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EMPLOYMENT AND THE BUSINESS CYCLE*

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This paper investigates the differences in the cyclical dynamics in employment on non-agricultural payroll (ENAP) and total civilian employment (TCE), and the implications for monitoring US business cycles in real time. We find that employment measures have diverged considerably around the last three recessions and subsequent recoveries. This significantly impacts identification of turning points. Models that use TCE are more in line with the National Bureau of Economic Research (NBER) recession dating, and deliver faster call of troughs in real time, whereas models that include ENAP series yield delays in signaling troughs, especially the most recent ones.

1 Introduction

Aggregate employment is one of the most important indicators of current macroeconomic conditions. The US Bureau of Labor Statistics (BLS) publishes the comprehensive 'Employment Situation' reports on a monthly basis, which are closely followed by policymakers, economic and financial market analysts, the media and the public at large. These reports are based on two surveys from which the BLS collects two main sets of employment data every month. The Employment on Non-Agricultural Payroll series (ENAP or 'payroll employment') is based on a survey of business establishments, and questions employers about how many jobs are counted on payrolls. The Total Civilian Employment series (TCE or 'civilian employment') is based on a survey among households, and entails asking questions of a sample of households each month over the telephone on the number of people employed. This survey is also used to calculate the unemployment rate.

Although these two separate surveys of employment had historically given similar assessment of the US labor market performance, this has changed considerably, especially since the early 1990s. The conflicting information from these surveys has significantly contributed to the uncertainty about economic conditions around business cycle turning points, and has played an important role in influencing government's economic policy,

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businesses and consumers' economic planning, the dynamics of financial markets, and even presidential elections and evaluation of presidential performance.

This paper investigates the extent of the divergences and convergences in these series, with a particular focus on their cyclical dynamics across stages of the business cycle, and on their turning points compared with aggregate economic conditions, using revised and real-time data. Our goal is to evaluate the possible implication of these potential differences for US business cycle monitoring, particularly in real time.

There are several reasons why these two series may diverge at some points in time, which are related to differences in conceptual definitions and measurement of labor conditions, as well as methodologies underlying the two surveys. The reliability and differences between these two series can be particularly accentuated in real time. The payroll employment series only includes job destruction and creation with a lag, it does not include self-employment, contractors, limited liability companies, or off-the-books employment, and it double counts jobs if a person changes jobs within a payroll survey reference period. These can be very important cyclical factors around business cycle turning points. In particular, the first three can lead payroll employment to signal a more severe recession and delay detection of a recovery, while the fourth one can overestimate employment around peaks. In addition, the first release of payroll employment is preliminary and undergoes substantial revisions in subsequent months. There is also a significant revision of this series once a year when the smaller initial sample collected is adjusted by using as a benchmark the universe count of employment derived from Unemployment Insurance Tax Records that almost all employers are required to file. These corrections make real-time data on payroll employment very different from the revised versions. Thus, although the revised payroll employment may be a good indicator of labor conditions *ex post*, its performance in real time is compromised by these problems.[1]

We start our analysis by investigating the cyclical properties of each of the employment series individually. Business cycle turning points in payroll employment and civilian employment are obtained from univariate Markov-switching models fitted to the growth of the employment series, and from the

[1]See, for example, Chauvet and Hamilton (2006) and Haltom *et al.* (2005). The BLS has acknowledged problems with its sampling methodology regarding job turnover in the Establishment survey. In addition, it has created an alternative employment series that corrects for population trend and addition of non-farmer workers in the TCE series (Di Natale, 2003; Bowler *et al.*, 2003). This is discussed, for example, in Juhn and Potter (1999) and in the comprehensive summary of these results by Kane (2004). While the correction by the BLS brought these two series closer together in level, important cyclical differences remain. The adjusted series shows a deeper decline during the last two recessions compared with payroll, and a faster recovery after their end.

Bry and Boschan (1971) algorithm applied to their level. These turning points are compared with those established for the aggregate economy by the National Bureau of Economic Research (NBER).[2]

Next, we investigate how the inclusion of the alternative employment series contribute or modify multivariate inferences regarding the timing of aggregate business cycle turning points. We use the dynamic factor model with regime switching (DFMS) applied to the four monthly coincident variables used by the NBER in dating business cycle turning points: industrial production, real manufacturing and trade sales, real personal income and employment. This is one of the most successful models in predicting turning points in sample or in real time (see, for example, Chauvet, 1998; Chauvet and Hamilton, 2006; Chauvet and Piger, 2008).[3] We compare the results obtained from a specification that includes payroll employment with one that uses instead civilian employment.

We find that while during robust economic growth these surveys convey similar information about labor market conditions, the two employment measures have increasingly diverged in the recent period. In particular, the difference in the dynamics of these series became more accentuated around the last three recessions in 1990–91, in 2001, and in 2007–9, particularly during their subsequent recoveries.

The univariate analysis (Markov switching and Bry-Boschan) indicates that, compared with payroll employment, turning points using civilian employment have gotten relatively more coincident with the NBER turning points over time, and this increased coincidence is most notable at business cycle troughs, with a difference of at most two months. On the other hand, the troughs obtained from payroll employment diverge considerably from NBER troughs for the last three recessions. According to this measure of labor market conditions, the 1990–91 recession continued for almost one year after the trough called by the NBER, the 2001 recession for almost two years, and the 2007–9 recession for over eight months. On the other hand, according to univariate analysis of civilian employment, the last recession ended in mid-2009, coinciding with the trough established by the NBER.[4]

[2]The NBER uses several coincident series to date business cycle turning points such as measures of output, employment, income and sales. Regarding employment, the focus is mainly on payroll employment, although civilian employment is also taken into account: http://www.nber.org/cycles/.

[3]The probabilities of recession from the DFMS model are updated on a monthly basis and posted at Chauvet's website (using payroll employment and civilian employment): https://sites.google.com/site/marcellechauvet/probabilities-of-recession and at Piger's website (using payroll employment): http://pages.uoregon.edu/jpiger/us_recession_probs.htm and at the Saint Louis Fed Database (using payroll employment) http://research.stlouisfed.org/fred2/series/RECPROUSM156N.

[4]At the time the first version of this paper was written, in July 2010, the NBER had not yet announced the end of the 2007–9 recession. In September 2010 the NBER announced the trough of this recession as June 2009.

These results are corroborated by the multivariate analysis (DFMS). The identification of turning points from the DFMS model when civilian employment is used is much more accurate than when payroll employment is used, compared with the NBER dating. The probabilities of recession from the payroll employment specification and from the civilian employment specification are very similar around all business cycle peaks, but very different for the last three business cycle troughs. While the probabilities for the payroll employment specification depict jobless recoveries, the probabilities of recession from the civilian employment specification fall right around the trough of the last three recessions as determined by the NBER. This difference in the probabilities of recession reflects the fact that payroll employment has shown sluggishly recovery while civilian employment has displayed a much more prompt recovery in the last three recessions. The DFMS model with payroll employment identifies the end of the 1990–91 recession as taking place eight months after the NBER trough. The most dramatic difference is with respect to the end of the 2001 recession, which the model identifies as occurring only 19 months after the NBER trough. For the most recent recession, the trough from the DFMS with payroll employment is identified as December 2009, whereas the trough from the DFMS with civilian employment is identified as in June 2009, the same trough as dated by the NBER.[5]

Finally, we evaluate how the use of the different employment series affects the performance of the DFMS model in predicting turning points in real time. The real-time analysis is implemented based on recursive estimation using just-in-time information, which includes unrevised, preliminary data. We also find here that the turning points identified by the DFMS model estimated using civilian employment are in closer agreement with the NBER business cycle phases. In addition, this specification delivers a faster call of troughs in real time. On the other hand, as payroll employment in real time tends to underestimate employment around the end of recessions, the use of this employment series yields delays in signaling troughs for most recessions, especially the most recent ones.

Thus, the evidence found in this paper indicates that at the very uncertain time surrounding the end of recessions, especially during recoveries, civilian employment can be a more reliable series than payroll employment. Although civilian employment is more volatile and yields low signal to noise ratio in univariate models, this drawback is mitigated in multivariate models, for which the real-time reflection of labor market conditions conveyed by this series can be effectively exploited.[6]

[5]The DFMS model with TCE identified the trough of the last recession as June 2009 using data available as of September 2009.

[6]This evidence is also found in Chauvet and Hamilton (2006). Kitchen (2003) and Kane (2004) also find that civilian employment is a more reliable measure of labor market conditions in real time. In particular, Kitchen (2003) finds that real-time payroll employment is biased

The remainder of this paper is organized as follows. The second section presents univariate analysis of turning points of the two employment measures, payroll and civilian employment. The third section studies how inclusion of these different employment measures in a multivariate setting influences turning point analysis using revised or real-time data, and presents comparisons for the last few recessions. The fourth section concludes.

2 Univariate Analysis of Turning Points in Payroll and Civilian Employment

In this section we investigate the coincidence of turning points in payroll employment and civilian employment with business cycle turning points established for the aggregate economy. To highlight the cyclical properties of each series individually, we focus in this section on univariate analysis only. In the next section we investigate how the alternative employment series contribute to multivariate inference regarding the timing of aggregate business cycle turning points.

In order to measure aggregate business cycle turning points, we use the monthly dates of business cycle peaks and troughs established by the Business Cycle Dating Committee of the NBER.[7] To measure turning points in each employment series, we use a two-regime Markov-switching model, which was popularized for modeling regime shifts in economic activity between expansion and recession phases by Hamilton (1989). For robustness, at the end of this section we consider an alternative, non-parametric technique for dating turning points in a series due to Bry and Boschan (1971).

The Markov-switching model we use models employment growth as arising from two regimes that differ by their mean growth rate. In particular:

$$\begin{aligned} e_t &= \mu_0 + \mu_1 S_t + \varepsilon_t \\ \varepsilon_t &\sim N(0, \sigma^2) \end{aligned} \tag{1}$$

where e_t is a measure of employment growth, $S_t = \{0, 1\}$ is a state variable that governs the regime, and changes in S_t generate turning points in the employment series. The state variable S_t is unobserved, but, as in Hamilton (1989), we assume that it follows a first-order Markov process with transition probabilities:

downward, overstating the decline in employment around recessions. This bias reduces somewhat as the series is continuously revised over time. See also Haltom *et al.* (2005).

[7]These are available at http://www.nber.org/cycles/main.html. The NBER does not specify whether the months of peaks and troughs belong to expansion or recession phases. Here we take the convention that a peak is the last month of an expansion phase, while a trough is the last month of a recession phase.

$$P(S_t = 0 \mid S_{t-1} = 0) = p_{00}$$
$$P(S_t = 1 \mid S_{t-1} = 1) = p_{11} \tag{2}$$

Given the Markov assumption, these transition probabilities completely describe the probability distribution of S_t. As discussed in detail in Hamilton *et al.* (2007), an additional normalization assumption is needed to identify the model in (1). In particular, if the values of μ_0 and μ_1 were reversed and S_t set equal to $1 - S_t$, this would have no effect on the model likelihood function. Here we normalize the model by enforcing the restriction that $\mu_1 < 0$, so that $S_t = 0$ has the interpretation of the 'high employment growth' state, in which the mean growth rate is μ_0, while $S_t = 1$ has the interpretation of the 'low employment growth' state, in which the mean growth rate is $\mu_0 + \mu_1$. As we will see below, the parameter estimates are consistent with $\mu_0 > 0$ and $\mu_0 + \mu_1 < 0$, suggesting the high and low employment growth regimes can be interpreted as 'employment expansion' and 'employment recession' regimes respectively, and switches of S_t from 0 to 1 and 1 to 0 represent peaks and troughs in employment.

The model in (1) is quite simple, in that the regime switches in employment are experienced in the mean growth rate only, and there are no dynamics in employment beyond that generated by the Markov regime switching process. Hamilton's (1989) original model, which was applied to real GDP growth, assumed linear autoregressive dynamics in addition to Markov switching in mean, while a number of authors have allowed for regime switching in the variance of the disturbance term. We focus on the simple model here as it has been shown in previous work, e.g. Chauvet and Piger (2003), to capture regime-switching in alternative series of economic activity that mimic traditional notions of expansions and recession, and is quite robust to structural changes in the economy, such as the so-called 'Great Moderation' in the volatility of economic activity measures.

We estimate the model in (1) using both monthly payroll employment growth and civilian employment growth, defined as the log first difference of the level of monthly payroll employment and civilian employment multiplied by 100 (Fig. 1). Our payroll employment and civilian employment growth series extend from February 1959 to March 2010, and are taken from the 2 April 2010 data release. Estimation is conducted via maximum likelihood using the recursive filter developed in Hamilton (1989). To draw inference on the unobserved state variable, we construct smoothed probabilities, which are probabilities regarding the value of S_t conditional on all employment data in the sample. These smoothed probabilities, denoted $\Pr(S_t = k|T)$, $k = 0, 1$, are constructed using the filter in Kim (1994).

Table 1 presents the maximum likelihood estimates of the Markov-switching model. For both employment measures, the model is identifying two regimes that correspond to positive and negative average growth, or

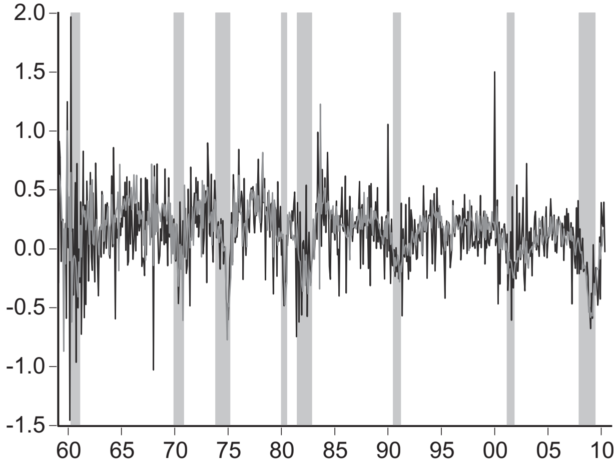

Fig. 1. Civilian Employment (TCE) and Payroll (ENAP) and NBER Recessions (Shaded Area)

Table 1
Maximum Likelihood Estimates of Univariate Markov-switching Model Autoregressive Process of Order 0, AR(0)

Parameter	*Payroll employment*	*Civilian employment*
μ_0	0.228	0.171
	(0.008)	(0.018)
μ_1	−0.376	−0.303
	(0.016)	(0.061)
P_{00}	0.981	0.983
	(0.072)	(0.007)
P_{11}	0.931	0.914
	(0.024)	(0.052)
σ	0.166	0.305
	(0.005)	(0.006)

expansion and recession. For expansions, the estimate of μ_0 is 0.228 for ENAP and 0.171 for TCE, which correspond to annualized growth rates of approximately 2.8 per cent and 2 per cent respectively. For recessions, the estimates of $\mu_0 + \mu_1$ are −0.148 and −0.132 for ENAP and TCE, which correspond to annualized growth rates of approximately −1.78 per cent and −1.58 per cent. Thus, both expansions and recessions appear to be more accentuated for ENAP growth as compared with TCE growth. The transition probability estimates also suggest that recession phases last longer for ENAP than TCE. Specifically, the expected duration of the recession regime, given by $p_{11}/(1 - p_{11})$, is 13.5 months for ENAP and 10.6 months for TCE. This is consistent with the phase duration as obtained from the smoothed probabilities as discussed below.

The estimates in Table 1 suggest that expansion and recession regimes are more clearly identified for ENAP growth than for TCE growth. One way to see this is through the metric μ_1/σ, which gives the size of the switch in mean growth rates measured relative to the size of the standard deviation of the model disturbance term. This can be interpreted as a signal to noise ratio, as it measures the size of the signal sent by a phase shift relative to the noise produced by the model disturbance term. This signal to noise ratio is 2.265 for ENAP and 0.993 for TCE, which, given the assumed normality of the model disturbance term, is a substantial difference. A typical shift in mean growth rate observed for ENAP growth would be unlikely to be interpreted as a shock to the disturbance term, as a 2.265 standard deviation shock would correspond to a low probability event for a normal distribution. However, for TCE growth this is not the case, as a typical shift in mean growth rate is equivalent to only a 0.993 standard deviation shock to the disturbance term. The reason for the higher signal to noise ratio for ENAP growth is partly due to a larger absolute value for μ_1, but also due to a much lower estimated value for the standard deviation of the model disturbance term, which is nearly half that for TCE growth. This suggests that there is less variation in ENAP growth left unexplained by the Markov-switching process than for TCE growth.

Figure 2 shows the smoothed probability of recession for both measures of employment, i.e. $\Pr(S_t = 1|T)$. From the top panel, we see that the probabilities of recession from ENAP growth are very sharply defined, as there are few instances where the probability of recession is far from 0 or 1. This is consistent with the large signal to noise ratio for ENAP growth discussed above. In terms of coincidence with the NBER turning points for the aggregate business cycle (shaded in the graph) there is a mixed picture. The recession and expansion phases in ENAP growth are generally associated with NBER defined turning points, the one exception being a recession in ENAP growth in 1959 that did not correspond to a NBER recession. The timing of recessions in ENAP growth is close to those for the aggregate business cycle in some cases, most notably recessions early in the sample. However, for the last three aggregate recessions in the sample, the timing of the employment recession, particularly the date of the trough, is shifted significantly later from that for the aggregate recession. This is consistent with the well publicized 'jobless recoveries' associated with recent recessions.[8]

From the bottom panel of Fig. 2, the smoothed probabilities from TCE growth are less clearly defined than those for ENAP growth, with many more

[8]This is also found in the recent paper by Summers and Warren (2011).

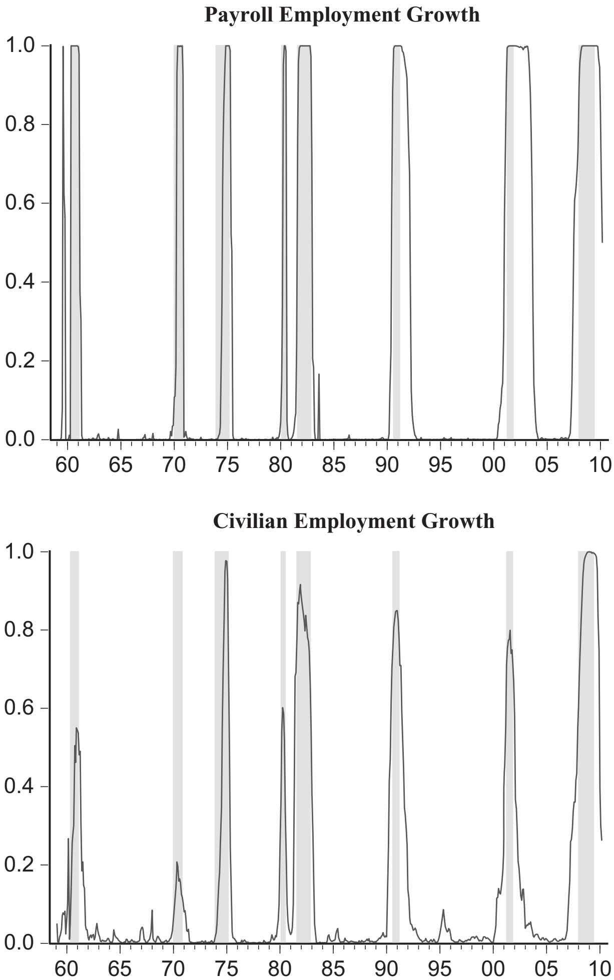

FIG. 2. Smoothed Probabilities of Recession from Univariate Markov-switching Models and NBER Recessions (Shaded Area)

instances of probabilities that fall near 0.5. Again, this is consistent with the relatively small signal to noise ratio for TCE growth discussed above. The recessions in TCE growth also differ from ENAP growth in terms of their coincidence with the aggregate reference cycle. Like those for ENAP growth, the recession probabilities for TCE growth tend to move upward around NBER recessions. However, unlike ENAP growth, the probabilities for TCE growth generally improve on their ability to match the NBER reference cycle later in the sample. In particular, for the first two recessions in the sample, the TCE recession probabilities remain quite low, and indeed remain below 50

TABLE 2
BUSINESS CYCLE DATES FROM UNIVARIATE MARKOV-SWITCHING MODEL AR(0) APPLIED TO PAYROLL EMPLOYMENT (ENAP) GROWTH AND CIVILIAN EMPLOYMENT (TCE) GROWTH

Peak date: NBER	*Peak date: ENAP*	*Peak date error: ENAP*	*Peak date: TCE*	*Peak date error: TCE*
—	Jul 1959	—	—	—
Apr 1960	Apr 1960	0	Sep 1960	+5
Dec 1969	Mar 1970	+3	—	—
Nov 1973	Jul 1974	+8	Jul 1974	+8
Jan 1980	Mar 1980	+2	Feb 1980	+1
Jul 1981	Jul 1981	0	May 1981	–2
Jul 1990	May 1990	–2	May 1990	–2
Mar 2001	Dec 2000	–3	Feb 2001	–1
Dec 2007	June 2007	+6	Nov 2007	–1
Mean error		+1.8 months		+1.1 months
Mean absolute error		3 months		2.9 months
False peaks		1		0
Missed peaks		0		1
Trough date: NBER	*Trough date: ENAP*	*Trough date error: ENAP*	*Trough date: TCE*	*Trough date error: TCE*
—	Oct 1959	—	—	—
Feb 1961	Feb 1961	0	Feb 1961	0
Nov 1970	Nov 1970	0	—	—
Mar 1975	May 1975	0	Mar 1975	0
Jul 1980	Jul 1980	0	Jun 1980	–1
Nov 1982	Dec 1982	+1	Dec 1982	+1
Mar 1991	Feb 1992	+11	Jul 1991	+4
Nov 2001	Aug 2003	+21	Jan 2002	+2
June 2009	([a])	([a])	Dec 2009	+6
Mean error		+4.7 months		+1.7 month
Mean absolute error		4.7 months		1.6 months
False troughs		1		0
Missed troughs		0		1

[a]The probabilities of recession from the univariate Markov-switching AR(0) model fitted to ENAP had not determined a trough using data up to March 2010.

per cent for the remainder of the 1970 recession. However, for the last five recessions, the TCE probabilities are roughly coincident with the dates established by the NBER. This is in contrast to the ENAP recession probabilities, which remained high long after the end of the last three aggregate recessions. As a consequence, the average duration of recessions as measured by the average months in which the probabilities of recession are above 0.5 is 16 months for ENAP and 11 months for TCE.

Table 2 provides more specifics regarding the dates of turning points in the employment series relative to the NBER turning points. In particular, Table 2 gives peak and trough dates in both employment series, where we establish a peak date when the smoothed probability of recession rises above 0.5 and a trough when the recession probability moves below 0.5. The top panel of Table 2 provides this detail for peaks, while the bottom panel is for troughs.

From the top panel of Table 2, there is not a strong average difference in the coincidence of peaks in ENAP growth and TCE growth with NBER peaks. Both measures of employment have an episode early in the sample where they either experience a non-NBER recession (ENAP growth in 1959) or miss a NBER recession (TCE growth in 1970). For the remainder of peaks, the average and average absolute deviation from the NBER peak is similar across employment measures. Again, however, there does appear to be some changes over time in the relative coincidence of the employment measures with the aggregate business cycle. Recession peaks from ENAP growth are closer to NBER peaks early in the sample, while those from TCE growth are closer in more recent recessions.

From the bottom panel of Table 2, the dates of employment troughs are closer to the NBER trough dates for TCE than for ENAP. For example, the average absolute discrepancy between ENAP troughs and NBER troughs is nearly five months, but is only one month for troughs in TCE. Closer inspection reveals that the relatively closer coincidence with NBER trough dates for TCE is coming entirely from recent recessions. In particular, troughs for both measures of employment are close to the NBER trough in recessions through the 1981–82 recession. However, for the 1990–91 recession and 2001 recession, troughs in ENAP are delayed considerably over the NBER trough, while troughs for TCE are also delayed, but significantly less so. This pattern also holds for the most recent recession. The NBER dated the end of this recession as June 2009. The ENAP trough again lagged behind the NBER and TCE troughs.

To gain more insight into the differences in the troughs of the last three recessions in TCE versus ENAP, Figs 3–5 highlight the paths of ENAP and TCE in a window around these three recessions. Each figure begins at the date of the NBER peak of the aggregate recession, and the two employment series are normalized to zero at this point. Interestingly, the three figures do not tell a consistent story regarding the reason for the difference in the trough dates. For the 1990–91 recession, depicted in Fig. 3, both series stop falling at a point roughly coincident with the NBER trough (March 1991), and then begin to move sideways for several months (until late 1991 for TCE and early 1992 for ENAP). However, while the recession probabilities for TCE fall when TCE stops falling, and date the trough in July 1991, the recession probabilities for ENAP fall only when ENAP begins to rise. A potential reason for this difference is the lower signal to noise ratio for TCE as compared with ENAP. In particular, the low growth in TCE following the 1991 recession is more likely to be attributed to the model disturbance term due to the relatively large size of the standard deviation of the model disturbance term for TCE.

In the 2001 recession, depicted in Fig. 4, there is a much clearer picture regarding the difference between the TCE and ENAP trough. In particular,

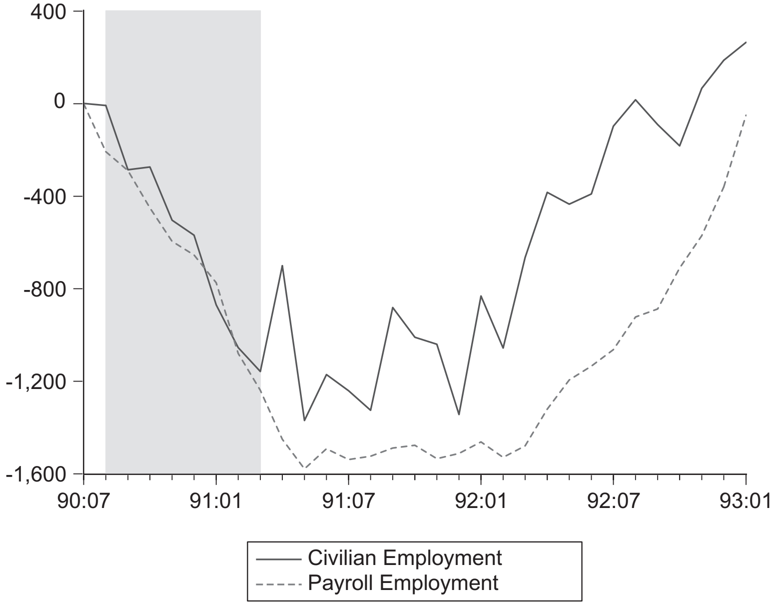

FIG. 3. Normalized TCE and ENAP around the 1990–91 Recession and NBER Recession (Shaded Area)

while ENAP experienced significant declines for an extended period following the NBER trough, TCE began to climb soon after the NBER trough. In other words, the 'jobless recovery' following the end of the 2001 recession was a unique feature of ENAP.

Finally, in the 2007–9 recession, depicted in Fig. 5, TCE again began to climb relatively quickly as compared with ENAP. Correspondingly, the recession probabilities for TCE have already fallen below 0.5, establishing the TCE trough to be in December 2009, while the recession probabilities for ENAP were still above 0.5 as of March 2010. However, additional data are needed to determine how large this discrepancy will be as compared with the previous two recessions.

The above results were based on the use of Markov-switching models to establish turning point dates in the alternative employment series. Table 3 presents results instead based on the non-parametric algorithm of Bry and Boschan (1971), which, roughly speaking, identifies turning points in the level of a time series as local minima and maxima in the path of the time series. Results using this algorithm are roughly similar to those using the Markov-switching model. In particular, as compared with ENAP, turning points using TCE have gotten relatively more coincident with the NBER turning points

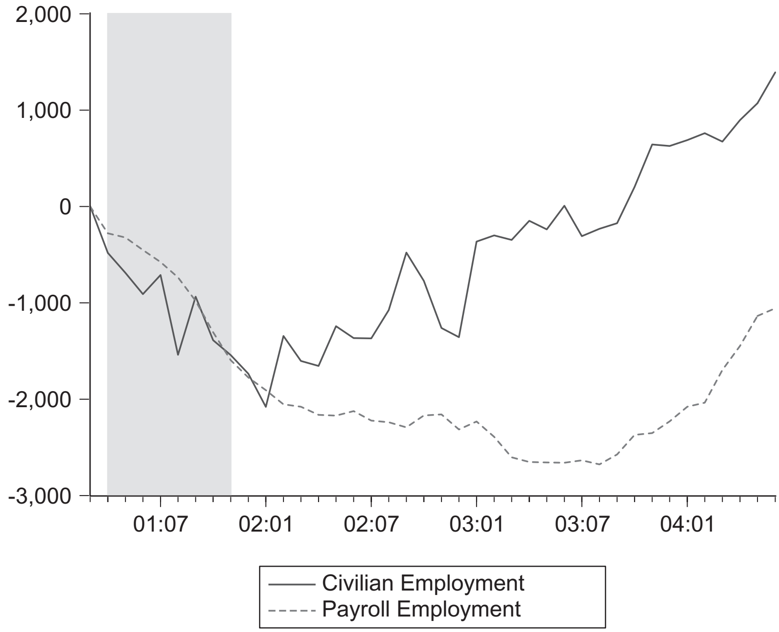

FIG. 4. Normalized TCE and ENAP around the 2001 Recession and NBER Recession (Shaded Area)

over time, and this increased coincidence is most notable at business cycle troughs.[9]

3 Employment and the Business Cycle—Evidence from Multivariate Analysis

In this section we study the differences between the two employment series in terms of identification of business cycle turning points in a multivariate setting. We use the dynamic factor model with regime switching applied to coincident economic variables, as in Chauvet (1998), Chauvet and Hamilton (2006) and Chauvet and Piger (2008), which is one of the most successful

[9]One significant difference between the results in Table 3 versus those based on the Markov-switching model is with regards to the trough of the 1991 recession. In particular, the Bry and Boschan (1971) algorithm establishes this trough to be the same for the two series, while the Markov-switching model establishes the trough for ENAP to be significantly later than for TCE. The Bry and Boschan results, which are based on local minima and maxima in the series, are not surprising given Fig. 2, which shows that ENAP and TCE reach a local minimum at a similar time. On the other hand, the Markov-switching model results are based on the probability that the low employment growth experienced following the trough in 1991 was drawn from the expansion or recession regime, which will depend on a number of factors beyond simply whether the series is increasing or decreasing.

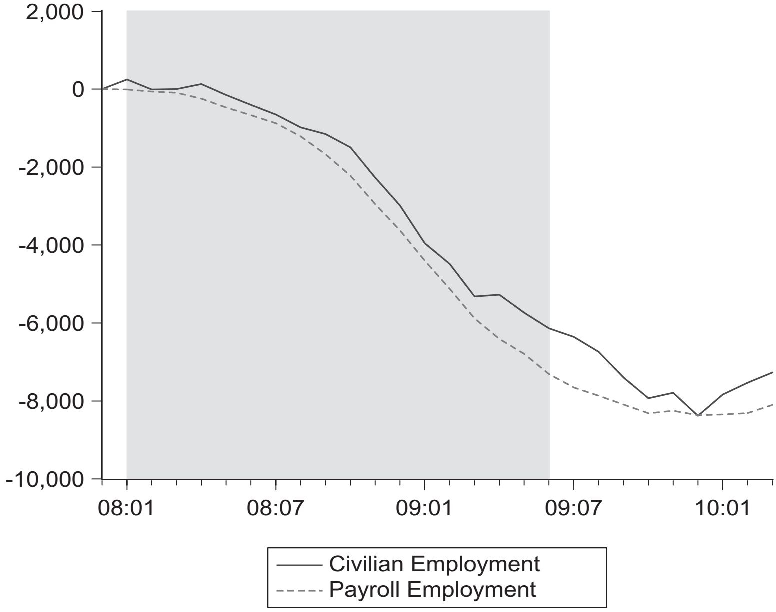

FIG. 5. Normalized TCE and ENAP around the 2007–9 Recession and NBER Recession (Shaded Area)

models in predicting turning points in real time. The model combines several coincident variables and extracts their co-movements into a single common factor. This latent factor follows a two-state Markov-switching process, capturing the recession and expansion phases of the business cycle, as described below.

3.1 Dynamic Factor Markov-switching Model

Let y_{it} be the log first difference of the ith time series. The dynamic factor model with regime switching (DFMS) is

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ . \\ . \\ y_{It} \end{bmatrix} = \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ . \\ . \\ \gamma_I \end{bmatrix} c_t + \begin{bmatrix} u_{1t} \\ u_{2t} \\ . \\ . \\ u_{It} \end{bmatrix} \tag{3}$$

That is, the first difference of each series is made up of a component common to each series, given by the dynamic factor c_t, and a component idiosyncratic to each series, given by u_{it}. The common component is assumed to follow a stationary autoregressive process:

Table 3
Deviation from NBER Business Cycle Dates of Business Cycle Dates from Bry-Boschan Algorithm Applied to Payroll Employment (ENAP) Growth and Civilian Employment (TCE) Growth

Peak date: NBER	*Peak date error: ENAP*	*Peak date error: TCE*
Apr 1960	0	0
Dec 1969	+3	+4
Nov 1973	+8	+8
Jan 1980	+2	+1
Jul 1981	0	–3
Jul 1990	–1	–4
Mar 2001	–1	0
Dec 2007	0	–1
Mean error	1.4 months	0.6 months
Mean absolute error	1.9 months	2.6 months
Trough date: NBER	*Trough date error: ENAP*	*Trough date error: TCE*
Feb 1961	0	+2
Nov 1970	0	–5
Mar 1975	+1	0
Jul 1980	0	–1
Nov 1982	+1	–1
Mar 1991	+2	+2
Nov 2001	+12	+2
Mean error	2.3 months	–0.1 month
Mean absolute error	2.3 months	1.9 months

$$\phi(L)(c_t - \mu_{S_t}) = \varepsilon_t \tag{4}$$

where ε_t is a normally distributed random variable with mean zero and variance σ_ε^2 set equal to unity for identification purposes, and $\phi(L)$ is a lag polynomial with all roots outside of the unit circle. The common component is assumed to have a switching mean, given by $\mu_{S_t} = \mu_0 + \mu_1 S_t$, where $S_t = \{0, 1\}$ is a state variable that indexes the regime. The state variable is unobserved, but is assumed to follow a Markov process with transition probabilities $P(S_t = 1|S_{t-1} = 1) = p_{11}$ and $P(S_t = 0|S_{t-1} = 0) = p_{00}$. As in the previous section, we identify the regimes by setting $\mu_1 < 0$, so that regime 1 is the recession state. Finally, each idiosyncratic component is assumed to follow a stationary autoregressive process:

$$\theta_i(L)u_{it} = \omega_{it} \tag{5}$$

where ω_{it} follows a normal white noise process with variance σ_ω^2, and $\theta_i(L)$ is a lag polynomial or order one with roots outside the unit circle. The model yields as output estimated probabilities of the regime at time t conditional on the data, denoted $P(S_t = k|T)$, $k = 0, 1$, and a business cycle index, c_t.

3.2 Full-sample Multivariate Analysis

Chauvet (1998) constructs a coincident indicator of the US business cycle through the DFMS model using the four monthly variables highlighted by the NBER in establishing turning point dates: industrial production (IP), real manufacturing and trade sales (MTS), real personal income excluding transfer payments (PILTP) and employment. However, instead of focusing on ENAP, Chauvet (1998) uses several alternative measures of employment.

Chauvet (1998) and Stock and Watson (1989) find that monthly ENAP is a lagging rather than a coincident variable, as it is necessary to introduce a high order autoregressive process to eliminate the misspecification in the measurement equation. Since this would amount to study a lagging indicator, Chauvet (1998) considers other measures of employment such as civilian employment (TCE), non-agricultural civilian employment (NACE) and hours of employees on non-agricultural payrolls (HENAP). For this same reason, Stock and Watson (1991) replace ENAP with HENAP. Parsimonious versions of the coincident indicator obtained from the switching dynamic factor model pass specification tests when these alternative employment series are used. More recently, Chauvet and Hamilton (2006) opt to use TCE rather than ENAP as the former presents a better performance in predicting turning points in real time than the latter, as discussed in the next section. These findings are in agreement with the evidence found in Section 2, which shows that ENAP delivers delayed business cycle signals compared with TCE, especially with regards to troughs.

We estimate two versions of the DFMS model applied to the four coincident series described above: one using TCE as the employment series, and another with TCE replaced by ENAP. We use Kim's filter (1994) to estimate the model and to obtain the probabilities of recession at time t conditional on the full-sample data, denoted $P(S_t = 1|T)$.

Table 4 shows the maximum likelihood estimates. The model identifies two regimes that correspond to business cycle recessions and expansions. As found in the univariate analysis, both expansions and recessions are more accentuated when the model is estimated with ENAP compared with the version using TCE. However, differently from the univariate analysis, the coefficient of variation as measured by the metric μ_1/σ_ε is very close for both specifications, indicating that they yield similar signal to noise ratios.

Figure 6 plots the smoothed probabilities of recession from the multivariate DFMS model using the four coincident series described above—the top panel—with TCE as the employment series, whereas the bottom panel shows the probabilities of recession obtained when TCE is replaced by ENAP. The shaded areas represent recessions as dated by the NBER. The transition probabilities (Table 4) and the probabilities of recession also indicate that recessions are longer when using ENAP series than with TCE series.

Table 4
Maximum Likelihood Estimates of the Dynamic Factor with Markov-switching Model

Parameters	*Payroll employment*	*Civilian employment*
μ_0	1.484 (0.204)	1.418 (0.275)
μ_1	−0.609 (0.169)	−0.567 (0.257)
P_{00}	0.978 (0.007)	0.976 (0.009)
P_{11}	0.924 (0.027)	0.876 (0.056)
σ_{ε}^2	1	1
ϕ	0.508 (0.050)	0.383 (0.066)
$\lambda_{\text{Production}}$	0.313 (0.021)	0.373 (0.026)
λ_{Income}	0.174 (0.011)	0.236 (0.014)
λ_{Sales}	0.249 (0.019)	0.333 (0.025)
$\lambda_{\text{Employment}}$	0.131 (0.006)	0.118 (0.008)
$\sigma_{\omega,\text{Production}}^2$	0.377 (0.023)	0.322 (0.024)
$\sigma_{\omega,\text{Income}}^2$	0.098 (0.006)	0.081 (0.007)
$\sigma_{\omega,\text{Sales}}^2$	0.821 (0.042)	0.673 (0.042)
$\sigma_{\omega,\text{Employment}}^2$	0.006 (0.001)	0.073 (0.005)
$\theta_{\text{Production}}$	0.154 (0.04)	0.135 (0.052)
θ_{Income}	0.271 (0.042)	0.077 (0.057)
θ_{Sales}	−0.232 (0.039)	−0.325 (0.041)
$\theta_{\text{Employment}}$	−0.495 (0.075)	−0.281 (0.042)
Log L	−1405.724	−1597.121

Asymptotic standard errors in parentheses. The model is estimated with four coincident variables: sales, employment, personal income and industrial production.

The probabilities of recession from the different specifications closely match NBER expansion and recession phases. That is, $P(S_t = 1|T)$ is high during recessions and low during expansions. However, in contrast with the univariate analysis of the TCE series, the multivariate DFMS with TCE yields probabilities of recession that are in close agreement with the NBER dating for *both* the first and the second part of the sample. On the other hand, as in the univariate analysis, the probabilities of recessions from the ENAP specification also exhibit a marked different pattern in the last three recessions compared with the first part of the sample. In particular, the probabilities of recession only decrease long after the end of these recessions as determined by the NBER.

Figure 7 compares the probabilities of recession from the ENAP specification and from the TCE specification. Although these probabilities are very close to each other around all business cycle peaks, they are very different for the last three business cycle troughs. While the probabilities for the ENAP specification depict the jobless recoveries, the probabilities of recession from the TCE specification fall right around the trough of the last three recessions as determined by the NBER. As also found in the previous section, this reflects the fact that payroll employment has been very sluggish to recover while civilian employment has shown a much more prompt recovery

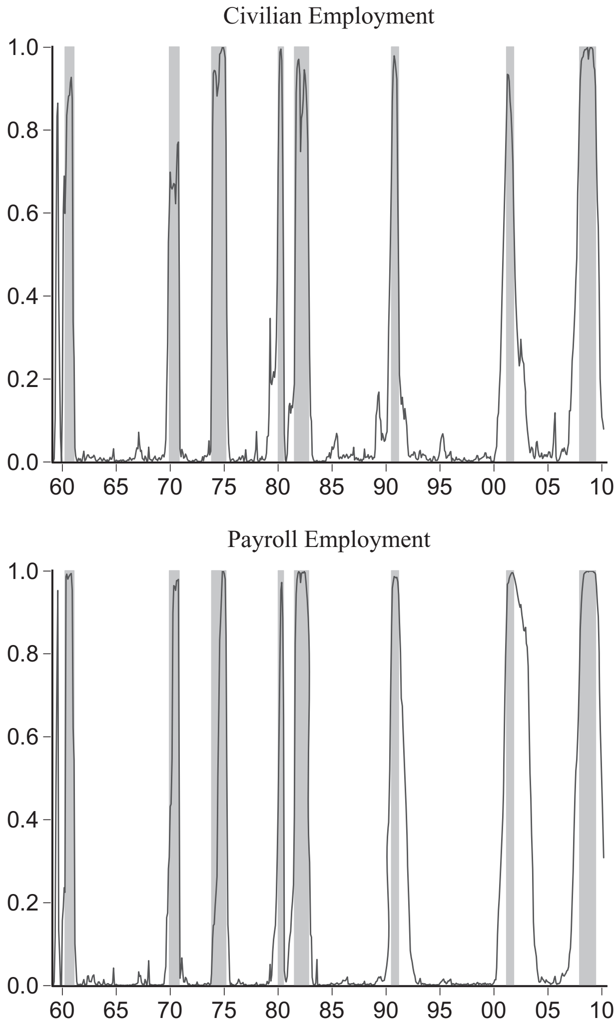

FIG. 6. Smoothed Probabilities of Recession Obtained from the DFMS Model Using Employment, Sales, Personal Income, and Industrial Production and NBER Recession (Shaded Area)

in the last three decades. In particular, the probabilities of recession from the ENAP specification reflect the puzzling jobless recoveries that followed the 1990–91 recession, the 2001 recession, and the 2007–9 recession. These jobless recoveries have been a great source of uncertainty regarding the strength or weakness of economic conditions in real time.

In order to obtain specific turning points dates, we again use a simple rule to convert the recession probabilities into a 0/1 dummy variable that

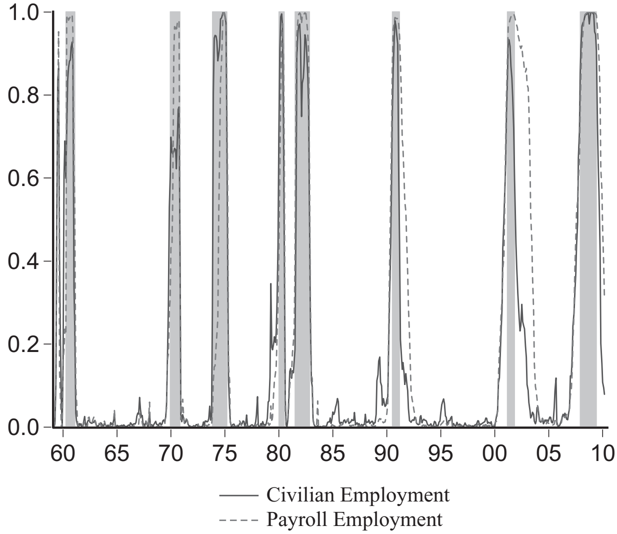

FIG. 7. Smoothed Probabilities of Recession and NBER Recession (Shaded Area)

defines whether the economy is in an expansion or recession regime at time t. The first month of a recession (expansion) phase is identified as the first month t for which the probability of recession (expansion) moves above 50 per cent. That is, if $P(S_{t-1} = 1|T) < 0.50$ and $P(S_t = 1|T) \geq 0.50$ then t is the peak date for this recession phase. A similar procedure is implemented for a trough date.

Tables 5 and 6 show the business cycle dating from the multivariate DFMS model with the four series described above using, respectively, TCE and ENAP as the employment series. The first and fourth columns of both tables report the NBER dating of business cycle peaks and troughs respectively. The second and fifth columns give the business cycle peaks and troughs assigned by the DFMS model respectively. The third and six columns give the lead or lag time of the turning point dating assigned by the DFMS model compared with the NBER dating.

We begin with Table 5, which shows the results for the DFMS model using TCE. The DFMS model identifies all 15 turning points in the sample, each of which corresponds to a NBER turning point, with no missing signals. The DFMS model also identifies these turning points with a high level of accuracy. In particular, for 13 out of the 15 turning points, the dates identified by the model are within one month of the NBER dates. The most distant turning point is the peak of the 2001 recession, in which the date identified by the model is four months prior to the NBER date. Stock and Watson (2010) show that several formal models for dating turning points also indicate that

TABLE 5
DATES OF RECESSIONS AS DETERMINED BY THE NBER AND THE DYNAMIC FACTOR MARKOV-SWITCHING MODEL (DFMS) BASED ON FULL-SAMPLE SMOOTHED PROBABILITIES, USING CIVILIAN EMPLOYMENT, SALES, PERSONAL INCOME AND INDUSTRIAL PRODUCTION

Start of recession			*End of recession*		
NBER	*DFMS*	*Lead/Lag Months*	*NBER*	*DFMS*	*Lead/Lag Months*
Apr 1960	Feb 1960	–2	Feb 1961	Jan 1961	–1
Dec 1969	Nov 1969	–1	Nov 1970	Nov 1970	0
Nov 1973	Dec 1973	+1	Mar 1975	Apr 1975	+1
Jan 1980	Jan 1980	0	Jul 1980	Jul 1980	0
Jul 1981	Aug 1981	+1	Nov 1982	Nov 1982	0
Jul 1990	Jun 1990	–1	Mar 1991	Mar 1991	0
Mar 2001	Nov 2000	–4	Nov 2001	Dec 2001	+1
Dec 2007	Dec 2007	0	Jun 2009	Jun 2009	0

TABLE 6
DATES OF RECESSIONS AS DETERMINED BY THE NBER AND THE DYNAMIC FACTOR MARKOV-SWITCHING MODEL (DFMS) BASED ON FULL-SAMPLE SMOOTHED PROBABILITIES, USING PAYROLL, SALES, PERSONAL INCOME AND INDUSTRIAL PRODUCTION

Start of recession			*End of recession*		
NBER	*DFMS*	*Lead/Lag Months*	*NBER*	*DFMS*	*Lead/Lag Months*
Apr 1960	May 1960	+1	Feb 1961	Mar 1961	+1
Dec 1969	Mar 1970	+3	Nov 1970	Nov 1970	0
Nov 1973	Jun 1974	+7	Mar 1975	Jun 1975	+3
Jan 1980	Feb 1980	+1	Jul 1980	Aug 1980	+1
Jul 1981	Aug 1981	+1	Nov 1982	Dec 1982	+1
Jul 1990	May 1990	–2	Mar 1991	Nov 1991	+8
Mar 2001	Dec 2000	–3	Nov 2001	Jun 2003	+19
Dec 2007	Dec 2007	0	Jun 2009	Dec 2009	+6

Notes: Leads or lags are represented by – or +, respectively, and indicate how many months the Markov-switching model anticipates or lags the NBER dating, whereas 0 indicates that the two dating systems coincide. A business cycle downturn is identified when the smoothed probability of recession rises above 0.5. An upturn is identified when the probability of recession falls below 0.5.

the peak of this recession might have occurred earlier.[10] For the most recent recession, the DFMS model using TCE identify the peak as in December 2007, coinciding with the NBER dating. The DFMS calls the end of this recession as in June 2009. Although the NBER had yet not determined the end of the 2007–9 recession at the time this paper was written (July 2010), the NBER committee later on (in September 2010) dated June 2009 as the end of the recession.

[10]Some previous members as well as the current members of the NBER Business Cycle Dating Committee have informally discussed the possibility of revising the NBER peak date for this recession accordingly.

The performance of the DFMS model using ENAP is quite different compared with the specification using TCE, as reported in Table 6. In several instances, the DFMS model identifies turning point dates with a discrepancy of three or more months compared with the NBER dating, with a maximum discrepancy of 19 months. In the first part of the sample, the DFMS with ENAP identifies the 1973–74 recession as starting eight months after the beginning of this recession as called by the NBER. In the second part of the sample, and especially for the last three recessions, the model identifies their end as taking place a lot later than the NBER troughs. The end of the 1990–91 recession is identified as taking place eight months after the NBER trough. The most dramatic difference is with respect to the end of the 2001 recession, which the model identifies as occurring 19 months after the NBER trough. For the most recent recession, the trough is identified as December 2009, which is six months after the NBER trough in June 2009.

3.3 *Real-time Multivariate Analysis*

In this section, we evaluate how the use of the different employment series can affect the performance of the DFMS model in predicting turning points in real time. We implement a similar real-time exercise as in Chauvet and Hamilton (2006) and Chauvet and Piger (2008).

3.3.1 Data Set. We use a combination of the real-time data set collected in Chauvet (1998), Chauvet and Hamilton (2006) and Chauvet and Piger (2008). Real-time data for PILTP and MTS were hand collected as part of a larger real-time data collection project at the Federal Reserve Bank of St. Louis and first used in Chauvet and Piger (2008). The ENAP and IP data series were obtained from the Federal Reserve Bank of Philadelphia real-time data archive described in Croushore and Stark (2001). The real-time data for TCE were hand-collected as part of Chauvet (1998) and Chauvet and Hamilton's (2006) research.

The data collected are realizations, or *vintages*, of these time series as they would have appeared at the end of each month from November 1976 to June 2010. For each vintage from November 1976 to June 1996, the sample collected begins in January 1959 and ends with the most recent data available for that vintage. For each vintage from February 1996 to June 2006, the sample begins in January 1967, and for each vintage from July 2006 to June 2010, the sample begins in January 1959. For the series ENAP, TCE, IP and PILTP, data are released for month t in month $t + 1$. Thus, for these variables the sample ends in month $R - 1$ for vintage R. For MTS, data are released for month t in month $t + 2$. Thus, for this variable the sample ends in month $R - 2$ for vintage R. Thus, for each monthly vintage R we create a monthly data set of ENAP, TCE, IP, MTS and PILTP that would have been available at the end of month R.

In order to assess the real-time performance of the multivariate model using the two different measures of employment, we apply the DFMS model described in Section 3.1 to the real-time data set described above. The business cycle model is estimated on the end of each month, which is soon after the release of MTS data for that monthly vintage, and recursive real-time probabilities of recessions are computed.

3.3.2 Real-time Analysis of Turning Points of the DFMS Model Using ENAP and TCE. We now turn to the real-time performance of the DFMS model using the alternative measures of employment. We evaluate the differences between the two specifications in identifying business cycle turning points in real time for the 2001 and the 2007–9 recessions.

Figures 8 and 9 plot the real-time probabilities of recession obtained from different vintages around the turning points of the 2001 and the 2007–9 recessions. That is, these figures show a sequence of $P(S_t = 1|\Psi_T)$, where Ψ_T corresponds to the information available in the month in which the probability was calculated (vintage R), which uses the final data point information available, $R-2$—the last month for which data are available for MTS. These probabilities are recursively estimated using just-in-time information, which includes unrevised and preliminary data. Since these probabilities use real-time information, they also reflect the uncertainty about the economy at each month.

As in the previous section, we use the simple rule of 50 per cent as the threshold indicating the transition between business cycle phases. This rule yields a fast assessment on the state of the economy.[11] The turning points identified by the DFMS model estimated using TCE are in closer agreement with the NBER business cycle phases. In addition, this specification delivers a much faster call of turning points in real time, as illustrated below. On the other hand, ENAP in real time tends to overestimate employment around the beginning of recessions and to underestimate employment around their end. The use of this employment series yields delays in signaling troughs, especially the most recent ones.

[11]Although this rule maximizes the speed at which a turning point might be identified, it also increases the chances of declaring a false positive. A more reliable inference can be obtained using more information to verify a turning point as in Chauvet and Hamilton (2006) and in Chauvet and Piger (2008), who propose to use a low-order smoothed probability in addition to the current real-time probability to increase accuracy. The information from the readily available real-time probabilities is combined with the more precise information obtained from one-step or two-step ahead smoothed probabilities in real-time assessment of the business cycle phases. The metrics considered in these papers improve the quality of the inference in terms of accuracy, but they decrease speed in which turning points can be identified. Ideally, a combination of these metrics with the one used in this paper can be implemented in real time to first identify a turning point, and subsequently confirm the phase transition.

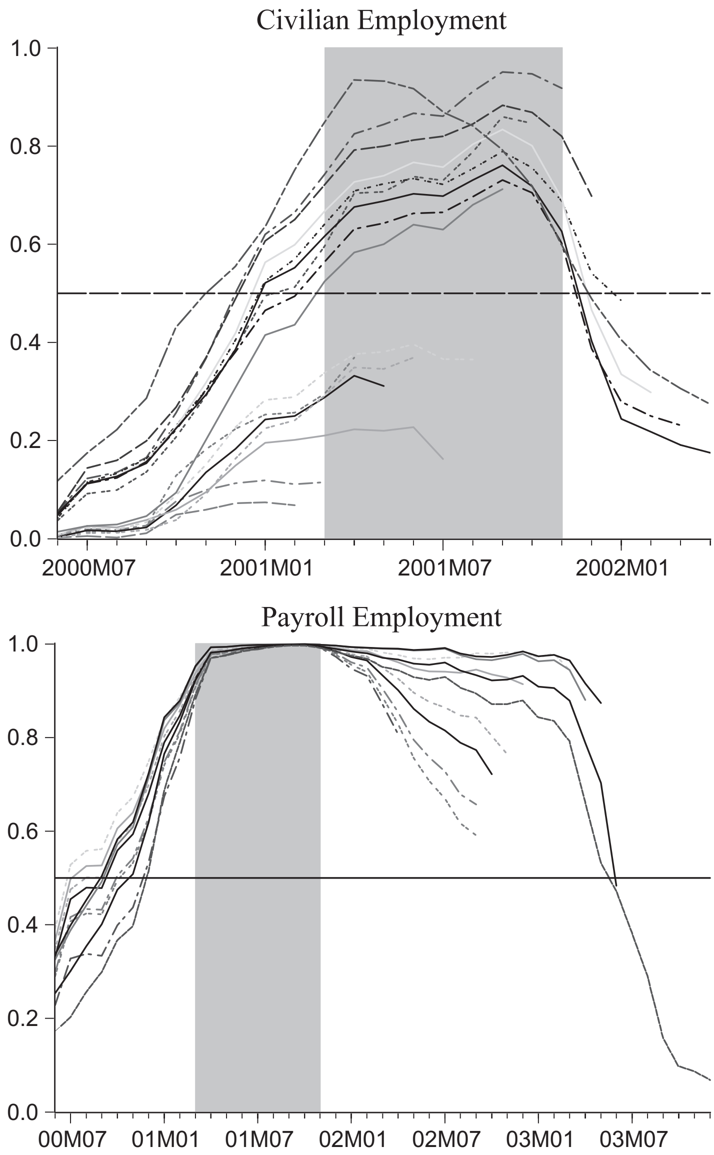

FIG. 8. Recursive Real-time Probabilities of 2001 Recession for each Vintage from 2000:06 to 2002:04—DFMS using Employment, Sales, Personal Income, and Industrial Production and NBER Recession (Shaded Area)

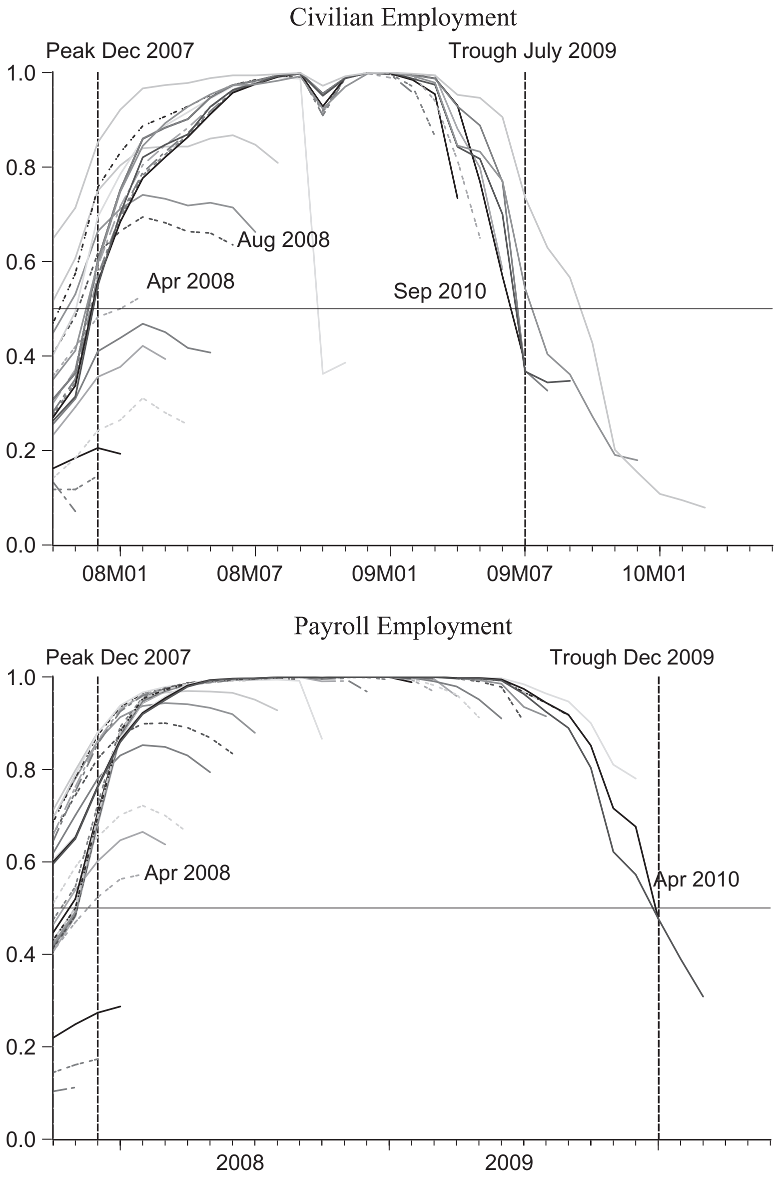

FIG. 9. Recursive Real-time Probabilities of 2007–9 Recession for Each Vintage from 2007:10 to 2010:06—DFMS using Employment, Sales, Personal Income, and Industrial Production

3.3.3 2001 Recession. According to Fig. 8, real-time assessment of the 2001 recession using the DFMS with TCE (top panel) would have indicated that this recession started in March 2001, using the vintage of June 2001. Interestingly, when subsequent data are used, which were continuously revised, the peak of this recession is indicated to have started earlier, in the fourth quarter of 2000 instead. With respect to the end of this recession, the DFMS with TCE indicates that the trough was in December 2001, using vintage data of January 2002.[12]

Figure 8 (bottom panel) shows the real-time probabilities of recession for different vintages for the DFMS estimated using ENAP. As for the DFMS with the TCE data, the DFMS with ENAP also indicates that the 2001 recession started in the fourth quarter of 2000. However, there is a major difference between the information from the DFMS with ENAP compared with the DFMS with TCE regarding the end of this recession. The DFMS with ENAP would have indicated that this downturn did not end until 2003. The real-time probabilities of recession obtained when this measure of employment is considered suggest that there was a slight recovery in economic activity from October 2001 to July 2002. In particular, the DFMS model would have first established the trough date of November 2001 by the end of August of 2002. However, for a brief period, for vintages in mid-2003, the recession probabilities from the DFMS model for 2002 and 2003 rose significantly to levels consistent with a continuation of the 2001 recession. This was the result of very weak employment data observed in 2002 and 2003, or the so-called 'jobless recovery'. This is consistent with findings in Chauvet and Hamilton (2006) and in Chauvet and Piger (2008).

3.3.4 2007–9 Recession. Figure 9 shows the real-time probabilities of recession obtained from different vintages of the DFMS model using TCE (top panel) or using ENAP (bottom panel) around the 2007–9 recession. The probabilities from both specifications indicate that the peak of this recession occurred in December 2007, which is in agreement with the NBER dating. The NBER only announced the recession peak in December 2007 12 months later, in December 2008. Using payroll employment as one of the four coincident variables, the recession would have been confirmed by the DFMS model as of April 2008 (using vintage of February 2008), while using civilian employment instead, the recession would have been confirmed by the DFMS model as of August 2008 (using vintage of June 2008).

While there is an agreement regarding the peak date when TCE or ENAP are used in the DFMS model, this is not the case for the end of this recent recession. The probabilities of recession from the DFMS with TCE

[12]Chauvet and Hamilton (2006) find that the vintage of March 2002 would have indicated the end of this recession in November 2001, using the more conservative rule described in the previous footnote.

indicate that the trough of this recession occurred in June 2009, using information available in August 2009 and vintage of June 2009). On the other hand, the DFMS model with ENAP indicates that the trough only occurred a couple of months later, in December 2009, using information available in April 2010 (vintage of February 2010).

4 Conclusions

This paper examines the implication for prediction of business cycle phases of recent changes in the cyclical behavior of employment. Non-linear univariate and multivariate models show that the most important discrepancies between the two main employment series—payroll employment and civilian employment occur around transitions of business cycle phases. In particular, the employment series used by the NBER, payroll employment, has displayed a very slow recovery in the last three recessions, while civilian employment has exhibited a more swift recovery.

The conflicting information from the employment series has significantly contributed to the uncertainty about economic conditions during recessions and recoveries. The jobless recoveries measured by payroll employment and their real significance in terms of gauging the strength or weakness of labor market conditions and aggregate economic conditions on a timely basis is a crucial issue as they have played an important role in influencing economic agent's decisions as well as monetary and fiscal policy, as illustrated in the recent economic downturn.

We find that the identification of business cycle turning points, especially troughs, is sensitive to the measure of employment utilized. This is the case not only when unrevised real-time data are considered, but also for fully revised data. In particular, the non-linear multivariate dynamic factor model that includes civilian employment yields more precise and faster identification of business cycle troughs than the specification of this model that includes instead payroll employment.

The cyclical differences between these series may be related to the nature of these series and the facet of the labor market that they measure, but are also possibly related to potential structural changes in the labor market in the recent decades. We are currently examining in an ongoing project the possible economic causes of the divergences between payroll employment and civilian employment, the possible implications for the most recent as well as for future recessions and recoveries, and the potential implications for implementation of monetary and fiscal policies.

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