Enhanced reliability of the leading indicator in identifying turning points in Taiwan? an evaluation

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Abstract

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Abstract

Using Taiwan data, we employ Dueker's (1997, 2002) Probit-Markov switching model to evaluate the performance of Taiwan's leading indicator in identifying turning points. The merit of the Probit-MS model is that it incorporates the dependent structure of the leading indicator which is not taken consideration in the traditional Probit model. It is unambiguous that the best forecast horizon for Taiwan's leading indicator in predicting business conditions is three months. The performance of Taiwan's leading index in identifying turning points based on the Probit-MS model is greatly enhanced when compared with that based on the Probit model, and beyond this, the model-identified business cycle dates are highly consistent with the officially identified turning points.

JEL classification: E32, C22

Keywords: business cycle, leading indicator, Probit-Markov switching model

1 Introduction

Dating the turning points of a business cycle has long been not only in the interest of the public, but also of major concern to both academic circles and the government alike. It should come as no surprise, therefore, that the first attempt can be traced as far back as 1920 when the National Bureau of Economic Research (hereafter the NBER) identified the chronology of business cycles in the United States. Since then, the stylized fact about asymmetric adjustments that a recovery takes a longer period of time than a recession has continually been gaining support. Hamilton (1989) was among the first to apply a Markov switching model to the U.S. GNP to date business cycle turning points and found a pattern in the generated recessionary and recovery periods that was remarkably consistent with that of the NBER-defined chronology of business cycles. He also confirmed characteristic asymmetric adjustments.

Compiled by the NBER, the leading indicator is a core economic index to monitor and forecast U.S. business fluctuations. An abundance of studies has focused on evaluating its ability to forecast U.S. turning points and those of other OECD countries. Diebold and Rudebusch (1989, 1996), Stock and Watson (1989, 1993), Filardo (1994), Hamilton and Perez-Quiros (1996), Chauvet (1998), Kim and Yoo (1995), Kim and Nelson (1998), Camacho and Perez-Quiros (2002) and Kim and Piger (2002), among others. Despite the wealth of studies on the leading indicator in forecasting turning points in the extant literature, rarely has this issue been investigated for the Asian area. This paper fills this gap by studying the performance of Taiwan's leading indicator in identifying turning points.

We employ two Probit forecasting methods. One is the simple Probit model, while the other is based on a Probit-Markov switching model (hereafter the Probit-MS), as first proposed by Dueker (1997, 2002).[1] The merit of the Probit-MS model is that it incorporates the dependent structure of the leading indicator which is ignored in the traditional Probit model. We show that, compared to the Probit model, when we use the Probit-MS model, the performance in identifying turning points is improved substantially. Equally important, the recession dates identified by the Probit-MS model are also beyond a doubt much more consistent with the officially-identified recession dates than are those from the Probit model.

The remainder of this paper is organized as follows. Section II introduces the econometric models. Section III describes the source of the data and reports the empirical results. Section IV

[1] Basically, this paper is simply transposing Dueker's (1997) approach to the Taiwanese case.

concludes the paper.

2 Model Specifications

We define a recession dummy variable R_t based on the reference dates identified by the Council for Economic Planning and Development (hereafter the CEPD). $R_t = 1$ if the economy is in a recession in period t, but $R_t = 0$ if the economy is in an expansion in period t. One way to think of a Probit model is to assume that a normally distributed latent variable, R_t^*, lies behind the recession indicator:

$$R_t^* = -c_0 - c_1 X_{t-k} + u_t, \tag{1}$$

where u_t is a normally distributed error term with a mean of zero and variance σ_u^2. X_{t-k} is the leading indicator explanatory variable lagged k periods — the forecasting horizons. The probability of a recession is associated with each possible value of the latent variable, where the latent variable is assumed to be negative during a recession ($R_t = 1$ if $R_t^* \leq 0$) but positive during an expansion ($R_t = 0$ if $R_t^* > 0$). Then:

$$\begin{cases} R_t = 1 & \text{if} \quad u_t \leq c_0 + c_1 X_{t-k} \\ R_t = 0 & \text{if} \quad u_t > c_0 + c_1 X_{t-k} \end{cases} \tag{2}$$

In this case, the forecasting probability of a recession is:

$$\begin{aligned} \text{prob}(R_t = 1) &= \text{prob}(R_t^* \leq 0) \\ &= \text{prob}(u_t \leq c_0 + c_1 X_{t-k}) \\ &= \Phi(c_0 + c_1 X_{t-k}), \end{aligned} \tag{3}$$

where Φ is the CDF of the standard Normal distribution. Then, the log-likelihood function of the Probit model is as follows:

$$L_u = \sum_t \{R_t \ln \text{prob}(R_t = 1 | X_{t-k}) + (1 - R_t) \ln \text{prob}(R_t = 0 | X_{t-k})\}. \tag{4}$$

As a measure of fit for the Probit model, Estrella and Mishkin (1998) proposed a pseudo-R^2 in which the log-likelihood of a model, L_u, is compared with the log-likelihood of a nested model, L_c, which, by construction, must have a lower likelihood value:

$$\text{pseudo-}R^2 = 1 - (\frac{L_u}{L_c})^{-(2/n)L_c}. \tag{5}$$

Estrella and Mishkin (1998) made the argument that Eq. (5) corresponds well with the standard R^2 function from linear regressions.

Taking the Probit model further, Dueker (1997, 2002) took the dependent structure of the leading indicator into account and proposed the Probit-Markov switching model. In a Markov switching model, the parameters change value on the basis of an unobserved binary state variable, S_t, which follows the Markov process:

$$\begin{aligned} S_t &\in \{0,\ 1\}, \\ c_{it} &= c_i(S_t), \\ \text{prob}(S_t = 1 | S_{t-1} = 1) &= q, \\ \text{prob}(S_t = 0 | S_{t-1} = 0) &= p. \end{aligned} \tag{6}$$

The transition probabilities, p and q, indicate the persistence of the states and determine the unconditional probability of state $S_t = 0$ becoming $(1-q)/(2-p-q)$. It is assumed the economy is inclined to be in a recessionary state if $S_t = 1$ but in an expansionary one if $S_t = 0$.[2] We can rewrite the above equation as follows:

$$\begin{cases} R_t = 1 & \text{if} \quad u_t \leq c_0(S_t) + c_1(S_t) X_{t-k} \\ R_t = 0 & \text{if} \quad u_t > c_0(S_t) + c_1(S_t) X_{t-k} \end{cases} \tag{7}$$

According to Hamilton (1989), we can compute the so-called filtered probability (Eq. (8)) and predicted probability (Eq. (9)) based on a simple Bayes rule as follows:

$$\begin{aligned} &\text{prob}(S_t = 1 | R_t = 1,\ X_{t-k}) \\ = &\frac{\text{prob}(S_t = 1 | X_{t-k}) \text{prob}(R_t = 1 | S_t = 1,\ X_{t-k})}{\sum_{s=0}^{1} \text{prob}(S_t = s | X_{t-k}) \text{prob}(R_t = 1 | S_t = s,\ X_{t-k})} \end{aligned} \tag{8}$$

$$\begin{aligned} &(\text{prob}(S_t = 0 | X_{t-k}),\ \text{prob}(S_t = 1 | X_{t-k})' \\ = &G^k (\text{prob}(S_{t-k} = 0 | X_{t-k}),\ \text{prob}(S_{t-k} = 1 | X_{t-k})' \end{aligned} \tag{9}$$

where G is the transition matrix of the Markov state variable:

$$G = \begin{bmatrix} \text{prob}(S_t = 0 | S_{t-1} = 0) & \text{prob}(S_t = 0 | S_{t-1} = 1) \\ \text{prob}(S_t = 1 | S_{t-1} = 0) & \text{prob}(S_t = 1 | S_{t-1} = 1) \end{bmatrix} \tag{10}$$

[2] We can assume that there are negative shocks that cause the economy to be more inclined to be in a recessionary state, while there are also positive shocks that contribute to the economy moving into an expansionary state.

Then, the log-likelihood function of the Probit-MS model is:

$$\begin{aligned} L &= \sum_t \{R_t \ln \text{prob}(R_t = 1|X_{t-k}) + (1-R_t) \ln \text{prob}(R_t = 0|X_{t-k})\} \\ &= \sum_t \{R_t \ln(\sum_{s=0}^{1} \text{prob}(S_t = s|X_{t-k})\text{prob}(R_t = 1|S_t = s,\ X_{t-k})) \\ &+ (1-R_t) \ln(\sum_{s=0}^{1} \text{prob}(S_t = s|X_{t-k})\text{prob}(R_t = 0|S_t = s,\ X_{t-k}))\}. \end{aligned} \tag{11}$$

The unknown parameters can be estimated using the numerical method.

3 Data and Results

We use the reference dates identified by the CEPD as the dependent variable, and take the leading indicator as the explanatory variable. The sample runs from January 1962 to October 2004, which amounts to 514 observations.[3] The scatter plot of Taiwan's leading indicator is presented in Figure 1. The shaded areas are the contraction reference dates, as identified by the CEPD.

We first employ the pseudo-R^2, proposed by Estrella and Mishkin (1998), to choose the best "fitted" model. We consider various growth rates for the leading indicator, namely hat for 1 month, 3 months, 6 months and 12 months,[4] and different forecast horizons, k, also for 3 months, 6 months, 9 months and 12 months. In Table 1, we observe that from the estimated pseudo-R^2, the 3-month forecast horizon, i.e., $k = 3$, has a better forecast performance than the other forecast horizons because it has a higher pseudo-R^2 value relative to the others. The six-month growth rate of the leading indicator, $LD(-6)$, has a better forecasting performance relative to the others. Overall, we can deduce that $LD(-6)$ with the three-month forecast horizon ($k = 3$) has the highest pseudo-R^2 value compared to the others, strongly implying that the best forecast horizon for Taiwan's leading indicator in predicting business conditions is three months. These results lend credence to the theory that the leading indicator is ahead of the business conditions by three to six months.

The second column of Table 2 shows the parameter estimates of the Probit model. It is obvious that all the estimates are significantly different from zero at the 5% level. Figure 2 shows

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[3]The data can be downloaded from the CEPD website `http://www.cepd.gov.tw/index.jsp`.

[4]The symbol $LD(-1)$ in Table 1, for example, denotes the one-month growth rate of the leading indicator. That is, $LD(-1) = (\ln(y_t) - \ln(y_{t-1})) \times 100$. y_t is the leading indicator.

the corresponding recession probabilities from the simple Probit model using a lagged dependent variable for the six-month forecast horizon (prob$(R_t = 1) = \Phi(\hat{c}_0 + \hat{c}_1 X_{t-k})$). Once the conditional regime probabilities are generated, the issue pertaining to a decision rule to translate these probabilities into binary regime predictions remains. Birchenhall et al. (1999) suggested using the sample rule to convert a predicted probability into a predicted classification. The horizon line is the sample rule $\hat{p}$, as suggested by Birchenhall et al. (1999). A future recession is plausible if the predicted probability exceeds $\hat{p}$, where $\hat{p}$ is the sample proportion of the recessionary periods. We observe that the recession dates identified by the Probit model are close to the reference dates identified by the CEPD although some "noise" remains. In Table 3, several false signals are found to have occurred in 1967:m6–1967:m11, 1970:10–1971:m7, 1976:m8–1977:m4, 1988:m2–1988:m8 and 2003:m2–2003:m9.[5] It is worth noting that , during the February 2003 to September 2003 period, two events contributed to a slowdown in Taiwan's economy. The first was the second Gulf War which started on February, 18, 2003, and the second was the outbreak of SARS in the Asian area.

Does the Probit-MS model have a superior performance when it comes to identifying turning points? The parameter estimates for the Probit-MS model are summarized in the third column of Table 2. The estimates, again, are significantly different from zero at the 5% level. The likelihood ratio (LR) test suggests that the Probit-MS model is considerably better than the Probit model because $-2 \times (-210.919 + 150.029) = 121.78$ which is significant at the 5% level ($\chi^2(4) = 9.49$).[6] There is one econometric issue when the LR is used. Because the transition parameters p and q are not identified under the null, the conventional LR test does not yield the standard asymptotic distribution (Davies, 1977). Hansen (1992, 1996) proposed a bound test that addresses the problem, but its computational difficulty has limited its applicability. Ang and Bekaert (1998) conducted Monte Carlo experiments which imply that the true underlying distribution may be approximated by a $\chi^2(q)$ distribution, with q being the sum of the linear restrictions and nuisance parameters. We recommend following the suggestion by Ang and Bekaert.[7]

The estimates of the transition probabilities are $q = 0.921$ and $p = 0.972$, indicating that the

[5]Two error signals might have occurred in the predictions. The first is the missed signal failure, i.e., when there is a recession, but the model fails to predict it. The other is the false signal failure, namely when the model predicts that there is a recession, but one does not actually occur.

[6]Dueker (1997, 2002) did not perform a formal test of the significance of the Markov switching model.

[7]We thank an anonymous referee for pointing this out.

duration periods for negative and positive shocks are $(1-q)^{-1} = 12.7$ and $(1-p)^{-1} = 35.7$ months, respectively. If we regard the state of a negative shock as representative of a recessionary state, then the model-estimated duration periods for the contraction and expansionary regimes are 13 and 36 months, respectively. These are indeed quite close to the officially defined average duration periods (16 and 43 months for contraction and expansion, respectively.)

If we plug the coefficient estimates from the Probit-MS into equation (2), we observe that a recession is rarely predicted in the state where $S_t = 0$, as shown in Figure 3. In contrast, recessions are commonly predicted in the regime where $S_t = 1$, as shown in Figure 4. Figure 5 shows the probability of a recession after the two states are summed:

$$\text{prob}(R_t = 1|X_{t-k}) = \sum_{s=0}^{1} \text{prob}(S_t = s|X_{t-k})\ \text{prob}(R_t = 1|S_t = s,\ X_{t-k}). \tag{12}$$

Table 4 shows the model-identified turning points as determined the Probit-MS model based on the recession probabilities in Figure 5. In contrast to those from the Probit model, we can easily determine that the contraction dates identified by the Probit-MS model are strikingly more consistent with the officially identified recession chronologies.

Following Dueker (2002), we consider two criteria to signal recessions. The first approach (model 1) is to choose a critical value, cr, such that a recession is signaled if

$$\text{prob}(R_t = 1|X_{t-k}) - cr > 0. \tag{13}$$

The second approach (model 2) is based on the regime-dependent critical values, cr_0 and cr_1, such that a recession is signaled if

$$\begin{aligned} &\text{prob}(S_t = 0|X_{t-k})(\text{prob}(R_t = 1|S_t = 0,\ X_{t-k}) - cr_0) \\ &+\text{prob}(S_t = 1|X_{t-k})(\text{prob}(R_t = 1|S_t = 1,\ X_{t-k}) - cr_1) > 0. \end{aligned} \tag{14}$$

The weight given to each depends upon the regime probabilities. We find that the value of $cr = 0.291$ of $cr_0 = 0.115$ and of $cr_1 = 0.645$. The optimal value of cr sholud lie between optimal cr_0 and cr_1 since it is trying to fill both roles (Dueker, 2002). The top panel in Figure 6 shows the fit of the recession-signaling with one critical value, while the bottom panel in Figure 6 shows the recession-signaling with two regime-dependent critical values. Dueker (2002) emphasized "one might pay special attention to how the model predicts the onset dates of recessions". In Figure 6, we readily observe that the two graphs do not perform very well in terms of predicting the onset of recessions. We postulate a probable explanation is that we use the six-month growth rate for the leading indicator in our estimation. Figure 7 zooms in on the 1998 and 2001 recessions. Model 1 fails to signal the onset of the 1998 and 2001 recessions. Although model 2 also fails to signal the onset of the1998 recession, it does successfully signals the onset of 2001 recession in Taiwan.

4 Concluding Remarks

This paper evaluates the performance of Taiwan's leading indicator in identifying turning points. We use two Probit forecasting methods. One is the simple Probit model, whereas the other is based on a Probit-Markov switching model, as championed by Dueker (1997, 2002). The merit of the Probit-MS model is that it incorporates the dependent structure of the leading indicator which is not taken into consideration in the traditional Probit model. The empirical results of the pseudo-R^2 suggest that $LD(-6)$ with the three-month forecast horizon has the highest pseudo-R^2 compared to that with other horizons, strongly implying that the best forecast horizon for Taiwan's leading indicator to predict a business condition is three months. The performance of Taiwan's leading index in identifying turning points based on the Probit-MS model is vastly improved when compared to that based on the Probit model, and the turning points are much more consistent with the officially identified business cycle turning points.

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Table 1: Results of the Pseudo-R^2

	$k = 3$	$k = 6$	$k = 9$	$k = 12$
LD(-1)	0.109	0.099	0.055	0.019
	(-279.47)	(-282.26)	(-293.63)	(-302.74)
LD(-3)	0.285	0.190	0.070	0.022
	(-233.19)	(-258.77)	(-289.82)	(-302.11)
LD(-6)	0.368	0.175	0.047	0.028
	(-210.91)	(-262.76)	(-295.64)	(-300.44)
LD(-12)	0.254	0.076	0.029	0.064
	(-242.41)	(-288.26)	(-300.38)	(-291.73)

The number in parentheses is the log-likelihood value.

$L_c = -307.64$.

Table 2: Results of the Probit and Probit-MS Models

Parameter	Probit	Probit-MS
$c_0(S_t = 0)$	-0.689 (0.072)	-2.968 (1.205)
$c_0(S_t = 1)$		-0.492 (0.173)
$c_1(S_t = 0)$	-0.262 (0.023)	2.943 (1.536)
$c_1(S_t = 1)$		-0.749 (0.323)
$p = \text{prob}(S_t = 0 \mid S_{t-1} = 0)$		0.972 (0.007)
$q = \text{prob}(S_t = 1 \mid S_{t-1} = 1)$		0.921 (0.016)
L	-210.919	-150.029

The number in parentheses is the standard error.

Table 3: Recession dates identified by the Probit model

	CEPD	Probit Model	
Cycle	Peak (Trough)	Peak (Error)	Trough (Error)
II	64:m9 (66:m1)	64:m9 (+0)	66:m5 (+4)
III	68:m8 (69:m10)	68:m9 (+1)	69:m9 (−1)
IV	74:m2 (75:m2)	74:m5 (+3)	75:m4 (+2)
V	80:m1 (83:m2)	79:m3 (−10)	82:m5 (−10)
VI	84:m5 (85:m8)	84:m6 (+1)	85:m12 (+4)
VII	89:m5 (90:m8)	89:m2 (−3)	90:m3 (−5)
VIII	95:m2 (96:m3)	95:m2 (+0)	96:m8 (+6)
IX	97:m12 (98:m12)	98:m3 (+3)	99:m6 (−6)
X	00:m10 (01:m11)	00:m10 (+0)	01:m12 (+1)
False	67:m6–67:m11	70:10–71:m7	76:m8–77:m4
Signal	88:m2–88:m8	03:m2–03:m9	

+A denotes lag behind the officially identified dates A periods.

−A denoted lead ahead of the officially identified dates A periods.

Table 4: Recession dates identified by the Probit-MS model

	CEPD	Probit-MS Model	
Cycle	Peak (trough)	Peak (Error)	Trough (Error)
II	64:m9 (66:m1)	64:m12 (+3)	66:m5 (+4)
III	68:m8 (69:m10)	68:m11 (+3)	69:m10(−1)
IV	74:m2 (75:m2)	74:m5 (+3)	75:m4 (+2)
V	80:m1 (83:m2)	81:m3 (+14)	83:m4 (+2)
VI	84:m5 (85:m8)	84:m8 (+3)	85:m11 (+3)
VII	89:m5 (90:m8)	89:m7 (+2)	90:m3 (−5)
VIII	95:m2 (96:m3)	95:m6 (+4)	96:m6 (+3)
IX	97:m12 (98:m12)	98:m3 (+3)	99:m3 (+3)
X	00:m10 (01:m11)	00:m10 (+0)	01:m12 (+1)

+A denotes lag behind the officially identified dates A periods.

−A denoted lead ahead of the officially identified dates A periods.

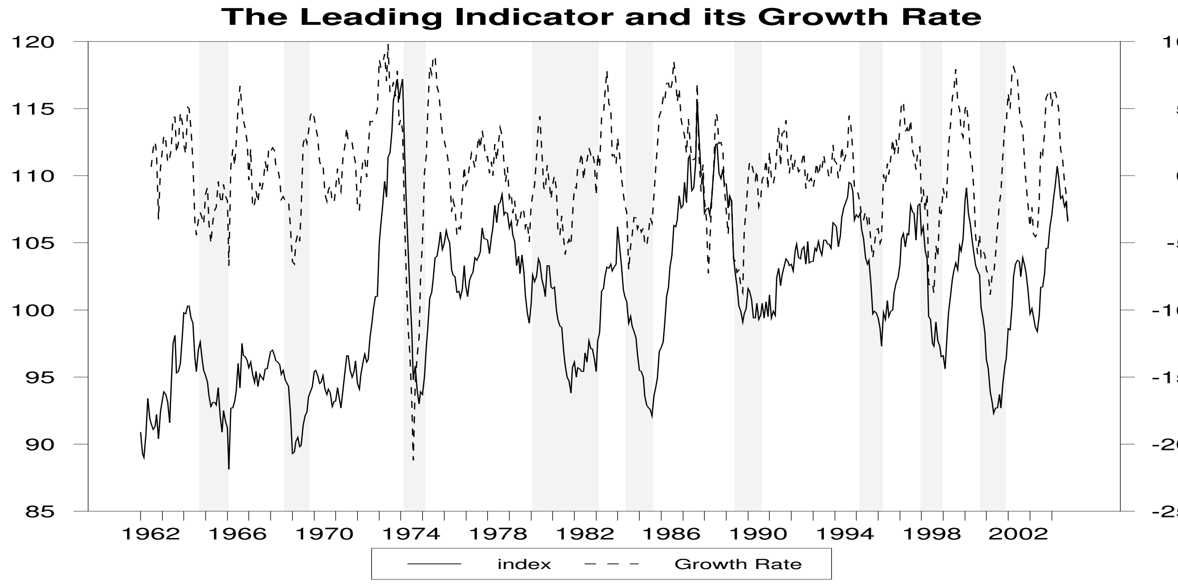

Figure 1: Scatter plots of Taiwan's leading indicator and its growth rate.

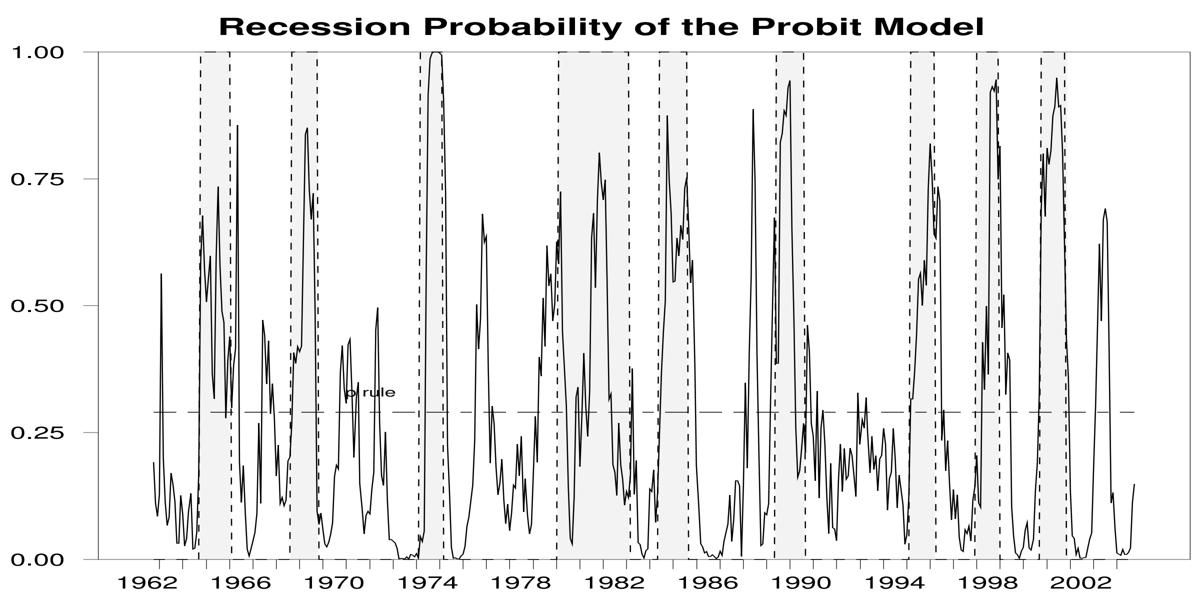

Figure 2: Contraction dates identified by the Probit model. The shaded areas are the reference recession dates, as identified by the CEPD.

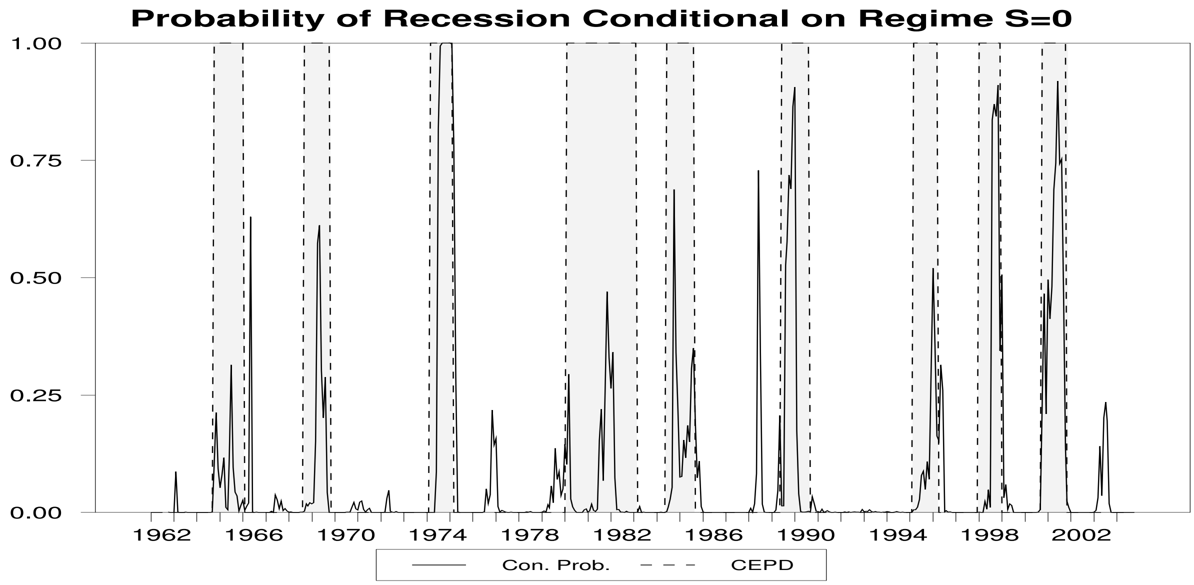

Figure 3: Probability of recession conditional on regime $S_t = 0$. The shaded areas are the reference recession dates, as identified by the CEPD.

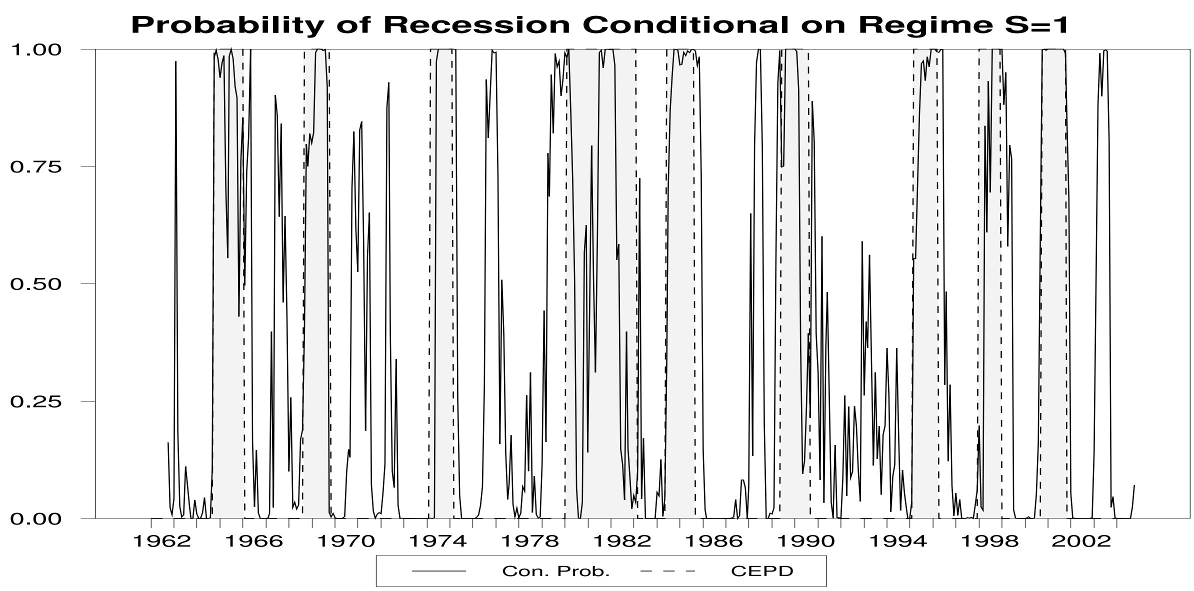

Figure 4: Probability of recession conditional on regime $S_t = 1$. The shaded areas are the reference recession dates, as identified by the CEPD.

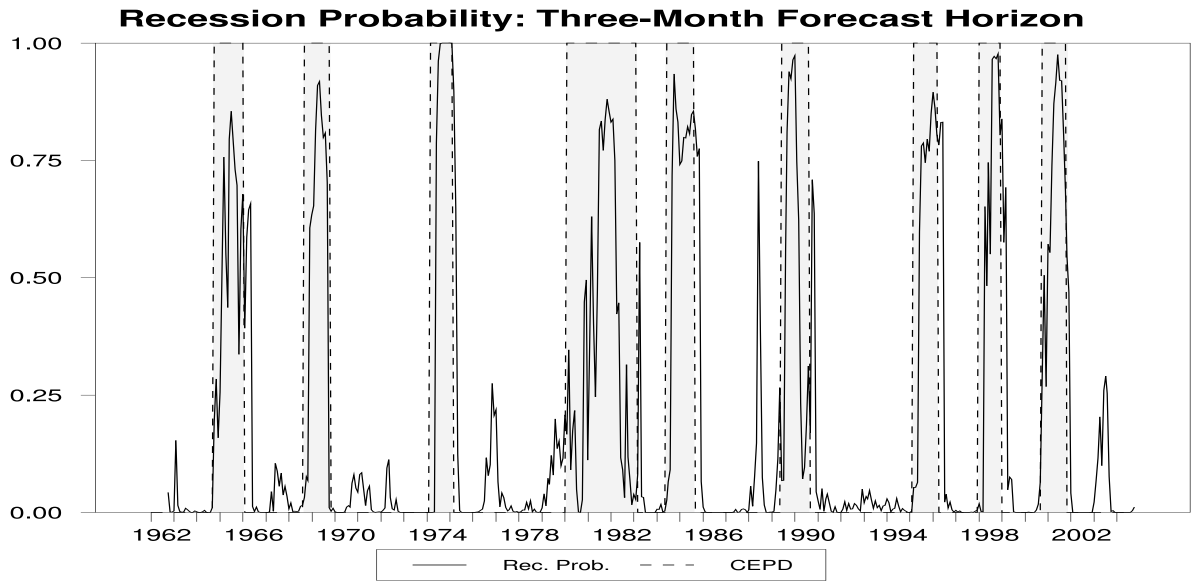

Figure 5: Contraction dates identified by the Probit-MS model. The shaded areas are the reference recession dates, as identified by the CEPD.

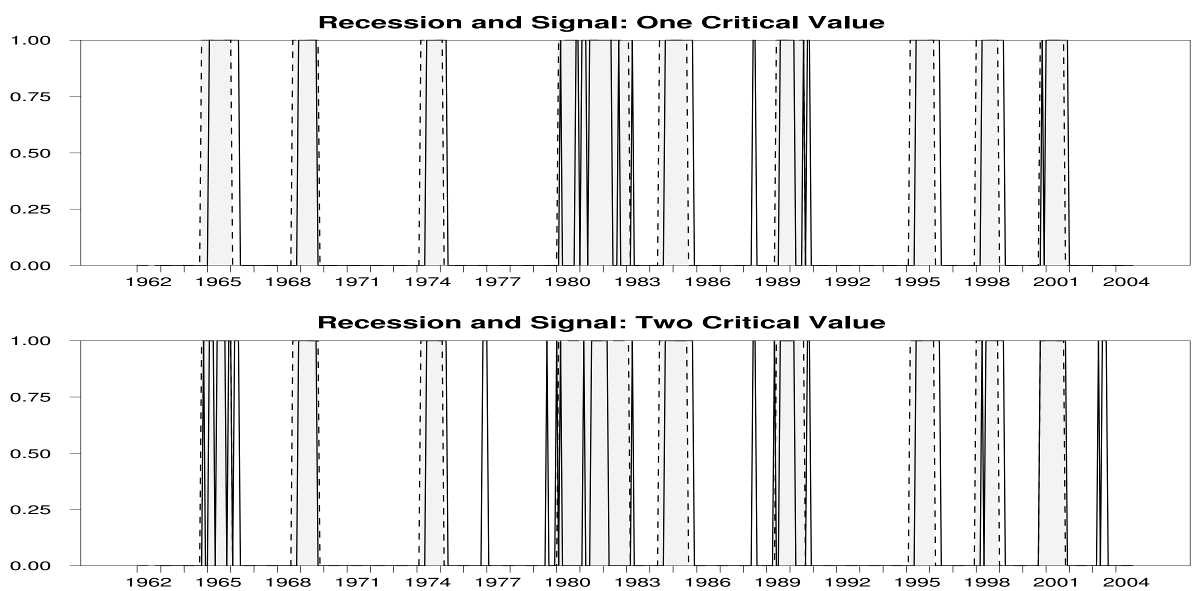

Figure 6: Recessions and signal. The shaded areas are the reference recession dates, as identified by the CEPD.

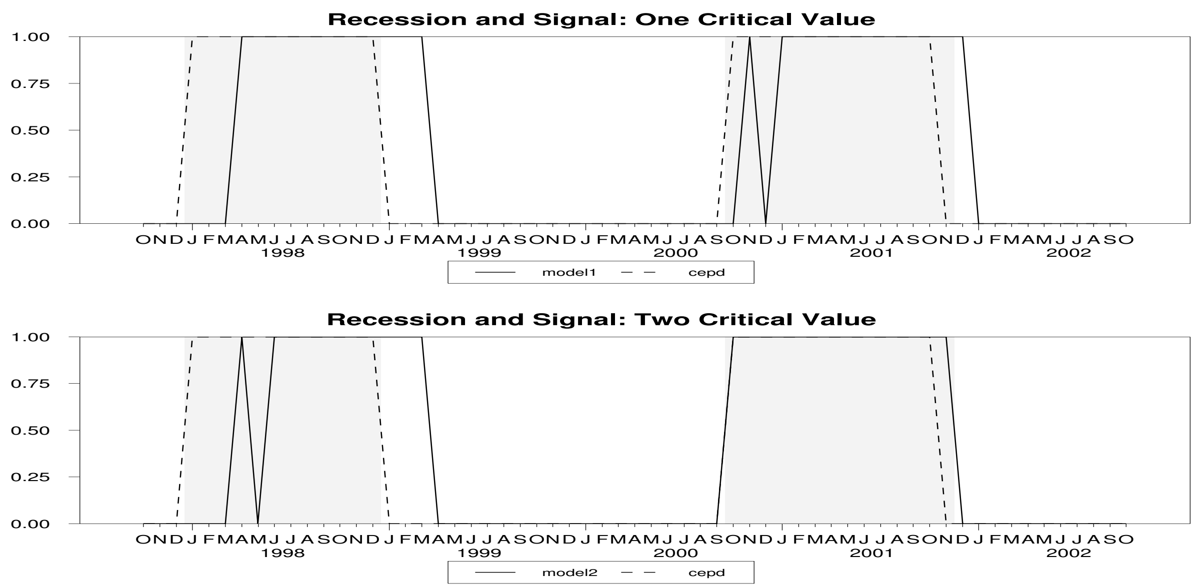

Figure 7: 1998 and 20001 recessions and signal. The shaded areas are the reference recession dates, as identified by the CEPD.