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2018-005

Please cite this paper as:
Cajner, Tomaz, Leland Crane, Ryan Decker, Adrian Hamins-Puertolas, Christopher Kurz, and Tyler Radler (2018). “Using Payroll Processor Microdata to Measure Aggregate Labor Market Activity,” Finance and Economics Discussion Series 2018-005. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2018.005.

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Using Payroll Processor Microdata to Measure Aggregate Labor Market Activity

Tomaz Cajner, Leland Crane, Ryan A. Decker, Adrian Hamins-Puertolas, Christopher Kurz, and Tyler Radler

Abstract
We show that high-frequency private payroll microdata can help forecast labor market conditions. Payroll employment is perhaps the most reliable real-time indicator of the business cycle and is therefore closely followed by policymakers, academia, and financial markets. Government statistical agencies have long served as the primary suppliers of information on the labor market and will continue to do so for the foreseeable future. That said, sources of “big data” are becoming increasingly available through collaborations with private businesses engaged in commercial activities that record economic activity on a granular, frequent, and timely basis. One such data source is generated by the firm ADP, which processes payrolls for about one fifth of the U.S. private sector workforce. We evaluate the efficacy of these data to create new statistics that complement existing measures. In particular, we develop a set of weekly aggregate employment indexes from 2000 to 2017, which allows us to measure employment at a higher frequency than is currently possible. The extensive coverage of the ADP data—similar in terms of private employment to the BLS CES sample—implies potentially high information value of these data, and our results confirm this conjecture. Indeed, 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.

JEL Codes: J2, J11, C53, C55, C81

1 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 Erik Hurst, Alan Krueger, Mark Zandi, and thank seminar participants at the Federal Reserve Board, the ADP State of the Labor Market Summit 2017, the 2017 CAED conference, and the 2018 ASSA Meetings.

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Obtaining accurate and timely measurement of economic activity is a key challenge facing economic policymakers. Government statistical agencies have long served as the primary source of information on labor and product markets, producing “gold standard” measurements that are methodologically consistent over long periods of time and have solid theoretical underpinnings (e.g., random probability samples or comprehensive administrative data). But new sources of “big data” are becoming increasingly available through collaborations with private businesses engaged in commercial activities that record economic activity on a granular, frequent, and timely basis. New statistics, created using these nontraditional data sources, can complement existing government measurement and may enhance the ability of policymakers to measure economic activity in real time. One such data source is generated by ADP, a large payroll processor and the publisher of the National Employment Report (NER). ADP processes the payroll of about a half million business establishments accounting for roughly one fifth of U.S. private sector employment. In this paper we use ADP’s establishment-level payroll microdata to measure the U.S. labor market.

The ADP data have several appealing features. First, the data capture payroll employment, perhaps the most important economic indicator for tracking the health of the economy in real time. Second, ADP microdata provide scope for improvement to the timeliness, frequency, and accuracy of payroll employment measurement. While the monthly Current Employment Statistics (CES) data produced by the BLS are typically a reliable measure of true underlying payroll employment, ADP data can provide higher-frequency readings (weekly or biweekly data for many businesses), timelier estimates (data for a pay period are typically available the week after the end of the pay period), coverage of non-reference weeks (e.g., the whole month rather than just the pay period including the 12th as in CES), and an additional sample of businesses complementing the CES sample. Improvements in timeliness, frequency, and accuracy are important for policymakers. Third, the quality of ADP data can be assessed through comparisons both with the CES and with the Quarterly Census of Employment and

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3 See a description of the methodology behind the ADP National Employment Report (NER) at https://www.adpemploymentreport.com/common-legacy/docs/ADP-NER-Methodology-Full-Detail.pdf.
4 We use the term “payroll microdata” to refer to the ADP data in its somewhat raw form: establishment payroll dates with the attached employment counts. We avoid using the term “payroll data” without qualification since that brings to mind the CES payroll survey.
Wages (QCEW) published by the BLS (the latter of which comprises the near-universe of Unemployment Insurance tax records but is released several months after the CES).\textsuperscript{5}

In this paper we examine the informational value of the ADP data from several angles. First, we provide a detailed comparison between ADP and BLS data in terms of pay frequency, region, establishment size, and industry composition. ADP data appear to be quite representative of the U.S. economy, though the data do have slightly higher coverage in the Northeast region of the U.S. and are more likely to include establishments with more than 1000 employees when compared to the QCEW universe. That said, ADP data appear to be less skewed toward larger establishments than is the CES sample. This represents a benefit of the ADP sample, since its coverage complements the CES sample by providing additional representation of small establishments.

Next, we build employment indexes from the raw ADP microdata. This requires linking establishments longitudinally, interpolating employment changes to a weekly frequency, dropping outliers, weighting and aggregating growth rates, and finally seasonally adjusting the aggregated data. These steps are described in more detail in the subsequent sections and in the appendix. We produce weekly and monthly indexes; indeed, to the best of our knowledge we are the first to produce U.S. employment indexes at the weekly frequency.

Real-time data considerations are important for us, both because of the timeliness of our weekly index and because our estimates of weekly and monthly employment growth revise as data for establishments with longer pay frequencies arrive. Consequently, we calculate several versions of the monthly index: four real-time versions and one final series. Each real-time index uses information up through a particular week in the month (for example, one monthly index relies on information through the first two weeks of each month, another uses information through the third week, and so on).

We then analyze our ADP employment indexes and compare them to the official data. We find that several of our indexes are highly correlated with the officially produced employment statistics. Finally, we use our indexes to predict BLS CES payroll employment gains. We find that our indexes help to predict BLS payroll employment gains in real time, even after accounting for the expectations of professional forecasters. These results hold both in and

\textsuperscript{5} The QCEW collects employment data from states’ unemployment insurance (UI) tax systems and is also the primary source of benchmark data for the BLS’ Current Employment Statistics (CES) survey.
out of sample. We also find that the indexes have information that predicts revisions to CES gains, and we demonstrate this revision prediction with a case study of August revisions.

The reductions in forecast errors we obtain are statistically significant, yet are somewhat modest. In this context it is important to note that further reductions in forecast errors are likely to be difficult to achieve. In particular, CES is a survey based on a sample and thus has sampling error. BLS estimates that the standard error of the monthly CES statistic is about 67,500 jobs.\(^6\) The standard deviation of the CES private employment series itself has been about 68,000 jobs since 2010, suggesting that a great deal of the recent variation in CES is attributable to sampling error.\(^7\) Thus, only modest improvements in forecasting performance might be expected, since there is little reason to think that the sampling error component of CES should be forecastable.

ADP has long used its payroll data to contribute to economic measurement, most prominently through its monthly NER.\(^8\) Consistent with its goal of forecasting monthly CES employment, ADP constructs the NER by combining ADP microdata with other information such as weekly unemployment insurance claims and the Composite of Leading Indicators (see ADP 2016). Several authors have evaluated the forecasting properties of the ADP NER. Gregory and Zhu (2014) show that the NER helps predict the first print of CES, but this utility disappears when consensus forecasts are conditioned on. Similarly, Hatzius et al. (2016) show that the NER can forecast the first print of CES, but only when variables such as UI claims are excluded. Phillips and Slijk (2015) report that the NER series for Texas has a strong relationship with CES employment in that state. In contrast to these studies, we do not use the ADP NER and instead generate new series from the ADP microdata alone. This allows us to evaluate the strengths of the ADP data independent of other indicators. Our approach also allows for exploration of the rich detail available in the microdata, such as variation in pay frequency (including many businesses with weekly payroll), payroll data for weeks other than the CES reference week, and the differences between paid and active employment at the business level, each of which is useful for purposes beyond the forecasting of CES. In addition, we focus on forecasting fully revised CES numbers, rather than the first print. While the first print is

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\(^6\) See https://www.bls.gov/web/empsit/cestd.htm.

\(^7\) The standard deviation is, of course, significantly larger when the Great Recession is included in the sample.

\(^8\) Initially launched in 2006 in collaboration with Macroeconomic Advisers and since 2012 constructed in collaboration with Moody’s Analytics.
obviously of wide interest, the final print should be the best estimate of the true state of the economy.⁹

The remainder of this paper is organized as follows. In Section I, we describe the ADP data and how they compare with the data used in official measures of employment. In Section II we introduce aggregate employment indexes constructed using ADP microdata and explain the development and methodology used to create each series. Section III provides an overview of our indexes and presents stylized facts about the weekly and monthly data relative to officially published aggregates. Section IV explores the usefulness of our indexes to predict CES monthly private payroll employment. Section V concludes.

I. The ADP Payroll Microdata

ADP provides human capital management services, 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 typically, but not always, correspond to business establishments as defined by the Census Bureau and BLS. Each PAC generates a new record at the end of each pay period.¹⁰ The record consists of the date payroll was processed, employment information for the pay period, and many time-invariant PAC characteristics (such as the PAC identifier, industry code, location, etc.). In terms of employment information, 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 like. Paid employees include any wage or salary workers issued regular paychecks during the pay period as well as bonus checks and payroll

⁹ Koeing et al. (2003) suggest that forecasters may want to use real-time vintage variables as the dependent variables, even when their interest is in the fully revised versions. Their argument is that if initial releases are informationally efficient, no data available at the time of the release can help forecast the revision, and trying to do will, in finite samples, introduce noise and reduce precision. A regression of revisions to CES employment on first print growth indicates that revisions can in fact be predicted, so the informational efficiency condition does not hold in this context.

¹⁰ A PAC can actually represent more than one establishment, as long as the payroll is processed at a particular location. For comparison, the establishment concept for the CES sample is an unemployment insurance (UI) account. For QCEW the establishment concept is a worksite.
corrections. We discuss the active vs. paid distinction in more detail below. In addition, ADP records PAC zip codes, NAICS industry codes (nonmissing for over 90 percent of employment), and other descriptive information about the PAC including EIN, business parent, and franchise identifier. Data available to us begin in July 1999.

Figure 1 plots total active and paid employment from January 2000 to March 2017. The figure plots raw, non-seasonally adjusted data from ADP. Paid employment is substantially more volatile than active employment, likely as a result of seasonal variation in utilization as well as variation in bonuses, payroll corrections, and other unusual pay events. While both series declined markedly during the Great Recession, paid employment continues to remain below its 2007 pre-recession peak, in contrast with both ADP active employment and BLS measures of payroll employment, which have now surpassed pre-recession levels. Figure 1 reflects not only employment growth within ADP businesses but also entry and exit of businesses from the ADP sample; as we will show below, a series based on longitudinally linked observations better matches BLS measures.

11 Industry information is taken from Dun and Bradstreet data.
12 The initial few months of data appear unusually noisy. As a result, for the analysis in this paper we only use data from January 2000 onward.
We will next turn to discussing the ADP payroll microdata vis-à-vis the QCEW universe and the CES (unweighted) sample data, but first we need to cover the relevant features of these datasets.

The BLS publishes the CES employment report every month, a few days after the end of the reference month. The CES is then revised in the subsequent two months as well as during annual benchmark revisions with the January employment situation release. The CES estimate is based on the survey that tracks the payroll employment of about 500,000 private establishments, covering 23 percent of all private employees in the U.S. Note that the CES contains data for total nonfarm payroll employment, but here we focus only on the private part, i.e., we exclude government employment. We focus on private payroll employment for two reasons. First, private payrolls arguably carry a better signal of the current state of the economy, while government employment might be affected by factors not necessarily linked to the business cycle (e.g., change in government policies). Second, the ADP data are more informative of private as opposed to total nonfarm payrolls.
sampling weights are applied after data collection to make the estimates representative of the U.S.

In contrast, the QCEW is an administrative dataset built from unemployment insurance tax records. As such, there is no sample and no traditional sampling error. The tax records cover nearly the universe of (UI-covered) employment. However, the QCEW data are only available with a delay of several months. Although employment is measured for each month, it is more common to use the QCEW data on a quarterly or annual basis. We will reference the QCEW primarily as a measure of the “true” number of workers and establishments and of the composition of employment in terms of size, industry, and other characteristics.

Table 1 clarifies the overall establishment and employment coverage in the ADP microdata. In this paper we tentatively treat PACs as establishments, although PACs can, in some cases, cover multiple worksites. ADP-covered establishments with nonmissing industry data comprise about 5 percent of total U.S. establishments (as measured in QCEW). This share has been roughly constant since 2005. These establishments account for just over or just under 20 percent of U.S. employment in 2015, depending on whether we use the “active” or “paid” employment concept. The coverage of ADP PAC industry codes deteriorates over time, from nearly 90 percent of PACs in 2005 to roughly 80 percent in 2015. That said, the increase in non-classified PACs primarily reflects smaller organizations, as the share of employment for which industry information is available has been roughly constant at about 96 percent.

In table 2 and figure 2 and figure 3 we compare ADP data to BLS in terms of pay frequency, region, establishment size, and industry composition. These comparisons have to be made at a relatively high level of aggregation to ensure the confidentiality of the ADP client base. Table 2 reports data for March 2017. As shown in Panel A, ADP PACs have diverse pay schedules, with 22 percent issuing paychecks weekly, 46 percent biweekly, 21 percent semi-monthly (i.e., twice per month), and 11 percent monthly.14 The composition of businesses by

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14 Pay frequency is self reported by ADP PACs; we report aggregate figures based on these self reports. We do observe occasional paycheck issuance patterns that differ from self-reported pay frequency; moreover, roughly 15 percent of PACs change observed pay frequency in our sample. Note also that the data available to us do not always include every pay period. Prior to 2006, our data consist of once-monthly mid-month ADP extracts reporting the most recent pay period for each PAC, regardless of actual pay frequency. Over this period, then, about three quarters of payrolls will not be captured for weekly payers, and about half of payrolls will not be captured for biweekly and semimonthly payers. ADP extracts are biweekly beginning in May 2006 and weekly beginning in July 2009. In recent years, then, we can expect to capture nearly all payroll events for all frequencies of pay. The mixed-frequency nature of the data present some challenges, but weekly and biweekly payers provide valuable
pay frequency in the ADP data is roughly comparable to the population estimates, labeled as the QCEW in Table 2. PACs reporting biweekly payroll frequency are somewhat more common and those reporting weekly pay are somewhat less common in the ADP payroll microdata than in the official BLS data.

ADP data provide reasonable geographic representation of the country as a whole. As shown in Panel B in Table 2, ADP coverage is quite strong in the Northeast (likely resulting from the firm’s long-standing presence in the region) and somewhat weak in the South Census region. ADP coverage in the West and Midwest is reasonably similar to QCEW and CES shares in terms of establishments and employment. In sum, each region is well covered by the ADP data.

While the ADP data include businesses of all sizes (in terms of employment), ADP PACs generally tend to be larger than U.S. establishments. Figure 2 plots the cumulative employment distribution of the ADP sample, the CES sample, and the QCEW. The horizontal axis marks progressively larger establishment size bins, and the black line represents the cumulative share of ADP employment accounted for by establishments no larger than a given size. The red line and blue line plot the same quantities for the CES sample and QCEW, respectively. Note that QCEW establishments are well defined (i.e., single business locations), while both ADP PACs and CES UI units can potentially map to multiple establishments. That said, the comparisons are encouraging.

For context, establishments with fewer than five employees comprise almost 7 percent of employment in the QCEW, while UI units of the same size comprise less than ½ percent of employment in the CES sample. Large establishments with more than 1000 employees account for about 10 percent of QCEW, but UI units in that size class cover more than 65 percent of CES sample employment. Comparing CES and QCEW in Figure 2 illustrates the large-unit weighting of the CES sample relative to the QCEW universe. The ADP PAC size distribution marks a middle ground between the CES sample and the QCEW universe, with relatively more opportunities for timely measurement. A negligible share of businesses report quarterly pay frequency; we excluded those from our analysis.

15 Technically, the BLS data on pay frequency are obtained through the CES sample, but reweighted with QCEW weight, so they effectively represent the population estimate, which is way we report them in column QCEW of Table 2. The BLS data on pay frequency for March 2013 are reported by Burgess (2014); we obtained the updated numbers for March 2017 through email correspondence with the BLS.

16 The horizontal axis scale is ordinal.
employment in small units compared to CES. Notably, however, ADP has significantly more employment in mid-sized units than does CES, with a distribution that looks reasonably similar to QCEW. Given the potential (but rare) differences between establishment, UI, and PAC concepts, these comparisons should be interpreted with caution; however, we are encouraged by the potential for the ADP sample to complement the coverage of CES in terms of small- and medium-sized business units.

![Cumulative Distribution of Employment](image)

**Figure 2**

Crucially, it is not the case that both ADP and CES are dominated by just a few large employers; if it were, there could be significant overlap between CES reporters and ADP reporters, leading to correlated errors. The fact that ADP has little weight on the largest employers (compared to CES) suggests that much of ADP employment is at firms not reporting to CES, making the ADP series a (relatively) independent signal.
Data on industry representativeness also suggest a limited but nontrivial role for selection in the ADP sample. Figure 3 reports employment shares by broad sectors for ADP, the CES sample, and the QCEW universe. Compared to both the CES sample and the QCEW universe, the ADP sample modestly overweights manufacturing employment and slightly overweights employment in services. Trade (including retail and wholesale), 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). These differences notwithstanding, each major sector is again well represented in the ADP data.
**Additional sample differences between the ADP and BLS data**

A variety of other issues impose constraints on the representativeness of ADP data. As mentioned above, the ADP microdata consist of payroll processing clients, giving rise to several sources of sample selection. First, at a point in time, businesses that use an external payroll processor may be different from businesses that handle payroll internally. For example, new or extremely small businesses may not need—or be able to afford—external payroll services, and extremely large businesses may often prefer to develop internal payroll processing units. Moreover, the returns to outsourcing human resources could also vary by industry. Second, at a point in time, ADP clients may be different from businesses that engage other large payroll processors due to differences in the specific characteristics (including price) of the services provided, and businesses that engage large nationally operating payroll processors may be different from businesses that engage small, local payroll processors (sometimes simply local accounting firms). These sources of “static” bias are nontrivial, but we can address them to some extent by comparing ADP businesses and the universe of employers (such as those comparisons described above) and through the use of weights.

A third source of bias is that there may be dynamic selection issues associated with lifecycle dimensions of demand for external payroll processing and associated with the labor demand decisions of businesses around the time they enter or exit ADP records. Indeed, we observe volatile behavior among new ADP PAC records and among soon-to-be-absent ADP PAC records. We have no way of knowing whether a PAC’s first appearance in ADP files corresponds with the beginning of that establishment’s existence (though such a coincidence is likely to be rare), and we have no way of knowing whether a PAC’s final appearance in ADP files corresponds to a true establishment exit. The cessation of the relationship between a client business and ADP could result from other outcomes beside true firm exit, such as the acquisition

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17 Note that data produced by government statistical agencies can also suffer from selection bias. For example, with the exception of four states where participation is mandatory, the CES participation is voluntary, which can lead to selection bias due to nonresponse. See [https://www.bls.gov/respondents/ces/faqs.htm#2](https://www.bls.gov/respondents/ces/faqs.htm#2).

18 In fact, ADP has developed a separate “Enterprise” platform that caters to about 500 very large firms with specific, highly customized payroll needs; we do not have access to data from this platform.

19 Another source of selection is ADP’s historical growth, beginning as a small New Jersey payroll manager. ADP’s current clientele likely reflects in some part older customers acquired when the company’s market reach was much more limited.
of the business by another firm, a choice by the business to engage another payroll processor, or a choice by the business to bring payroll processing activities inside the firm.

An implication of the dynamic selection issue described above is that we cannot accurately observe firm or establishment entry and exit in the ADP microdata. While incumbent firms account for the bulk of employment in the U.S. at any given time, entry and exit are important margins of aggregate employment growth, particularly over the business cycle (Adelino, Ma, and Robinson, 2016; Fort et al., 2013). The real-time measurement of establishment entry and exit is a challenge in any data source, including official statistics, and it creates a nontrivial source of non-sampling error. This issue also affects the CES, which draws its sample from a frame of unemployment insurance tax accounts that, for the purposes of monthly statistics, introduces lags in the observation of new businesses. BLS statisticians address this problem with the CES Net Birth/Death Model to predict net entry.20 In our present work we do not attempt to model establishment birth and death with ADP data but instead rely entirely on ADP’s continuing establishments for our inferences, mirroring CES’s matched sample methodology. As described later in the paper, we are careful to limit the influence of changes in ADP’s customer base on the estimates of aggregate employment dynamics we derive from the ADP data.

All of these selection issues can potentially bias our results in ways that are difficult to predict or test. We rely heavily on both the CES and QCEW as benchmarks to verify that our indexes are valid and to make adjustments for factors such as industry composition. Our task would be much more difficult, if not impossible, without high-quality comparison datasets.

The ADP payroll microdata do have certain advantages when compared to the BLS CES data. First, ADP data incorporate (since 2009) all pay periods, while the BLS CES data only contain information for the pay period that includes the 12th day of the month. As a result, the BLS CES data might be unrepresentative of employment activity in a 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 numbers 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. The weekly frequency of the ADP payroll microdata allows us to record employers

20 See https://www.bls.gov/web/empsit/cesbd.htm.
making up for lost employment due to a shock, and ADP’s detailed information on geography allows for identification of the local area most affected by the shock. In addition, higher frequency data in principle make it easier to identify outliers (for example, due to unusual hiring patterns) and thus seasonally adjust the data.

Second, the ADP data provide more timely estimates, as the data for a pay period is available the week after the end of the pay period. That means information for a given month begins to accrue at the start of the second week of the month. As a result, accurate readings for a month can be achieved a few weeks into the month, as opposed to waiting for the start of the following month.

Third, the ADP data may be able to provide a more accurate reading of establishment-level employment since payroll processing data are a form of (private) administrative data. Survey data are prone to reporting errors and nonresponse, and while payroll data are not likely to be free of mistakes, the fact that the data reflect actual processed paychecks with significant costs to employers suggests that incentives for accuracy are strong. Moreover, the population benchmark of the CES survey data is only anchored in March of each year with other months being linearly wedged in order to ensure the levels are consistent. As a result, the monthly changes in CES employment are never truly benchmarked with the administrative data.

Fourth, the ADP data include information on a larger set of employees. The CES data only include employees who received pay and exclude individuals on unpaid leave. In contrast, ADP data provide information for both active employees (which includes individuals who did not receive pay during the pay period but nevertheless maintain an active employment relationship) and paid employees. The information on active employees might be useful in contexts such as the estimation of labor market slack.

Taking these points together, the ADP microdata can complement government-generated statistics in important ways. While it is essential to have quality statistics generated from true probability samples and comprehensive administrative data to serve as a “gold standard”

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21 For example, Applebaum, Fairman, Groen, and Phipps (2008) find that human error is a substantial contributor to the errors that arise in monthly CES survey responses.
22 See Monthly Labor Review, “Benchmarking the Current Employment Statistics national estimates,” October 2017.
benchmark, payroll microdata can provide more timely, more frequent, and more variety of measures of payroll employment.

II. Methodology

This section describes the methodology we employ to create aggregate ADP employment series. Our goal is to create seasonally adjusted indexes of employment at both the weekly and monthly frequencies. We construct several variants of our ADP employment series, which differ in terms of concepts of employment, timing of the data, aggregation methodology, interpolation methods, and data cleaning processes. In this section we first describe in more detail the different categories of our employment series. We then outline our interpolation methodology and its implications for the different employment series. Following that, we present our approach to calculating growth rates and eliminating outliers. We then provide a brief overview of our weighting methodology. Once an index is estimated in levels, we seasonally adjust both the weekly and monthly data.

Three primary categories of employment series

The three primary categories of employment series we generate from the ADP data are “standard,” “real-time,” and “CES mimicking” series. The standard series we generate are both weekly and monthly, with the monthly series calculated as the average of the weekly levels for the month. Given that not all employers report every week, our weekly (and therefore monthly) series require interpolation for establishments that do not report during a particular week. Our two interpolation methodologies and the assumptions they entail are described in the next section.

The real-time series allow us to estimate the current month’s employment change while the month is still in progress. ADP microdata are made available each week, with new information reflecting paychecks issued over the previous week (which, in turn, reflect employment in the pay period just preceding the paycheck issuance). These weekly updates of

23 The appendix contains additional information on the methodology underlying the data series construction.
24 Throughout this project we make the assumption that payrolls through a particular week refer to employment in the previous week since paychecks are typically issued a few days after the end of a pay period. That is, three weeks of payroll data reported in a month would cover two weeks of employment information for that month.
ADP microdata allow us to create four vintages of a real-time monthly employment estimate; the vintages are numbered 2 through 5 and use, respectively, information for the first two weeks of a month’s payroll data, the first three weeks, and so on until five weeks of payroll data for the month are accumulated. Each successive vintage causes a revision of the monthly estimate not only because new data provide coverage of an additional week of the month but also because biweekly or monthly paychecks provide data that allow revision of multiple previous weeks’ growth rates.

The monthly **CES-mimicking** series also have a vintage structure, but they replicate the CES reference period methodology. The CES survey collects data on employment for persons on establishment payrolls who received pay for any part of the pay period that includes the 12th day of the month. Accordingly, the CES-mimicking series estimate employment on the 12th of the month, rather than measuring employment for the whole month as the real-time indexes do.

There are three variants of the CES mimicking series, based the number of days that have passed since the 12th day of the month: we calculate CES-mimicking indexes for 7, 10, and 14 days after the 12th of the month. These series only uses the payroll data that is in hand 7 days after the 12th, 10 days after the 12th, and 14 days after the 12th, respectively.

As noted previously, the ADP microdata include information on both active and paid employment. For the standard and real-time employment series, we generate two variants based on active and paid employment. Recall, the active and paid employment series exhibit different seasonal and trend behavior (see figure 1) and, as a result, contain different information about employment.

**Interpolation**

The varying pay frequencies we observe in the data, as well as the fact that even PACs with the same pay frequency can have different pay period start and end dates, introduce complications for measuring changes in aggregate employment. We choose uniform measurement dates and estimate each PAC’s employment level as of those dates. For our weekly indexes, we choose Saturdays as our measurement dates. The day of week is of little importance, since the employment data are for pay periods, not for individual workdays. In any case, estimating a PAC’s employment on a specific day requires interpolation since payroll

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25 See [https://www.bls.gov/web/empsit/cesbd.htm](https://www.bls.gov/web/empsit/cesbd.htm) for details.
microdata only report employment as often as paychecks are issued. We consider two interpolation methods, stepwise and linear.

Our first—and preferred—method is stepwise interpolation. Employment on day $t$ is set equal to pay period employment for the pay period containing day $t$. Thus interpolated employment is constant within each pay period and may jump discretely up or down on the seam between pay periods. This method of interpolation will exactly match true employment if hires and separations only occur between pay periods. The stepwise interpolation method possesses two key advantages. First, this method gives a well-defined answer to a well-defined question: What is pay-period employment for the pay period including day $t$? Alternative methods in which employment is smoothed between pay periods, such as the linear method described below, provide less concrete employment concepts. Second, the stepwise method matches the methodology of CES, which measures the number of workers for the pay period including the 12th of the month. Note that the econometrician cannot calculate stepwise-interpolated employment for day $t$ until the end of the pay period including $t$. It is only at the end of the pay period that employment is reported to ADP.

A second approach is linear interpolation, which converts pay period observations into daily employment estimates under the assumption that PAC employment evolves linearly between pay dates. More precisely, we assume that a PAC’s actual employment on a pay date is equal to the number of employees paid on that day, and employment on days between pay dates is determined by a linear path between pay dates. This approach has the effect of smoothing out changes in the levels of employment. Note that linear interpolation relies on data from the pay periods prior to day $t$ and immediately following day $t$, so it cannot be calculated in real time as of day $t$.

**Data Cleaning**

We occasionally observe events in the payroll microdata that cannot appropriately be included in the calculation of our aggregate indexes. These generally fall into three categories: outliers, payroll gaps, and PAC endpoints. We drop observations with very large swings in

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26 In the appendix, we briefly discuss an additional challenge to point-in-time measurement: worker churn.
27 One may worry that true employment is smoother than the stepwise method implies, that is, that employment changes are not all synchronized to the pay period. While this is a concern, industry anecdotes suggest that many hires and routine separations are timed to occur at the beginning and end of the pay period, respectively.
employment and very long gaps between payrolls. We describe procedures to identify and exclude these types of events in the appendix.

**Aggregation and Weighting**

With the cleaned, interpolated PAC-level panel data in hand, we calculate growth rates and aggregate. For each establishment-week of data, we calculate weekly growth as

$$g_{it} = \frac{e_{it} - e_{i,t-1}}{e_{i,t-1}},$$

where $e_{i,t-1}$ is employment in the previous week and $e_{i,t}$ is employment in the current week. This requires valid observations for the establishment in both periods, so establishments entering in week $t$ or exiting in week $t-1$ are dropped. Aggregate growth is the weighted sum of establishment-level growth:

$$g_t = \left( \sum_{i \in I_t} e_{i,t-1} \right)^{-1} \sum_{i \in I_t} e_{i,t-1} g_{i,t},$$

where $I_t$ is the set of establishments with valid observations in both weeks $t$ and $t-1$.

The expression above gives the aggregate growth rate of continuing establishments in the ADP universe; as such, it represents the industry and establishment size distribution of the ADP businesses. We also compute growth rates that are weighted to match the industry and size distribution of the QCEW. From the QCEW files, we obtain employment counts for 2-digit NAICS groups crossed with six size classes. In the ADP data we calculate employment (both paid and active, separately) for the same cells. Then the weight for industry-size cell $j$ is

$$w_{j,t} = \frac{e_{j,t}^{QCEW}}{e_{j,t}^{ADP}},$$

where the numerator is total QCEW employment in cell $j$, and the denominator is total ADP employment in cell $j$. Then weighted aggregate growth is

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28 For each week of ADP data we use Q1 QCEW data for that year. Employment shares change very little even year-to-year, so there is no noticeable impact from using annual QCEW data. We focus on private nonfarm employment (i.e., private industries excluding all of NAICS 11 except NAICS 1133).

29 Where industry information is missing from the ADP files, we assume that it is missing-at-random conditional on the available date and size class information.
\[ g_{t,\text{weighted}} = \left( \sum_{j \in J} \sum_{i \in I_{j,t}} w_{j,t-i} e_{i,t-1} \right) \sum_{j \in J} \sum_{i \in I_{j,t}} w_{j,t-i} e_{i,t-1} \]  

where \( J \) is the set of size-industry cells, and \( I_{j,t} \) is the set of establishments in cell \( j \) in week \( t \). The resulting data are weekly growth rates.

### Transforming ADP Indexes into Employment Levels

In some of the empirical tests of ADP data that we explore later in the paper, we need employment levels (and their first differences). To transform ADP indexes into employment levels, we set the ADP index equal to BLS CES private payroll employment in a base period. We have chosen the level of private payroll employment in 2004 as our base period. Lastly, we seasonally adjust the resulting index levels (see appendix).

### III. ADP Employment Indexes

Before evaluating the efficacy of ADP payroll microdata to provide additional information about the labor market, we first establish some basic stylized facts. The sheer number of series generated by the possible permutations of the various approaches discussed in the earlier section makes this task difficult, so we focus on a small subset of the possibilities. As mentioned, each series we create is in terms of growth rates for the entire nonfarm private sector, similar to the private nonfarm payroll employment series published by the BLS. Specifically, we present the first and second moments of the series, along with correlations with the BLS series for nonfarm private employment. We then plot and discuss our preferred monthly and weekly indexes. We present an example of how the real-time estimates evolve over the month of March 2010. We conclude this section by answering the question of how many weeks of real time information is needed before a meaningful estimate of employment is available.

### Moments of the ADP series

Table 3 contains the means and variances of 14 select ADP employment indexes and for the BLS nonfarm private payroll employment series.\(^3\) The first and second moments are for

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\(^3\) Results and moments of other employment series are available upon request.
growth rates (percent changes at monthly rate) and are measured over three separate time periods: 2000 to 2017 (the time frame of data to which we have access); 31 2009 to 2017 (the time period over which weekly data are available); and 2011 to 2017. The last time period is important since the labor market was posting steady, if not entirely predictable, gains on a month-to-month basis. The series summarized in the table include both paid and active employees, the stepwise interpolation methodology and the linear interpolation methodology, and the active employment CES-mimicking indexes measured at 7, 10, and 14 days after the 12th of the month. We report on both the QCEW-weighted and the non-QCEW-weighted series (unwgtd).

We start by noting that the average monthly growth rate for the BLS private nonfarm payroll series is 0.06 percent over the entire sample. The standard deviation for the series is about 0.2 percent. While these moments should not be considered absolute benchmarks—or “truth”—for the various employment series, we should be able to rule out series with moments of their growth rates that are significantly different from these values.

The three findings we now discuss pertain to the full-month indexes (the non-CES mimicking indexes). First, as we saw in Figure 1, the active and paid employment series behave very differently. The standard deviations of the active employment series (the first four rows of Table 3) are smaller than those of the paid employment series. Moreover, the moments of the paid employment series do not align well with the CES, which is benchmarked (albeit annually) to the QCEW. Of note, the ADP National Employment Report (NER) uses active employment rather than paid employment, most likely due to similar findings.

Second, the mean and standard deviation of the unweighted (non-QCEW weighted) series are in most cases higher than the QCEW weighted series. It is also generally the case that the QCEW weighted series more closely match the average growth rates for the CES. Recall that we apply weights to the ADP indexes from the QCEW data at the industry and size-class level. Higher growth rates in the ADP sample—exhibited by the unweighted series throughout most of the sample and by the weighted series in some areas—may be indicative of selection bias toward

31 We actually get data from mid-1999, but we drop the first six months of data due to data quality concerns. The 2017 data extend through March.
high-growth firms among ADP clientele. The difference between the weighted and unweighted series suggests that much of this bias is eliminated with proper weighting on observables.

Third, interpolation methodology matters for the means and standard deviations. The linearly interpolated versions of most series have lower average growth rates for weighted and higher averages for unweighted relative to their stepwise interpolated counterparts. For all time periods and cases, the variability is higher for the linearly interpolated data. In some cases, the non-QCEW weighted linearly interpolated series more closely mirror the BLS data’s moments.

The CES-mimicking series occupy the bottom portion of Table 3. We only report the numbers for active employment. We report the means and variances for the 7, 10, and 14 day series (days after the 12th of the month). As before, the weighting matters for the first and second moments of the series. For a particular weighting scheme, the means and standard deviations remain relatively unchanged as the amount of information in the series (the gap between 12th and the measurement date) varies. The average growth rate for the QCEW-weighted CES-mimicking indexes of active employment are significantly closer to the BLS moments.

**Comovement of the ADP series with CES Employment**

Table 4 presents correlations between the growth rates of our ADP indexes with the growth rate of CES nonfarm payroll employment. Over the entire sample, the ADP employment indexes all have relatively high correlations with CES, except for the linearly interpolated paid employment series. In particular, the correlations for both of the stepwise interpolated active employment series are above 80 percent. One important aspect of correlations is that they can be determined by aggregate cycles. We can see this by looking at the second column of values, which reports the 2009-2017 correlations, and the third column, which reports the 2011-2017 correlations, thus excluding the Great Recession. The correlations drop dramatically, particularly for the active series, which moves from a near-perfect correlation from 2009-2017 to near zero in the 2011-2017 period.

We draw two additional conclusions from Table 4. First, stepwise interpolation generally performs better in terms of correlations than linear interpolation. Second, turning to the CES-
mimicking series, both the weighted and unweighted CES-mimicking active employment series have relatively high correlations, particularly for the entire sample and for the 2009-2017 period.

Taken together, the analysis so far points towards the weighted active employment indexes as the more tightly linked to CES private employment. In the following, we will focus primarily on the weighted, stepwise-interpolated, active employment series.

Plots of our Preferred Series

The correlations and moments presented earlier focused on our monthly series. The raw ADP payroll microdata we access are weekly data. The importance of weekly data is not only based on the frequency of updates, but the frequency for which many exogenous shocks can be identified. We present a graph of the growth rate (at the weekly frequency) of our seasonally adjusted, weighted, stepwise-interpolated active employment series (from here on out, our standard series) in Figure 4. The weekly series is highly volatile, even after seasonal adjustment.

![Graph of the growth rate of the ADP Employment Data](image)

**Figure 4**

Weekly Index of ADP Employment Data

Note: Shaded bar indicates a period of business recession as defined by NBER. Data are seasonally adjusted, active employment.
The inset panel in figure 4 transforms the growth rates into first differences. The within-month variation in employment changes is rather large, with different weeks contributing substantially to the overall monthly employment change.

We now turn to the monthly series. The monthly data are converted from weekly data—by averaging the weekly levels—and then seasonally adjusted. We plot the ADP employment index (for stepwise-interpolated active employment), both weighted and unweighted, and the CES private payroll series employment in Figure 5. The top panel plots the growth rates and the bottom panel plots the levels, indexed to 2010. The growth rate series visually reinforces the average growth rate results from Table 3, where the unweighted growth rates of ADP active employment sit above both the CES private payroll rates and the QCEW-weighted ADP employment series. Importantly, the weighted ADP series posts growth rates very similar to the CES. Moreover, the cyclical behavior between the ADP series, and the CES data are very much aligned. We can also see that while the ADP series are volatile, many of the outsized monthly swings do not correspond with the monthly swings in the BLS data. These differences are mostly likely due to three factors: (1) Our ADP monthly index takes the average level of employment over the entire month, (2) The ADP data have a different sample of establishments, and (3) The ADP indexes do not employ BLS seasonal factors. As a result, the ADP series do not reflect some of the monthly swings evident in the BLS data. For example, the marked decline recorded in private payrolls by the BLS in December 2013 does not appear in the monthly ADP series. The decline in the CES was reported by the BLS to be related to inclement weather during the payroll survey reference period, and the ADP weekly index presented in Figure 4 showed a dramatic decline in the week in which the December 2013 winter weather event occurred. The full-month ADP series appropriately averages through this one-week employment drop.
The lower portion of Figure 5 presents the levels for the weighted and unweighted ADP employment series as well as the levels for the BLS nonfarm private employment series (all indexed to 2010). The unweighted series again reflects a much faster growth rate relative to the official data.

**Tracking Employment in Real Time**

Weekly payroll data allow for a better understanding of how information accumulates throughout a month. As additional weeks of employment information are added to a monthly estimate, we see how the estimate converges toward its final value. Our real-time vintage data also allow for an empirical test of which weekly estimates contain useful leading information about the CES estimates.
We first turn to an example of how the monthly employment estimate for March 2010 evolved as additional weekly data was added to the information set. March 2010 was the turning point for employment after the dramatic losses of the great recession. These dynamics can be seen in Figure 6, which presents our final, fully revised ADP standard series (in index levels) from October of 2009 until September 2010, along with the real-time data vintages from within March 2010. Each additional week of information changes the estimate for March 2010 employment growth. Prior to week 5, the indexes predicted continued declines in employment for the month of March. This reverses with the fifth week of data, which brings the estimate very close to the final, fully revised value. While this is a somewhat extreme example, it illustrates the evolution of monthly employment estimates in real time. We next evaluate how much information each vintage of real-time data adds to the current-month estimate.
How many weeks of data are necessary for an accurate reading of monthly employment?

The real-time indexes generate monthly growth rates based on the data in hand after a particular number of weeks. We calculate 4 real-time indexes: for two weeks, three weeks, four weeks, and five weeks of payroll data for a given month. We then estimate the value of the real-time indexes to predict current month employment. The basic specification for the tests is:

$$\Delta EMP_t^j = \alpha + \beta \cdot \Delta EMP_{RTi,t}^{ADP} + \epsilon_t,$$

where $\Delta EMP_t^j$ is defined as the (final, fully revised) percent change in monthly employment at time $t$ for monthly employment series $j \in \{ADP, BLS\}$. That is, the employment series of interest can either be the final version of our ADP employment index or the final version of BLS employment. $\Delta EMP_{i,t}^{ADP}$ is the percent change in the real-time ADP series using data through week $i$, where $i \in \{2,3,4,5\}$. We estimate the regression of monthly employment growth on the real-time series for each $i$ separately. There is also a set of specifications in which we include all of the real-time indexes to test which contains the most signal about a particular month’s employment.

The results can be found in Table 5. The first five columns present the $R^2$ and $\beta$ for the specifications with current monthly ADP employment growth as the dependent variable, whereas the second five columns are estimates using the CES series as the dependent variable. For all specifications, the real-time indexes are statistically significant and positively related to the final monthly value. Importantly, the adjusted $R^2$ values in columns (1) through (4) increase markedly as more weeks of payroll data are added to the real-time indexes. This indicates that, as might be expected, the forecasts are better the more weeks of data we have. It is also worth noting that the regression coefficients in columns (1) through (4) are positive, less than unity, and increasing. This pattern is consistent with a model where the real-time indexes are equal to the final index plus noise, and the variance of the noise is decreasing in $i$. With zero noise the regression coefficient would be unity, but the noise attenuates the magnitude, biasing the estimates toward zero. Decreasing the variance of the noise (adding more weeks of data) brings the coefficient closer to unity.
Each real-time index is statistically significant when using monthly CES employment as the dependent variable. Similar to the results using ADP final growth as the dependent variable, \( R^2 \) values increase as more information on employment is added to each real-time index. To be sure, the \( R^2 \) for the 2-week index is substantially smaller than the third, fourth, and fifth week indexes. As before, when all the indexes are included the regression estimates a coefficient near unity for the 5-week index, and coefficients near zero for the other series. Taken together, each vintage of the real-time indexes provides information about both the final ADP indexes and the CES data. We now turn to a more formal forecasting framework to test the efficacy of our ADP employment indexes to estimate CES private nonfarm employment.

IV. Using ADP Data to Predict BLS CES Private Payroll Employment

In this section, we investigate the ability of the ADP data to predict private payroll employment as measured by the CES.

Monthly Employment Growth Models

CES employment estimates are revised over time, sometimes substantially.\(^{32}\) For example, during the period 2004-2015 the standard deviation of revisions (current vintage estimate minus first estimate) to monthly private payroll employment gains was 79,000, and some revisions were larger than 225,000 (figure 7).

\(^{32}\) See Neumark and Wascher (1991) for an early reference.
We are interested whether the ADP data (together with other labor market indicators that are available in real time) can help predict final private payroll employment growth—that is, after several rounds of revisions, which include the incorporation of additional survey responses that were not available for earlier reports, benchmark revisions to comprehensive counts from state unemployment insurance tax records, revisions to birth-death model estimates, and revisions to seasonal factors—published by the BLS. To this end, we estimate the equation:

\[
\Delta EMP_{t}^{CES, \text{current vintage}} = \alpha + \beta_{1}\Delta EMP_{5,t}^{ADP} + \beta_{2}\Delta EMP_{t-1}^{CES, \text{first print}} + \beta X_t + \omega_t,
\]

(1)

where

\[
\omega_t = \epsilon_t + \rho \epsilon_{t-1}.
\]

In the above equation the ADP and CES series are first differences.\(^{33}\) The specifications include the ADP real-time indexes with 5 weeks of payroll information (\(\Delta EMP_{5,t}^{ADP}\)). We

\(^{33}\) Here we use first differences of employment. Using the first difference is preferable for employment forecasts, as the change in employment for a particular month is the quantity focused upon by the policymakers and market participants.
include either active ADP employment or both active and paid ADP employment in the analysis. 

$EMP_{t-1}^{CES, first print}$ corresponds to the previous month’s real-time vintage of the CES data, while $X_t$ includes real-time labor market variables, including initial claims for unemployment insurance, unemployment expectations from the Michigan Survey, lags of the unemployment rate change, and professional forecaster expectations of the change in private employment.  

This regression specification corresponds to the situation where current month ADP data are already available, but the BLS has not published its employment situation report. The autoregressive structure of the errors corrects for time series dependence.

Additionally, we would like to predict the fully revised CES employment growth with current month data from both ADP and CES:

$$
\Delta EMP_t^{CES, current vintage} = \alpha + \beta_1 \Delta EMP_{t-1}^{ADP} + \beta_2 \Delta EMP_{t-1}^{CES, first print} + \beta X_t + \epsilon_t.
$$

This amounts to predicting the revision to CES after we already know the first print CES data.  

It is important to note that we retain the $\Delta EMP_{t-1}^{ADP}$ explanatory variable for this version of the revision prediction specification, but a more realistic specification would involve the inclusion of a later vintage of the ADP series. After the release of the first print BLS data, the econometrician would have at least a month of additional information to predict the BLS revisions.

Table 6 presents estimation results from regressions that use real-time data from 2007 to March 2017.  

When only non-payroll employment data are included in the regression model (UI claims, Michigan Survey unemployment expectations, lagged unemployment rate changes), the root-mean-square error (RMSE) of the forecast is 132 thousand (column 2). Including the previous month (first-print) estimate of CES private employment gains lowers the RMSE to 101 thousand (column 3). In column 4 we add Bloomberg market expectations. Market expectations are statistically significant and reduce the RSME by about 15 thousand. This result is similar to

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34 Expectations are median Bloomberg expectations for private nonfarm employment. Expectations can be updated by participants up until the moment prior to the data release.

35 The primary different between this specification and equation (1) is the time subscript on the first print of the CES data variable.

36 This is the period for which we have ADP data available at least at the bi-weekly frequency (recall that before May 2006, only monthly data are available; weekly data exist since July 2009 onwards).
the finding related to the importance of market expectations in Gregory and Zhu (2014). We add the ADP indexes to the estimation of current vintage payroll employment growth in columns 5 through 7. In contrast to the findings of Gregory and Zhu (2014) for the ADP NER, our results indicate that when conditioning on market expectations our ADP active and paid employment series are statistically significant. Moreover, the real-time ADP measures of employment lower the RMSE to 82 thousand with only active employment included and to 80 thousand—a decline of 8 percent relative to column 4—with both active and paid employment included (columns 5 and 6, respectively).37

Turning to the forecasting of revisions (columns 8 through 12), we see that having the first release of current-month CES (and the current-month unemployment rate change) reduces the RMSE to about 60 thousand (columns 8 and 9). Of note, the market expectation is not significant when the observed first print of employment growth is included in the regressions. By contrast, even when the first-release current month CES data are known, the real-time ADP data for active employment are statistically significant (columns 10-12). That said, the declines in the RMSEs are quantitatively modest.38

While the RMSEs do not fall substantially in columns 10 through 12, it is important to note that the actual information set included in the ADP data could be larger than that contained in the \( \Delta EMP_{5,t}^{ADP} \) series we employ in Table 6 if the prediction was made several weeks after the end of the month. In addition, the short sample period for 2007 to 2009 real-time estimates implies some difficulties with seasonal adjustment. That is, early-sample seasonal adjustment uses less data and results in less precise adjustment. Moreover, the 2007-2009 vintage data is bi-monthly and our real time indexes are therefore less precise.39

Table 7 addresses these concerns by presenting the results from a similar series of regression specifications that use the standard (non-real time) ADP data. The results in Table 7 are qualitatively similar to those found in table 6, highlighting the value of the ADP indexes for forecasting private payroll employment. Of note, the RSME declines are substantially larger. In

37 We perform the forecast error equality test, similar to that of Gregory and Zhu (2014) that is based on Diebold and Mariano (1995) and Clark and West (2006, 2007). The results of the test for equality of forecast errors indicate that the decline in the RMSE is statistically significant as we add the ADP payroll microdata in table 6.
38 The results of the forecast error equality test are consistent with this statement.
39 These issues are of less importance today, as we have 8 years of weekly data, more than enough to seasonally adjust.
particular, when estimating current vintage BLS payroll growth with the first vintage data in hand, the RSME falls from 61 to 56—roughly 8 percent—by employing the ADP payroll microdata.\footnote{The appendix tables A1 and A2 include a similar set of specifications for the interpolated indexes and the CES mimicking indexes.}

While the specifications above are reasonably mindful of real-time data considerations, all the results are in sample. Out-of-sample forecasting more closely approximates the problem of projecting the current information set into the future. We next use ADP data for active employment from June 2006 to June 2008 to estimate the model and make a prediction for the CES employment change in July 2008. Then we extend the estimation sample by one month at the time and make the prediction for the following month. Table 8 provides the RMSEs of this exercise, with five columns corresponding to the specifications of columns 1 through 5 in table 7.

The results in Table 8 indicate that the ADP indexes reduce the RMSEs out of sample, even when including real-time labor market indicators and Bloomberg expectations. Specifically, with our standard real-time index (the stepwise-interpolated index with QCEW weights), we achieve a 5½ percent reduction in RMSE. Taken together, the indexes derived from ADP payroll microdata improve forecasting in and out of sample, particularly for our “standard series.” As noted above, given the sampling properties and usual variation of CES employment, significant further reductions in RMSE are likely to be difficult; in this respect, the reductions we do obtain are notable.\footnote{Again, the declines in the RMSE from column 4 to the step, interpolated, and step (RT) results are statistically significant.} To further illustrate the value of improved forecasts, we next turn to the case of August revisions in the CES data.

**Predicting August Revisions**

In the previous subsection, we analyzed whether ADP data can be used to predict the current vintage the BLS CES private employment gains. As shown in Table 9, initial readings on the BLS CES private employment gains are much more prone to revisions in some months.
than in others. In particular, a well-known problem during 2011-2014 was that BLS data for August underwent large, positive revisions between the first and the third releases.

We next investigate whether ADP data could be used to predict the large 2011-2014 August revisions. Figure 8 depicts the BLS CES first release of private employment gain in August for years 2011 to 2017, the BLS CES current vintage gain, and the employment gain calculated from an adjusted version of the real-time ADP data that corrects for differences in long-run averages. As can be seen in the chart, the real-time ADP data can be quite helpful in predicting the large August revisions to the CES data. Specifically, the ADP standard index provides a more accurate reading of the growth in private payrolls during the problematic 2011-2014 large-revision years. More recently, the 2015 BLS data revised down, and in 2017 the ADP read was in line with the first print BLS data.

Figure 8
August Revisions and Real-Time ADP data

42 The revisions were calculated for the period from May 2003 (when several major changes had been introduced to the CES, such as NAICS conversion, completion of the CES sample redesign, and start of concurrent seasonal adjustment) to March 2016 (the last month that underwent the CES benchmark revision at the time of this writing). Note that we do not report first to third revisions for November and December, since the revisions for these two months are affected by the benchmark revision.

43 Since over period 2011-2016 ADP employment was growing slightly faster than CES employment, we adjust the ADP gains in all months for the average discrepancy of about 40,000 per month. This type of adjustment is implicit in regression-based forecasts described previously.
V. Conclusion

This paper introduces a set of aggregate employment indexes derived from ADP payroll microdata that provide high-frequency information on the labor market. The indexes take payroll data at the weekly frequency, impose a timing structure to construct a measure of employment, and aggregate up with a QCEW-based weighting scheme to arrive at nationally-representative series. The series are seasonally adjusted to provide both weekly and monthly measures of nonfarm private payroll employment.

The underlying data that are used to construct the employment indexes are reflective of a broad swath of U.S. employment. Indeed, the underlying ADP payroll microdata cover 20 percent of the workforce. Moreover, analyzing the payroll frequency, geographic distribution, and industry composition indicates that the ADP data are reasonably representative of the overall economy.

The indexes we create are—to the best of our knowledge—the first U.S. employment indexes at the weekly frequency. Moreover, the series allow for an estimate of current-month payroll employment a few weeks into the month. After conversion to monthly frequency, we find that the indexes track movements in the BLS series quite well.

We evaluate the ability of these indexes to predict labor market movements with both real-time and non-real-time indexes. We find that our indexes help to predict BLS payroll employment gains in real time, even after accounting for market expectations of these gains. Indeed, the inclusion of our ADP employment indexes in the forecasting regression significantly reduces in- and out-of-sample root-mean-square errors (RMSE). We also find that ADP employment indexes have information that predicts revisions to BLS CES gains, even after factoring in market expectations. We make our ability to predict revisions concrete by focusing on the case of August revisions.

To be sure, the success of the indexes derived from the ADP payroll microdata should not be overstated. The conventional employment data are constructed by an agency whose core mission is to conduct economic measurement. As a result, the BLS data are constructed with an appreciation for the importance of methodological consistency over time, and they are designed to comprehensively cover the U.S. economy. The BLS makes extraordinary efforts to ensure the quality of its employment estimates through sample collection, benchmarking, tracking
collection rates, and tracking revisions to the data. By contrast, the ADP payroll microdata are derived from a client base, albeit a client base that is extremely large and diverse.

Significant uncertainty remains about the direct comparability between private payroll data from ADP and the officially produced statistics of the Bureau of Labor Statistics. First, there remain significant questions about the selection issues for firms that chose to outsource their payroll processing. Second, the monthly BLS estimates of employment contain an adjustment for births and deaths, which we have not yet undertaken. Third, the official CES sample is weighted by QCEW weights at a much finer level of detail. We hope to further address these concerns in future research.

All of that said, the success of our ADP employment indexes in matching moments and predicting movements in both employment and revisions in real time is remarkable. And the aforementioned drawbacks suggest that the indexes can be improved upon further. Moreover, there are broader questions that can be answered with the payroll microdata. Can we combine the information from both the officially produced employment statistics with our indexes to develop a better measure of the “true” gains in employment for each month? And, can the data on employment from the ADP sample be used to better understand the gross flows of jobs in the U.S. economy in a more timely fashion? We leave these questions for future research.
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Appendix: Data Construction

I. Timing of the data

When ADP clients process payroll, ADP’s database is updated with (1) the payroll date and (2) the counts of active and paid employees. The microdata we use are weekly snapshots of this database. Each snapshot contains only the most recent payroll for each business. If, for example, a firm processed payroll twice in one week, only the second payroll would be in the microdata. This is only a minor issue, since regular payrolls do not occur at frequencies higher than one week, and irregular payrolls are relatively rare.

A concern is that even with daily snapshots of the ADP database, we would need to wait until the end of each pay period to learn pay period employment. A current estimate of employment one or two weeks in the past will revise as more firms with biweekly, semimonthly and monthly pay periods process payroll. This delay means that we must be careful about the real-time nature of the data.

It is important to note that payroll microdata do not contain exact employment counts for any particular day. Rather, pay period employment is the total number of workers employed at the PAC for any period of time during the pay period. This implies pay-period employment is equal to point-in-time employment only if the PAC had no hires or separations during the pay period. If the PAC hires or separates workers then payroll employment will be (weakly) greater than point-in-time employment. Without direct data on hires and separations it is impossible to infer point-in-time employment from payroll microdata.

II. Real-Time Indexes

The real-time indexes are similar to the standard indexes described in the paper. The difference is that the real-time indexes use only data through a certain date—they have different vintages. For example, one real-time series uses only data through the second week of the most recent month, and another uses data through the fourth week. For a given date, using later vintages of data adds more employers to the reporting pool and increases accuracy. But earlier

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44 More precisely, active employment includes all workers who were attached to the establishment for any part of the pay period. Paid employment includes all workers who received a paycheck for the pay period.
vintages are available earlier and so are of interest to forecasters and policy makers. The literature on data revisions and vintages is reviewed in Croushore and Stark (2001).

Consider an example to illustrate the nature of the real-time indexes. Suppose we are estimating indexes as of Saturday, April 15, 2017—this is the vintage date. Payroll data for the 15th or later has not arrived, so the most recent weekly employment statistics we can calculate are those for April 8th. Employment for the 8th will be based on whatever payrolls were reported between the 8th and the 15th. These will tend to be weekly payers, but some biweekly and semimonthly payers will also be included. The incomplete sample available with April 15th vintage data means that our estimates for the 8th will be noisy and possibly biased. More accurate estimates can be obtained by moving to a later vintage. If we use, say, April 22nd vintage data then all biweekly and semimonthly payers should have reported for the 8th, and only monthly payers will be missing.

We calculate vintage versions of the stepwise and linearly interpolated indexes. We organize the series by number of “revisions” (number of weeks passed since the date of interest). So one series is calculated two weeks after each date of interest, another is calculated with data three weeks after each date of interest, etc. In the terminology of Koenig, Dolmas, and Piger (2003) and Chang and Hanson (2015), these series are real-time vintage data. We use four real-time vintages, calculated using data from two to five weeks after the date of interest. An alternative would be to calculate an entire history for each measurement date: end-of-sample vintage data. This is unnecessary with ADP data because there are few if any revisions to the month after the fifth week.

The real-time indexes are augmented in two ways. First, the remaining weeks of data for the month are assumed to grow at the same rate as the average of the weeks of data in hand. Second, we implement a regression-correction factor to account for predictable revisions due to biweekly reporters that are not included in a given weekly file.

45 This assumption does not hold well for months with strong weekly seasonality within month, such as November, December, and January. As we continue to refine our approach we will augment the monthly average assumption with information from a historical average for a particular month’s final weeks’ growth.

46 Monthly payers aside, the first read of a weekly growth rate only includes weekly payers and biweekly reporters that report zero growth. In the second read for a particular week, when the rest of the biweekly reporters arrive and the weekly growth rate revises. As a result, we estimate a historical regression of the revision upon the data available in a given week. We can then predict the revision which is used to augment the monthly estimates.
III. CES-Mimicking Indexes

The CES-mimicking indexes attempt, insofar as is possible, to replicate the methodology of the CES. The CES asks establishments for the number of workers that received pay for the pay period including the 12th of the month. This employment concept corresponds to our “paid” employment measures, though as noted elsewhere we use both paid and active employment in our exercises. In practice, then, our approach with the CES-mimicking indexes is similar to the stepwise index, except that we focus on the 12th of each month as in CES rather than on Saturdays as in the stepwise index. In particular, to estimate employment at an establishment for month $m$, we locate the two payroll dates that bracket the 12th day of month $m$. We assume that the pay period begins on the day after the first payroll date and ends on the day of the second payroll date, so we assign the employment reported on the second payroll to month $m$.

The CES-mimicking indexes are also designed to be calculated in real-time, so there are separate indexes for each gap between the 12th and the day they are constructed. Suppose that we are on the 20th day of the month and want to measure employment as of the 12th. Weekly payers will have already reported payroll for the pay period containing the 12th—these data would arrive between the 12th and the 19th. But establishments that pay monthly will not process payroll until the last day of the month. Thus, as of the 20th only a subset of employers are available for estimation.

Following our practice with the real time indexes, we calculate several versions of the CES-mimicking indexes, each series distinguished by the number of weeks that have passed since the 12th of the month. Indexes calculated 7 days after the 12th will be available earlier but will be noisier. Indexes calculated 14 days after the 12th should be closer to the final “full information” estimates.

IV. Data Cleaning

Outliers—large swings in PAC-level employment—may occur due to processing errors or, alternatively, due to payroll processing events created to correct mistakes (e.g., paying some workers for the wrong number of hours) or to pay bonuses to a subset of workers. As might be expected, the paid employment series are more prone to outliers than the active series. There are no indicators on such payroll observations to distinguish them from standard payroll events, but they are unlikely to be reflections of meaningful employment activity; and since our weighted
series can dramatically increase the influence of a sparsely populated size-by-industry cell with an outlier growth rate, such outliers can have an outsized effect on final indexes. We apply a simple rule-of-thumb outlier rule by removing PAC payroll observations with employment that is dramatically different from the immediately previous observation. We choose weekly growth rate thresholds and drop observations that exceed these thresholds. We use the Davis-Haltiwanger-Schuh (1996) (DHS) growth rate that treat positive and negative growth symmetrically. 47 We drop observations where weekly stepwise DHS growth is greater than 1.8 or less than -1.8. These values correspond roughly to a 100-worker establishment separating 95 workers, or, symmetrically, a 5-worker establishment adding 95 workers; such behavior in the data over a single pay period is more likely to reflect unusual payroll events than changes in actual employment.

We also observe some cases where establishments report no payroll for weeks or months in a row. Our interpolation methods fill in the intervening period just like any other establishment, but it is likely that long gaps in payroll indicate a temporary shutdown or some other unusual event. We identify such events using rules that vary by year consistent with the changing nature of ADP reporting: prior to May 2006, we identify payroll gaps in which more than 61 days pass between pay dates. After that time, we identify gaps greater than 29 days (note that these thresholds flag PACs with quarterly payroll frequency). When constructing aggregate series, we do not use information from the first two pay dates following gap events. In this respect, a PAC’s reappearance after a gap is equivalent to the appearance of a new PAC for the purposes of our aggregate series.

V. Seasonal Adjustment

We form the monthly indexes by averaging the non-seasonally adjusted weekly indexes and then seasonally adjusting the resulting monthly series. When we study weekly indexes, we adjust the weekly data directly.

The seasonal procedures for weekly data follows combines a fixed coefficient regression with locally weighted regressions (see Cleveland and Scott, 2007 for details). The approach allows the seasonal factors to change over time which tends to smooth the seasonally adjusted

47 The DHS growth rate is the change in employment from $t-1$ to $t$ divided by the average of employment in times $t-1$ and $t$. This measure is bounded by -2 and 2.
series. The Cleveland and Scott approach was employed by the BLS to seasonally adjust the weekly unemployment claims release.

The monthly seasonal adjustment approach is based on X-12-ARIMA (Bureau of the Census, 2002).
### Table 1

#### Counts of Employment and Establishments

|                      | 2005      | 2010      | 2015      |
|----------------------|-----------|-----------|-----------|
| PAC                  | 444,741   | 444,356   | 569,701   |
| PAC nonmissing NAICS | 396,379   | 399,710   | 444,892   |
| EMP Active           | 22,564    | 23,821    | 27,028    |
| EMP Active nonmissing NAICS | 21,732 | 23,134    | 25,506    |
| EMP PAID             | 19,192    | 18,707    | 20,884    |
| EMP PAID nonmissing NAICS | 18,625 | 18,255    | 19,899    |
| CES (QCEW) EMP       | 106,469   | 102,480   | 114,056   |
| CES (QCEW) ESTABL    | 7,925,511 | 8,365,294 | 8,847,107 |

Note: Counts are for private employment. Employment figures are in thousands. PAC refers to ADP payroll units.
## Table 2

| Establishment Counts | Employment (thousands) |
|----------------------|------------------------|
|                      | ADP Active Emp. | QCEW | CES | ADP Active Emp. | ADP Paid Emp. | QCEW |
| A. Pay frequency*    |              |      |     |              |              |      |
| Weekly               | 22.4         | 32.2 | 23.4 | 20.5         |              |      |
| Biweekly             | 45.8         | 40.0 | 55.1 | 57.7         |              |      |
| Semi-Monthly        | 20.6         | 18.5 | 17.5 | 18.8         |              |      |
| Monthly              | 11.2         | 9.3  | 4.0  | 3.0          |              |      |
| b. Region**          |              |      |     |              |              |      |
| Northeast            | 28.1         | 18.2 | 17.8 | 28.2         | 27.5         | 18.2 |
| South                | 30.2         | 34.9 | 37.6 | 29.4         | 30.2         | 34.9 |
| Midwest              | 16.6         | 20.1 | 21.5 | 20.2         | 20.8         | 20.1 |
| West                 | 25.2         | 26.8 | 23.1 | 22.2         | 21.5         | 26.8 |

*QCEW column for pay frequency distribution is an estimate from the March 2017 CES sample.

**A small number of state-by-industry cells have censored employment. In these cases we apply the national size distribution by industry to the cell, multiplying this average by the cell establishment count to estimate employment.

Notes: The ADP columns are derived from the March 2017 ADP microdata. The QCEW column reports shares for the March 2017 employment universe, except where otherwise noted. The CES column reports statistics for the March 2017 CES sample. The establishment concept for ADP is a PAC, and for the CES sample is an UI account. For QCEW the establishment concept is a worksite, except for Panel A where sample UI account data have been weighted to make them representative of the UI account universe.
## Table 3
Mean and Variance of the growth rate of ADP and CES series

|                    | 2000-2017 |     | 2009-2017 |     | 2011-2017 |     |
|--------------------|-----------|-----|-----------|-----|-----------|-----|
|                    | mean      | std dev | mean     | std dev | mean     | std dev |
| CES nonfarm private payroll | 0.06 | 0.20 | 0.10 | 0.21 | 0.17 | 0.06 |
| Monthly Series     |           |         |           |         |           |         |
| Stepwise Active    | 0.04      | 0.22   | 0.12     | 0.21   | 0.21     | 0.05   |
| Stepwise Active (unwgtd) | 0.22 | 0.22 | 0.27 | 0.21 | 0.35 | 0.08 |
| Linear Active      | 0.00      | 0.28   | 0.03     | 0.24   | 0.13     | 0.06   |
| Linear Active (unwgtd) | 0.28 | 0.26 | 0.26 | 0.21 | 0.34 | 0.06 |
| Stepwise Paid      | -0.08     | 0.30   | 0.02     | 0.28   | 0.12     | 0.09   |
| Stepwise Paid (unwgtd) | 0.04 | 0.29 | 0.09 | 0.29 | 0.17 | 0.15 |
| Linear Paid        | 0.03      | 2.10   | 0.26     | 0.40   | 0.36     | 0.21   |
| Linear Paid (unwgtd) | 0.30 | 2.56 | 0.53 | 0.50 | 0.64 | 0.32 |
| CES Mimicking Series |           |         |           |         |           |         |
| Active 7-day       | 0.03      | 0.24   | 0.10     | 0.23   | 0.20     | 0.09   |
| Active 10-day      | 0.02      | 0.24   | 0.09     | 0.23   | 0.18     | 0.08   |
| Active 14-day      | 0.02      | 0.23   | 0.09     | 0.21   | 0.17     | 0.06   |
| Active 7-day (unwgtd) | 0.19 | 0.26 | 0.27 | 0.26 | 0.36 | 0.11 |
| Active 10-day (unwgtd) | 0.19 | 0.25 | 0.25 | 0.24 | 0.34 | 0.09 |
| Active 14-day (unwgtd) | 0.20 | 0.24 | 0.24 | 0.22 | 0.32 | 0.10 |

Note: Monthly growth rates in percentage points; ADP data seasonally adjusted by Federal Reserve Board. First and second moments calculated from 2000m1 to 2017m3.
### Table 4
Correlations of ADP Indexes with BLS Private Employment

|                         | 2000-2017 | 2009-2017 | 2011-2017 |
|-------------------------|-----------|-----------|-----------|
| **Monthly Series**      |           |           |           |
| Stepwise Active         | 0.84      | 0.91      | 0.11      |
| Stepwise Active (unwgtd)| 0.80      | 0.88      | -0.02     |
| Linear Active           | 0.66      | 0.91      | 0.09      |
| Linear Active (unwgtd)  | 0.60      | 0.90      | -0.08     |
| Stepwise Paid           | 0.72      | 0.90      | 0.21      |
| Stepwise Paid (unwgtd)  | 0.64      | 0.80      | 0.10      |
| Linear Paid             | 0.05      | 0.48      | 0.09      |
| Linear Paid (unwgtd)    | 0.04      | 0.35      | -0.01     |
| **CES-Mimicking Series**|           |           |           |
| Active 7-day            | 0.77      | 0.86      | 0.10      |
| Active 10-day           | 0.79      | 0.88      | 0.02      |
| Active 14-day           | 0.79      | 0.88      | 0.02      |
| Active 7-day (unwgtd)   | 0.73      | 0.85      | 0.03      |
| Active 10-day (unwgtd)  | 0.73      | 0.86      | -0.09     |
| Active 14-day (unwgtd)  | 0.74      | 0.84      | -0.11     |

Note: Correlations of growth rates taken at the monthly frequency; ADP data seasonally adjusted by Federal Reserve Board. Correlations calculated from 2000m1 to 2017m3.
Table 5
Explaining Variation in Monthly Employment with Real-Time Indexes

|                  | Monthly FRB ADP |                  | Monthly BLS Employment |                  |
|------------------|-----------------|-----------------|------------------------|-----------------|
|                  | (1)            | (2)            | (3)        | (4)            | (5)            | (6)            | (7)            | (8)            | (9)            | (10)           |
| 2 Week Index     | 0.13 ***       | 0.02           | 0.08 ***   | -0.01          | (0.027)        | (0.012)        | (0.027)        | (0.017)        |
| 3 Week Index     | 0.61 ***       | -0.20 ***      | 0.51 ***   | -0.16          | (0.040)        | (0.069)        | (0.046)        | (0.102)        |
| 4 Week Index     | 0.65 ***       | -0.11          | 0.54 ***   | -0.17          | (0.039)        | (0.076)        | (0.046)        | (0.112)        |
| 5 Week Index     | 0.84 ***       | 1.16 ***       | 0.72 ***   | 1.07 ***       | (0.030)        | (0.084)        | (0.043)        | (0.123)        |
| Observations     | 135            | 135            | 135        | 135            | 135            | 135            | 135            | 135            | 135            | 135            |
| R²               | 0.14           | 0.64           | 0.68       | 0.86           | 0.87           | 0.07           | 0.49           | 0.52           | 0.68           | 0.70           |

Note: Each "week index" includes information on a number of weeks of data for the month. For instance, the "2 Week Index" contains information for the month from 2 weeks of employment data available in the third week. Each specification includes a constant and is estimated from January 2006 to March 2017. ***, ** and * denote significance at the 1, 5, and 10 percent levels, respectively. Standard errors in parentheses. R²’s are adjusted.
## Table 6

**Real-Time Data: Monthly Employment Growth Models**

| Dependent variable: Private Employment Change (latest) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|--------------------------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-------|------|
| Constant                                               | 68.68 *** | 51.03 *** | 1.11 | -20.00 * | -25.29 ** | -19.26 | -6.43 | -14.16 * | -17.76 ** | -19.85 ** | -18.29 ** | -17.74 ** |
|                                                        | (26.59) | (17.21) | (9.86) | (11.57) | (12.19) | (12.00) | (10.43) | (8.10) | (8.31) | (9.22) | (9.28) | (8.91) |
| Claims                                                 | -0.59 | -2.60 *** | -0.43 | -0.34 | -0.12 | -2.43 *** | -0.40 | -0.39 | -0.47 | -0.45 | -0.48 |
|                                                        | (0.80) | (0.79) | (0.78) | (0.77) | (0.75) | (0.86) | (0.51) | (0.53) | (0.55) | (0.56) | (0.54) |
| Unemployment Expectations                              | 148.96 *** | 43.44 *** | 34.12 *** | 21.52 * | 21.37 | 30.03 ** | 26.66 *** | 23.12 ** | 18.66 * | 18.69 * | 20.47 ** |
|                                                        | (16.14) | (12.55) | (11.71) | (12.69) | (13.14) | (13.40) | (10.15) | (10.70) | (11.06) | (11.16) | (10.40) |
| Lagged UR change                                        | -168.37 * | -128.48 ** | -40.74 | -33.71 | -30.56 | -99.68 * |
|                                                        | (99.56) | (63.31) | (52.29) | (47.12) | (46.30) | (58.00) |
| Lagged Privemp (Pre-Empsit Release)                     | 0.83 *** | -0.24 | -0.36 ** | -0.38 ** | 0.61 *** |
|                                                        | (0.07) | (0.17) | (0.15) | (0.15) | (0.11) |
| Market expectation                                      | 1.27 *** | 1.18 *** | 1.10 *** | 0.14 | 0.10 | 0.08 |
|                                                        | (0.19) | (0.15) | (0.16) | (0.12) | (0.12) | (0.13) |
| UR change                                               | 26.19 | 37.62 | 45.45 | 47.69 | 38.98 |
|                                                        | (38.43) | (37.26) | (35.80) | (36.25) | (36.96) |
| Priveemp (With Empsit Release)                          | 1.09 *** | 0.99 *** | 0.95 *** | 0.93 *** | 1.01 *** |
|                                                        | (0.06) | (0.10) | (0.10) | (0.10) | (0.07) |
| ADP act                                                | 0.24 *** | 0.27 *** | 0.27 *** | 0.10 * | 0.11 * | 0.11 ** |
|                                                        | (0.09) | (0.08) | (0.09) | (0.06) | (0.06) | (0.05) |
| ADP emp                                                | 0.08 ** | 0.02 |
|                                                        | (0.04) | (0.03) |
| RMSE                                                   | 181 | 132 | 101 | 87 | 82 | 80 | 96 | 61 | 61 | 60 | 59 | 60 |

Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Estimation period: 2007m1-2017m3.

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).
### Table 7
Standard Series: Monthly Employment Growth Models

|                       | (1)       | (2)       | (3)       | (4)       | (5)       | (6)       | (7)       | (8)       | (9)       | (10)      | (11)      | (12)      |
|-----------------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Dependent variable:   | Private Employment |
| Change (latest)       |           |           |           |           |           |           |           |           |           |           |           |           |
| Constant              | 68.68***  | 51.03***  | 1.11      | -20.00*   | -22.55**  | 0.94      | -8.10     | -14.16*   | -17.76**  | -19.54**  | -3.16     | -18.25**  |
|                       | (26.59)   | (17.21)   | (9.86)    | (11.57)   | (10.32)   | (14.30)   | (9.66)    | (8.10)    | (8.31)    | (8.72)    | (10.75)   | (8.18)    |
| Claims                | -0.59     | -2.60***  | -0.43     | -0.04     | -0.05     | -1.30*    | -0.40     | -0.39     | -0.32     | -0.35     | -0.35     | -0.32     |
|                       | (0.80)    | (0.79)    | (0.78)    | (0.68)    | (0.61)    | (0.74)    | (0.51)    | (0.53)    | (0.52)    | (0.50)    | (0.51)    |
| Unemployment Expectations | 148.96*** | 43.44***  | 34.12***  | 12.50     | 7.27      | 18.33*    | 26.66***  | 23.12**   | 15.37     | 11.68     | 16.35     |
|                       | (16.14)   | (12.55)   | (11.71)   | (10.26)   | (10.46)   | (10.10)   | (10.15)   | (10.70)   | (10.75)   | (10.44)   | (10.32)   |
| Lagged UR change       | -168.37*  | -128.48** | -40.74    | -33.33    | -33.74    | -74.97    |
|                       | (99.56)   | (63.31)   | (52.29)   | (41.58)   | (40.40)   | (50.44)   |
| Lagged Privemp (Pre-Empsit Release) | 0.83*** | -0.24     | -0.34**   | -0.37***  | 0.38***   |
|                       | (0.07)    | (0.17)    | (0.14)    | (0.12)    | (0.13)    |
| Market expectation     | 1.27***   | 0.94***   | 0.91***   | 0.14      | 0.06      | 0.05      |
|                       | (0.19)    | (0.15)    | (0.13)    | (0.12)    | (0.12)    | (0.12)    |
| UR change              | 26.19     | 37.62     | 56.99     | 65.44*    | 53.70     |
|                       | (38.43)   | (37.26)   | (37.55)   | (36.03)   | (38.07)   |
| Privemp (With Empsit Release) | 1.09*** | 0.99***   | 0.88***   | 0.85***   | 0.92***   |
|                       | (0.06)    | (0.10)    | (0.09)    | (0.09)    | (0.09)    |
| ADP act                | 0.43***   | 0.31***   | 0.52***   | 0.19**    | 0.12      | 0.20***   |
|                       | (0.10)    | (0.12)    | (0.10)    | (0.08)    | (0.07)    | (0.07)    |
| ADP emp                | 0.17***   | 0.12***   |           |           |           |
|                       | (0.06)    | (0.05)    |           |           |           |
| RMSE                   | 181       | 132       | 101       | 87        | 77        | 86        | 61        | 61        | 58        | 56        | 58        |

Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Estimation period: 2007m1-2017m3.

Notes: Dependent variable is final print of CES private employment. ADP series are current vintage. RSMEs are calculated in-sample.
| Dependent variable: Private Employment Change (latest) | (1) | (2) | (3) | (4) | (5) |
|------------------------------------------------------|-----|-----|-----|-----|-----|
| No ADP Data                                          | 194 | 154 | 123 | 113 |     |
| Step                                                  |     |     |     |     | 98  |
| CES Mimicking                                        |     |     |     |     | 110 |
| Interpolated                                          |     |     |     |     | 103 |
| Step (RT)                                             |     |     |     |     | 107 |
| Interp (RT)                                           |     |     |     |     | 109 |

Note: RMSE of one-step-ahead forecasts. Estimation sample begins in 2006m6; first forecast period is 2008m7. Specifications are as follows: (1) constant only, (2) contains real-time labor market data (claims, unemployment expectations, and lagged unemployment), (3) contains lagged private employment, and (4) contains Bloomberg expectations of private employment.
Table 9
Revisions to Private CES Payrolls

| Month     | 1st to 3rd release | 1st to current release |
|-----------|--------------------|------------------------|
|           | mean               | st. dev.               | mean       | st. dev   |
| January   | -8.8               | 56.9                   | 16.6       | 91.6      |
| February  | 20.1               | 41.2                   | -3.0       | 36.3      |
| March     | 9.8                | 30.3                   | 15.8       | 63.7      |
| April     | -6.3               | 31.0                   | -20.1      | 92.0      |
| May       | 9.2                | 31.6                   | 21.5       | 62.6      |
| June      | -4.8               | 21.0                   | 1.8        | 63.3      |
| July      | 2.3                | 30.0                   | -4.3       | 74.1      |
| August    | 31.5               | 42.5                   | 20.6       | 85.8      |
| September | 27.0               | 82.1                   | 37.5       | 103.1     |
| October   | -3.0               | 57.4                   | -8.8       | 81.6      |
| November  | NA                 | NA                     | 8.2        | 89.2      |
| December  | NA                 | NA                     | -5.8       | 80.5      |

Note: data for the period May 2003 to March 2016.
Table A1
CES Mimicking Series: Monthly Employment Growth Models

| Dependent variable: Private Employment Change (latest) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|------------------------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-------|-------|------|
| Constant                                             | 70.18*** | 59.14*** | 4.13 | -12.33 | 20.71* | 22.37* | 39.94*** | -12.94 | -15.16* | 0.71  | 1.28  | -0.85 |
|                                                      | (25.15) | (16.56) | (10.27) | (12.51) | (12.44) | (7.92) | (8.17) | (10.51) | (10.44) | (8.51) |       |
| Claims                                               | -0.53 | -2.48*** | -1.42* | -1.08 | -0.99 | -1.55** | -0.37 | -0.38 | -0.37 | -0.35 | -0.37 |       |
|                                                      | (0.78) | (0.78) | (0.75) | (0.73) | (0.74) | (0.49) | (0.51) | (0.50) | (0.50) | (0.51) |       |
| expectations                                          | 144.11*** | 40.15*** | 34.55*** | 23.31** | 26.77** | 24.94** | 23.95** | 21.77** | 17.09* | 18.39* | 16.69* |       |
|                                                      | (15.87) | (12.47) | (11.22) | (9.98) | (10.65) | (10.24) | (9.69) | (10.06) | (9.77) | (10.38) | (9.54) |       |
| Lagged UR change                                      | -168.60* | -129.28** | -35.03 | -9.29 | -19.94 | -54.23 |       |       |       |       |       |       |
|                                                      | (97.02) | (63.06) | (56.58) | (55.64) | (57.15) | (54.61) |       |       |       |       |       |       |
| Lagged Privemp (Pre-Empsit Release)                   | 0.85*** | 0.13 | 0.00 | 0.00 | 0.41*** |       |       |       |       |       |       |       |
|                                                      | (0.07) | (0.14) | (0.15) | (0.15) | (0.14) |       |       |       |       |       |       |       |
| Market expectation                                    | 0.87*** | 0.61*** | 0.60*** | 0.09 | -0.03 | -0.03 |       |       |       |       |       |       |
|                                                      | (0.14) | (0.14) | (0.14) | (0.09) | (0.12) | (0.12) |       |       |       |       |       |       |
| UR change                                             | 28.18 | 34.15 | 55.29 | 57.48 | 55.96 |       |       |       |       |       |       |       |
|                                                      | (38.55) | (37.72) | (38.87) | (39.43) | (39.06) |       |       |       |       |       |       |       |
| Privemp (With Empsit Release)                         | 1.11*** | 1.04*** | 0.98*** | 0.97*** | 0.96*** |       |       |       |       |       |       |       |
|                                                      | (0.06) | (0.09) | (0.09) | (0.09) | (0.08) |       |       |       |       |       |       |       |
| ADP act                                              | 0.33*** | 0.33*** | 0.42*** | 0.16** | 0.16** | 0.15*** |       |       |       |       |       |       |
|                                                      | (0.11) | (0.11) | (0.11) | (0.07) | (0.07) | (0.06) |       |       |       |       |       |       |
| ADP emp                                               | -0.01 |       |       |       |       |       |       |       |       |       |       |       |
|                                                      | (0.01) |       |       |       |       |       |       |       |       |       |       |       |
| RMSE                                                  | 177   | 131   | 101   | 92   | 86   | 85   | 90   | 61   | 60   | 58    | 58    | 58    |

Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Estimation period: 2007m1-2017m3.

Notes: Dependent variable is final print of CES private employment. ADP series are real-time vintage, as of 18 days after the 12th of the month. RSMEs are calculated in-sample.

Source: adp/paper/code_and_data/mems_paper/progs/mems_new/model_paper_clean.do
| Dependent variable: Private Employment Change (latest) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|-----------------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Constant                                      | 68.68 *** | 51.03 *** | 1.11 | -20.00 * | 16.19 | 17.42 | 42.37 *** | -14.16 * | -17.76 ** | -0.01 | 0.27 | 0.22 |
|                                               | (26.59) | (17.21) | (9.86) | (11.57) | (12.93) | (12.72) | (8.10) | (8.31) | (11.97) | (11.86) | (9.11) |
| Claims                                        | -0.59 | -2.60 *** | -0.43 | -0.48 | -0.44 | -1.67 ** | -0.40 | -0.39 | -0.47 | -0.45 | -0.47 |
|                                               | (0.80) | (0.79) | (0.78) | (0.68) | (0.65) | (0.75) | (0.51) | (0.53) | (0.53) | (0.53) |
| expectations                                   | 148.96 *** | 43.44 *** | 34.12 *** | 21.12 ** | 24.07 ** | 24.35 ** | 26.66 *** | 23.12 ** | 18.59 * | 19.69 * | 18.64 * |
|                                               | (16.14) | (12.55) | (11.71) | (10.02) | (10.77) | (9.96) | (10.15) | (10.70) | (10.17) | (10.90) | (9.88) |
| Lagged UR change                               | -168.37 * | -128.48 ** | -40.74 | -21.66 | -29.89 | -53.83 |
|                                               | (99.56) | (63.31) | (52.29) | (53.82) | (56.09) | (55.21) |
| Lagged Privemp (Pre-Empsit Release)            | 0.83 *** | -0.24 | -0.31 * | -0.30 * | 0.37 *** |
|                                               | (0.07) | (0.17) | (0.17) | (0.16) | (0.14) |
| Market expectation                             | 1.27 *** | 0.94 *** | 0.92 *** | 0.14 | 0.00 | 0.01 |
|                                               | (0.19) | (0.18) | (0.18) | (0.12) | (0.15) |
| UR change                                      | 26.19 | 37.62 | 60.88 | 62.23 | 60.76 |
|                                               | (38.43) | (37.26) | (39.81) | (40.14) | (40.27) |
| Privemp (With Empsit Release)                  | 1.09 *** | 0.99 *** | 0.93 *** | 0.92 *** | 0.93 *** |
|                                               | (0.06) | (0.10) | (0.10) | (0.10) | (0.08) |
| ADP act                                        | 0.37 *** | 0.37 *** | 0.50 *** | 0.18 ** | 0.18 ** | 0.18 *** |
|                                               | (0.13) | (0.13) | (0.12) | (0.09) | (0.09) |
| ADP emp                                        | -0.01 | -0.00 |
|                                               | (0.00) | (0.00) |
| RMSE                                           | 181 | 132 | 101 | 87 | 81 | 80 | 88 | 61 | 61 | 59 | 59 | 59 |

Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Estimation period: 2007m1-2017m3.

Notes: Dependent variable is final print of CES private employment. ADP series are current vintage. RSMEs are calculated in-sample.

Source: adp/paper/code_and_data/mems_paper/progs/mems_new/model_paper_clean.do