Indicators for Dating Business Cycles: Cross-History Selection and Comparisons

By James H. Stock and Mark W. Watson*

The National Bureau of Economic Research (NBER) Business Cycle Dating Committee and the Center for Economic and Policy Research (CEPR) Business Cycle Dating Committee date business cycle turning points using a small number of aggregate measures of real economic activity. For example, in its memorandum explaining the December 2007 peak (NBER Business Cycle Dating Committee 2008), the NBER committee mentioned that it considers five series, quarterly real GDP and the "big four" monthly series, real personal income less transfers, real manufacturing and wholesale-retail trade sales, industrial production, and nonfarm employment. (These series do not in general receive equal weight.) In contrast, when the NBER research program on dating business cycles commenced, researchers examined turning points in hundreds of series and dated business cycles by detecting clusters of specific-cycle turning points; see Arthur Burns and Wesley Mitchell (1946, 13 and 77–80). The dating of turning points evidently has shifted from aggregating the turning points of many disaggregated series to using the turning points of a few highly aggregated series. This shift raises a methodological question: should reference cycle turning points be determined by aggregating then dating, or by dating then aggregating?

This paper provides some preliminary evidence on the question of whether it is better to date then aggregate or aggregate then date using 270 monthly disaggregated real economic indicators.

The questions considered in this paper parallel those in the large literature on forecasting using many series, ranging from the early work of Ray Fair and Robert Shiller (1990) to work over the past decade on forecasting using hundreds of series and dynamic factor models; see Stock and Watson (2009) and Sandra Eickmeier and Christina Ziegler (2008) for recent work and Stock and Watson (2010a) for a survey. The problem of dating turning points differs from the forecasting problem because turning points are estimated retrospectively (in-sample) and because the turning point estimator is nonlinear, whereas the forecasts considered in the many-series literature are predominantly linear. Our approach to dating reference cycles is conceptually related to the approach developed by Donald Harding and Adrian Pagan (2006) and studied by Marcelle Chauvet and Jeremy Piger (2008); however, our methods differ in the details, and we focus on using many disaggregated series, something not considered by these two papers. Additionally, we treat reference cycle dating as a frequentist estimation problem and provide standard errors for turning points, something that seems to be new in the literature.

I. Methodological Considerations

We begin by briefly summarizing our methods; details can be found in Stock and Watson (2010b). We consider two approaches to dating reference cycles. The first ("date then aggregate") is based on aggregating turning points in a large number of subaggregates, and the second ("aggregate then date") is based on the turning points from a single aggregate time series constructed from the subaggregates. In both cases, turning points for individual time series are based on the algorithm of Gerhard Bry and Charlotte Boschan (1971).

Aggregation of Bry-Boschan Dates.—We consider the problem of dating a reference cycle turning point, once it has been established that

a turning point has occurred. This allows us to partition the data into S non-overlapping episodes, each of which contains a single turning point of unknown date. Conditioning on the knowledge that an episode contains a single turning point introduces potential two-step or pretest bias, but it allows a useful simplification, and (we suspect) this two-step assumption could be relaxed by iterating on the definitions of the episodes.

Suppose we have n specific series, each with a specific chronology and with turning point date τ_{is} for series i in episode s, $i = 1, \ldots, n, s = 1, \ldots, S$ (if series i has no turning point or is unavailable in the episode then τ_{is} is treated as missing data). Let D_s be the reference cycle turning point in episode s, let k_i be the mean lag of series i relative to the reference cycle, and let η_{ij} be the deviation of the specific cycle turning point from the reference cycle turning point, so that

$$(1) \qquad \tau_{is} = D_s + k_i + \eta_{is}.$$

The individual series lead/lag $\{k_i\}$ are normalized to have mean zero. In our empirical implementation, we compute the specific-cycle date τ_{is} using the Bry-Boschan (1971) algorithm.

The panel data model (1) treats $\{D_s\}$ and $\{k_i\}$ as unknown parameters. By segmenting the data into episodes, the data have a standard panel data structure and the parameters can be estimated by fixed effects panel data regression with an unbalanced panel and missing observations. We estimate these unknown parameters by ordinary least squares (OLS), which also produces standard errors for the estimated reference cycle turning point dates.

Reference Cycles Based on Aggregates.—For comparison purposes, we also consider reference cycles based on two aggregate coincident indexes. The first is the estimated factor in a dynamic factor model estimated by Gaussian maximum likelihood using the full unbalanced panel of 270 disaggregated series. The second aggregate index is the coincident index published monthly by The Conference Board, which is a weighted average of the "big four" monthly series. Both of these aggregate coincident indexes are weighted averages of the underlying 270 series, so both provide different implementations of the "aggregate then date" strategy.

II. Empirical Results

Data.—We consider 270 monthly time series from 1959:1 through 2009:7. The 270 series consist of 69 subaggregates of industrial production, 14 subaggregates of personal income less transfers, 92 subaggregates of manufacturing and trade sales, and 95 subaggregates of nonfarm employment. Because many series are unavailable for the full span, the panel is not balanced.

Results.—Table 1 reports results for the "date then aggregate" chronology produced by the OLS estimates of the panel data model (1) (rounded to the nearest integer), and the two "aggregate then date" chronologies obtained by applying the Bry-Boschan algorithm to the dynamic factor model aggregate index and to The Conference Board coincident index. All three chronologies are expressed as deviations from the official NBER chronology, which is given in the first column (along with whether the turning point is a peak or trough). The final two rows of the table include two summary statistics, the mean and the standard deviations of the difference between the estimated chronology and the NBER chronology.

Table 1 suggests three conclusions. First, the chronology estimated using the specific cycles (the OLS panel data chronology) and the chronology based on the two aggregate indexes are in most cases very close, typically within a month of each other. Moreover, all three of these chronologies are typically close to the NBER chronology, with standard deviations between 1.9 and 3.5. Second, the OLS estimator, which is the only chronology for which a standard error is available, have 95 percent confidence bands that range from ± 0.8 months to ± 1.8 months around the point estimates. Evidently, the use of many series provides precise estimates of turning points; however, the precision of those estimates varies across episodes. Because sampling distributions for the other estimators are not available we cannot compare standard errors across estimators. Third, there are three episodes in which all three chronologies in Table 1 differ substantially from the NBER chronology: the 1960:4 peak, the 1969:12 peak, and the 2001:3 peak; in all three cases, the alternative chronologies date the peaks as falling earlier than the NBER peak.

Figure 1 takes a closer look at one of these episodes, the 1969:12 peak. The figure portrays

TABLE 1—ESTIMATED REFERENCE CYCLE CHRONOLOGIES, RELATIVE TO NBER DATES

|		Estimated turning point (deviation from NBER date)		
NBER turning point		OLS panel data (SE)	Dynamic factor model	The Conference Board coincident index
1960:4	P	−3 (0.91)	−12	−3
1961:2	T	0 (0.56)	0	0
1969:12	P	−2 (0.65)	−4	−2
1970:11	T	2 (0.60)	0	0
1973:11	P	3 (0.57)	0	0
1975:3	T	3 (0.39)	1	1
1980:1	P	−3 (0.69)	0	0
1980:7	T	1 (0.62)	0	0
1981:7	P	1 (0.49)	0	1
1982:11	T	0 (0.52)	0	1
1990:7	P	0 (0.55)	0	−1
1991:3	T	3 (0.45)	0	0
2001:3	P	−5 (0.45)	−6	−6
2001:11	T	0 (0.56)	0	1
2007:12	P	−1 (0.48)	0	−2
Mean		−0.1	−1.4	−0.7
SD		2.4	3.5	1.9
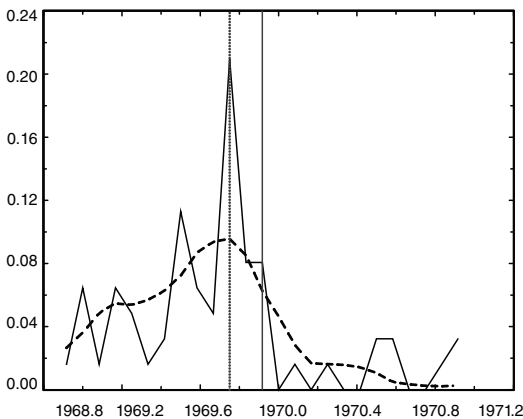
FIGURE 1. DISTRIBUTION OF SPECIFIC TURNING POINTS NEAR THE 1969 PEAK

Note: Histogram (solid line), kernel density estimate (dashed line), NBER turning point (solid vertical), OLS turning point (dotted vertical)

the distribution of the specific turning points, both the raw histogram of specific turning points (solid line) and the kernel density estimator of the distribution after adjusting for the estimated series-specific average lead/lag, $\hat{k}_i$ (dashed line). The two vertical lines are the NBER peak (1969:12) and the OLS panel data estimated peak (1969:10). The raw histogram shows some turning points well before and after the peak, but many of those turning points are associated with leading and lagging indicators, and after lag adjustment their estimated dates shift towards the center of the distribution. The lead/lag-adjusted kernel density estimator shows that the specific cycle turning points are clustered around the late summer through fall 1969. The mode of the kernel density estimator of the distribution of lead-lag-adjusted turning points happens to coincide with the OLS estimator of the turning point, which is October 1969, although the mode of this distribution never entered the calculation of the OLS estimated turning points. Evidently, most of the disaggregated series considered here peaked before the NBER date of 1969:12, and the evidence based on the disaggregated series points towards a peak of October 1969.

These preliminary results suggest that further work on the "date then aggregate" approach could be fruitful. Additional work which could shed light on this possibility includes examining estimation methods other than OLS, recognizing that some of the disaggregate series might be more useful for dating turning points than others, using filtering methods (not just the

Bry-Boschan algorithm) for estimating specific series turning points, and allowing series-specific average lead-lags to differ at peaks and troughs and to evolve over time. One evident advantage of using a large number of data series, illustrated here using the panel data estimator, is that the tools of frequentist distribution theory can be brought to bear on the dating problem. As a result, we can provide standard errors and confidence intervals for turning points. On the substantive level, the "date then aggregate" approach provides new information that has the potential to be useful for informing dating decisions today, just as it was for Burns and Mitchell (1946).

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