

Examining Predictors of U.S. Recessions: A Regime-Switching Approach

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1. INTRODUCTION

A number of recent empirical studies have been carried out to evaluate the performance of financial and macroeconomic variables as predictors of real economic activity. For the United States, ESTRELLA and HARDOUVELIS (1991) and ESTRELLA and MISHKIN (1996, 1998) provide evidence that the yield curve slope significantly outperforms other indicators in predicting recessions, particularly with horizons beyond one quarter¹. Forecasting recessions rather than real output growth in these studies is done by estimating probit models. In such probit estimations the dependent variable is a recession dummy that equals one if the economy is in recession and zero otherwise, whereas the explanatory variable is a lagged potential recession indicator. ESTRELLA and MISHKIN (1996, 1998) find that the percentage difference between the yields on 10-year Treasury bonds and three-month Treasury bills has superior predictive power to, among others, the following four variables: the change in the Commerce Department's index of leading indicators (CLI); real money (M2) growth; the percentage spread between the six-month commercial paper and the six-month Treasury bill rates («paper-bill-spread»); the percentage change in the Standard and Poor's 500 index of stock prices (S&P 500). In his recent analysis DUEKER (1997) confirms this result for almost the same data set using a modified probit model which includes a lagged dependent variable. Additionally, he allows for Markov-switching coefficient variation in the model structure.

In this paper, the predictive power of the five explanatory variables listed above is reconsidered by applying a different and more simple regime-switching approach. Following LAHIRI and WANG (1994, 1996), we just fit a simple univariate Markov-switching model to each candidate recession predictor without using the probit estimation framework. Thereby we investigate whether one of the estimated states is related to economic recessions. Following conventional practice, a recession is defined to start with a business cycle peak and to end with a trough. While recognizing that the identification of

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1. As regards the yield curve, the research in ESTRELLA and MISHKIN (1996, 1998) was extended to multi-country analyses by BERNARD and GERLACH (1996), ESTRELLA and MISHKIN (1997) and AHRENS (1998).

business cycle turning points is a problem on its own, our analysis relies, like the studies cited above, on the popular starting and ending dates of recessions as determined by the National Bureau of Economic Research (NBER).

The main object of our contribution is to show that accurate turning point predictions can be obtained by fitting simple regime-switching models to indicator variables. Thus, the essential question of the present paper concerns the optimal filtering of indicator signals and the methodically adequate assessment of their forecasting ability. Though previous research already evaluated the predictive performance of most of the variables mentioned above within a markov-switching framework, an extensive forecasting comparison has not been done until now. LAHIRI and WANG (1994), and HAMILTON and PEREZ-QUIROS (1996) estimated univariate regime-switching models for the CLI. HAMILTON and PEREZ-QUIROS additionally estimated bivariate specifications combining CLI and real output growth whereas HAMILTON and LIN (1996) proposed bivariate Markov-models for S&P 500 returns and real output growth. The yield curve indicator as well as the paper-bill spread were studied originally by LAHIRI and WANG (1996). To our knowledge, real money growth has not been modelled as a regime-switching process so far. Thus, we extend the empirical evidence especially by analyzing this variable. Conceptually, our approach is also related to the work presented by DAHLQUIST and GRAY (1995) as well as by GÓMEZ-PUIG and MONTALVO (1997) where short term interest rates or international interest rate differentials are used to extract a credibility indicator for currencies belonging to the European Monetary System².

To anticipate, our empirical findings presented in this paper are the following. First, each one of the evaluated indicator series can be characterized as following a two-state regime-switching process. Second, for all candidate predictors one of the two regimes is more or less closely related to recessions, while the other one corresponds to economic expansion phases. Third, our simple univariate markov-switching model turns out to be a filter that produces accurate turning point predictions. Fourth, the yield curve is confirmed to be the best recession predictor, because it generally signals recessions a considerable time before they actually begin. Moreover, the yield curve produced almost no signals that falsely indicated recession beginnings or endings. A fifth impressive result is that the estimated average predictive lead times for individual indicators are in many cases identical with the most successful forecasting horizon according to the probit estimations performed by ESTRELLA and MISHKIN (1998) and DUEKER (1997). Finally, estimations of bivariate markov-models generally support the hypothesis that industrial production as a measure of real output is driven by the same fundamentals as the various indicator series. Particularly, a model specification in which the shift in regime affects the indicator series one month before it affects industrial production describes the data well and thus formally supports the predictive content of the indicator variables.

2. In these studies, the credibility of a particular exchange rate is calculated using probabilities directly derived from estimated univariate regime-switching models of the respective interest rate or interest rate differential without taking into account actual realignment dates in the estimation.

The paper is structured as follows. In the next section, we briefly describe our univariate regime-switching specification, the general estimation method and the main empirical results. In section 3 we explicitly incorporate real economic activity in the analysis by estimating bivariate regime-switching models. Section 4 concludes the paper.

2. FORECASTING TURNING POINTS WITH UNIVARIATE MARKOV-SWITCHING MODELS

2.1 Model Specification and Estimation

The model we use to describe the regime-switching behaviour of the considered time series corresponds to the so-called segmented trends model proposed by ENGEL and HAMILTON (1990), which is a simple application of the popular Markov-switching approach developed by HAMILTON (1988, 1989, 1990). The estimation procedure we apply was introduced by GRAY (1996). Depending on the value of an unobserved regime indicator S_t , the mean and the variance of a stationary series are allowed to take two different values. That is, the observed realization of the respective recession predictor y_t is presumed to have been drawn from a $N(\mu_1, \sigma_1^2)$ distribution when $S_t = 1$, whereas y_t is distributed $N(\mu_2, \sigma_2^2)$ when $S_t = 2$. Concerning the indicator variables under consideration, we expect that one of the two regimes corresponds with recession or low growth phases, while the other regime is presumed to be associated with phases of economic expansion or recovery. Note that each indicator is assumed to be distributed as an iid normal variate around the mean of the corresponding state. At first glance, this simplicity of the statistical specification seems to be surprising. In markov-models, however, serial correlation could be captured well by the persistence of the two states. Thus, *a priori* there is no need to incorporate autoregressive terms in the mean as part of the regime switching model if it is constructed for forecasting purposes. In addition, earlier research has shown that forecasts generated by more complicated models are often worse, despite the fact that they fit the data better (LAHIRI and WANG [1994]).

The regime indicator S_t is parameterized as a first-order Markov process. Thus, the switching or transition probabilities P and Q have the typical Markov structure:

$$\begin{aligned} \Pr[S_t = 1 | S_{t-1} = 1] &= P \\ \Pr[S_t = 2 | S_{t-1} = 1] &= (1 - P) \\ \Pr[S_t = 2 | S_{t-1} = 2] &= Q \\ \Pr[S_t = 1 | S_{t-1} = 2] &= (1 - Q). \end{aligned} \tag{1}$$

Under the assumption of conditional normality for each regime, the conditional distribution of y_t is a mixture of normal distributions,

$$y_t | \Phi_{t-1} \sim \begin{cases} N(\mu_1, \sigma_1^2) \text{ w.p. } p_{1t} \\ N(\mu_2, \sigma_2^2) \text{ w.p. } p_{2t} = (1 - p_{1t}) \end{cases}, \quad (2)$$

where $p_{1t} = \Pr(S_t = 1 | \Phi_{t-1})$ is the probability that the analyzed process is in regime 1 at time t conditional on information available at time $t-1$. The probability p_{1t} is called «ex ante regime probability», because it is based solely on information already available and because it forecasts the prevailing regime in the next period. Hence, this probability can be used directly to forecast turning points in the business cycle³. If regime 1 is associated with recessions and p_{1t} is higher than 0.5 we will conclude that a recession is near or already prevailing, provided the evaluated indicator performs well⁴.

Following GRAY (1996) and HAMILTON (1994) we formulate the unobserved regime probability as a recursive process,

$$p_{1t} = P \left[\frac{f_{1t-1} p_{1t-1}}{f_{1t-1} p_{1t-1} + f_{2t-1} (1 - p_{1t-1})} \right] + (1 - Q) \left[\frac{f_{2t-1} (1 - p_{1t-1})}{f_{1t-1} p_{1t-1} + f_{2t-1} (1 - p_{1t-1})} \right],$$

with the regime-dependent conditional distributions $f_{1t} = f(y_t | S_t = 1)$ and $f_{2t} = f(y_t | S_t = 2)$. This specification is very similar to a GARCH model where unobserved conditional variances follow a recursive structure with unknown parameters. The recursive representation of the Markov-switching model allows us to construct the log-likelihood function conveniently as

$$L = \sum_{t=1}^T \log \left[p_{1t} \frac{1}{\sqrt{2\pi} \sigma_1} \exp \left\{ \frac{-(y_t - \mu_1)^2}{2\sigma_1^2} \right\} + (1 - p_{1t}) \frac{1}{\sqrt{2\pi} \sigma_2} \exp \left\{ \frac{-(y_t - \mu_2)^2}{2\sigma_2^2} \right\} \right]. \quad (3)$$

3. LAHIRI and WANG (1994, 1996) and GÓMEZ-PUIG and MONTALVO (1997) use the more popular filter probability $\Pr(S_t = 1 | \Phi_t)$ to infer the *current* regime. See GRAY (1996, p. 42) for a short discussion.
4. The boundary of $\Pr(S_t = 1) > 0.5$ was suggested by HAMILTON (1989, p. 374) as a decision rule. Following the proposal of NEFTCI (1982), LAHIRI and WANG (1994) imposed a much higher «critical value» of 0.9.

All models were estimated by (quasi) maximum likelihood (BOLLERSLEV and WOOLDRIDGE [1992], GRAY [1996], TREVOR [1994]) using RATS 4.2. Parameter estimates were obtained using the BFGS algorithm. The reported t-statistics are based on heteroskedastic-consistent standard errors (WHITE [1980]).

2.2 Comparative Advantages of Regime-Switching Models in Predicting Business Cycles

There are some good reasons why regime-switching models should be used in order to predict turning points. First, compared to the probit approach the pure Markov-switching technique has the advantage of determining lead times of the candidate predictors endogeneously, because the optimal forecasting horizon is data-driven and does not follow an *a priori* selection of lag-length. Second, the main result of estimating regime-switching models is, beside the parameter estimates, a time series of probabilities for the occurrence of discrete events. Thus, the Markov-approach allows us to investigate directly whether the indicators are able to predict turning points. Third, an additional advantage over probit regressions is that the applied estimation procedure does not rely on the ex-post knowledge of recession dates. Hence, the turning points supplied by the NBER are only used for reference purposes. As it is typical for Markov-switching models, we let the data decide when to switch into a regime that may be generally associated with recessions. A last benefit of the regime-switching approach is the possibility to take into account the number of false turning point signals. This statistic should be a further important criterion of accuracy in business cycle predictions. We define «false turning point signals» as changes of an indicator series into a regime which is generally associated with recessions but without an actual recession following, or as changes into a regime associated with expansions which are not followed by an actual recession ending.

2.3 Empirical Analysis

2.3.1 Examined Indicators and Model Estimations

The estimates in this section are derived from almost the same data set of monthly observations used in DUEKER (1997)⁵. The sample extends from January 1959 to May 1995. All five indicator series are originally analyzed on a quarterly basis in ESTRELLA and MISHKIN (1998) where a detailed description of the data and data sources is provided. A short summary can be found in the appendix⁶.

5. In contrast to DUEKER (1997) we use M2 instead of M1 to calculate real money growth rates. Furthermore, we use the 3-month T-Bill rate instead of the 6-month T-Bill rate to construct the term structure spread.
6. Besides the five series evaluated in this study, ESTRELLA and MISHKIN (1998) examined 22 additional indicator series.

Though it is beyond the scope of this study to discuss theoretical relations between the examined indicators and future economic activity in detail, we will make some few remarks concerning this issue. In general, prices of financial assets are supposed to contain expectations about the future path of the economy. The most convincing theoretical foundation for this assumption is the expectations theory of the term structure. The expectations hypothesis postulates that, for any choice of holding period, investors do not expect to realize different returns from holding bonds or bills of different maturities. Thus, a downward sloping («inverted») yield curve implies an expected fall of future interest rates which equalizes the ex ante returns of different investment opportunities. As a result, the current long-term rate is an average of expected future short-term rates. Building upon the expectations hypothesis, two arguments explain why the yield curve contains information about future recessions. The first argument relates to the role of monetary policy. When a central bank raises short term interest rates, agents view this contraction as temporary and, consequently, raise their expectations of future short-term rates by less than the observed current change in the short rate. From the expectations theory it follows that long-term rates rise by less than the short-term rate, resulting in a flat or inverted yield curve. Since the real sector of the economy is affected by monetary policy measures with a considerable time lag, agents expect future real economic growth to decline. Hence, the monetary tightening flattens the yield curve and simultaneously increases the likelihood of a recession onset. The second argument focusses on inflationary expectations that are contained in long term interest rates. Since recessions are generally associated with low inflation rates, an anticipation of a recession probably results in a falling long-term rate. Consequently, when the short rate does not change, the yield curve flattens or becomes inverted. Both theoretical arguments suggest a positive relationship between the yield curve spread and future real output.

Whereas stock prices are thought of as carrying information about future economic development because they reflect expected present values of future dividend streams, the difference between interest rates on commercial paper and Treasury bills are mainly supposed to reflect perceptions of default risk⁷. The informational content of the three financial variables discussed so far is compared with the predictive ability of the change in the real supply of M2. A traditional macroeconomic indicator, the CLI, is a further benchmark for our analysis. For all the five considered indicators, Table 1 reports maximum likelihood estimates of univariate Markov-switching models.

7. See FRIEDMAN and KUTTNER (1993) for further arguments and a thorough discussion.

Table 1: Parameter Estimates of Univariate Markov-Switching Models for Different Recession Predictors

$y_t - \mu_{S_t} = \varepsilon_t$					
Parameter	Yield Curve	Lead	Money	Spread	Stock
μ_1	0.12 (1.44)	-0.37*** (3.99)	-0.14*** (3.09)	0.64*** (10.20)	-1.00 (0.81)
μ_2	2.08*** (27.84)	0.21*** (5.59)	0.51*** (16.87)	0.03 (1.56)	0.91*** (4.13)
σ_1^2	0.73*** (6.46)	0.20*** (5.29)	0.18*** (6.74)	0.19*** (3.09)	28.98*** (3.97)
σ_2^2	0.41*** (9.02)	0.11*** (7.95)	0.13*** (4.62)	0.04*** (9.28)	6.25*** (8.57)
P	0.97*** (88.48)	0.88*** (26.07)	0.96*** (33.98)	0.92*** (39.30)	0.80*** (3.86)
Q	0.97*** (133.51)	0.95*** (58.42)	0.96*** (43.26)	0.97*** (96.23)	0.95*** (23.38)
Log. Likelihood	-518.66	-224.58	-249.69	-65.17	-1113.93
Wald Tests					
$H_0: \mu_1 = \mu_2$	927.06***	74.59***	158.95***	131.63***	2.20
$H_0: \sigma_1^2 = \sigma_2^2$	7.13***	5.02**	1.42	5.91**	10.67***

Notes: The sample contains monthly observations from January 1959 to May 1995. The examined five indicator variables y_t are: the percentage difference between the yields on 30-year Treasury bonds and 3-month Treasury bills (yield curve); the change in the Commerce Department's index of leading indicators (lead); real M2 growth (money); the percentage spread between the 6-month commercial paper and 6-month Treasury bill rates (spread); the percentage change in the Standard and Poor's 500 index of stock prices (stock). t-statistics in parentheses are based on heteroskedastic-consistent standard errors. * (**) (***) denotes significance at the 10% (5%) (1%) level. The Wald test statistics are asymptotically $\chi^2(1)$. The critical value at 5% is 3.84.

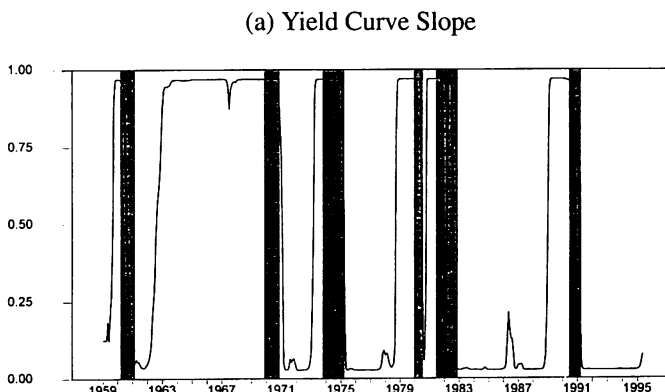
According to Table 1, all of the candidate indicator series are successfully modelled as regime-switching processes. The estimated switching probabilities P and Q are highly significant and range from 0.80 to 0.98 indicating persistence in both regimes for all variables. In the case of the yield curve spread the second regime is obviously characterized as a period of an upward-sloping yield curve with an average percentage spread of 2.08.

The average spread in regime one is small and not significantly different from zero. Therefore, regime one is supposed to represent periods in which a flat or even inverted yield curve prevails. Moreover, as the estimated variances suggest, regime one is a «high-volatility» regime compared to regime two. The reported t- and Wald test statistics imply the conclusion that the two respective regimes describing the variables «lead» and «spread» are separated by differential means and variances as well. In contrast, the regimes describing the indicator «stock» differ mainly with regard to their variances, as already reported by HAMILTON and LIN (1996), whereas the estimated regimes of the indicator «money» are characterized by different means only.

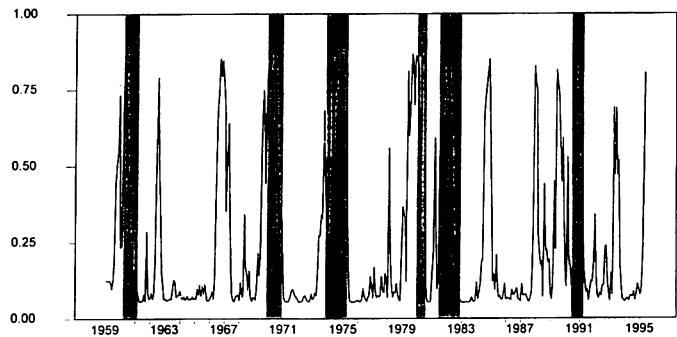
2.3.2 Analysis of Regime Probabilities

The results presented so far show that all considered series are sensibly modelled within a Markov-switching framework. As a next step we want to investigate whether the identified regimes are associated with business cycle phases. By looking at the reported zero or negative mean estimates for the variables «yield», «lead», «money», and «stock» and the high average percentage spread between commercial papers and Treasury bills, we roughly anticipate, with the above mentioned theoretical considerations in mind, regime one to correspond with recession phases for all variables. To address this question more precisely and to examine the forecasting ability of the various indicators with respect to future recessions, one has to take a look at the panels (a) to (e) of Figure 1. These panels contain series of ex ante regime probabilities – as defined in section 2 – for the process of a particular indicator being in regime one at date t conditional on available information at date $t-1$. Shaded areas indicate recessions starting with the month for which the NBER defined a business cycle peak and ending with the month for which the NBER designated a trough.

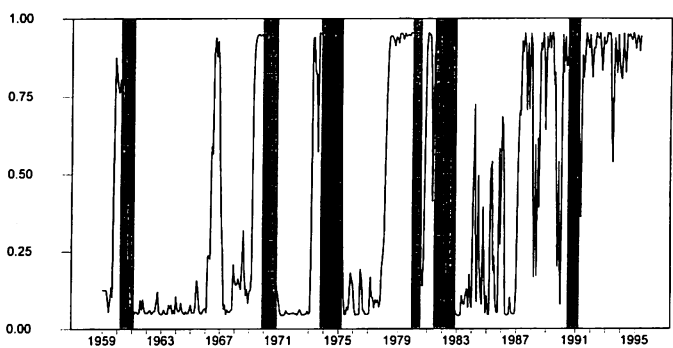
Figure 1: Forecasting Recession Probabilities using Five Leading Indicators



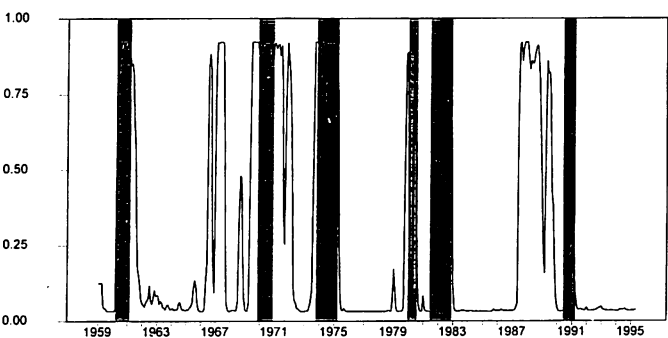
(b) Change in the Index of Leading Indicators



(c) Real Money (M2) Growth



(d) Percentage Spread between Commercial Paper and Treasury bill rates



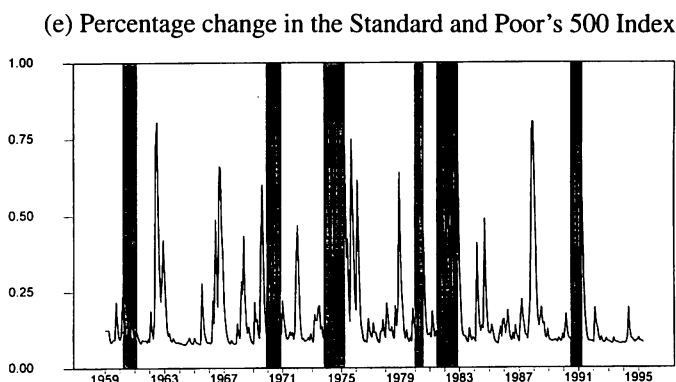


Fig. 1. The panels (a) to (e) contain time series plots of ex ante probabilities that the process of the respective recession predictor is in regime one at time t according to the estimated markov-switching models (see table 1). The ex ante probabilities are based on information available at time $t-1$ ($\Pr[S_t = 1 | \Phi_{t-1}]$). Parameter estimates are based on a data set of monthly observations used in ESTRELLA and MISHKIN (1996) and DUEKER (1997). The sample period is January 1959 to May 1995. Shaded areas indicate recessions starting with business cycle peaks and ending with troughs. Business cycle turning points are determined by the National Bureau of Economic Research (NBER).

Figure 1 shows that for all candidate predictors, regime one is in fact related to recession phases, though this relation is of variable strength. According to panel (a) the yield curve performs impressingly well not only in signalling recessions but also in predicting their beginnings. With the exception of the 1969–70 recession start, all business cycle peaks were preceded directly by shifts into regime one. Panel (a) also reveals that the performance of the yield curve was generally worse in the sixties. For the period from 1962 through 1969 the Markov-model continuously calculates a high probability for staying in regime one without any obvious relation to the prevailing business cycle phases. However, as LAHIRI and WANG (1996, p. 305) pointed out, the 1966–67 period can be characterized as a growth recessionary phase. During this period the onset of the recession was probably avoided or temporarily delayed by a considerable growth of defense spending. Thus, the early regime shift in 1962 is explained sufficiently, although it cannot be interpreted as an indicator of the 1969–70 recession in the narrowest sense. The most important result of our empirical analysis is that regime one is exclusively associated with recessions for the rest of the sample. In addition, the lead time of the yield curve indicator seems to be extraordinary long compared to the other predictors under examination. The results presented by panel (a) further suggest that the lead time varies considerably across the sample period. As far as the recession endings are concerned, the predictive power of the yield curve is significantly lower. Nevertheless, all business cycle troughs are associated with shifts into regime two which reflects an upward sloping yield curve. A last satisfying property of the yield curve indicator is the almost comple-

te absence of false signals. Beside the above discussed shift in 1962 there is only one misleading regime change indicating too early an ending of the 1981–82 recession. The results documented above generally correspond to the empirical findings of LAHIRI and WANG (1996) who used the one-year Treasury bill rate instead of the three-month rate to calculate the yield spread.

Panel (b) reveals for the CLI variable that there is a high probability for staying in regime one during and, in most cases, immediately before recessions. In this respect, the CLI matches the business cycle well. However, compared with the yield curve indicator, the CLI series switched more frequently, thereby indicating recession phases falsely for eight times. As LAHIRI and WANG (1994) pointed out, most of these misleading regime changes are in fact due to growth retardations. Hence, the performance record of this traditional indicator is better than it seems. Note however, that the CLI series is only available two months after the period covered by the data. If we account for this information lag, the CLI is clearly dominated by the yield curve indicator that is continuously observable and, in addition, indicates turning points much earlier.

As panel (c) shows, the forecasting power of real money growth significantly weakened in the eighties. Since then, a high probability for staying in regime one no longer has been exclusively corresponding with recession phases. Consequently, false turning point signals are observed frequently during the last fifteen years of the sample. Nevertheless, this indicator gave strong signals. Especially, it indicated all recessions more than one quarter before they actually started⁸. As far as business cycle troughs are concerned, real money growth produced coincident signals in three cases, while three recession endings were predicted a few months in advance. Note that the strong performance of real money growth is somewhat limited, because there is an information lag of one month for this variable.

The percentage spread between the 6-month commercial paper and Treasury bill rates generally failed to predict recession endings. According to panel (d), it merely signalled them coincidentally or even with a lag. Again, this finding is consistent with the results presented by LAHIRI and WANG (1996). In the case of business cycle peaks the evidence is mixed. While the recession in 1990–91 was not identified by the spread, three recessions were predicted, one recession was indicated coincidentally and one was identified more than one year after it had started⁹. Furthermore, there are some false turning point signals produced by the spread. One of them is surely related to the stock market crash in 1987 where the default risk premium for commercial papers went up without an economic downturn following.

8. ESTRELLA and MISHKIN (1998, p. 50, Appendix A: Table A1) conclude that most of the predictive power of monetary aggregates comes from inflation and not from a change in the nominal money supply.

9. Some explanations for the failure of the paper-bill spread to anticipate the 1990–91 recession are given by FRIEDMAN and KUTTNER (1998).

As panel (e) indicates, the probability for the S&P 500 index to stay in regime 1 always rose after the recessions had already begun. Recession endings were, with the exception of the trough in 1970:11, also indentified with a lag, whereas the identification of the 1960–61 recession was completely missed. HAMILTON and LIN (1996, p. 591) concluded that stock market dynamics may be useful for identifying and forecasting economic turning points, as well as real economic activity may be useful for forecasting stock market volatility. Our results strongly support the view that the stock market reflects or even follows current business cycle phases without predicting them in advance. Similarly to the CLI, the S&P 500 index produces some false recession signals. Moreover, the stock market series sometimes switched into regime two during recessions without an actual business cycle trough following.

To summarise these results, the univariate regime-switching model turns out to be an appropriate filter that efficiently transforms changes in the indicator variables into accurate and unambiguous turning point predictions. Particularly this becomes clear in the case of the yield curve indicator: compared to the recession probabilities documented in DUEKER (1997, pp. 45–46) the ones reported in Panel (a) of Figure 1 are clearer to interpret and much less volatile. This is surprising because probit models use actual recession dates in the estimation process which are important additional information.

2.3.3 Some comparative Statistics

In order to complement our graphical analysis and to present the empirical results more comprehensively, Table 2 contains the dates of the predicted regime changes that signalled the beginnings and the endings of all six historical recessions. To allow for a fair and consistent assessment of the candidate predictors, we introduce a rule of thumb that should prevent us from following too noisy signals. According to that rule, a regime-change that predicts a business cycle peak (trough) has to persist at least until a recession begins (ends). In the meantime, only one possible re-switch into regime two (regime one) is allowed, staying there for at most one month. As an obvious counter-example, take a look at the estimated regime probability series based on the markov-model for the paper-bill spread as reported in panel (d). In the end of the eighties the probability to stay in the recession regime one was high. According to our rule this may not be viewed as a prediction of the 1990–91 recession, since the regime probability declined immediately prior to the business cycle peak in July 1990 and was far below 0.5 during the recession phase itself.

Table 2: Estimated Regime-Changes indicating Business Cycle Turning Points

	NBER	Yield Curve	Lead	Money	Spread	Stock
P	60:04	59:10 (6)	59:10 (6)	59:10 (6)	60:04 (0)	NO
T	61:02	60:09 (5)	60:07 (7)	60:08 (6)	61:08 (-6)	NO
P	69:12	NO	69:07 (5)	69:04 (8)	69:05 (7)	70:06 (-6)
T	70:11	71:02 (-3)	70:07 (3)	70:09 (2)	71:08 (-9)	70:08 (3)
P	73:11	73:03 (8)	73:09 (2)	73:04 (7)	73:09 (2)	73:12 (-1)
T	75:03	75:04 (-1)	75:04 (-1)	75:04 (-1)	75:05 (-2)	75:05 (-2)
P	80:01	78:10 (15)	79:05 (8)	78:03 (22)	79:10 (3)	80:04 (-3)
T	80:07	80:07 (0)	80:07 (0)	80:08 (-1)	80:08 (-1)	80:08 (-1)
P	81:07	80:11 (8)	81:07 (0)	80:11 (8)	82:10 (-15)	81:10 (-3)
T	82:11	82:09 (2)	82:03 (8)	82:10 (1)	82:12 (-1)	83:01 (-2)
P	90:07	89:01 (18)	90:09 (-2)	90:02 (5)	NO	90:09 (-2)
T	91:03	91:03 (0)	91:03 (0)	91:04 (-1)	NO	91:05 (-2)

Notes: At the documented dates labelled «P» («T») a switch of the respective indicator series into the «recession regime» one («normal growth» regime two) took place. After such regime changes, the series remained in regime one (regime two) at least until the particular recession started (ended), with the possible exception of one short intermediate re-switch into regime two (regime one) for at most one month. A change between regimes generally occurs at dates where the estimated ex ante regime probability to stay in a certain regime increases from less than 0.5 to more than 0.5 or decreases from more than 0.5 to less than 0.5. The respective lead times are in parentheses. For example, the yield curve series switched into the «recession» regime in October 1978, that is 15 months before the 1980 recession actually started. It switched back in July 1980, that is one month before the expansion phase began. «Lead times» with a negative sign indicate a lagged identification of turning points. «NO» indicates that turning points were not identified at all.

It becomes clear from Table 2 that business cycle troughs were generally harder to predict than peaks. Obviously, the best performing predictors of recession onsets are the yield curve slope and real money growth. In strong accordance with ESTRELLA and MISHKIN (1998), who show that the term structure has a high informational content up to six quarters ahead, in our study the longest calculated lead time for this variable is 18 months. Although the forecasting power of the CLI compares favourably for most of the sample, it missed to signal the two most recent recessions in advance. For business cycle troughs, the predictive performance does not vary that much across these three indicators. In general, they all indicated recession endings only a few months ahead. Again, note the advantage of the yield curve of having no information lag. As mentioned earlier, the signals extracted from the paper-bill spread and, especially, the stock market index often came late, thereby indicating turning points with a lag.

To compare the empirical findings of this study more directly with the results presented by ESTRELLA and MISHKIN (1998) and DUEKER (1997), Table 3 contains the individual average predictive lead times of the examined indicators.

Table 3: Average Predictive Lead Times of Recession Indicators

	Yield Curve ^a	Lead	Money	Spread ^a	Stock ^a
Peak	9.17	3.17	9.33	-0.50	-2.50
Trough	0.50	2.83	1.00	-3.17	-0.67

Note: Average lead times are calculated as simple averages of the predictive lead times presented in Table 2.

(a) Not identified turning points are taken into account with zero values.

In the studies cited above probit estimation results inform us about the ability to predict the occurrence of recessions. Given a prespecified lead time, the pseudo R^2 measure together with calculated t-statistics summarizes the forecasting performance of a particular indicator throughout the sample. Against this background, a useful statistic for comparison purposes seems to be the simple average lead time of predicting recession onsets. Of course, as it is also the case when estimating probit models, much information is lost due to building averages. Note, in this respect, that «lead times» relating to those turning points which were not identified at all are taken into account with an arbitrary value of zero¹⁰.

As presented in the first row of Table 3, the yield curve and the money growth variable again are confirmed to perform best. Both indicators forecast business cycle peaks with an average horizon of nine months. It deserves attention that this is exactly the predictive lead time for which DUEKER (1997, pp. 44, 46, 48) finds the yield curve to be most successful. Our empirical finding is also consistent with the results presented by ESTRELLA and MISHKIN (1998, pp. 49, 52)¹¹. They show that the yield curve indicator performs best with three to four quarter horizons. In contrast to our results, ESTRELLA and

10. The calculation of the average lead time for recessions is biased as misses are included as zeros. In order to avoid that a miss gets the same score as a coincident warning, one could prefer to assign a penalty (probably equal to the length of the recession).

11. Whereas DUEKER's (1997) results are based on in-sample estimations only, ESTRELLA and MISHKIN (1998) additionally take into account out-of-sample comparisons. Conceptually, the approach applied in this paper lies somewhere in between. Following the regime-switching literature, however, we view the calculated and reported regime probabilities as ex ante forecasts of the prevailing state in the following period. Nevertheless, we did some out-of-sample exercises to forecast regime probabilities one-step-ahead. For the sub-period from 1975 to 1995 nearly the same results are produced as plotted in Figure 1.

MISHKIN find real M2 growth to be most useful in indicating future recessions only one to two quarters ahead. As Table 3 further reveals, the CLI is a relative short term predictor with an average lead time of three months. This again corresponds extremely well with the results presented by ESTRELLA and MISHKIN (1998) and DUEKER (1997). Both studies find evidence that the CLI is most powerful in forecasting recessions one quarter in advance. Table 3 shows furthermore that, on average, the S&P 500 index is clearly dominated by nearly all other predictors. This disappointing result again corresponds exactly with the findings published by DUEKER. In sharp contrast, however, ESTRELLA and MISHKIN find this stock index to contain useful information, especially for one quarter ahead predictions. In the case of the paper-bill-spread, which is, according to Table 3, also a very poor recession predictor, our results are more strongly supported by previous research. The authors of both of the studies cited above demonstrate that this variable has among all candidates the lowest informational content. Particularly, it performs worse for horizons beyond one quarter. Average lead times for predicting recession endings, as reported in the second row of Table 3, mirror the already mentioned asymmetry in forecasting business cycle turning points. Note that only the stock index gave signals prior to troughs earlier than to peaks.

The univariate analysis is completed with Table 4 which contains the number of observed false signals. To be consistent, we again used a rule of thumb. A false signal is defined as a change into the recession regime one (normal growth regime two) that persists for at least two consecutive months without an actual business cycle turning point following while being in the particular state.

Table 4: Number of estimated Regime-Changes without corresponding Business Cycle Turning Points

	Yield Curve	Lead	Money	Spread	Stock
Falsely pre-dicted Peaks	1	8	6	5	4
Falsely pre-dicted Troughs	1	0	1	1	3

Notes: The counted regime changes in the first row (second row) are characterized as follows: a switch of the respective indicator series into the «recession regime» one («normal growth» regime two) took place; the series remained there for at least two consecutive months; the regime change was not followed by a recession onset (ending), because the series did not remain in regime one (regime two) until a particular recession started (ended). A change between regimes generally occurs at dates where the estimated ex ante regime probability to stay in a certain regime increases from less than 0.5 to more than 0.5 or decreases from more than 0.5 to less than 0.5.

The relative high amount of falsely indicated recessions by the competing variables ultimately strengthens the case for the yield curve as the most useful predictor of U.S. recessions.

3. MARKOV-SWITCHING MODELS INCLUDING OUTPUT GROWTH

3.1 Bivariate Model Specifications

So far, our analysis does not use any actual measure of real economic activity in the estimation. For a forecasting comparison to be convincing in a statistical sense, however, the incorporation of real output growth is necessary. As it is typical for studies using monthly data, we take the Total Index of Industrial Production (IIP) as an output measure. In order to assess formally the predictive content of the five examined indicator variables, we estimate bivariate markov-switching models which should capture the joint behaviour of the IIP and the predictors.

Following HAMILTON and LIN (1996) we allow the mean of two time series to depend on individual unobserved state variables, where in our case S_t^* belongs to real output and S_t^+ drives the leading indicator under examination:

$$x_t - \eta S_t^* = u_t \quad y_t - \mu S_t^+ = \varepsilon_t. \quad (4)$$

Note, that x_t denotes the percentage change of the IIP, y_t denotes one of the leading indicators as defined in section 2, and η (μ) represents the regime-dependent mean of x_t (y_t). Our main task now is to describe the relation between the phase of the business cycle and the phase of the leading indicator. If we expand the regime space by defining $S_t = (S_t^*, S_t^+)$, the bivariate stochastic process (4) can be rewritten within the framework presented in section 2 using just one indicator variable S_t :

$$S_t = \begin{cases} 1 & \text{if } S_t^+ = 1 \text{ and } S_t^* = 1 \\ 2 & \text{if } S_t^+ = 2 \text{ and } S_t^* = 1 \\ 3 & \text{if } S_t^+ = 1 \text{ and } S_t^* = 2 \\ 4 & \text{if } S_t^+ = 2 \text{ and } S_t^* = 2. \end{cases} \quad (5)$$

As regards the link between real output and leading indicators, the scheme described in (5) allows us to estimate two restricted and simple models, each one corresponding with a distinct hypothesis and each one being a special case of (5). The first hypothesis is that

the factor that causes the economy to go into a recession and the factor that causes a regime change in the behaviour of the respective leading indicator represent one and the same event. In this case we have $S_t^* = S_t^+$ and the process described in (5) reduces to the simple Markov structure represented by (1). The second hypothesis is that both variables are driven by the same fundamentals but are not in phase together. If, for example, the leading indicator is affected by an event that causes a recession one period before industrial production starts to fall, we have $S_t^* = S_{t-1}^+$ and the process characterizing the state variable is:

$$S_t = \begin{cases} 1 & \text{if } S_t^+ = 1 \quad \text{and} \quad S_{t-1}^+ = 1 \\ 2 & \text{if } S_t^+ = 2 \quad \text{and} \quad S_{t-1}^+ = 1 \\ 3 & \text{if } S_t^+ = 1 \quad \text{and} \quad S_{t-1}^+ = 2 \\ 4 & \text{if } S_t^+ = 2 \quad \text{and} \quad S_{t-1}^+ = 2 \end{cases} \quad (6)$$

Here the business cycle state variable S_t follows a four-state Markov chain. The transition probabilities characterizing the Markov process are contained in the following matrix¹²:

$$\Pi = \begin{bmatrix} P & 0 & P & 0 \\ (1-P) & 0 & (1-P) & 0 \\ 0 & (1-Q) & 0 & (1-Q) \\ 0 & Q & 0 & Q \end{bmatrix} \quad (7)$$

Note, that the row j , column i entry of Π is $\Pr[S_t = j \mid S_{t-1} = i]$.

After estimation of the two restricted models described above, the predictive content of the indicators can be evaluated simply by comparing their log likelihood values¹³. If an indicator indeed predicts recessions, the value for the likelihood of the model with delayed states driving the output variable should be higher than the likelihood of the model with simultaneous states. This allows us to check the results presented in section 2.

12. See HAMILTON (1994), p. 691 and HAMILTON and LIN (1996) for details.

13. Note that in both models the joint behaviour of the two variables is captured solely by common non-linearities associated with regime switching. In addition to the common cyclical shift, vector autoregressive markov switching models allow real output to be determined directly by lagged values of the indicator variable (see HAMILTON and PEREZ-QUIROS [1996]). We do not use this kind of specification, because the univariate models used in section 2 are constructed without autoregressive dependence.

The relative high amount of falsely indicated recessions by the competing variables ultimately strengthens the case for the yield curve as the most useful predictor of U.S. recessions.

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the factor that causes the economy to go into a recession and the factor that causes a regime change in the behaviour of the respective leading indicator represent one and the same event. In this case we have $S_t^* = S_t^+$ and the process described in (5) reduces to the simple Markov structure represented by (1). The second hypothesis is that both variables are driven by the same fundamentals but are not in phase together. If, for example, the leading indicator is affected by an event that causes a recession one period before industrial production starts to fall, we have $S_t^* = S_{t-1}^+$ and the process characterizing the state variable is:

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3.2 *Empirical Results*

3.2.1 *Identifying Business Cycle Phases with a Univariate Switching Model of Real Output*

In section 2, we took NBER recessions as a reference. Thus, estimating bivariate models including the Total Index of Industrial Production (IIP) as a measure of real output can only be justified if the behaviour of this index is described by NBER cycles. Due to the pioneering work of HAMILTON (1989) the ex post determination of business cycle phases has become a main application of regime-switching models¹⁴. In the last decade, numerous researchers have documented that the turning points which are inferred by various switching-specifications modelling real output growth or coincident indicators correspond well with those determined by the NBER (see, for example, GOODWIN [1993], DURLAND and MCCURDY [1994], FILARDO [1994], KIM and YOO [1995], LAYTON [1996, 1998], KROLZIG [1997], RAYMOND and RICH [1997], FILARDO and GORDON [1998], KIM and NELSON [1998]). Because the present paper is primarily concerned with forecasting issues, we only shortly demonstrate in the second column of Table 5 that the IIP can be modelled as following a two-state regime-switching process with regime-independent variances. With all parameters being highly significant, state one clearly indicates recessions and state two represents normal growth periods.

14. Different methods of identifying turning points are evaluated and discussed in BOLDIN (1994).

Table 5: Parameter Estimates of Bivariate Markov-Switching Models including Real Output and Different Recession Predictors

$$x_t - \eta_{S_t}^* = u_t \quad y_t - \mu_{S_t}^+ = \varepsilon_t$$

$$S_t^* = S_t^+$$

Parameter	IIP	Yield Curve	Lead	Money	Spread	Stock
η_1	-1.03*** (3.57)	0.13* (1.86)	-0.62*** (2.63)	0.06 (0.78)	-0.19 (1.51)	-0.73*** (5.55)
η_2	0.46*** (9.51)	0.39*** (5.93)	0.50*** (9.63)	0.47*** (5.07)	0.43*** (10.79)	0.48*** (13.89)
$\sigma^2_{(x)}$	0.57*** (5.92)	0.81*** (8.89)	0.62*** (6.11)	0.79*** (7.63)	0.75*** (7.91)	0.61*** (7.37)
μ_1	—	0.17** (2.02)	-0.33 (1.61)	-0.11*** (2.60)	0.64*** (10.31)	-0.83 (1.49)
μ_2	—	2.11*** (34.59)	0.15*** (2.57)	0.51*** (16.43)	0.03 (1.32)	0.81*** (6.32)
$\sigma^2_{(y)1}$	—	0.76*** (9.30)	0.31 (1.15)	0.19*** (8.41)	0.19*** (3.04)	30.51*** (6.94)
$\sigma^2_{(y)2}$	—	0.40*** (8.95)	0.13*** (5.52)	0.14*** (4.78)	0.04*** (8.48)	6.91*** (12.99)
P	0.80*** (9.96)	0.97*** (111.46)	0.87*** (12.10)	0.97*** (54.51)	0.91*** (29.46)	0.84*** (16.43)
Q	0.97*** (108.82)	0.98*** (156.16)	0.97*** (36.87)	0.96*** (61.88)	0.97*** (123.97)	0.96*** (102.72)
Log- Likelihood	-541.51	-691.27	-368.37	-419.39	-225.52	-1255.82

Notes: The sample contains monthly observations from January 1959 to May 1995. Real economic activity is measured by the Total Industrial Production Index IIP, whose percentage change is denoted with x_t . The examined five indicator variables, denoted with y_t , are the same as described in Table 1. t-statistics in parentheses are based on heteroskedastic-consistent standard errors. * (**) (***) denotes significance at the 10% (5%) (1%) level.

As shown in Figure 2, it can further be demonstrated that one of the two regimes corresponds pretty well to NBER recessions. In panel (a) the ex ante probabilities are plotted. For the purpose of inferring if and when regime switches occurred in the past, rather than forecasting them, one usually looks at the smoothed probabilities $\Pr(S_t = 1 | \Phi_T)$ which are calculated ex post using the entire information set of the whole sample and are contained in panel (b).

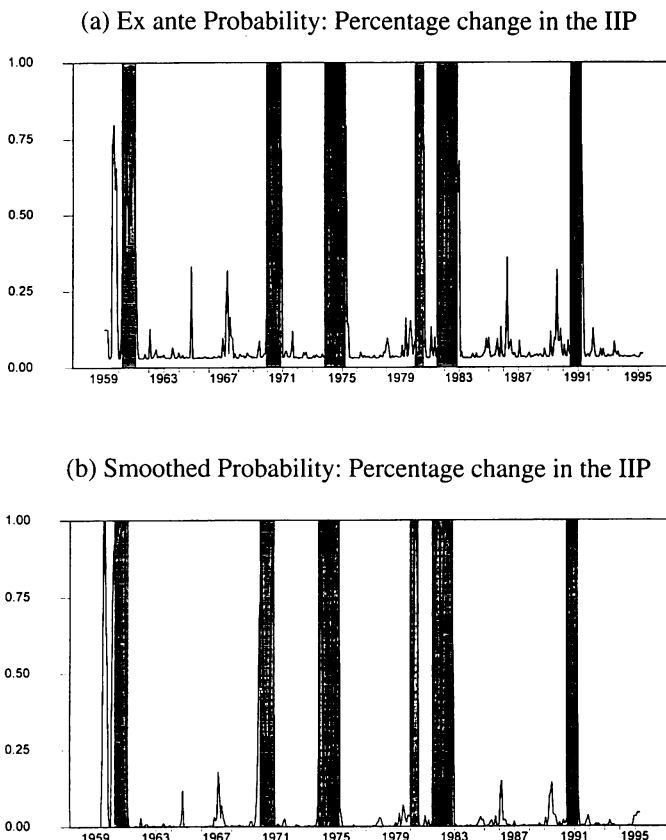
Figure 2: Identifying Recessions

Fig. 2. Panel (a) contains the time series plot of the ex ante probability that the process is in regime one at time t according to the estimated markov-switching model for the Total Industrial Production Index (see the second column in tables 5 and 6). The ex ante probability is based on information available at time $t-1$ ($\Pr[S_t = 1 | \Phi_{t-1}]$). Panel (b) shows the time series plot of the corresponding smoothed probability which is calculated ex post using the entire information of the whole sample ($\Pr[S_t = 1 | \Phi_T]$). Parameter estimates are based on monthly observations. The sample period is January 1959 to May 1995. Shaded areas indicate recessions as determined by the National Bureau of Economic Research (NBER).

Three aspects are worth mentioning. First, the estimated regime probabilities match almost exactly the NBER business cycle phases. Second, though the probabilities do give a reliable contemporaneous identification of recessions and expansions they cannot signal turning points in advance. Third, among all markov-switching models developed so

far we have selected the simplest possible specification¹⁵. To our surprise it works equally well like more complicated models used in some of the analyses cited above.

3.2.2 Estimation of Bivariate Models

Results of estimating models imposing the restriction that regime shifts affect both series at the same time are documented in Table 5. To be consistent, we model the stochastic process of the IIP with a regime-independent variance, whereas regime shifts do affect the variance of the indicator series. Looking at Table 5, we conclude that there is evidence in favour of *common* non-linearities associated with regime-switching. Under the contrary assumption that cyclical movements are independent of each other univariate log likelihoods can simply be added together to obtain the joint log likelihood. If we add one of the log likelihood values documented in Table 1 together with the log likelihood value of the univariate estimation for IIP as documented in the second column of Table 5, we get in all cases a joint log likelihood value which is far below the one of the bivariate model estimation. Moreover, the hypothesis that various indicators and the IIP are driven by the same fundamentals is generally confirmed by the parameters describing the bivariate processes. Most of them have plausible values and are very similar to those estimates obtained by univariate analyses.

The last step of our study consists in the estimation of bivariate models which impose the restriction that regime shifts affect the indicator series one period before they affect real output. The results are documented in Table 6 where univariate estimates for IIP are repeated in the second column.

15. Because its variance does not depend on regimes, it is even more simpler than the specification used in section 2. We have also estimated a model for IIP with a regime-dependent variance. However, it performs poorly in characterizing business cycles.

Table 6: Parameter Estimates of Bivariate Markov-Switching Models with delayed States including Real Output and Different Recession Predictors

$$x_t - \eta_{S_t}^* = u_t \quad y_t - \mu_{S_t}^+ = \varepsilon_t$$

$$S_t^* = S_{t-1}^+$$

Parameter	IIP	Yield Curve	Lead	Money	Spread	Stock
η_1	-1.03*** (3.57)	0.10* (1.65)	-0.35 (1.54)	0.03 (0.30)	-0.20* (1.42)	-0.75*** (4.70)
η_2	0.46*** (9.51)	0.43*** (9.19)	0.56*** (6.60)	0.51*** (4.66)	0.43*** (12.42)	0.47*** (17.00)
$\sigma_{(x)}^2$	0.57*** (5.92)	0.80*** (8.86)	0.65*** (7.38)	0.77*** (7.80)	0.75*** (7.72)	0.62*** (7.47)
μ_1	—	0.16* (1.93)	-0.31*** (3.67)	-0.10* (1.83)	0.65*** (8.36)	-1.14** (2.03)
μ_2	—	2.11*** (38.00)	0.23*** (3.43)	0.52*** (16.49)	0.03 (1.37)	0.86*** (6.91)
$\sigma_{(y)1}^2$	—	0.75*** (7.90)	0.20*** (4.30)	0.19*** (6.67)	0.19*** (2.84)	30.10*** (5.61)
$\sigma_{(y)1}^2$	—	0.40*** (11.09)	0.12*** (5.18)	0.13*** (4.46)	0.04*** (7.55)	6.99*** (14.04)
P	0.80*** (9.96)	0.97*** (109.12)	0.90*** (26.19)	0.97*** (42.98)	0.91*** (27.64)	0.85*** (15.64)
Q	0.97*** (108.82)	0.97*** (198.97)	0.95*** (35.70)	0.96*** (46.05)	0.97*** (100.60)	0.97*** (88.93)
Log- Likelihood	-541.51	-687.89	-362.97	-416.37	-225.69	-1254.49

Notes: The sample contains monthly observations from January 1959 to May 1995. Real economic activity is measured by the Total Industrial Production Index IIP, whose percentage change is denoted with x_t . The examined five indicator variables, denoted with y_t , are the same as described in Table 1. t-statistics in parentheses are based on heteroskedastic-consistent standard errors. * (**) (***) denotes significance at the 10% (5%) (1%) level.

While there is no remarkable difference between the parameter estimates in Tables 5 and 6¹⁶, comparing the log likelihood values leads to interesting insights. In the cases of the yield curve, the CLI and real money growth, the model with delayed regime dependence has a substantial better fit than the competing model presented in Table 5. We therefore reach the conclusion that these variables do indeed predict real output as our univariate results in section 2 have already suggested. Considering the S&P 500 index, there is only a marginal improvement in the likelihood function. This result corresponds with the low predictive content of the stock market found in section 2. The paper-bill-spread is the only indicator for which the delayed state dependence does not improve the fit of the bivariate model specification. This finding reflects the low predictive content of the paper-bill spread during the sample as documented in section 2.

4. CONCLUSION

This paper has studied the ability of five business cycle indicators to predict the likelihood of future recessions. We have compared the forecasting performance of the yield curve spread, the CLI, the paper-bill-spread, the S&P 500 index and real money growth within a markov-switching framework. The main advantage of this approach is the data-driven determination of optimal lead times for predicting discrete events like onsets and endings of recessions. Another important benefit of the applied strategy is that, in contrast to the popular probit estimations, *ex post* dated business cycle turning points were not used in the estimation process.

To a great extent our results confirm recent research by ESTRELLA and MISHKIN (1998) and DUEKER (1997). The yield curve slope, which is continuously available without an information lag, is the most reliable recession predictor with the longest average forecasting horizon. Real money growth has a considerable informational content too, whereas the Commerce Department's index of leading indicators is only useful within short horizons. Although the Standard & Poor's 500 index of stock prices as well as the paper-bill-spread are successfully modelled as two-state regime-switching processes, the predictive performance of these indicators is low. Nevertheless, for both variables, one of the estimated regimes is clearly associated with recession phases as theory suggests. The individual predictive content of the considered indicators was generally supported by estimations of bivariate markov-models. We also found that business cycle troughs are generally less predictable than peaks. Our main result, however, is that a simple univariate regime switching specification is able to produce accurate and often reliable forecasts of recessions. Obviously, the regime-switching model is an appropriate filter of turning point signals and should therefore be used in practical business cycle research.

16. In this respect, HAMILTON and LIN (1996, p. 581) obtain similar results.

APPENDIX

This appendix contains a short description of the paper's basic data series and data sources according to ESTRELLA and MISHKIN (1998, p. 61). It further explains the construction of the candidate indicator series according to DUEKER (1997, p. 51) which is applied by transforming the basic series.

BASIC DATA SERIES:

BILL	3-month Treasury bill rate
BILLSIX	6-month Treasury bill rate
CPSIX	6-month commercial paper rate
BOND	10-year Treasury bond rate
SP500	Standard and Poor's 500 composite index, monthly average
M2	M2, seasonally adjusted
CPI	Consumer price index, all urban consumers, all items, seasonally adjusted
CLI	Commerce Department, composite index of 11 leading indicators, seasonally adjusted
IIP	Total Industrial Production Index

DATA SOURCES:

The Total Industrial Production Index stems from «Federal Reserve Economic Data» (FRED) and was supplied online by the Federal Reserve Bank of St. Louis. All other data, including the binary recession variable, were kindly supplied by ARTURO ESTRELLA and FREDERIC S. MISHKIN. The interest rates are originally from an internal data source at the Federal Reserve Bank of New York. The remaining series stem from the Haver Analytics Database, US-ECON.

CONSTRUCTION OF RECESSION PREDICTORS:

Yield curve:	$\ln([1 + \text{BOND}/100] / [1 + \text{BILL}/100])$
Lead:	$\text{CLI}_t - \text{CLI}_{t-1}$
Money:	$\ln(\text{M2}/\text{CPI})_t - \ln(\text{M2}/\text{CPI})_{t-1}$
Stock:	$\ln(\text{SP500}_t / \text{SP500}_{t-1})$
Spread:	$\ln([1 + \text{CPSIX}/100] / [1 + \text{BILLSIX}/100])$

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SUMMARY

This study uses univariate and bivariate regime-switching models to compare the predictive performance of five popular business cycle indicators. The empirical results suggest that all considered series are sensibly modelled as following a two-state regime-switching process. For each variable one regime more or less strongly indicates recession periods, while the other one is associated with phases of economic recovery or expansion. The yield curve spread is confirmed to be the most reliable recession predictor with an average predictive lead time of three quarters. As the most important result, our simple univariate model turns out to be a filter that transforms accurately term spread changes into turning point predictions.

ZUSAMMENFASSUNG

Diese Arbeit untersucht den Informationsgehalt finanzieller und makroökonomischer Konjunkturindikatoren hinsichtlich der Wahrscheinlichkeit von Rezessionen in den USA. Hierzu werden univariate und bivariate Regime-Switching-Modelle geschätzt, die gegenüber traditionellen Methoden einige Vorteile haben. Die empirischen Ergebnisse zeigen, dass sich alle untersuchten Variablen als Prozesse mit stochastischen Regime-wechseln modellieren lassen. Eines der jeweils identifizierten zwei Regime steht darüber hinaus in einem engen Zusammenhang mit rezessiven Konjunkturphasen. Wie in vorangehenden Untersuchungen erweist sich die Zinsstruktur als äusserst verlässlicher Prediktor künftiger Rezessionen. Da Regime-Switching-Modelle geeignet sind, Veränderungen der untersuchten Variablen in eindeutige Wendepunktsignale zu transformieren, empfiehlt sich ihre Nutzung in der angewandten Konjunkturanalyse.

RESUME

Cette contribution examine la teneur en information d'indicateurs conjoncturels financiers et macro-économiques en vue de la probabilité de récessions aux Etats-Unis. A cette fin, des modèles à une ou deux variables dits «de changement de régime» sont estimés. Ces modèles présentent divers avantages par rapport aux méthodes traditionnelles. Les résultats empiriques démontrent que toutes les variables examinées peuvent être modelées comme procès à changement de régime stochastiques. En outre, l'un des deux régimes respectifs identifiés se caractérise par une relation étroite avec les phases de récession. Comme dans des études antérieures, la structure des taux d'intérêts s'avère être un présage particulièrement sûr de récessions futures. Comme les modèles de changement de régime sont capables de transformer les changements des variables observées en signaux clairs d'un tournant conjoncturel, l'utilisation de ces modèles dans l'analyse conjoncturelle pratique peut être recommandée.