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Predicting the bear stock market: Macroeconomic variables as leading indicators

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ABSTRACT

This paper investigates whether macroeconomic variables can predict recessions in the stock market, i.e., bear markets. Series such as interest rate spreads, inflation rates, money stocks, aggregate output, unemployment rates, federal funds rates, federal government debt, and nominal exchange rates are evaluated. After using parametric and nonparametric approaches to identify recession periods in the stock market, we consider both in-sample and out-of-sample tests of the variables' predictive ability. Empirical evidence from monthly data on the Standard & Poor's S&P 500 price index suggests that among the macroeconomic variables we have evaluated, yield curve spreads and inflation rates are the most useful predictors of recessions in the US stock market, according to both in-sample and out-of-sample forecasting performance. Moreover, comparing the bear market prediction to the stock return predictability has shown that it is easier to predict bear markets using macroeconomic variables.

1. Introduction

There has long been interest in making reliable predictions for stock markets. The idea that publicly available information can be used to predict stock returns is a violation of the principle of semistrong market efficiency. There are now many documented violations of market efficiency. For instance, Keim and Stambaugh (1986) find that several observable variables from bond and stock markets explain a substantial portion of future stock return movements. Pontiff and Schall (1998) show that the book-to-market ratio is able to predict market returns. Lewellen (2004) demonstrates the predictive power of financial ratios such as dividend yield, book-to-market ratio, and earnings-price ratio. A recent study by Hong et al. (2007) presents evidence that a significant number of industry portfolios' returns forecast stock market movements.

Other than financial variables, macroeconomic (henceforth, macro) variables are also good candidates for predicting stock market movements. Since macrovariables affect future consumption and investment opportunities, they play a key role in determining aggregate stock market behavior in consumption capital asset-pricing model (CCAPM). A number of empirical studies have investigated the predictability of stock returns using macrovariables. Macrovariables such as the term structure of interest rates are commonly associated with expectations of future economic events that may affect the stock market. Unemployment rates, inflation rates, and economic growth may affect future consumption and investment, which would also alter stock returns. Macrovariables representing monetary policy, such as money stocks and interest rates, have also been investigated. Using money aggregate data as a measure of money supply, some empirical studies agree that stock returns lag behind changes in monetary policy, for instance, see Hamburner and Kochin (1972).[1] Using the interest rate as the instrument of monetary policy, Thorbecke (1997) demonstrates that shifts in monetary policy help to explain US stock returns. A recent study by Rapach et al. (2005) examines a large set of macrovariables and presents evidence that stock returns can be predicted using macrovariables. Using data from 12 industrialized countries after the 1970s, they present evidence that interest rates are the most consistent and reliable predictors of stock returns across the countries.

However, all the papers mentioned above focused on the predictability of stock returns. In this paper, we examine the usefulness of various macro variables in predicting recessions in the stock market, i.e., bear stock markets. There are two reasons why this exercise is useful and appealing. First, market participants may benefit from such predictions because the predictability would help them to form market-timing strategies. As suggested by Shen (2003), investors may earn more returns by following a market-timing strategy rather than a buy-and-hold strategy. Second, predicting recessions in the stock market would help policy makers. As documented in Rigobon and Sack (2003) and Bohl et al. (2007), there is evidence that monetary authorities may re-

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[1] In contrast, Cooper (1974) shows that past changes in money have no significant forecasting power.

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spond to the stock market. Therefore, in this paper we focus on predicting stock market recessions rather than returns.

In order to predict stock market recessions, we first need to characterize the fluctuations in the stock market. Cyclical variations in stock returns are widely reported in the literature. For instance, see Coakley and Fuertes (2006), and Perez-Quiros and Timmermann (2000). However, as discussed in Candelon et al. (2008), there is no consensus in the academic literature on what bear and bull markets actually are. Parametric and nonparametric methods have both been employed to identify recessions and booms in the stock market. In particular, bull and bear markets are explicitly identified in Maheu and McCurdy (2000) using parametric models (Markov-switching models), while nonparametric approaches are used in Candelon et al. (2008). For instance, Candelon et al. (2008) use nonparametric methods to measure the synchronization of bull and bear markets in East Asian countries.

Following the above literature, we examine empirically the cyclical variations in stock returns using both parametric and nonparametric approaches. In particular, a modified version of the Markov-switching model and the Bry-Boschan dating method are employed. After the recession periods (bear markets) are identified by different models, we investigate whether the recessions can be predicted by various macro variables. The variables that we consider are interest rate spreads, inflation rates, money stocks, aggregate output, unemployment rates, federal funds rates, federal government debt, and nominal effective exchange rates. Both in-sample and out-of-sample tests are conducted.

It is worth noting that the forecasting exercise we conduct here is closely related to the literature on early warning systems (EWS). For instance, Berg and Pattillo (1999) use a general probit-based model of predicting currency crises with a number of macrovariables as predictors. They have shown that the bilateral real exchange rate, reserve growth, export growth, growth of M2/reserves, current account deficit and ratio of M2 to reserves are important risk factors for the prediction of currency crises.

The empirical results from monthly data on the Standard & Poor's 500 price index suggest that among the macrovariables we consider, yield curve spreads and inflation rates are the most consistent and useful predictors of bear markets, whether the forecasting performance is evaluated via in-sample or out-of-sample tests. A further out-of-sample test for nonnested models is conducted, and the results suggest that yield curve spreads and inflation rates are equally accurate in forecasting. The empirical results are robust for different measures of the bear markets. It is worth noting that the macrovariables considered in this paper do a better job in predicting the probability of a recession than in predicting quantitative returns in the US stock market. This result may demonstrate the usefulness and superiority of forecasting bear markets rather than returns.

The paper is structured as follows. Section 2 presents the econometric framework. Section 3 describes the data and reports the empirical results of bear market predictability when using macrovariables as leading indicators. Robustness checks and the economic value of predicting bear markets are provided in Sections 4 and 5. Finally, concluding remarks are offered in Section 6.

2. Econometric framework

2.1. Characterizing the stock market fluctuations

Before conducting a forecasting exercise, we need first to characterize stock market fluctuations, i.e., identify the recessions (bears) and booms (bulls) in the stock market. As discussed in Candelon et al. (2008), there is no consensus in the academic literature on the identification of bear and bull markets. Two main approaches have been proposed. The first is a parametric approach based on the Markov-switching model. Studies such as Maheu and McCurdy (2000) and Frauendorfer et al. (2007) apply this approach. The second approach is based on a nonparametric methodology. For instance, Candelon et al. (2008) use Quarterly Bry-Boschan method to examine monthly stock price series.

In this paper, we use both parametric and nonparametric approaches (denoted by Model 1 and Model 2) to identify the bear and bull stock markets. Moreover, we also apply a naive moving average approach (Model 3) as an alternative measure of the cyclical behavior of the stock market.

Model 1: A two-state Markov-switching model Let $r_t = 100 \cdot \Delta p_t$, where p_t is the logarithm of the nominal stock price. Therefore, r_t can be interpreted as stock returns. Consider a simple two-state mean/variance Markov-switching model of stock returns:

$$r_t = \mu_{s_t} + \epsilon_t, \epsilon_t \sim \text{i.i.d.} \quad \mathcal{N}(0, \sigma^2_{s_t}), \tag{1}$$

where μ_{s_t} and $\sigma^2_{s_t}$ are the state-dependent mean and variance of r_t, respectively. The unobserved state variable s_t is a latent dummy variable set at either 0 or 1. Let $s_t = 0$ indicate the bear market and $s_t = 1$ the bull market. The stock return is assumed to follow a two-state Markov process with a fixed transition probability matrix:

$$P = \begin{bmatrix} p^{00} & 1 - p^{11} \\ 1 - p^{00} & p^{11} \end{bmatrix}, \tag{2}$$

where

$$p^{00} = P(s_t = 0 | s_{t-1} = 0), \tag{3}$$

$$p^{11} = P(s_t = 1 | s_{t-1} = 1). \tag{4}$$

When the two regimes (the bear and bull markets) have been statistically identified, we can compute the filtered probabilities of each state:

$$Q_{j,t} = P(s_t = j | y^t), \quad j = \{0, 1\},$$

where y^t denotes the information set at time t. That is, the filtered probability $Q_{0,t} = P(s_t = 0 | y^t)$ is an estimate for the probability of the bear market.

Model 2: A nonparametric approach Candelon et al. (2008) discuss that the key feature of nonparametric dating algorithms is the location of turning points (peaks and troughs) that correspond to local maxima and minima of the series. We follow the setting in Candelon et al. (2008) to identify a peak (or trough) in the stock market when r_t reaches a local maximum (or minimum) in a window of 6 months using the monthly Bry-Boschan algorithm. That is, a local peak occurs at time t whenever $\{r_t > r_{t\pm 6}\}$. Likewise, there will be a trough at time t if $\{r_t < r_{t\pm 6}\}$. Once turning points are obtained, the peak-to-trough period and the trough-to-peak period are identified as the bear ($D_t = 1$) and the bull ($D_t = 0$) markets, respectively. D_t is a binary dummy variable to indicate the recessions and booms in the stock market.

Model 3: A naive moving average approach Under the naive moving average approach, the bull or bear market is decided by the mean return over the last couple of periods. We may define $\bar{r}^k_t$ as the moving average of the last k values of the stock returns, $\bar{r}^k_t = \frac{r_{t-1} + r_{t-2} + \cdots + r_{t-k}}{k}$. We then define a dummy variable D_t as follows:

$$D_t = \begin{cases} 1 \text{ (bear market)} & \text{if } \bar{r}^k_t < 0, \\ 0 \text{ (bull market)} & \text{if } \bar{r}^k_t > 0. \end{cases} \tag{5}$$

That is, if the mean return over the last k periods is negative, we identify the current market status as a bear market. On the other hand, a bull market is defined as a positive mean return over the last k periods.

2.2. Predictive regression model and out-of-sample tests for Markov-switching models

After obtaining the filtered probability of the bear market from the Markov-switching model (Model 1), we consider the following predictive regression model:

$$Q_{0,t+k} = \alpha + \beta x_t + e_t, \tag{6}$$

where x_t is a macrovariable that may potentially predict bear markets. The in-sample test is conducted as a test of the null hypothesis of no predictive power for future recessions: $\beta = 0$ against the alternative hypothesis, $\beta \neq 0$. Thus, the predictability of x_t is evaluated by the t-statistic corresponding to $\hat{\beta}$, as well as the conventional measure of the goodness-of-fit, R^2.

In this paper, we also conduct out-of-sample tests to evaluate bear market predictability. Consider the following nested models:

$$\text{restricted model}: \ Q_{0,t+k} = \alpha_1 + u_{1,t}, \tag{7}$$
$$\text{unrestricted model}: \ Q_{0,t+k} = \alpha_2 + \beta x_t + u_{2,t}. \tag{8}$$

It is clear that the unrestricted model nests the restricted model under the no-predictability null: $\beta = 0$. A positive out-of-sample test means that the predictive ability of the unrestricted model is better than that of the restricted model. For instance, if we use mean square prediction error (MSPE) as a measure of prediction performance, then MSPE(unrestricted) < MSPE(restricted) implies that the unrestricted model has better forecasting performance; that is, the macrovariables x_t have predictive power. In order to test formally whether the unrestricted model forecasts are significantly superior to the restricted model forecasts, we use a newly proposed statistic developed by Clark and West (2007), 'MSPE-adj'.

The total sample of T observations is divided into in-sample and out-of-sample portions. There are R in-sample observations, $t = 1, \ldots, R$, and P out-of-sample observations, $t = R+1, \ldots, R+P$. Obviously, $R + P = T$. A recursive estimation scheme is used. Now, $\hat{u}^1_{t+k}$ and $\hat{u}^2_{t+k}$ are forecasting errors for the restricted and unrestricted models, respectively. The forecasts of $Q_{0,t+k}$ from the two models are denoted $\widehat{Q}^1_{0,t+k}$ and $\widehat{Q}^2_{0,t+k}$. Clark and West (2007) MSPE-adj statistic is computed as:

$$\text{MSPE-adj} = \frac{\sqrt{P}\bar{f}}{\sqrt{\widehat{V}}}, \tag{9}$$

where $\bar{f} = P^{-1}\sum_t \hat{f}_{t+k}, \hat{f}_{t+k} = (\hat{u}^1_{t+k})^2 - [(\hat{u}^2_{t+k})^2 - (\widehat{Q}^1_{0,t+k} - \widehat{Q}^2_{0,t+k})^2]$, and $\widehat{V}$ is the sample variance of $(\hat{f}_{t+k} - \bar{f})$. The Clark–West test is an approximately normal test for equal predictive accuracy in nested models. The null hypothesis specifies equal MSPEs, while the alternative is that the unrestricted model has a smaller MSPE than the restricted model. The null hypothesis is rejected if the test statistic is sufficiently positive. The asymptotic distribution for the statistic is simply the standard normal distribution.

2.3. Predictive regression model and out-of-sample tests for nonparametric and naive approaches

For Model 2 and Model 3, we obtain a binary variable: $D_t = 1$ indicates a bear market while $D_t = 0$ indicates a bull market. We thus consider the following probit model:

$$P(D_{t+k} = 1) = F(\alpha + \beta x_t). \tag{10}$$

To measure the in-sample fit, we follow Estrella and Mishkin (1998) to compute the pseudo R^2 developed by Estrella (1998). Let L_u denote the value of the maximized probit likelihood, and let L_c denote the value of the maximized likelihood under the constraint that all coefficients are zero except for the constant. Then the measure of fit is defined by:

$$\text{Pseudo-}R^2 = 1 - \left(\frac{\log L_u}{\log L_c}\right)^{-(2/T)\log L_c}. \tag{11}$$

A low value of the pseudo-R^2 suggests "no fit", while a high pseudo-$R^2 = 1$ represents "perfect fit".

To evaluate out-of-sample probit model forecasts, we adopt the quadratic probability score (QPS) proposed by Diebold and Rudebusch (1989):

$$\text{QPS} = T^{-1}\sum_t 2[P(D_{t+k} = 1) - D_{t+k}]^2. \tag{12}$$

The QPS ranges from 0 to 2, with a score of 0 corresponding to perfect accuracy.

3. Data and empirical results

3.1. Data

This paper focuses on the US stock market and investigates its stock returns using the monthly returns on the S&P 500 price index from 1957M2 to 2007M12. The S&P 500 price index is obtained from International Financial Statistics, published by the International Monetary Fund (IMF). Yield spreads (the difference between the 3-Month Treasury Bill Rate and the 10-Year Treasury Constant Maturity Rate, and the difference between the 3-Month Treasury

Table 1
Unit root tests

Variable	ADF	PP	DF-GLS
Nominal returns	−9.67	−18.81	−8.43
Term spreads (3M-10Y)	−3.56	−4.31	−2.51
Term spreads (3M-5Y)	−3.87	−4.72	−2.84
Inflation rates	−2.18	−11.97	−2.18
Industrial production growth	−7.09	−16.36	−5.48
M1 growth	−5.04	−18.04	−5.04
M2 growth	−5.96	−11.00	−5.10
Changes in unemployment rates	−7.15	−22.67	−3.64
Changes in federal funds rates	−16.55	−16.17	−15.84
Changes in exchange rates	−4.27	−14.60	−0.89
Changes in public debt	−1.99	−7.40	−1.15

Note: ADF, PP and DF-GLS are Augmented Dickey-Fuller, Phillips-Perron and Elliott-Rothenberg-Stock DF-GLS test statistics, respectively. In each test, the null hypothesis is that the series has a unit root. Test critical values for ADF and PP are −3.44 (1%), −2.87 (5%) and −2.57 (10%). Test critical values for DF-GLS are −2.58 (1%), −1.95 (5%) and −1.62 (10%). Lags in ADF and DF-GLS tests are chosen by Modified Akaike Information Criterion.

Table 2
Linear and Markov-switching models of stock returns

	Linear	Markov-switching
μ	0.60	
	(0.14)	
μ_0		−1.12
		(0.65)
μ_1		1.13
		(0.15)
σ	3.48	
σ_0		5.17
		(0.39)
σ_1		2.53
		(0.12)
p^{00}		0.85
p^{11}		0.95
LogLik	−1625.69	−1581.22

Note: The entries in brackets are the standard errors. The dependent variable is stock returns. The linear model is $r_t = \mu + \varepsilon_t$ with mean μ and variance σ^2. The Markov-switching model is $r_t = \mu_{s_t} + \varepsilon_t$ with mean/variance (μ_0, σ_0^2) in regime 0 and (μ_1, σ_1^2) in regime 1.

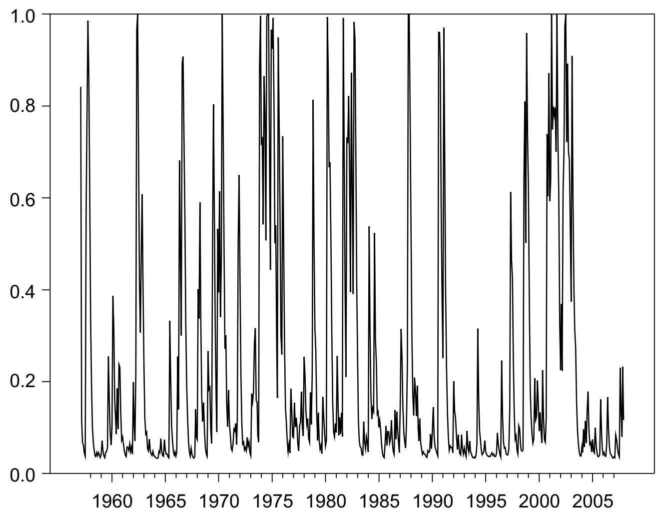

Fig. 1. Filtered probabilities in state 0 (bear markets).

Bill Rate and the 5-Year Treasury Constant Maturity Rate), inflation rates (consumer prices), money stocks (M1 and M2), aggregate output (industrial production), unemployment rates, federal funds rates, nominal effective exchange rates, and federal government debts are from FRED II (Federal Reserve Economic Data).

For all the variables mentioned above, unit root tests were conducted to investigate whether these series were stationary. The results of the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Elliott-Rothenberg-Stock DF-GLS test are reported in Table 1. Clearly, the hypothesis of a unit root process is rejected for each series.

3.2. Estimation results from Markov-switching models

Table 2 presents the estimation results for the linear and Markov-switching model. First of all, it is obvious that the Markov-switching model yields a higher value of the likelihood function than the linear model. The likelihood-ratio (LR) statistic is 88.94. Therefore, although the conventional LR test is not applicable because of the nuisance parameter problem, Garcia (1998) tabulates critical values for the simple two-means, two-variances model. The LR statistic is much larger than the 99%-critical value, 14.02. This finding may suggest that the Markov-switching model performs better than the simple linear model. Moreover, although we specify a two-state Markov switching model to identify the bear and bull markets, it is possible that there may exist a third market status (regime), such as huge bears or bulls. Since the distribution for such an LR statistic (two-regime versus three-regime)

Table 3
In-sample predictability test results for predicting bear stock markets (Model 1: Markov-switching model)

	Term spreads (3M-10Y)				Term spreads (3M-5Y)			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	0.02	2.00	**0.046**	0.0083	0.02	1.48	0.139	0.0048
$k = 3$	0.04	3.74	**0.000**	0.0292	0.04	3.06	**0.002**	0.0211
$k = 6$	0.06	5.75	**0.000**	0.0620	0.06	5.04	**0.000**	0.0484
$k = 12$	0.07	8.33	**0.000**	0.1028	0.08	7.95	**0.000**	0.0955
$k = 24$	0.05	6.14	**0.000**	0.0512	0.06	5.52	**0.000**	0.0444
	Narrow money growth (M1)				Broad money growth (M2)			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	−1.38	−0.60	0.546	0.0008	3.83	1.27	0.205	0.0023
$k = 3$	−3.77	−2.13	**0.033**	0.0061	−1.01	−0.29	0.769	0.0002
$k = 6$	−2.26	−1.24	0.216	0.0022	4.04	1.33	0.184	0.0026
$k = 12$	3.08	1.21	0.227	0.0040	8.68	2.69	**0.007**	0.0119
$k = 24$	−2.89	−1.48	0.139	0.0034	7.36	2.24	**0.025**	0.0085
	Inflation rates				Industrial production growth			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	16.90	4.10	**0.000**	0.0362	−8.00	−5.82	**0.000**	0.0630
$k = 3$	23.31	6.19	**0.000**	0.0687	−5.22	−3.86	**0.000**	0.0268
$k = 6$	20.96	5.34	**0.000**	0.0554	−3.44	−2.97	**0.003**	0.0117
$k = 12$	17.94	4.30	**0.000**	0.0418	−0.04	−0.04	0.972	0.0000
$k = 24$	15.27	4.05	**0.000**	0.0296	0.77	0.62	0.537	0.0006
	Change in unemployment rates				Change in federal funds rates			
	$\hat{\beta}$	*t*-stat	*p*-value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	0.34	5.75	**0.000**	0.0561	−0.07	−3.03	**0.002**	0.0220
$k = 3$	0.27	4.45	**0.000**	0.0337	−0.03	−1.51	0.130	0.0039
$k = 6$	0.12	2.07	**0.039**	0.0065	0.01	0.28	0.780	0.0001
$k = 12$	0.01	0.24	0.807	0.0001	−0.01	−0.32	0.749	0.0002
$k = 24$	0.01	0.12	0.906	0.0000	0.04	1.73	0.083	0.0080
	Change in exchange rates				Change in public debt			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	−0.45	−0.49	0.621	0.0007	0.05	0.02	0.981	0.0000
$k = 3$	0.92	1.11	0.267	0.0030	−2.84	−1.24	0.215	0.0033
$k = 6$	1.58	1.95	**0.051**	0.0087	−4.62	−2.21	**0.027**	0.0087
$k = 12$	0.94	1.19	0.232	0.0032	−9.32	−4.45	**0.000**	0.0352
$k = 24$	0.00	0.00	0.996	0.0000	−5.94	−2.30	**0.021**	0.0143

Note: The predictive regression model is $Q_{0,t+k} = \alpha + \beta x_t + e_t$, where $Q_{0,t+k}$ is the filtered probability obtained from the Markov-switching model. Bold entries indicate significance at the 10% level; 0.000 indicates the value is smaller than 0.0005.

is not available, we compute the information criteria proposed by Psaradakis and Spagnolo (2003) for Markov-switching models. The Psaradakis–Spagnolo Akaike information criterion (AIC) and Beyesian information criterion (BIC) are 1587.22 and 1600.46, respectively, for the two-state Markov-switching model; they are 1614.25 and 1636.32 for the three-state Markov-switching model. Clearly, a Markov-switching model with two regimes is chosen via the information criteria.

The Markov-switching model, where the process is allowed to switch between regimes, identifies a regime with a higher mean ($\mu_1 = 1.13$) and lower variance ($\sigma_1 = 2.53$) and a regime with a lower mean ($\mu_0 = -1.12$) and greater variance ($\sigma_0 = 5.17$). This result is coincident with the findings in Maheu and McCurdy (2000) and Perez-Quiros and Timmermann (2000), who investigate returns from the portfolio provided by the Center for Research in Security Prices. The high-return stable and low-return volatile states in stock returns are conventionally labeled as bull markets and bear markets, respectively. Obviously, the Markov-switching model has well identified the bull and bear markets in stock returns. Finally, the transition probabilities show that both bull and bear market states are highly persistent. The bull market regime persists, on average, for $1/(1-p^{11}) = 1/(1-0.95) = 20$ months, while it is expected that the bear market regime will persist for $1/(1-p^{00}) = 1/(1-0.85) = 6.67$ months.

3.3. In-sample results

After obtaining estimates from the Markov-switching model, we calculate the filtered probability. Fig. 1 plots the filtered probability of state 0 (bear market), the low-return/high-volatility state. We then use the filtered probability to run the predictive regression shown in Eq. (6). The empirical results, including coefficient estimates, t-statistics, p-values and R^2, are reported in Table 3. The predictive ability is measured at horizons of 1, 3, 6, 12, and 24 months. Investigating each macrovariable in turn shows that term spreads and inflation rates produce consistently strong results across all horizons. According to R^2, the term spread has better goodness-of-fit beyond 6 months, while inflation rates provide a better fit within 3 months. Other macrovariables, such as federal funds rates, industrial production growth, and unemployment rates, are strong predictors in the short run, but the significance generally declines within a year. The exchange rate movement does not have significant predictive power in all horizons, while the public debt is able to predict the bear market for a longer horizon (6 months and above).

Because the focus of this paper is the capacity of macrovariables to predict bear markets, no particular theoretical implication is tested via the sign of β. However, it is worth noting that term spreads, inflation rates, and unemployment rates are positively

Table 4
In-sample predictability test results for predicting bear stock markets: probit regression models (Model 2: Bry-Boschan Method)

	Term spreads (3M-10Y)				Term spreads (3M-5Y)			
	$\hat{\beta}$	t-stat	p-value	Pseudo-R^2	$\hat{\beta}$	t-Stat	p-Value	Pseudo-R^2
$k = 1$	0.09	1.96	**0.050**	0.0066	0.09	1.71	**0.087**	0.0050
$k = 3$	0.07	1.67	**0.095**	0.0013	0.09	1.67	**0.095**	0.0013
$k = 6$	0.07	1.66	**0.097**	−0.0039	0.11	2.01	**0.045**	−0.0016
$k = 12$	0.10	2.22	**0.026**	−0.0053	0.12	2.21	**0.027**	−0.0052
$k = 24$	0.31	6.17	**0.000**	0.0540	0.35	5.71	**0.000**	0.0431
	Narrow money growth (M1)				Broad money growth (M2)			
	$\hat{\beta}$	t-Stat	p-Value	Pseudo-R^2	$\hat{\beta}$	t-Stat	p-Value	Pseudo-R^2
$k = 1$	1.75	0.18	0.861	−0.0277	55.27	3.33	**0.001**	−0.0074
$k = 3$	−3.35	−0.36	0.722	−0.0316	73.87	4.49	**0.000**	0.0029
$k = 6$	5.67	0.60	0.548	−0.0373	98.79	5.67	**0.000**	0.0220
$k = 12$	−16.45	−1.61	0.106	−0.0452	85.66	4.74	**0.000**	−0.0030
$k = 24$	−47.86	−3.71	**0.000**	−0.0160	16.97	1.02	0.306	−0.0552
	Inflation rates				Industrial production growth			
	$\hat{\beta}$	t-Stat	p-Value	Pseudo-R^2	$\hat{\beta}$	t-Stat	p-Value	Pseudo-R^2
$k = 1$	−4.54	−0.26	0.793	0.0001	40.19	5.72	**0.000**	0.0611
$k = 3$	−24.11	−1.39	0.163	−0.0001	20.82	2.92	**0.004**	0.0156
$k = 6$	−8.26	−0.48	0.628	−0.0084	7.87	1.25	0.210	−0.0060
$k = 12$	−25.40	−1.49	0.136	−0.0110	−17.39	−2.80	**0.005**	−0.0018
$k = 24$	12.41	0.71	0.477	−0.0248	−3.58	−0.59	0.553	−0.0251
	Change in unemployment rates				Change in federal funds rates			
	$\hat{\beta}$	t-Stat	p-Value	Pseudo-R^2	$\hat{\beta}$	t-Stat	p-Value	Pseudo-R^2
$k = 1$	−1.08	−3.97	**0.000**	0.0239	0.26	2.45	**0.014**	0.0119
$k = 3$	−0.51	−1.83	**0.067**	0.0021	0.04	0.48	0.630	−0.0031
$k = 6$	0.11	0.38	0.703	−0.0085	−0.10	−1.07	0.286	−0.0071
$k = 12$	1.11	3.99	**0.000**	0.0100	−0.16	−1.59	0.112	−0.0104
$k = 24$	0.60	2.07	**0.038**	−0.0179	0.08	0.93	0.352	−0.0243
	Change in exchange rates				Change in public debt			
	$\hat{\beta}$	t-Stat	p-Value	Pseudo-R^2	$\hat{\beta}$	t-Stat	p-Value	Pseudo-R^2
$k = 1$	2.73	0.74	0.459	−0.5118	−33.52	−3.31	**0.001**	−0.1922
$k = 3$	1.91	0.52	0.605	−0.5211	−32.12	−3.14	**0.002**	−0.1967
$k = 6$	2.20	0.60	0.551	−0.5337	−14.38	−1.43	0.153	−0.2202
$k = 12$	−3.66	−0.98	0.326	−0.5573	−23.65	−2.32	**0.021**	−0.2355
$k = 24$	0.94	0.25	0.802	−0.6017	−46.86	−4.24	**0.000**	−0.2511

Note: The predictive regression model is $P(D_{t+k} = 1) = F(\alpha + \beta x_t)$, where D_{t+k} is a dummy variable so that $D_{t+k} = 1$ if in a bear market and $D_{t+k} = 0$ if in a bull market. The bear market is identified by a Bry-Boschan method as described in Eq. (5). Bold entries indicate significance at the 10% level; 0.000 indicates the value is smaller than 0.0005.

Table 5
In-sample predictability test results for predicting bear stock markets: probit regression models (Model 3: MA(5) model)

	Term spreads (3M-10Y)				Term spreads (3M-5Y)			
	$\hat{\beta}$	*t*-Stat	*p*-Value	Pseudo-R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	Pseudo-R^2
$k = 1$	0.07	1.68	**0.092**	0.0030	0.07	1.22	0.222	0.0007
$k = 3$	0.13	2.91	**0.004**	0.0093	0.13	2.34	**0.019**	0.0036
$k = 6$	0.16	3.59	**0.000**	0.0112	0.17	3.11	**0.002**	0.0049
$k = 12$	0.14	3.28	**0.001**	0.0034	0.18	3.35	**0.001**	0.0035
$k = 24$	0.08	1.96	**0.050**	−0.0296	0.09	1.73	**0.084**	−0.0309
	Narrow money growth (M1)				Broad money growth (M2)			
	$\hat{\beta}$	*t*-Stat	*p*-Value	Pseudo-R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	Pseudo-R^2
$k = 1$	−12.85	−1.25	0.210	−0.0350	−24.50	−1.54	0.125	−0.0341
$k = 3$	−8.10	−0.81	0.420	−0.0413	−17.15	−1.07	0.283	−0.0405
$k = 6$	4.06	0.44	0.659	−0.0490	9.67	0.61	0.543	−0.0486
$k = 12$	22.44	2.10	**0.036**	−0.0468	40.21	2.53	**0.011**	−0.0451
$k = 24$	14.05	1.41	0.157	−0.0586	86.11	4.45	**0.000**	−0.0109
	Inflation rates				Industrial production growth			
	$\hat{\beta}$	*t*-Stat	*p*-Value	Pseudo-R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	Pseudo-R^2
$k = 1$	63.66	3.66	**0.000**	0.0204	−28.11	−3.51	**0.000**	0.0321
$k = 3$	91.01	4.96	**0.000**	0.0391	−13.90	−2.04	**0.042**	0.0027
$k = 6$	65.49	3.74	**0.000**	0.0120	0.91	0.15	0.882	−0.0116
$k = 12$	67.10	3.80	**0.000**	0.0100	7.59	1.15	0.248	−0.0124
$k = 24$	42.14	2.38	**0.018**	−0.0259	−11.68	−1.82	**0.069**	−0.0298
	Change in unemployment rates				Change in federal funds rates			
	$\hat{\beta}$	*t*-Stat	*p*-Value	Pseudo-R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	Pseudo-R^2
$k = 1$	1.32	4.54	**0.000**	0.0331	−0.21	−2.07	**0.038**	0.0059
$k = 3$	0.36	1.31	0.190	−0.0030	0.09	0.94	0.350	−0.0042
$k = 6$	−0.16	−0.58	0.561	−0.0111	0.22	2.00	**0.046**	−0.0032
$k = 12$	−0.50	−1.71	**0.087**	−0.0097	0.04	0.40	0.689	−0.0146
$k = 24$	0.56	2.03	**0.043**	−0.0290	−0.16	−1.70	**0.089**	−0.0308
	Change in exchange rates				Change in public debt			
	$\hat{\beta}$	*t*-Stat	*p*-Value	Pseudo-R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	Pseudo-R^2
$k = 1$	2.00	0.53	0.594	−0.4890	−2.33	−0.51	0.609	−0.2331
$k = 3$	−3.09	−0.82	0.415	−0.4973	−6.28	−1.36	0.173	−0.2323
$k = 6$	5.86	1.56	0.118	−0.4994	−6.37	−1.36	0.173	−0.2357
$k = 12$	−4.37	−1.17	0.244	−0.5147	−3.54	−0.74	0.460	−0.2614
$k = 24$	−0.93	−0.24	0.809	−0.5331	−2.31	−0.49	0.625	−0.3050

Note: The predictive regression model is $P(D_{t+k} = 1) = F(\alpha + \beta x_t)$, where D_{t+k} is a dummy variable so that $D_{t+k} = 1$ if in a bear market and $D_{t+k} = 0$ if in a bull market. The bear market is identified by an MA(5) model as described in Eq. (5). Bold entries indicate significance at the 10% level; 0.000 indicates the value is smaller than 0.0005.

associated with future bear markets, while industrial production growth is negatively associated with future bear markets. It is intuitive that lower output growth and higher unemployment rates lead recessions in the stock market because recessions in real economic activity would spread out to the equity market. Inflation rates are significantly and positively associated with future recessions in the stock market, which may suggest that supply-side shocks are particularly important in the US economy. This result is consistent with the findings in Rapach et al. (2005). They found that the inflation rate had strong predictive power for stock returns.

Finally, as reported in a number of empirical studies (for instance, see Estrella and Mishkin (1998)) the term spread (short-term rates less long-term yields) is an important leading indicator of future recessions in real activity. Here, we have shown that the term spread is positively associated with future bear markets. A possible explanation comes from the expectation theory of the term structure of interest rates. It can be shown that a long-term rate equals the average of the expected values of short-term interest rates into the future, plus a term premium. If people expect a bear stock market in the future, the expected short-term rate would decrease, since a loose monetary policy is expected in the future. Hence the long-term rate is lower so that the term spread increases.

In Tables 4 and 5, probit regression results are presented using the nonparametric Bry-Boschan dating algorithm and the moving average of order five, MA(5) model to identify the bear market.[2] Clearly, departing from the Markov-switching framework and using a different measure of bear markets (models 2 and 3) does not substantially alter the findings. Term spreads are still the most powerful predictors among the macro variables. The only exception is that under Model 2, inflation rates become nonsignificant predictors for all horizons.

3.4. Out-of-sample results

The out-of-sample results are obtained by setting the out-of-sample period to be 1967M3–2007M12 so that the ratio $P/R \approx 4$.[3] Table 6 presents the (Clark and West, 2007) MSPE-adj statistic for each macrovariable. Recall that a higher value of the MSPE-adj means that a particular macro variable has higher predictive power than the restricted model, where only a constant is included in the predictive regression model.

The out-of-sample test results, in general, exhibit patterns similar to the in-sample evidence in Table 3. Yield spreads and inflation rates still perform the best. As discussed in Rapach et al.

[2] The results do not change substantially when considering different orders of the MA model.

[3] This P/R ratio is set by following Clark and West (2007)'s empirical studies for the US stock market. However, results are qualitatively similar when considering $P/R \approx 3$, 2, 1 or 0.5.

Table 6
Out-of-sample predictability test results for predicting bear stock markets: Clark and West (2007)'s MSPE-adj statistics (Model 1: Markov-switching model)

	$k = 1$	$k = 3$	$k = 6$	$k = 12$	$k = 24$
Term spreads (3M-10Y)	**2.28**	**3.74**	**5.57**	**9.02**	**4.74**
Term spreads (3M-5Y)	**1.60**	**2.91**	**4.68**	**8.23**	**3.59**
Narrow money growth (M1)	**1.29**	**2.35**	0.07	0.88	**1.51**
Broad money growth (M2)	**2.44**	**2.12**	1.18	**2.17**	**1.44**
Inflation rates	**3.36**	**4.43**	**4.17**	**3.43**	**3.08**
Change in unemployment rates	**4.98**	**4.66**	**1.51**	−1.64	−2.39
Industrial production growth	**4.43**	**3.84**	**2.76**	−2.43	−1.67
Change in federal funds rates	**2.02**	0.02	0.45	−0.58	0.29
Change in public debt	0.72	0.70	0.70	1.08	1.23
Change in exchange rates	**2.03**	**2.13**	**2.10**	**1.80**	−0.96

Note: The critical values are 1.282 (10%) and 1.645 (5%). Bold entries indicate significance at the 10% level. The predictive regression model is $Q_{0,t+k} = \alpha + \beta x_t + e_t$, where $Q_{0,t+k}$ is the filtered probability obtained from the Markov-switching model.

(2005), the general agreement between the in-sample and out-of-sample test results may be because of the increased power of recently developed tests such as the (Clark and West, 2007) MSPE-adj statistic.

Because the evidence suggests that term spreads and inflation rates are the most consistent and useful leading indicators of bear markets, it is of interest to ask which variable has better predictive power. According to the in-sample R^2 in Model 1 (Table 3), it seems the term spread has better goodness-of-fit beyond 6 months. In contrast, within 3 months, a higher R^2 is obtained when using inflation rates as predictors. In order to test formally the equal accuracy of the predictive power in the competing models, we conduct an out-of-sample equal MSPE-t test for nonnested models, proposed by Diebold and Mariano (1995). Let $\hat{e}^1_{t+k}$ and $\hat{e}^2_{t+k}$ denote the forecasting errors for the inflation and spread models, respectively. The test statistic is:

$$\text{MSPE-t} = \frac{\sqrt{P}\bar{d}}{\sqrt{\widehat{\Omega}}}, \tag{13}$$

where $\bar{d} = P^{-1}\sum_t \hat{d}_{t+k}$, $\hat{d}_{t+k} = (\hat{e}^1_{t+k})^2 - (\hat{e}^2_{t+k})^2$, and $\widehat{\Omega}$ is a consistent estimator of the long-run variance of $d_t = (\hat{e}^1_t)^2 - (\hat{e}^2_t)^2$. To compute the MSPE-t statistic, we regress $\hat{d}_{t+k}$ on a constant and then compute the t-statistic with HAC standard errors so that the asymptotic normal critical values can be used. The term spread model is chosen to be the benchmark so that the hypotheses are

H_0: MSPE (inflation model) = MSPE (term spread model),
H_1: MSPE (inflation model) > MSPE (term spread model).

Therefore, a significantly positive MSPE-t statistic implies the higher predictive power of the term spreads.

The results are presented in Table 7. Clearly, at most horizons, we fail to reject the null hypothesis of equal forecasting accuracy. The sole exception is that for the 1-year ahead forecast ($k = 12$), significant evidence suggests better performance by the term spread. Nevertheless, the overall result could be interpreted as no significant difference between term spreads and inflation rates in terms of out-of-sample predictive power.

Finally, Tables 8 and 9 report the QPS for different variables at various horizons for models 2 and 3. Recall that the QPS ranges from 0 to 2 with a score of 0 corresponding to perfect accuracy. Clearly, all of the scores are lower than 0.55, which suggests that the macrovariables have good predictive power, as documented in the main empirical results obtained from Model 1.

3.5. A comparison with return predictability

In previous sections, we presented evidence that the macrovariables considered in this paper are useful for predicting bear markets. As a comparison, it may be of interest to ask how these variables perform when the forecasting object is stock returns rather than the bear markets. It is worth noting that the capacity of these macrovariables to predict returns has already been investigated in numerous studies, for instance, see Rapach et al. (2005). However, an exercise using the same data, sample periods, and econometric methods makes the comparison more informative.

Table 8
Out-of-sample predictability test results for probit regression models: Diebold and Rudebusch (1989) QPS (Model 2: Bry-Boschan method)

	$k = 1$	$k = 3$	$k = 6$	$k = 12$	$k = 24$
Term spreads (3M-10Y)	0.47	0.49	0.53	0.53	0.46
Term spreads (3M-5Y)	0.50	0.51	0.54	0.54	0.49
Narrow money growth (M1)	0.48	0.49	0.50	0.50	0.48
Broad money growth (M2)	0.47	0.48	0.48	0.49	0.52
Inflation rates	0.50	0.51	0.52	0.52	0.52
Change in unemployment rates	0.49	0.51	0.51	0.50	0.51
Industrial production growth	0.48	0.50	0.51	0.51	0.51
Change in federal funds rates	0.50	0.51	0.51	0.52	0.51
Change in public debt	0.47	0.47	0.48	0.48	0.47
Change in exchange rates	0.52	0.52	0.53	0.53	0.53

Note: The predictive regression model is $P(D_{t+k} = 1) = F(\alpha + \beta x_t)$, where D_{t+k} is a dummy variable so that $D_{t+k} = 1$ if in a bear market and $D_{t+k} = 0$ if in a bull market. The bear market is identified by a Bry-Boschan Method. The QPS ranges from 0 to 2 with a score of 0 corresponding to perfect accuracy.

Table 9
Out-of-sample predictability test results for probit regression models: Diebold and Rudebusch (1989) QPS (Model 3: MA (5) model)

	$k = 1$	$k = 3$	$k = 6$	$k = 12$	$k = 24$
Term spreads (3M-10Y)	0.47	0.47	0.47	0.47	0.47
Term spreads (3M-5Y)	0.49	0.49	0.48	0.48	0.48
Narrow money growth (M1)	0.49	0.49	0.48	0.48	0.49
Broad money growth (M2)	0.49	0.48	0.48	0.48	0.45
Inflation rates	0.47	0.46	0.48	0.48	0.47
Change in unemployment rates	0.46	0.47	0.48	0.48	0.47
Industrial production growth	0.46	0.47	0.48	0.48	0.47
Change in federal funds rates	0.48	0.48	0.47	0.49	0.48
Change in public debt	0.46	0.46	0.46	0.47	0.47
Change in exchange rates	0.46	0.46	0.46	0.46	0.46

Note: The predictive regression model is $P(D_{t+k} = 1) = F(\alpha + \beta x_t)$, where D_{t+k} is a dummy variable so that $D_{t+k} = 1$ if in a bear market and $D_{t+k} = 0$ if in a bull market. The bear market is identified by an MA(5) model as described in Eq. (5). The QPS ranges from 0 to 2 with a score of 0 corresponding to perfect accuracy.

Table 7
Out-of-sample predictability test results: Diebold and Mariano (1995) MSPE-t statistics with HAC standard errors

	$k = 1$	$k = 3$	$k = 6$	$k = 12$	$k = 24$
MSPE-t (inflation rates vs. term spreads)	−1.40	−1.11	0.04	**2.43**	0.71

Note: The null hypothesis is that term spreads and inflation rates have the same predictive power; the alternative hypothesis is that term spreads have better forecasting performance. The critical values are 1.282 (10%) and 1.645 (5%). Bold entries indicate significance at the 10% level.

The results from in-sample and out-of-sample returns predictions are reported in Tables 10 and 11, respectively. Comparing the results in previous sections, it is obvious that the macrovariables we consider do a better job in predicting bear markets than predicting returns. Only a few variables at particular horizons are able to predict stock returns. The evidence seems to suggest that, compared with predicting stock returns, it is easier to predict recessions in the stock market using macrovariables. This result may demonstrate the greater usefulness and superiority of conducting a forecast of bear markets over predictions of stock returns.

4. Robustness

To check the robustness of the empirical results, we consider the following modifications of the forecasting exercise. First, we use smoothing probability obtained from the Markov-switching model to measure the probability of bear markets. We also consider different subsample periods and different stock market indicators. We then employ a multivariate model incorporating several macro predictors. Finally, we consider other factors that may affect the stock market phases to complete our empirical analysis.

Table 11
Out-of-sample predictability test results for predicting stock returns: Clark and West (2007)'s MSPE-adj statistics

	$k = 1$	$k = 3$	$k = 6$	$k = 12$	$k = 24$
Term spreads (3M-10Y)	**2.48**	**1.37**	0.46	−0.86	0.70
Term spreads (3M-5Y)	**1.81**	0.90	0.63	−0.47	0.89
Narrow money growth (M1)	−0.93	−0.76	0.87	**2.15**	−0.65
Broad money growth (M2)	**1.46**	0.47	0.51	**1.44**	0.23
Inflation rates	**2.39**	1.16	−0.18	−1.59	−0.44
Change in unemployment rates	**1.75**	−0.86	**1.95**	1.21	0.17
Industrial production growth	−0.28	**1.38**	0.51	−0.30	−1.23
Change in federal funds rates	**2.67**	**1.77**	−0.01	0.39	0.25
Change in public debt	−0.82	−0.79	−0.67	−0.26	−0.00
Change in exchange rates	−0.46	−0.50	−0.50	−0.49	−1.26

Note: The critical values are 1.282 (10%) and 1.645 (5%). Bold entries indicate significance at the 10% level. The predictive regression model is $r_{t+k} = \alpha + \beta x_t + e_t$, where r_{t+k} is the stock return.

4.1. Smoothing probability

The smoothing probabilities of each state take the following form:

$$P(s_t = j|y^T), \quad j = \{0, 1\},$$

Table 10
In-sample predictability test results for predicting stock returns

	Term spreads (3M-10Y)				Term spreads (3M-5Y)			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	−0.27	−2.19	**0.028**	0.0092	−0.27	−1.73	**0.083**	0.0060
$k = 3$	−0.18	−1.40	0.161	0.0039	−0.18	−1.11	0.267	0.0025
$k = 6$	−0.13	−1.08	0.280	0.0021	−0.17	−1.15	0.248	0.0024
$k = 12$	−0.12	−1.03	0.304	0.0018	−0.19	−1.27	0.205	0.0028
$k = 24$	−0.08	−0.69	0.490	0.0008	−0.07	−0.46	0.646	0.0004
	Narrow money growth (M1)				Broad money growth (M2)			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	−15.56	−0.61	0.542	0.0006	56.90	1.63	0.104	0.0030
$k = 3$	23.24	0.97	0.334	0.0014	32.47	0.74	0.460	0.0010
$k = 6$	−8.64	−0.32	0.745	0.0002	−56.43	−1.47	0.142	0.0030
$k = 12$	−74.65	−2.87	**0.004**	0.0140	−92.73	−2.48	**0.013**	0.0081
$k = 24$	24.05	0.10	0.318	0.0014	−28.47	−0.65	0.515	0.0008
	Inflation rates				Industrial production growth			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	−161.13	−3.18	**0.001**	0.0198	−11.03	−0.60	0.547	0.0007
$k = 3$	−81.56	−1.51	0.131	0.0051	−32.67	−2.06	**0.040**	0.0063
$k = 6$	−24.10	−0.44	0.659	0.0004	−19.85	−1.19	0.235	0.0023
$k = 12$	−5.21	−0.09	0.927	0.0000	−17.31	−1.12	0.264	0.0018
$k = 24$	−25.63	−0.51	0.608	0.0005	9.90	0.62	0.538	0.0006
	Change in unemployment rates				Change in federal funds rates			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	1.91	2.33	**0.020**	0.0105	−1.02	−4.23	**0.000**	0.0267
$k = 3$	0.25	0.32	0.747	0.0002	−0.50	−2.03	**0.043**	0.0066
$k = 6$	1.77	2.54	**0.011**	0.0090	−0.21	−0.98	0.329	0.0012
$k = 12$	1.22	1.75	**0.080**	0.0044	−0.14	−0.48	0.631	0.0005
$k = 24$	−0.98	−1.48	0.138	0.0028	0.33	1.30	0.192	0.0028
	Change in exchange rates				Change in public debt			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	−4.48	−0.40	0.690	0.0004	48.55	1.60	0.109	0.0057
$k = 3$	−4.43	−0.42	0.672	0.0004	100.21	3.77	**0.000**	0.0242
$k = 6$	−11.55	−1.11	0.268	0.0029	12.37	0.46	0.648	0.0004
$k = 12$	−6.13	−0.63	0.530	0.0008	−18.15	−0.56	0.575	0.0008
$k = 24$	8.39	0.69	0.493	0.0017	−46.05	−1.28	0.199	0.0051

Note: The predictive regression model is $r_{t+k} = \alpha + \beta x_t + e_t$, where r_{t+k} is the stock return. Bold entries indicate significance at the 10% level; 0.000 indicates the value is smaller than 0.0005.

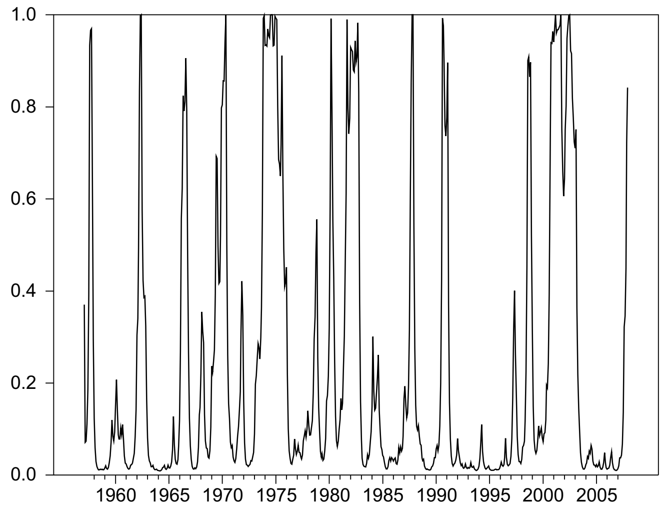

Fig. 2. Smoothing probabilities in state 0 (bear markets).

where y^T denotes the information set at time T. That is, it is the posteriori probability given that all sample observations are available. The smoothing probability is plotted in Fig. 2. The in-sample and out-of-sample results obtained from smoothing probabilities are presented in Tables 12 and 13. Clearly, the evidence indicates that the previous conclusion stands, which suggests that our main empirical results are robust.

Table 13

Robustness check: Out-of-sample predictability test results for predicting bear stock markets: Clark and West (2007)'s MSPE-adj Statistics

	$k = 1$	$k = 3$	$k = 6$	$k = 12$	$k = 24$
Term spreads (3M-10Y)	**4.09**	**5.77**	**7.94**	**11.81**	**5.53**
Term spreads (3M-5Y)	**3.21**	**4.77**	**7.01**	**11.07**	**4.24**
Narrow money growth (M1)	**1.79**	**2.17**	−0.10	1.05	**2.08**
Broad money growth (M2)	**2.63**	**2.30**	1.17	**2.95**	**2.21**
Inflation rates	**4.55**	**4.88**	**4.68**	**3.96**	**2.76**
Change in unemployment rates	**5.95**	**5.34**	1.28	−2.03	−0.26
Industrial production growth	**5.11**	**4.35**	**2.47**	−2.61	−0.83
Change in federal funds rates	1.04	0.31	0.51	0.47	0.07
Change in public debt	**1.35**	**1.33**	**1.38**	**1.89**	**2.18**
Change in exchange rates	**2.49**	**2.50**	**2.43**	**2.13**	−0.37

Note: The critical values are 1.282 (10%) and 1.645 (5%). Bold entries indicate significance at the 10% level. The predictive regression model is $Q_{0,t+k} = \alpha + \beta x_t + e_t$, where $Q_{0,t+k}$ is the smoothing probability obtained from the Markov-switching model.

Table 12

Robustness check: In-sample predictability test results for predicting bear stock markets using smoothing probability

	Term spreads (3M-10Y)				Term spreads (3M-5Y)			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	0.04	3.87	**0.000**	0.0286	0.05	3.15	**0.002**	0.0205
$k = 3$	0.07	5.95	**0.000**	0.0649	0.07	5.16	**0.000**	0.0508
$k = 6$	0.09	8.15	**0.000**	0.1148	0.10	7.50	**0.000**	0.0971
$k = 12$	0.11	11.39	**0.000**	0.1725	0.13	11.29	**0.000**	0.1667
$k = 24$	0.07	6.81	**0.000**	0.0635	0.08	6.20	**0.000**	0.0549
	Narrow money growth (M1)				Broad money growth (M2)			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	−3.36	−1.30	0.192	0.0035	1.87	0.48	0.634	0.0004
$k = 3$	−5.20	−2.16	**0.030**	0.0083	−0.94	−0.24	0.812	0.0001
$k = 6$	−2.26	−0.80	0.421	0.0016	4.87	1.28	0.202	0.0027
$k = 12$	2.51	0.86	0.391	0.0019	11.87	3.19	**0.001**	0.0160
$k = 24$	−4.48	−1.84	**0.066**	0.0060	10.35	2.60	**0.009**	0.0160
	Inflation rates				Industrial production growth			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	26.07	5.94	**0.000**	0.0622	−8.93	−5.54	**0.000**	0.0567
$k = 3$	29.12	6.79	**0.000**	0.0774	−6.70	−4.33	**0.000**	0.0319
$k = 6$	26.53	5.97	**0.000**	0.0640	−4.04	−2.88	**0.004**	0.0116
$k = 12$	22.62	4.84	**0.000**	0.0477	−0.07	−0.05	0.957	0.0000
$k = 24$	15.34	3.41	**0.001**	0.0214	1.07	0.78	0.434	0.0008
	Change in unemployment rates				Change in federal funds rates			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	0.41	6.01	**0.000**	0.0586	−0.06	−2.38	**0.017**	0.0131
$k = 3$	0.33	4.75	**0.000**	0.0376	−0.02	−0.87	0.383	0.0013
$k = 6$	0.16	2.37	**0.018**	0.0093	0.01	0.33	0.738	0.0002
$k = 12$	0.04	0.63	0.527	0.0005	0.02	0.71	0.475	0.0013
$k = 24$	−0.03	−0.40	0.688	0.0002	0.05	1.20	0.228	0.0069
	Change in exchange rates				Change in public debt			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
$k = 1$	0.09	0.09	0.932	0.0000	−2.19	−0.81	0.418	0.0014
$k = 3$	1.33	1.37	0.172	0.0044	−5.43	−2.12	**0.034**	0.0085
$k = 6$	1.47	1.52	0.128	0.0054	−9.44	−3.92	**0.000**	0.0258
$k = 12$	1.68	1.70	**0.089**	0.0072	−13.59	−5.20	**0.000**	0.0532
$k = 24$	−0.45	−0.45	0.652	0.0006	−9.91	−3.17	**0.002**	0.0282

Note: The predictive regression model is $Q_{0,t+k} = \alpha + \beta x_t + e_t$, where $Q_{0,t+k}$ is the smoothing probability obtained from the Markov-switching model. Bold entries indicate significance at the 10% level; 0.000 indicates the value is smaller than 0.0005.

Table 14
Robustness check: In-sample predictability test results for predicting bear stock markets in subsample periods. (Model 1: Markov-switching model)

	Term spreads (3M-10Y)				Inflation rates			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-value	R^2
1957:M2–2007:M12								
$k = 1$	0.02	2.00	**0.046**	0.0083	16.90	4.10	**0.000**	0.0362
$k = 3$	0.04	3.74	**0.000**	0.0292	23.31	6.19	**0.000**	0.0687
$k = 6$	0.06	5.75	**0.000**	0.0620	20.96	5.34	**0.000**	0.0554
$k = 12$	0.07	8.33	**0.000**	0.1028	17.94	4.30	**0.000**	0.0418
$k = 24$	0.05	6.14	**0.000**	0.0512	15.27	4.05	**0.000**	0.0296
	Term spreads (3M-10Y)				Inflation rates			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
1970:M1–2007:M12								
$k = 1$	0.02	2.04	**0.042**	0.0117	16.46	3.52	**0.000**	0.0345
$k = 3$	0.05	3.95	**0.000**	0.0444	21.68	4.95	**0.000**	0.0598
$k = 6$	0.06	5.99	**0.000**	0.0916	20.63	4.62	**0.000**	0.0538
$k = 12$	0.09	8.98	**0.000**	0.1640	18.13	3.82	**0.000**	0.0416
$k = 24$	0.06	6.99	**0.000**	0.0868	14.09	3.28	**0.001**	0.0242
	Term spreads (3M-10Y)				Inflation rates			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
1980:M1–2007:M12								
$k = 1$	−0.00	−0.03	0.976	0.0000	10.75	1.81	**0.071**	0.0125
$k = 3$	0.02	1.65	**0.099**	0.0101	14.24	2.57	**0.010**	0.0226
$k = 6$	0.04	3.58	**0.000**	0.0427	12.79	2.45	**0.014**	0.0190
$k = 12$	0.07	6.50	**0.000**	0.1100	10.08	1.93	**0.053**	0.0130
$k = 24$	0.07	6.97	**0.000**	0.1303	17.11	3.51	**0.000**	0.0376
	Term spreads (3M-10Y)				Inflation rates			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
1990:M1–2007:M12								
$k = 1$	0.01	0.49	0.623	0.0011	1.64	0.20	0.843	0.0002
$k = 3$	0.02	1.39	0.166	0.0101	2.14	0.30	0.767	0.0003
$k = 6$	0.04	2.39	**0.017**	0.0310	3.07	0.35	0.727	0.0006
$k = 12$	0.07	4.63	**0.000**	0.0818	−6.73	−0.82	0.413	0.0030
$k = 24$	0.12	8.59	**0.000**	0.2296	6.41	0.84	0.402	0.0024

Note: The predictive regression model is $Q_{0,t+k} = \alpha + \beta x_t + e_t$, where $Q_{0,t+k}$ is the filtered probability obtained from the Markov-switching model. Bold entries indicate significance at the 10% level; 0.000 indicates the value is smaller than 0.0005.

4.2. Subsample periods

It is suggested in Estrella et al. (2003) that because of the time-varying factors such as a monetary reaction function or the relative importance of real and nominal shocks, the predictive power of the term structure may change over time. We therefore reexamine the bear market prediction models over different subsample periods to check if the predictive power is stable. Empirical results for term structures and inflation rates are reported in Table 14. It is obvious that the overall conclusions regarding the forecasting content of the term spread and inflation rate do not change over different subsample periods. The only exception is the loss in predictive power of the inflation rate after 1990. This may be because of the decline in the variability of inflation rates, referred to as "the Great Moderation".

4.3. Other stock market indicators

We have used the S&P 500 index as our benchmark since it is one of the most commonly used indexes for the overall US stock market. The Dow Jones Industrial Average (DJIA) was at one time the most renowned index for US stocks; however, the DJIA contains only 30 companies. Therefore, it is commonly agreed that the S&P 500 is a better representation of the US market. Nevertheless, we consider other US stock market indexes, such as DJIA, NASDAQ Composite, and AMEX Average, as robustness checks. [4] Empirical results for term structures and inflation rates are reported in Table 15. Clearly, the high predictive power of the term spread remains, which suggests our main empirical results are robust for different stock price indexes.

4.4. Multivariate models

In our empirical specifications, macro variables are examined individually by prediction regression models. It is shown that the univariate model with the term spread outperforms models with other macrovariables. It is of interest to consider a multivariate model with several macrovariables. Using $k = 12$ as an example, we report the results in Table 16.[5] It is obvious that the term spread is still a good predictor in multivariate models.

4.5. Other factors affecting the stock market cycle

There may exist other factors that could be the origin of a change in the phase of the stock market. Other than macrofundamentals, the transmission of shocks and psychological effects would also play important roles in determining stock price movements. We thus consider changes in world oil prices, changes in UK interest rates, and UK inflation rates to account for global and foreign shocks. Furthermore, we use the consumer confidence index as a proxy for the psychological effect.[6] The empirical results are

[4] The NASDAQ Composite and AMEX Average indexes are available from the IMF's International Financial Statistics. The sample period is 1971M1–2007M12 for the NASDAQ Composite index and 1971M2–2007M12 for the AMEX Average index. The DJIA index is obtained from Datastream.

[5] Considering other prediction horizons gives similar results.

[6] World oil prices, UK interest rates (Euro dollar rates in London), and UK consumer prices are available from the IMF's International Financial Statistics. The consumer confidence index is obtained from Datastream.

Table 15
Robustness check: In-sample predictability test results for predicting bear stock markets using different indiexes (Model 1: Markov-switching model)

	Term spreads (3M-10Y)				Inflation rates			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
Dow Jones industrial average								
$k = 1$	0.01	1.23	0.218	0.0028	7.24	2.59	**0.009**	0.0186
$k = 3$	0.01	1.86	**0.063**	0.0075	9.65	3.16	**0.002**	0.0328
$k = 6$	0.01	2.04	**0.042**	0.0087	5.23	2.00	**0.046**	0.0096
$k = 12$	0.02	2.87	**0.004**	0.0169	4.30	1.42	0.154	0.0065
$k = 24$	0.01	1.30	0.194	0.0022	1.95	1.15	0.248	0.0013
	Term spreads (3M-10Y)				Inflation rates			
	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2	$\hat{\beta}$	*t*-stat	*p*-Value	R^2
NASDAQ composite								
$k = 1$	0.03	2.57	**0.010**	0.0165	4.04	0.84	0.398	0.0018
$k = 3$	0.05	3.93	**0.000**	0.0401	6.93	1.55	0.121	0.0054
$k = 6$	0.06	5.32	**0.000**	0.0704	7.98	1.68	**0.093**	0.0071
$k = 12$	0.09	7.31	**0.000**	0.1371	0.10	0.02	0.985	0.0000
$k = 24$	0.06	6.24	**0.000**	0.0757	−8.44	−2.32	**0.021**	0.0078
	Term spreads (3M-10Y)				Inflation rates			
	$\hat{\beta}$	*t*-State	*p*-Value	R^2	$\hat{\beta}$	*t*-Stat	*p*-Value	R^2
AMEX average								
$k = 1$	0.03	2.71	**0.007**	0.0215	25.52	5.45	**0.000**	0.0812
$k = 3$	0.05	3.93	**0.000**	0.0444	30.69	7.06	**0.000**	0.1171
$k = 6$	0.06	5.50	**0.000**	0.0757	27.00	6.01	**0.000**	0.0902
$k = 12$	0.07	6.15	**0.000**	0.0982	22.62	4.81	**0.000**	0.0646
$k = 24$	0.05	5.37	**0.000**	0.0577	26.15	5.84	**0.000**	0.0898

Note: The predictive regression model is $Q_{0,t+k} = \alpha + \beta x_t + e_t$, where $Q_{0,t+k}$ is the filtered probability obtained from the Markov-switching model. Bold entries indicate significance at the 10% level; 0.000 indicates the value is smaller than 0.0005.

Table 16
Robustness check: In-sample predictability test results for predicting bear stock markets using multivariate models (Model 1: Markov-switching model)

Term spreads (3M-10Y)	0.07	0.08	0.08	0.08	0.08	0.08	0.10	0.09
	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]
Narrow money growth		7.94	7.34	7.30	7.25	7.32	8.05	9.19
		[**0.01**]	[**0.01**]	[**0.01**]	[**0.01**]	[**0.01**]	[**0.01**]	[**0.00**]
Inflation rates			7.36	7.39	7.68	7.87	0.78	2.82
			[**0.07**]	[**0.07**]	[**0.06**]	[**0.05**]	[0.87]	[0.57]
Change in federal funds rates				−0.04	−0.04	−0.05	−0.06	−0.07
				[**0.09**]	[**0.06**]	[**0.05**]	[**0.02**]	[**0.02**]
Change in unemployment rates					−0.04	−0.02	0.05	0.06
					[0.44]	[0.72]	[0.49]	[0.40]
Industrial production growth						1.30	2.28	2.09
						[0.34]	[0.26]	[0.30]
Change in exchange rates							0.44	0.31
							[0.53]	[0.65]
Change in public debt								−8.10
								[**0.00**]

Note: The predictive regression model is $Q_{0,t+k} = \alpha + \beta x_t + e_t$, where $Q_{0,t+k}$ is the filtered probability obtained from the Markov-switching model. *P*-values are reported in parentheses. Bold entries indicate significance at the 10% level; 0.00 indicates the value is smaller than 0.005.

presented in Table 17. First of all, it is noteworthy that most global and foreign variables have insignificant predictive powers. Moreover, the coefficient estimates of the consumer confidence index are statistically significant but the magnitude of the coefficient estimates are relatively small. Finally, the term spread remains a good predictor with significant predictive power.

5. Economic values of predicting bear stock markets

Finally, we investigate whether predicting bear markets is useful for market participants seeking to time market fluctuations. We conduct a very simple out-of-sample exercise to compare the profitability of a switching strategy versus a benchmark buy-and-hold strategy, assuming no transaction costs. The switching strategy is employed as follows: holding stock if the probability of a bear market 1 month later is less than 30%, and holding bonds otherwise. The return on bounds is obtained from the corresponding 3-month Treasury Bill Rate. Table 18 shows the terminal values of a $1 investment over the 40-year period and the monthly compound returns. Investing $1 in a buy-and-hold strategy would yield $18.98 at year-end 2007 and a monthly compound return of 0.6%. On the other hand, a switching strategy based on different bear market predictive models with different predictors would produce higher terminal wealth and compound returns. This simple out-of-sample exercise illustrates the usefulness of predicting a bear market. Switching strategies, with forecasting information about the bear market probability, outperform buy-and-hold strategies.

6. Concluding remarks

This paper investigated whether macrovariables were useful in predicting bear markets, i.e., recessions in the stock market. Series

Table 17
Robustness check: In-sample predictability test results for predicting bear stock markets with other factors (Model 1: Markov-switching model)

Term spreads (3M-10Y)	0.08	0.09	0.08	0.09	0.09	0.09	0.09	0.08
	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]
Narrow money growth		9.06	8.90	9.02	9.08	9.16	9.39	9.95
		[**0.00**]	[**0.01**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]
Inflation rates			5.17	4.93	4.99	4.82	4.88	5.52
			[0.33]	[0.35]	[0.34]	[0.36]	[0.37]	[0.31]
Change in federal funds rates				−0.04	−0.04	−0.05	−0.05	−0.05
				[**0.09**]	[**0.10**]	[**0.07**]	[**0.08**]	[**0.08**]
Change in unemployment rates					0.03	0.06	0.09	0.09
					[0.65]	[0.41]	[0.24]	[0.24]
Industrial production growth						1.92	0.96	1.17
						[0.31]	[0.64]	[0.56]
Change in exchange rates							0.64	0.49
							[0.37]	[0.49]
Change in public debt								−6.71
								[**0.01**]
Change in world oil prices	0.05	0.04	−0.01	0.01	0.01	0.00	−0.01	−0.03
	[0.74]	[0.82]	[0.97]	[0.96]	[0.96]	[0.98]	[0.96]	[0.84]
Change in UK interest rates	−0.04	−0.04	−0.05	−0.03	−0.03	−0.03	−0.04	−0.04
	[**0.09**]	[**0.08**]	[**0.07**]	[0.30]	[0.30]	[0.28]	[0.14]	[0.15]
UK inflation rate	2.38	1.76	1.18	1.28	1.23	1.21	1.57	1.85
	[0.14]	[0.26]	[0.47]	[0.43]	[0.44]	[0.45]	[0.34]	[0.25]
US consumer confidence index	0.001	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	[**0.05**]	[**0.01**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.00**]	[**0.02**]

Note: The predictive regression model is $Q_{0,t+k} = \alpha + \beta x_t + e_t$, where $Q_{0,t+k}$ is the filtered probability obtained from the Markov-switching model. *P*-values are reported in parentheses. Bold entries indicate significance at the 10% level; 0.00 indicates the value is smaller than 0.005.

Table 18
Economic value of a switching strategy based on the prediction of bear markets: out-of-sample performance

			Buy-and-hold strategy
Terminal wealth ($)			18.98
Monthly compound return (%)			0.60
	Switching strategy		
	Terminal wealth ($)	Monthly compound return (%)	
Term spreads (3M-10Y)	109.47	0.96	
Term spreads (3M-5Y)	75.77	0.88	
Narrow money growth	27.92	0.68	
Broad money growth	42.84	0.77	
Inflation rate	264.95	1.14	
Change in unemployment rate	33.09	0.71	
Industrial production growth	30.05	0.60	
Change in federal funds rates	16.76	0.58	
Change in exchange rates	24.46	0.60	
Change in public debt	19.34	0.58	

such as interest rate spreads, inflation rates, money stocks, aggregate output, unemployment rates, federal funds rates, federal government debt, and nominal effective exchange rates were evaluated individually. We first estimated a Markov-switching model of stock returns and then identified bear markets using the filtered probability. Both in-sample and out-of-sample tests of predictive ability were conducted for the above macrovariables. We also examined different measures of the bear market.

The empirical evidence from monthly data on the Standard&Poor's S&P 500 price index can be summarized as follows. First, among the macro variables that we considered, term spreads and inflation rates are the most useful predictors of recessions in the US stock market, according to both in-sample and out-of-sample forecasting performance. Moreover, the null hypothesis of equal forecasting accuracy of term spreads and inflation rates cannot be rejected. It was also found that macrovariables do a better job in predicting bear markets than predicting returns in the stock market. It was shown that forecasts focusing on bear markets are useful for market participants conducting a market-timing strategy. Monetary authorities would also benefit from such forecasts when deciding monetary policy. Finally, we showed that the empirical results are robust for different measures of bear markets as well as different predictive regression models.

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