation errors are inflated somewhat. Finally, Specification 4 assumes that the unobserved state follows a random walk. All of the qualitative features of Specification 1 carry through to this model as well.

As discussed above, the BLS produces estimates of the sampling error of CES. These estimates are based on the observed cross-sectional variation in employment growth, and knowledge of the stratified sampling scheme. The estimated sampling standard error for private CES employment is about 65 thousand jobs, which implies a variance of about 4,200 thousand jobs. This figure is remarkably close to the estimates of σ^2_{CES} in Table 4. In the context of the state space model, σ^2_{CES} captures all sampling and non-sampling error in the CES series, so it is reassuring that our estimates of the error align so closely with those of BLS.

Given that both the CES and the ADP series have been benchmarked to the QCEW, it may not be surprising that the model tends to treat them symmetrically. It is possible that most of the identification is coming from year-over-year variation, which would be dominated by the QCEW. We address this concern in Specification 5, which uses an unbenchmarked ADP series. The results are remarkably similar to the other specifications, indicating that QCEW benchmark is not in fact dominating our estimates.

Taken together, the results in Table 4 suggest that is it reasonable to think of ADP and CES as two symmetric measurement series, each with approximately the same relation to the unobserved state (i.e., the same loading and intercept) and with approximately equal degrees of uncorrelated measurement error.

With these estimates in hand, we can extract estimates of the unobserved state process. Figure 3 shows the smoothed (two-sided) estimate of the state (the heavy black line), along with 90% confidence intervals (the gray shaded area). Naturally, the state estimate appears less volatile than either observation series. The smoothed state estimates use data for all available sample periods to estimate the state. A simpler exercise is also instructive. Following Mankiw et al. (1984) and Aruoba et al. (2013), we seek to approximate the state estimate

Parameter	Specification (1)	(2)	(3)	(4)	(5)
ρ	0.96***	0.96***	0.96***	1.00	0.96***
	(0.02)	(0.02)	(0.02)		(0.02)
α	4.39	4.31	4.21	0.88	4.31
	(4.84)	(4.84)	(4.69)	(5.03)	(4.58)
β_{CES}	1.00	1.00	1.00	1.00	1.00
β_{ADP}	1.03***	1.03***	1.00	1.03***	1.06***
	(0.03)	(0.03)		(0.03)	(0.04)
σ^2_U	3765.41***	3786.13***	3609.16***	3698.76***	3290.51***
	(827.64)	(832.95)	(678.03)	(805.89)	(733.10)
σ^2_{CES}	3796.51***	3779.60***	3984.78***	3860.32***	4727.96***
	(721.96)	(721.17)	(642.11)	(713.98)	(853.74)
$\sigma^2_{CES,ADP}$	−393.91	−388.67		−315.56	−869.32
	(573.61)	(573.63)		(563.56)	(560.55)
σ^2_{ADP}	3758.90***	3773.01***	4171.35***	3852.70***	3517.13***
	(792.63)	(793.08)	(680.98)	(782.16)	(761.84)
α_{ADP}		4.10			
		(8.15)			

Notes: Maximum likelihood parameter estimates. Measurement series are the monthly change in the number of jobs according to CES and ADP-FRB, in thousands of jobs. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses. Specification 2 allows for a non-zero intercept in the ADP observation equation. Specification 3 restricts both observation equation loadings to unity, and assumes that the observation errors are uncorrelated. Specification 4 imposes a random walk on the unobserved state. Specification 5 uses an unbenchmarked version of the ADP series. Estimation period: 2006m5-2018m8.

Table 4: Kalman Filter Parameter Estimates

using only contemporaneous observations of CES and ADP-FRB. In particular, let the estimator be

$$\Delta EMP_t^C = \lambda \Delta EMP_t^{ADP} + (1-\lambda)\Delta EMP_t^{CES}$$

where λ is the weighting parameter to be chosen. We minimize the distance between the state estimate and the weighted average:

$$\min_{\lambda} \left\{ \sum_{t=1}^{T} \left(\Delta \widehat{EMP}_t^U - \Delta EMP_t^C \right)^2 \right\} \tag{3}$$

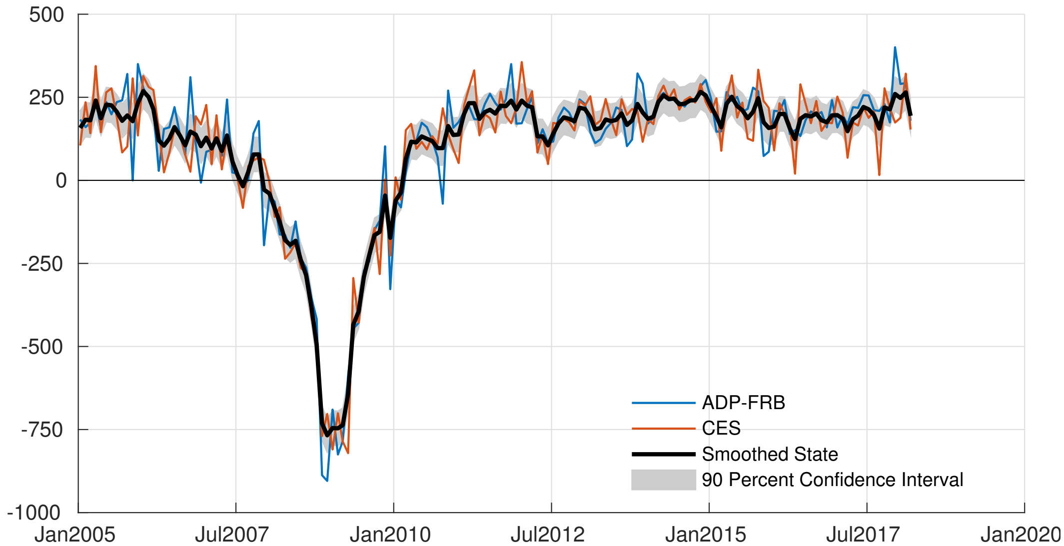
where $\Delta \widehat{EMP}_t^U$ is the state estimate from the Kalman smoother. This exercise is particularly simple under the assumptions of Specification 4, where both series are just truth plus uncorrelated noise. In that case, we can plug in the estimated parameters and solve for λ as

$$\lambda^* = \frac{\widehat{\sigma^2_{CES}}}{\widehat{\sigma^2_{ADP}} + \widehat{\sigma^2_{CES}}}.$$

where $\widehat{\sigma^2_{CES}}$ is the estimated variance of the observation error in CES, and similarly for $\widehat{\sigma^2_{ADP}}$. Using the values from Specification 4 yields $\lambda^* = 0.488$, so the optimal contemporaneous estimator puts nearly equal weight on the two series.[21] Relatedly, the Kalman gains for the two series (not shown) are also very similar.

Placing roughly equal weight on CES and ADP employment gains might seem counterintuitive. However, both datasets cover roughly a similar share of private U.S. payroll employment (23 percent for CES, 20 percent for ADP) and thus the sampling error could plausibly be of similar magnitude. Indeed, the BLS calculates that the 90-percent confidence interval for monthly change in private CES payroll employment is plus/minus 110,000. Al-

[21] Note that the linear combination of the ADP and CES series is nearly identical to the smoothed two-sided state estimate from the Kalman filter.

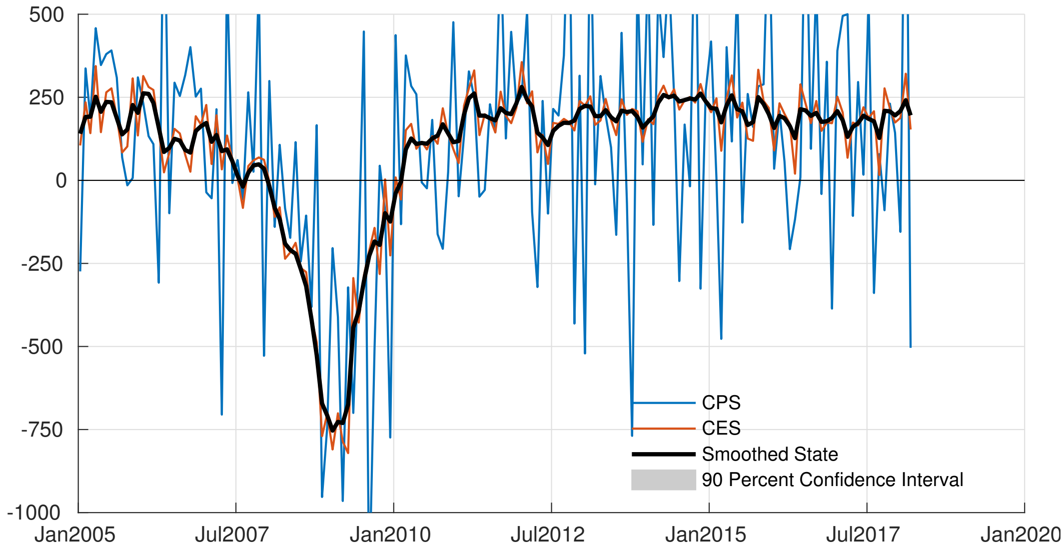


Note: Monthly data. Both CES and ADP-FRB are current vintage & benchmarked to QCEW. Smoothed state estimate is calculated from Specification 1.
Source: ADP, CES, authors' calculations.

Figure 3: Smoothed State Estimate

though the BLS eventually benchmarks CES payroll employment to the QCEW (which has nearly universal coverage), the benchmarking is done only for March each year, while the month-to-month changes are largely unaffected due to the procedure of linearly wedging-back the discrepancy between March estimates of employment in CES and QCEW. As a result, if in a particular month the CES sample estimate of payroll employment gain is distorted due to the sampling error, it is likely that the error will survive even the subsequent revisions. Since the ADP data rely on a (mostly) different sample, it should be unsurprising that taking a Kalman filter estimate of underlying gains based on both observed measures should give a more precise estimate of the current pace of employment growth, with weights being roughly similar due to the similar sample size.

For comparison and to show that the near-equal weighting scheme was not an inevitable result, we repeat the exercise replacing the ADP-FRB series with the change in employment calculated from the Current Population Survey (CPS), the household-side counterpart to CES that is used by BLS to estimate the unemployment rate. We adjust the CPS to align



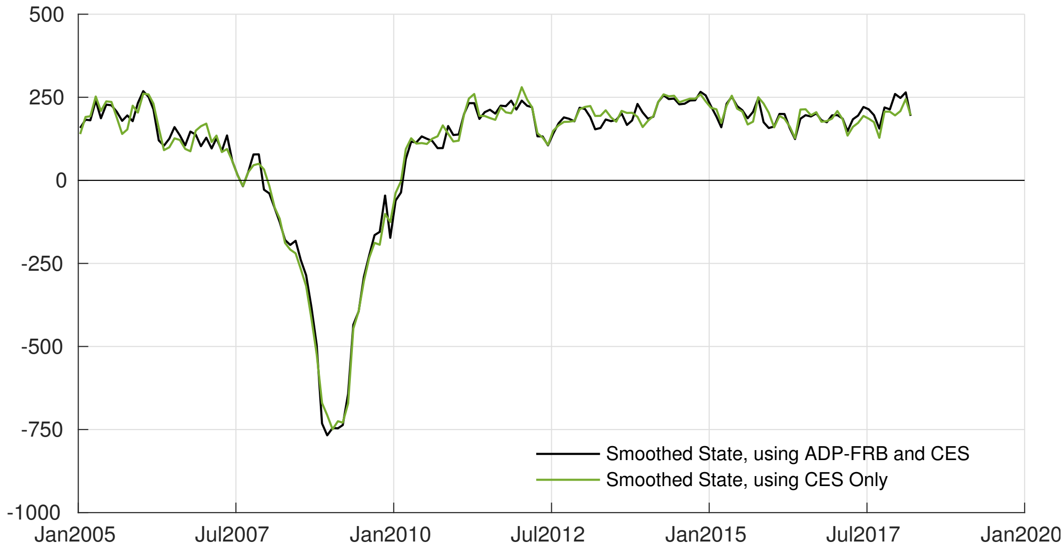
Note: Monthly data. Both CES and CPS are current vintage & benchmarked to QCEW. Smoothed state estimate is calculated from a model like Specification 1, but replacing ADP-FRB with CPS estimates, adjusted to match CES scope.
Source: CPS, CES, authors' calculations.

Figure 4: Smoothed State Estimate: CPS and CES

with the scope of CES private employment. Figure 4 plots CES, the adjusted CPS series, and a smoothed state estimate using the two as measurement series. It is clear that the CPS series is far noisier than either CES or ADP-FRB. Repeating the λ^* calculation with the CPS-CES model, we find that the optimal weighting only puts 4 percent of the weight on the CPS series. While CPS, CES and ADP-FRB all have approximately the same business cycle frequency behavior, the high-frequency noise in CPS makes it much less useful when extracting information about the state.

5.2 Estimating a State Space Model with only CES data

The Kalman filter approach combines information from before and after time t to form the state space estimate at time t. As a result, the state space estimate smooths through some of the volatility in the employment series inputs into the observation equation. To test whether the Kalman filter approach is just providing a less volatile series, we perform a robustness



Note: Monthly data. Both CES and ADP-FRB are current vintage & benchmarked to QCEW. Smoothed state estimate using ADP-FRB & CES is calculated from Specification 1.
Source: ADP, CES, authors' calculations.

Figure 5: Smoothed State Estimate: ADP-FRB and CES versus CES only

check that estimates a state-space model which includes only CES data. Results are shown in Figure 5. Not surprisingly the "CES only" state space estimate does not differ substantially from our combined estimate. Nevertheless, the two sets of estimates are not the same, consistent with the idea that having more series can improve measurement. We will include real-time estimates of the CES-only state space estimates in the next section's empirical exercises.

5.3 Evaluating the Estimated State's Predictive Content

Both the nontrivial Kalman gains and the fact that both the CES and ADP-FRB series receive equal weight provide support for the idea that combining the signal from both the BLS CES data and the ADP-FRB series can contribute to our understanding of "true" employment growth. Unfortunately, the aforementioned drawbacks of the CES data, including nonresponse, data revisions, and the role of the net birth-death model all contribute to sizable uncertainty around the monthly estimates of employment growth. All of that said, the CES is a very large, carefully conducted survey, which does an impressive job. In this section we tentatively treat the fully revised CES as truth, and employ the state-space estimates to predict the future readings of final CES employment gains.[22]

For the forecasting exercises, we employ a framework similar to that found in equation (2), without the additional controls. The dependent variable is the current vintage of the CES estimate. As independent variables we include various combinations of the ADP-FRB employment estimate, the CES employment estimate, the smoothed state as estimated using both ADP-FRB and CES, and the smoothed state as estimated by CES only. This final variable is included to distinguish the time-averaging effect of the state-space model from the additional information included in ADP-FRB. If the ADP-FRB series has no information then CES and the smoothed state base on CES only ought to be the only relevant predictors. Importantly, all the independent variables are real-time estimates. This means that the state-space estimates include no future information.

The results of this exercise can be found in Table 5. The first two columns include the $t+1$ current vintage CES employment value as its dependent variable. The second column adds the CES state as an additional explanatory variable. The third column contains the average employment growth over $t+1, t+2, t+3$, i.e., the average growth rate of next three months of employment. Estimated together, the only variable that is statistically significant, across the three specifications is the ADP-CES state. [23] The horserace results indicate that when comparing employment-based indicators of future CES readings of employment gains, the combination of the ADP-FRB series and the past CES gains, provides the most information about future employment.

[22] In ongoing work we use the QCEW as a monthly source of truth. There are several issues with using QCEW as the truth, including scope differences, differences in the seasonality of the source data, misreporting, and seam biases. However, it can still be informative to see which series best predict a (properly adjusted) QCEW series.

[23] In unreported results, we find that estimating each equation using only one of the explanatory variables indicates that each variable is independently significant. In addition, the horserace results are qualitatively similar when using first-print CES values as the dependent variable.

	(1) CES employment	(2) CES employment	(3) 3-month average CES employment
Constant	-28.14	-28.52	-17.05
	(19.43)	(18.78)	(20.35)
ADP-CES State	1.43***	1.50***	1.69***
	(0.49)	(0.55)	(0.44)
ADP-FRB Emp.	-0.18	-0.19	-0.30**
	(0.15)	(0.16)	(0.15)
CES Emp.	-0.18	-0.11	-0.41
	(0.34)	(0.55)	(0.31)
CES State		-0.12	-0.04
		(0.68)	(0.42)

Notes: The dependent variable in columns 1 and 2 is the fully revised change in CES private employment at time $t+1$; in column 3 the dependent variable is the average of the fully revised change in CES private employment for $t+1$, $t+2$ and $t+3$. ADP series are real-time vintage, as of 5 weeks after the start of the month. CES series appearing as independent variable or in state-space estimates are real-time vintage. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Estimation period: 2007m1-2018m9.

Table 5: Forecasting Monthly Employment Changes using State Space Estimates

6 Conclusion

In this paper we asked the question of whether or not additional information on payroll employment could improve the accuracy of employment estimates. We believe the answer is a qualified yes. At the monthly frequency, this is a tricky question, as there is no "true" measure of monthly employment gains. That said, the ADP-FRB estimates and the resulting state-space measures that combine both the ADP and CES information provide insight into the current state and future values of employment. Moreover, we find that the monthly ADP estimates outperformed CES in tracking the rapid employment decline seen during the Great Recession and can help predict the eventual revisions to the first prints of the BLS-CES data. At the annual frequency the official CES data best predicts benchmark revisions, though the sample is small. That said, the ADP-FRB data was closer to the QCEW levels in 4 out of the last 10 years.

Could the BLS make use of data from payroll processors to supplement the CES? Our understanding is that ADP almost never reports any client firm employment numbers to

BLS. The only exceptions are isolated cases where the client firm explicitly directs an ADP field office to submit their information for the CES survey. This being the case, the CES sample and the ADP sample are collected largely independently.

It is possible that improvements could be made through closer coordination. One possibility would be having payroll processors submit information to the BLS in a systematic way. This could allow for an increase in the sample size of CES, a reduction in collection costs, or both. BLS working directly with the payroll processors would reduce the burden on the sampled businesses. It could also reduce non-response, since business might be more willing to consent when they know their payroll company will handle the forms (even if the BLS obtains data directly from the processors, it would likely be necessary to obtain their consent.) The per-unit cost to BLS of collecting data could also fall, as collection for more sample units would be handled through centralized payroll processors.

Such an arrangement may benefit the respondents and BLS, but what incentive do the payroll processors have to take on the additional work? Civic duty may play some role, if processors see that a relatively low-cost contribution from them can measurably improve the national statistical framework. Payroll processors might also benefit from interaction with government statistical experts, who can suggest improvement and bring issues to their attention. Of course, payments may be necessary to get the cooperation of the processors. One approach would be allowing the sampled businesses to make a small payment to the payroll firm to avoid the survey paperwork. Another arrangement would have BLS paying the processor for access to the records. This would raise significant "hold up" problems: if the BLS becomes dependent on payroll processor data, reducing or eliminating surveys, then the payroll processors would be free to raise prices once the outside option is gone. The relatively concentrated nature of the payroll industry means that competition for BLS contracts would be sparse. This suggests that agencies should not substitute private data for their own surveys, unless the market for the data is sufficiently competitive. While the arranging for data collection through payroll processors may be challenging, we are actively exploring the possibilities.

There would be considerable benefits to linking the ADP microdata to BLS databases behind the BLS firewall, if such an undertaking were possible. Such an project would allow for much better weighting and evaluation of the ADP sample, improving the quality of any estimates. In particular, it would be possible to evaluate what types of sample selection bias are present in the ADP sample, by comparing ADP businesses to control groups, or comparing businesses before and after enrollment with ADP. In addition, we could better evaluate the differences between paid employment and active employment if we had BLS employment measures available. Finally, linking would also provide a check on BLS data, which can be subject to misreporting and other issues. Cross-checking employment counts, industry codes, and multi-unit status would be informative for all parties.

The results in this paper lay the foundation for future work employing private payroll microdata. We plan on testing the estimated state space results against other measures of employment, including state- and national-level measures of employment from the QCEW. We also plan on further exploring the geographic and industry detail to improve employment estimates. Importantly, there is additional information in the measure of ADP paid employment and at the weekly frequency that we have not fully leveraged in our current research.

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