The Use of the Composite Leading Index for Forecasting Business Cycle Turning Points

Max Chen

The Conference Board, 845 3rd Avenue, New York, NY 10022-6679, maxclchen@yahoo.com

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1. Introduction

At the quarterly frequency, GDP is regarded as the most important single economic series representing the state of the economy. However, at monthly frequency, there is no single economic series which can cover the overall activities of the economy. The Conference Board's Composite Index of Coincident Indicators (CCI), a composite index of employment, income, output and sales, is designed to trace the state of the economy at the monthly frequency. Peaks and troughs in CCI are very close to the official peak and trough dates from the National Bureau of Economic Research. It provides timely information about current economic conditions and is also highly correlated with GDP with raw correlation 0.99.

The Conference Board's Composite Index of Leading Indicators (CLI) is widely used to gauge the direction of the future path of the economy and forecast future business cycle turning points. The record of the CLI is less consistent. The average lead time for the peaks and troughs is nine and half months and four and half months, respectively. The standard deviations associated with the lead time of CLI are four and half months for the peaks and two and half months for the troughs. In general, sustained declines in the CLI are required in order to signal potential future downturns of the economy. However, there is no specific rule about how large the declines should be. A simple rule of thumb is to consider three-month consecutive declines in the leading index as a signal of a forthcoming recession. But this criterion alone is not sufficient to distinguish between slowdown and recession. And it often gives false signals.

Other rules may perform better than this simple rule. A more sophisticated approach is to examine "The Three Ds": the duration, depth, and diffusion of the leading indicators. The longer the weakness continues, the deeper it gets, and the more widespread it becomes, the more likely a recession will occur. This approach incorporates the important features of business cycles: the decline must be of significant size and duration, and the majority of the component series must be weakening. A 3-D rule described in details by The Conference Board's Business Cycle Indicator Handbook (2001) requires the six-month growth rate (annualized) of the CLI to fall below -3.5 and the six-month diffusion index to be lower than 50 percent. This 3-D rule generates acceptable recession signals with average 3-month lead time. It gives a false signal in 1966 and a close but still missing one for the 2001 recession.

The rules mentioned above give us early warning of future recession, but they encounter a common problem. They don't give us a precise signal of when the future recession may start. In addition, they also don't give us a quantitative measure of how likely a future recession is going to happen. How to extract useful information from the CLI to generate reliable recession signals and to forecast future recession probabilities is our focus here. One way to address this issue is to consider econometric models that are built to predict business cycle turning points. Camacho and Perez-Quiros (2002) conduct a detailed econometric study on the use of CLI for forecasting real GDP. They find that a combination of a regime-switching VAR and a nonparametric model is the best way to recession forecast. Their results are based on the quarterly frequency where GDP is available. However, the evidence is much weaker at monthly frequency, due to the noisy nature of the monthly data.

This paper tries to fill this gap. Using CCI and CLI, which are available at the monthly frequency, we develop four models that generate monthly recession probability statements for the CCI and explore the use of the CLI for predicting turning points in CCI. The four models we investigate are: Markov switching with fixed transition probabilities (MSFTP), Markov switching with time-varying transition probabilities (MSTVTP), dynamic factor with Markov switching and fixed transition probabilities (DFMSFTP), and dynamic factor with Markov switching and time-varying transition probabilities (DFMSTVTP).). We can view the last two models as multivariate extensions of the first two models that are univariate. The models with time-varying transition probabilities depend on the growth rate of CLI, and are constructed as extension of the fixed transition probabilities models. In general, all models produce recession and expansion periods that are consistent with the NBER chronology of business cycles. The multivariate models give better in sample fitting, CLI doesn't improve their performance. However, the results are reversed in out-of-sample forecasting evaluations. Univariate models perform better than multivariate models and CLI improves performance.

Section two discusses the methodology. Section three outlines the models that we use to generate recession probability. Section four discusses related empirical evidence about the performance of the models, both in sample and out-of-sample. Section five concludes.

2. Methodology

Different combinations of models and data have been proposed to identify and forecast business cycle turning points in the past 25 years; see, for example, Zarnowitz and Moore's (1982) simple filter rules with the composite and diffusion indicators, Neftci's (1982) optimal stopping time rule with the leading indicator, Hamilton's (1989) fixed transition probability Markov switching with quarterly GNP, Filardo's (1994) time-varying transition probability Markov switching with monthly industry production, Stock and Watson's (1993) dynamic factor model with individual coincident indicators, Kim and Yoo's (1995) dynamic factor model with Markov switching, Estrella and Mishkin's (1998) probit model with financial variables, and Bayesian approaches by Wecker (1979), Kling (1987), Zellner,Hong, and Ming (1989), Kim and Nelson (1998), Del Negro (2001), and Dueker (2001). For recent surveys on business cycles and turning point identification and forecasting, refer to McNees (1991), Boldin (1995), Filardo (1999), and Diebold and Rudebusch (2001).

In general, there are two approaches to recession probability forecasting. One way is to generate predictive distributions of future observations from a specific model and incorporate turning point signaling rules to construct probability forecasts of future turning points via Monte Carlo simulations. The other way is to use models that have explicit probability structures to generate out-of-sample probability forecast.

Both approaches have advantages and disadvantages. A nice feature of the first approach is that it generates the whole sampling distribution of future outcomes. This allows introduction of user's risk preference/loss functions to decide the optimal way of forecasting. The downside is that the outcome depends heavily on the selection of turning point signaling rules. Different rules generally lead to different results. The merit of the second approach is that it doesn't depend on turning point signaling rules. But the probability structure of the model determines its performance.

There are two main features in Burns and Mitchell's (1946) pioneer work which are important for forecasting. The first is the co-movement among individual economic variables. The second is the division of the business cycle into separate regimes (expansions and recessions). Noting this, Diebold and Rudebusch (1996) suggest interpreting business cycles through the lens of a dynamic factor model with Markov switching in which these two key features are incorporated.

The Markov switching (MS) model, by design, is good at capturing the asymmetric nature of business cycles. It assumes that the economy evolves over time between two distinct unobserved states, which can be classified as expansion and contraction. The transition from one state to the other is governed by a Markov chain process which gives the probabilities of switching to one state from the other. There are two types of transition probabilities, one is fixed, and the other is time-varying. The fixed transition probabilities (FTP) don't depend on other factors, they are self evolved over time. This implies that the expected duration of each state is constant. The time-varying transition probabilities (TVTP) specify the probabilities to depend on some exogenous variables, and the expected duration of states becomes time-varying.

The dynamic factor (DF) model, on the other hand, assumes that co-movements among key economic variables can be captured by an unobserved common factor. This common factor represents the general state of the economy. From the viewpoint of signal extraction, a multivariate model can more effectively filter out the noise and draw better information from the data, especially in the volatile monthly data, compared to the more smoothed quarterly data.

A logical extension is to combine both the MS and DF models within an integrated framework as Diebold and Rudebusch suggested. And this is the strategy we take here. In the following section, we first model the growth rate of CCI as a Markov switching process with fixed transition probabilities(MSFTP). Then we allow the transition probabilities to depend on the CLI. We next extend the univariate framework to a multivariate framework, and model the four coincident indicators within a dynamic factor model with Markov switching. Again the transition probabilities can be either fixed or time-varying.

3. Model Specification, Forecast, and Evaluation

Specification

In the univariate Markov switching models, we view an economic recession (expansion) as an abrupt shift from a positive (negative) to a negative (positive) monthly growth rate of CCI (y_t). That is, the economy is modeled as shifting between two regimes-expansions and recessions. Transitions between regimes are governed by a two-state Markov process. We don't include any lag terms of CCI here. Instead, we let the variance of y_t be regime dependent. This enables us to account for the volatility slowdowns in 90s. In the dynamic factor models with Markov switching, following the specification of Kim and Nelson (1999), one-month growth rates of the four coincident indicators (y_{it}) depend on current and lagged values of an unobserved common factor (c_t) which is interpreted as the composite index of coincident indicators. The intercept term of the common component ,in turn, depends on whether the economy is in the recession state or the expansion state. We adopt second-order autoregressive specifications for the error processes of both the common component and the four idiosyncratic components. In order to account the slight lagging of the employment variable (y_{4t}), we add 3 lagged terms of the common component for y_{4t}. Since the means of the variables are over-determined in the parameterization, the final form of the model is expressed in terms of deviation from mean (Δy_{ti}=y_{ti}-mean(y_i)) in order to solve the identification problem.

The state S_t is assumed to follow a first order Markov process. In the fixed transition probability case, S_t is self-evolved, doesn't depend on any exogenous variables. In the time-varying transition probability case, St depends on an exogenous variable which we use CLI. Due to the noisy nature of monthly data, month-to month decline in the CLI may not be associated with any cyclical downturns in the economy. As in Birchenhall, Jessen, Osborn, and Simpson(1999), we try different growth rates and lags for the choice of information variable(z_t) used in the time-varying transition probability models. In order to balance the timing and volatility, we choose the 3-month growth rate of the CLI (logCLIt-logCLIt-3) and lag it 6 months in the information variable. The 3-month growth rate and the 6-month time span correspond to the simple rule of 3-month consecutive decline and the average leading time of the CLI.

All four models are estimated via maximum likelihood estimation. Appendix gives details of the models. For estimation algorithm, please refer to Kim and Nelson (1999).

Forecast

The k-step ahead probability forecasts are calculated recursively as

$$P(S_{t+k}=j\mid\Psi_t)=$$
$$\sum_{i=0}^{1}P(S_{t+k}=j\mid S_{t+k-1}=i)P(S_{t+k-1}=i\mid\Psi_t)\quad j=0,1$$

where Ψ_t denotes the data available up to time t.

We define the k-step ahead recession probability forecast as

$$P_{t+k|t}=\ P(S_{t+k}=0\mid\Psi_t)$$

Evaluation

We use two measures to evaluate the performance of the recession probability models. Since the goal is to generate recession probabilities that are consistent with the NBER chronology of business cycles, traditional measures like R^2, mean square error, likelihood ratio test, are not very informative here. Instead, we focus on two forecast-base measures here. The first one is the quadratic probability score (QPS):

$$QPS(k)=1/T\sum_{t=1}^{T}2(P_{t+k|t}-D_{t+k})^2$$

The second measure (S) is proposed in Diebold and Mariano (1995):

$$S(k) = \bar{d} / \sqrt{V(\bar{d})} \approx N(0,1)$$

$$\bar{d} = (1/T) \sum_{t=1}^{T} d_t$$

$$d_t = (P^j_{t+k|t} - D_{t+k|t})^2 - (P^i_{t+k|t} - D_{t+k|t})^2$$

$$V(\bar{d}) = (1/T) \sum_{h=-(k-1)}^{k-1} r_h$$

$$r_h = (1/T) \sum_{h=-(k-1)}^{k-1} (d_t - \bar{d})(d_{t-h} - \bar{d})$$

(where $P_{t+k|t}$ refers to the probability forecast of recession at time $t+k$, using information up to time t, and D_{t+k} is a binary variable taking the value of 1 during a recession and 0 during expansion at time $t+k$ as identified by the NBER).

QPS is a probability measure discussed in Diebold and Rudebusch (1989) to evaluate the accuracy of the recession forecasts. It is a probability forecast analog of mean squared error. The QPS is between 0 to 2, with a score of 0 corresponding to perfect forecast. It measures how close, on average, the inferred probabilities and the NBER dates are.

When one set of forecasts only performs "marginally" better than another one, we may wonder how likely it is that the outcome is due to chance. Diebold and Mariano (1995) develop some statistics for forecast comparison in the classical hypothesis-testing framework. Given the QPSs of two alternative models, we can use the S statistics to test the null hypothesis that there is no difference in the accuracy of forecasts from two competing models.

4. Empirical Results

Data

We use the Conference Board's (TCB) monthly leading and coincident indexes, from 1/1959 to 2/2002. The calculation of both the composite coincident and leading indices uses a standardization method designed to equalize the volatility of each component in the index. For a discussion of the composite index methodology, see Conference Board's Business Cycle Indicators Handbook (2001), and Boldin (1998/1999). There are four components in CCI: real industrial production, real personal income less transfer payments, real manufacturing and trade sales, and number of employees on nonagricultural payrolls. The ten leading indicators in CLI are average manufacturing weekly hours, average weekly initial claims for unemployment insurance,manufacturers' new orders in consumer goods and materials industries, vendor performance, manufacturers' new orders in nondefense capital goods industries, new private housing permits, stock prices, real money supply, interest rate spread, and index of cunsumer expectations. For details on individual components and the composite indices, please refer to www.tcb.org or www.globalindicators.org.

In-Sample Analysis

We estimate the four models using the full sample data, from 1/59 to 2/02. The dependent variables used include the one-month growth rate of CCI in the univariate models and the one-month growth rates of four coincident indicators in the multivariate models. We select the 3-month growth rate of the CLI (logCLIt-logCLIt-3) and lag it 6 months for the information variable. Parameter estimates, along with their standard errors are displayed in Table 1.

Figure 1 shows the filtered and smoothed recession probabilities of CCI from model SFTP, MSTVTP, DFMSFTP, and DFMSTVTP. Conditioned on the parameter estimates of the model, the filtered recession probabilities are calculated using only the current information. For example, the probability of recession in November 2001 is obtained using information available at that month. The smoothed recession probabilities take all the information in the sample into account. As we can see, the filtered probabilities are more volatile than the corresponding smoothed probabilities. It's not surprising. We can view the filtered probabilities as an ex-ante recession indicator and smoothed probabilities as an ex-post recession indicator. Events that look significant beforehand may not appear so afterward. All the four models capture the NBER dated recessions very well during the sample periods from 1959 to 2001.

In order to determine whether a specific month is in recession, we need to choose a threshold value for the recession probability. If the estimated recession probability is higher than the threshold value, a recession is called. We choose the value 0.5 here since we only have 2 states in our models. It's like flipping a coin, head or tail, the chance is half-half. Alternative thresholds can be used, but there is always a trade-off between making a false recession signal and failures to signal a recession that occurs.

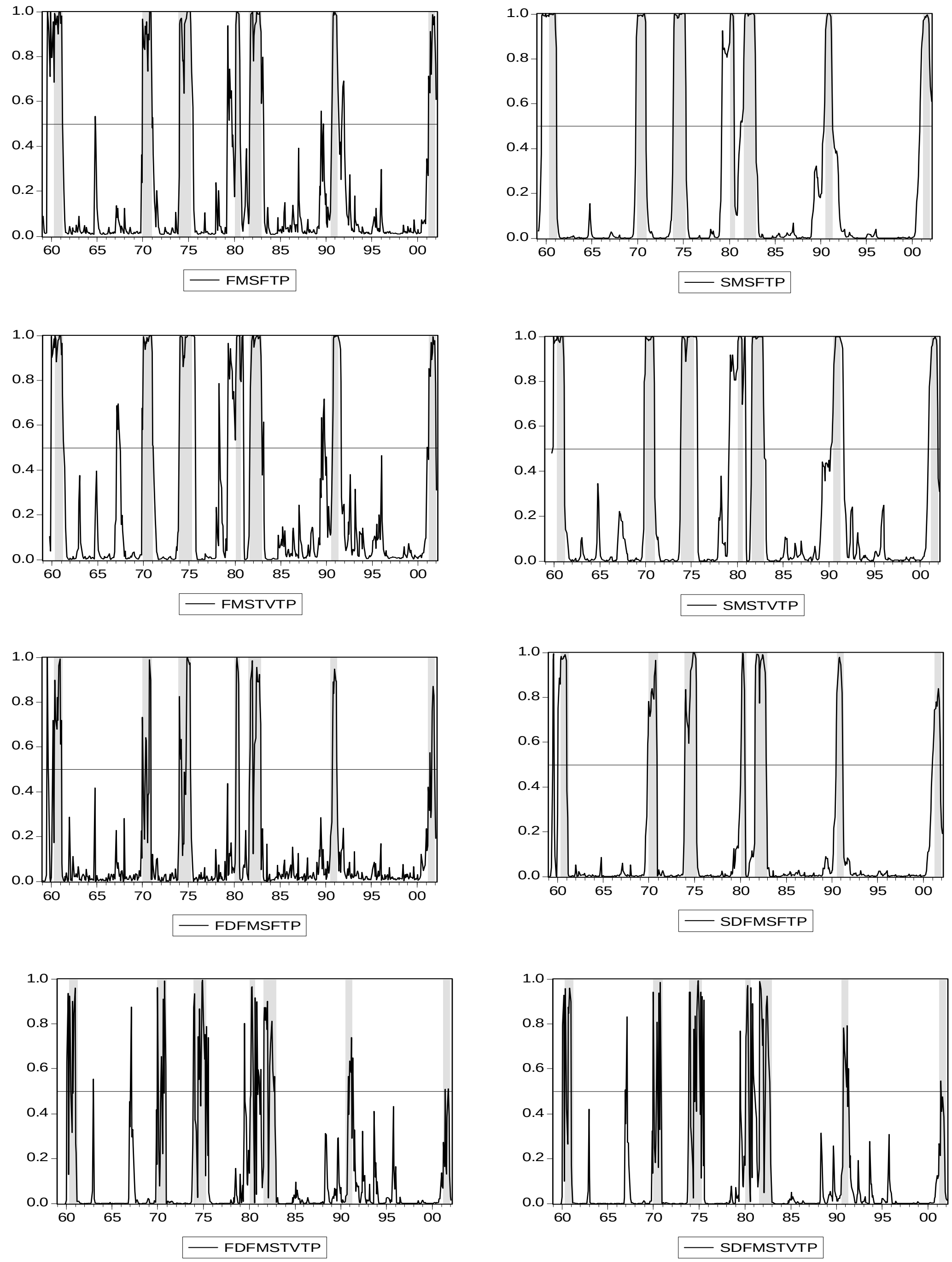

Figure 1: Filtered and Smoothed Probabilities of Recession from Markov switching model with fixed transition probabilities(FMSFTP), Markov switching model with time-varying transition probabilities(FMSTVTP), dynamic factor Markov switching model with fixed transition probabilities(FDFMSFTP), and dynamic factor Markov switching model with time-varying transition probabilities(FDFMSTVTP) respectively, 2/59 to 2/02. Shaded areas are NBER dated recessions.

	Model MSFTP	Model MSTVTP	Model DFMSFTP	Model DFMSTVTP
q_0	0.933 (0.029)	2.108 (1.080)	0.871 (0.059)	0.877 (0.633)
q_1		-1.452 (0.826)		0.391 (0.346)
P_0	0.979 (0.008)	3.761 (1.103)	0.976 (0.009)	5.861 (1.717)
P_1		1.295 (0.800)		3.254 (1.182)
u_0	-0.111 (0.054)	-0.039 (0.060)	-1.361 (0.250)	-1.306 (0.282)
u_1	0.334 (0.016)	0.324 (0.018)	0.257 (0.068)	0.197 (0.062)
σ_0	0.425 (0.033)	0.447 (0.056)		
σ_1	0.269 (0.011)	0.261 (0.020)	0.504 (0.025)	0.509 (0.025)
σ_2			0.299 (0.011)	0.300 (0.011)
σ_3			0.829 (0.029)	0.837 (0.029)
σ_4			0.122 (0.006)	0.118 (0.007)
ϕ_1			0.401 (0.069)	0.445 (0.073)
ϕ_2			-0.040 (0.014)	0.049 (0.065)
φ_{11}			-0.063 (0.067)	-0.087 (0.065)
φ_{12}			-0.001 (0.002)	-0.002 (0.003)
φ_{21}			-0.041 (0.050)	-0.046 (0.051)
φ_{22}			-0.000 (0.001)	0.020 (0.053)
φ_{31}			-0.381 (0.048)	-0.387 (0.049)
φ_{32}			-0.036 (0.009)	-0.037 (0.009)
φ_{41}			-0.037 (0.063)	-0.017 (0.065)
φ_{42}			0.330 (0.073)	0.360 (0.075)
γ_1			0.509 (0.030)	0.483 (0.032)
γ_2			0.191 (0.013)	0.189 (0.014)
γ_3			0.399 (0.031)	0.388 (0.032)
γ_4			0.122 (0.007)	0.118 (0.009)
γ_{41}			-0.000 (0.002)	-0.003 (0.009)
γ_{42}			0.010 (0.008)	0.004 (0.010)
γ_{43}			0.034 (0.007)	0.042 (0.007)
Lik	147.20	133.18	730.91	744.44

Table 1: Estimated Parameters with Standard Deviations (in parentheses) from Model MSFTP, MSTVTP, DFMSFTP, and DFMSTVTP, 1/59 to 2/02, Lik denotes likelihood value

Using 0.5 as the threshold value and the smoothed recession probabilities, table 2 shows the lead-lag months compared to NBER dates from the models. No recessions are missing. However, there is one false signal from model DFMSFTP and 17 false signals from model DFMSTVTP. If we impose one additional constraint, e.g., the switching must be persistent for at least 3 months, then the number of false signals is significantly reduced for model DFMSTVTP. Due to the volatile property of CLI, the multivariate model is very sensitive to the use of CLI when we extract signals from the four coincident indicators together.

The estimated recession probabilities also reveal some useful information about growth cycles. Business cycles consist of expansions and contractions in the level of total economic activity. Growth cycles are fluctuations (slowdowns and speedups) around a trended measure of the total economic activity. Not every slowdown will turn into recession, but slowdown often occurs before a recession. Every spike in the recession probability estimate, no matter how small, should be considered as a cyclical downturn signal. Based on the chronologies of US growth cycles in Zarnowitz and Ozyildirim (2002), there are seven business cycle recessions and eleven growth cycle slowdowns from 1959 to 2002. The growth cycle dates are closely related to the business cycle dates. The additional four growth cycle slowdowns occurred in 62-64, 66-67, 84-87, and 95-96. If we look at the filtered and smoothed recession probabilities from model MSTVTP and model DFMSTVTP that use CLI in their information set, the spikes are also observed during these periods. This suggests that the CLI is not only good at anticipating recessions but also slowdowns.

Table 3 gives the QPS statistics for filtered recession probabilities from these four models. Model DFMSFTP gives the lowest QPS, indicating the closest match with the NBER turning point dates. Both multivariate models give lower QPS values, relative to their corresponding univariate models. This implies that the use of four variables together enables a more precise identification of states of the economy.

Model	MSFTP	MSTVTP	DFMSFTP	DFMSTVTP
Business Cycle Peaks				
Apr-60	-9	-5	-2	-2
Dec-69	-1	-1	-1	+1
Nov-73	+1	+1	+1	+1
Jan-80	-9	-10	+1	+1
Jul-81	-3	+1	+1	+1
Jul-90	-1	-3	0	+3
Mar-01	-3	-3	-2	+3
Business Cycle Troughs				
Feb-61	+1	+1	-1	-1
Nov-70	+1	+2	+1	0
Mar-75	+2	+7	+1	+5
Jul-80	+1	+7	0	+1
Nov-82	+2	+2	+1	-1
Mar-91	+2	+6	+1	+1
Nov-01	+3	+1	+1	-4
False Signals	0	0	1	17

Table 2: Lead (-) and Lag (+) Months to NBER dates from Markov MSFTP, MSTVTP, DFMSFTP, DFMSTVTP, 1/59 to 2/02

MSFTP	MSTVTP	DFMSFTP	DFMSTVTP
0.116	0.160	0.083	0.123

Table 3: In-Sample Quadratic Probability Scores for Model MSFTP, MSTVTP, DFMSFTP, and DFMSTVTP, 1/59 to 2/02

Compared to the FTP models, the use of CLI in the TVTP models increase the value of QPS. However, it provides a time-varying expected duration which may improve the out-of sample forecasts. And this is verified later in the out-of-sample comparison.

Out of sample forecast

In order to generate out-of –sample forecasts, the last 14 observations (1/01 to 2/02) are held back for out-of-sample forecasting. We estimate the models using sample from 1/59 to 12/00. A sequence of 1 to 6 step-ahead forecasts is generated. Then the sample size is increased one observation at a time and the models are re-estimated, until all available data has been used. We have 14 one-step-ahead forecasts, down to 9 6-step-ahead forecasts.

Table 4 gives the out-of-sample results of QPS. Even though Model DFMSFTP has the smallest in-sample QPS, its out-of-sample QPS is highest among the four models. Model MSTVTP has the lowest QPS values, the second is Model MSFTP. Both of them are univariate models. This is a very interesting contrast. In terms of in-sample results, both multivariate models outperform their univariate models, but the results reverse for out-of-sample performance. It reminds us that a good in-sample fitting doesn't necessarily imply good out-of-sample performance, especially in the case of nonlinear models. A regime switching model (or any nonlinear model) may also not forecast any better than a linear model if the switching variable stays the same in the out-of-sample period.

We also notice that the use of CLI does improve the out-of-sample forecasts, compared to their in-sample performance. As expected, performance deteriotes as the forecast horizon increase.

K	MSFTP	MSTVTP	DFMSFTP	DFMSTVTP
1	0.517	0.337	0.791	0.734
2	0.660	0.386	1.020	0.918
3	0.795	0.397	1.172	1.027
4	0.936	0.459	1.198	1.107
5	0.916	0.432	1.093	1.044
6	0.948	0.438	1.050	0.994

Table 4: Out-of-Sample Quadratic Probability Scores for Model MSFTP, MSTVTP, DFMSFTP, and DFMSTVTP, 1/00 to 2/02

Table 5 gives the out-of-sample results of Diebold and Mariano S test. Choosing Model MSFTP as the benchmark, only Model MSTVTP outperforms the benchmark statistically. It provides additional support for the use of Model MSTVTP for out-of-sample forecasting.

Figure 2 gives the out-of-sample zero to six step ahead filtered probability of recession from model MSTVTP. The zero-step ahead probability is just the end period of recession probability from each re-estimation. It's very close to the filtered probability using the whole sample data (Figure 1). It implies that model MSTVTP is stable through time. We also find that the use of information variable in the transition probability also deliver interesting information about the state of the economy. At November 2001, while the current recession probability is still near one, the three and six month ahead recession probability forecasts are already down to near 0.6 and 0.5.

S(k)	MSFTP Versus MSTVTP	MSFTP versus DFMSFTP	MSFTP Versus DFMSTVTP
1	2.257(0.024)	-1.399(0.162)	-0.892(0.373)
2	2.703(0.007)	-1.235(0.217)	-0.658(0.511)
3	4.012(0.000)	-1.282(0.200)	-0.580(0.562)
4	4.634(0.000)	-1.036(0.300)	-0.578(0.563)
5	4.159(0.000)	-0.963(0.335)	-0.916(0.359)
6	4.298(0.000)	-0.964(0.335)	Inconclusive*

Table 5: Out-of-Sample Diebold/Mariano S test with p-value in the parentheses for Model MSFTP, MSTVTP, DFMSFTP, and DFMSTVTP, 1/00 to 2/02

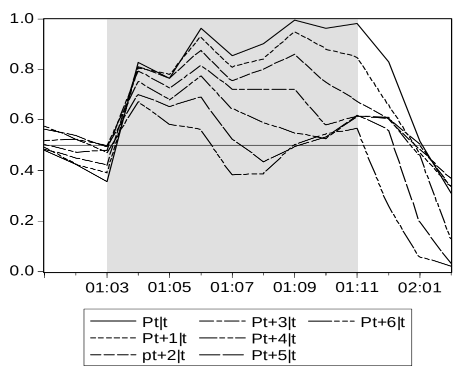

Figure 2 Out-of-Sample Zero to Six Step Ahead Filtered Probabilities of Recession (Pt+k|t,k=0 to 6) from Model MSTVTP, 1/01 to 1/02. Shaded area denotes the most recent recession.

5. Conclusions and Extensions

In this paper, we investigate four different regime-switching models for the identification and forecasting of business cycle turning points. Given the in-sample and out-of-sample results, we would like to suggest the use of dynamic factor model with fixed transition probabilities (DFMSFTP) for in-sample recession identification and the use of univariate Markov-switching model with time-varying transition probabilities (MSTVTP) for out-of-sample forecasts.

Model combined with different data and forecast horizons may produce very different results. Here we only focus on the use of the composite leading index in different models. Just as different models may prove most useful in different circumstances, so may different forms of the leading indicators do. There are two types of leading indicators, financial variables, and real variables. Individual leading indicators or other subclasses of the leading indicators might provide extra information, in addition to the composite leading index. An important extension is to explore the use of composite “real” and “financial” leading indices on forecasting recessions. Another extension will be the comparison of out-of sample forecasting in real time, in addition to the in-sample testing and out-of-sample forecast with historical data. However, a long time series of real-time CCI is still not available currently.

Appendix

Markov Switching(MS)

$$y_t = u_{s_t} + + e_{s_t}$$

$$e_t \sim N(0, \sigma_{S_t}^2)$$

$$u_{S_t} = u_0(1 - S_t) + u_1$$

$$\sigma_{S_t} = \sigma_0(1 - S_t) + \sigma_1$$

$$S_t = 0{,}1$$

where y_t denotes the one-month growth rate of the composite coincident indicator

Dynamic Factor with Markov Switching (DFMS)

$$\Delta y_{it} = r_i \Delta c_t + e_{it} \quad i = 1,2,3$$

$$\Delta y_{4t} = r_{40}\Delta c_t + r_{41}\Delta c_{t-1} + r_{42}\Delta c_{t-2} + r_{43}\Delta c_{t-3} + e_{4t}$$

$$(1 - \psi_1 L - \psi_2 L^2)\Delta e_{it} = \varepsilon_{it} \quad i = 1,2,3,4$$

$$(1 - \phi_1 L - \phi_2 L^2)\Delta c_t = u_{St} + v_t$$

$$u_{S_t} = u_0(1 - S_t) + u_1 S_t$$

$$S_t = 0{,}1$$

where y_{1t}, y_{2t}, y_{3t}, and y_{4t} are one-month growth rates of real industrial production, real personal income less transfer payments, real manufacturing and trade sales, and number of employees on nonagricultural payrolls respecively, Δ denotes standard deviation from mean growth rate

Fixed Transition Probabilities(FTP)

$$P(S_t = 1 \mid S_{t-1} = 1) = p$$

$$P(S_t = 0 \mid S_{t-1} = 1) = 1 - p$$

$$P(S_t = 0 \mid S_{t-1} = 0) = q$$

$$P(S_t = 1 \mid S_{t-1} = 0) = 1 - q$$

Time-varying Transition Probabilities(TVTP)

$$P(S_t = 1 \mid S_{t-1} = 1) = p(z_t)$$

$$P(S_t = 0 \mid S_{t-1} = 1) = 1 - p(z_t)$$

$$P(S_t = 0 \mid S_{t-1} = 0) = q(z_t)$$

$$P(S_t = 1 \mid S_{t-1} = 0) = 1 - q(z_t)$$

$$p(z_t) = \frac{\exp(p_0 + p_1 gcli3m_{t-6})}{1 + \exp(p_0 + p_1 gcli3m_{t-6})}$$

$$q(z_t) = \frac{\exp(q_0 + q_1 gcli3m_{t-6})}{1 + \exp(q_0 + q_1 gcli3m_{t-6})}$$

where *gcli3m* denotes the 3-month growth rate of CLI.

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