Further evidence on bear market predictability: The role of the external finance premium

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Abstract

In this paper, we revisit bear market predictability by employing a number of variables widely used in forecasting stock returns. In particular, we focus on variables related to the presence of imperfect credit markets. We evaluate prediction performance using in-sample and out-of-sample tests. Empirical evidence from the US stock market suggests that among the variables we investigate, the default yield spread, inflation, and the term spread are useful in predicting bear markets. Further, we find that the default yield spread provides superior out-of-sample predictability for bear markets one to three months ahead, which suggests that the external finance premium has an informative content on the financial market.

Keywords: Bear markets, stock returns, Markov-switching model

JEL Classification: G10, C53.

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1. Introduction

Stock return predictability has attracted considerable attention in the literature, and a number of variables have been identified as generally good predictors of future stock returns. For example, financial variables, such as the dividend–price, earnings–price, and book-to-market ratios and dividend growth, have been found to be significant in predicting future stock returns (Campbell and Shiller, 1988, 1989; Fama and French, 1988; Goetzmann and Jorion, 1993; Lettau and Ludvigson, 2005; Lewellen, 1999; Menzly et al., 2004; Pontiff and Schall, 1998). In addition, macroeconomic variables have also been found to be good candidates for the prediction of stock market movements (Rapach et al., 2005; Thorbecke, 1997). See Goyal and Welch (2008) for a comprehensive review of stock return predictability.

However, instead of predicting stock returns, some recent studies have shifted the focus to bear market predictability. Shen (2003) shows that by forecasting bear markets, investors can exploit profitable opportunities by optimally timing their portfolios. They can thus obtain higher returns by following a timing strategy rather than a buy-and-hold strategy. Therefore, predicting the turning points of stock markets becomes an informative task in investment. Furthermore, from a policy perspective, predicting the swings in the stock market provides useful information about business cycles (Estrella and Mishkin, 1998). In particular, widespread liquidity problems may account for credit crunches in financial markets during bear market periods (Bernanke and Lown, 1991). Thus, monetary authorities, which are generally responsible for maintaining and ensuring overall financial stability, can make use of information about future stock market booms and busts when implementing monetary policy *ex ante* (Rigobon and Sack, 2003). As an example, a recent study by Chen (2009) evaluates bear market predictability using various macroeconomic variables, and concludes that the term spread and inflation are useful in predicting the bear markets. Nyberg (2013) subsequently confirms the empirical findings in

Chen (2009) using dynamic binary time series models.

The purpose of this paper is to examine bear market predictability in stock markets using a range of financial variables, particularly those related to the presence of imperfect capital markets. There are several reasons why this exercise is both useful and appealing. First, although Chen (2009) shows that macroeconomic variables are informative in forecasting bear stock markets, it would be more practically relevant to consider financial variables as predictors, as these are not typically subject to revision. Second, focusing on variables related to imperfect capital markets is motivated by the well-known fact that imperfect capital markets play an important role in the propagation mechanism of exogenous shocks during business cycles (Bernanke and Gertler, 1995; Bernanke et al., 1999; Hubbard, 1998). Thus, it is intuitive to relate imperfect capital markets to stock market dynamics. To explore this possibility, we follow existing studies, such as Bernanke and Gertler (1995), Bernanke et al. (1999), and Carlstrom and Fuerst (1997), in measuring the changing conditions of credit markets using the external finance premium (EFP). This is because the literature regards the EFP as a key indicator of credit market imperfections. In brief, as the probability that borrowers will default increases, lenders will charge a higher premium to compensate for the greater default risk, and the EFP will rise. Clearly, the increased risk of borrowers defaulting coincides with a more pessimistic economic outlook, which tends to suppress the stock market. That is, changes in the EFP may have significant power to predict stock markets.

Compared with the voluminous literature on the predictability of stock returns, few studies explore the predictability of bear markets, particularly using financial variables and measures of EFP. Accordingly, our paper focuses on examining the predictability of bear markets, employing a measure of EFP in addition to other financial and macroeconomic variables.

Using US data from 1952M1 to 2011M12, we consider 14 stock return predictors as potential candidates for predicting bear markets. The variables we consider comprise several valuation ratios (including the dividend–price and earnings–price ratios and dividend yield), a number of variables related to corporate and equity market activity (the book-to-market and dividend–payout ratios, net equity expansion, and stock return variance), and a macro variable (inflation). We also specify a range of interest rate-related variables, including both short- and long-term interest rates and the term spread (Treasury bill rates, long-term bond yields, long-term bond returns, and the term spread). Finally, we also consider the default risk premium as a proxy for the EFP (default yield spread and default returns).[1] Given that existing empirical studies suggest that the cyclical variations in the US stock market are well characterized by Markov switching (MS) models (Maheu and McCurdy, 2000; Perez-Quiros and Timmermann, 2000), we identify bear markets by extracting the filtered probabilities using a two-state MS autoregressive (AR) model of aggregate returns. We then use predictive regression to investigate whether we are able to predict bear markets using various financial variables.

We conduct both in-sample and out-of-sample tests of predictability to evaluate forecasting performance. We find that among the variables investigated, the default yield spread, as measured by Baa-rated corporate bond yields minus Aaa-rated corporate bond yields, performs well in predicting bear markets, especially at horizons of one to three months. To compare our results with Chen (2009), we also implement non-nested tests. The results of these tests also demonstrate that the EFP yields better short-term market predictability than the term spread and inflation. On the other hand, inflation and the term spread best predict bear markets at medium to long horizons. Our findings therefore suggest that including the EFP, such as in the form of

[1] In the present analysis, we predict bear markets using monthly data exclusively. Recently, some studies have focused on linking the macroeconomy and financial markets and constructing new predictors of stock returns. Most of these assume the presence of a long-term cointegrating relationship between macroeconomic variables, including labor income, consumption, and asset wealth. For instance, Lettau and Ludvigson (2001) propose the prediction of stock returns using the consumption–wealth ratio. Lettau and Ludvigson (2005) employ a similar concept to construct the consumption–dividend ratio. Lastly, Lustig and Van Nieuwerburgh (2005) suggest the use of housing collateral to predict stock returns, as measured by the long-term cointegrating relationship between housing and human wealth. In general, there is now evidence that these variables are useful when predicting stock returns. However, monthly data are not available.

the default yield spread, which is generally perceived to be a measure of the credit conditions faced by firms, can significantly enhance the predictability of bear markets. This is also reminiscent of past findings that the EFP of firms helps explain asset market movements (Bernanke and Gertler, 1995).

To check for robustness, we apply different measures of bear stock markets. In particular, we use the nonparametric method proposed by Candelon et al. (2008) to obtain an indicator series showing periods of bear market. We also consider multivariate regression specifications and an alternative measure of the EFP– TED spread (the difference between the interest rates on interbank loans and short-term US government debt). Our results remain robust. That is, different measures of EFP all perform well as leading indicators of bear markets.

The remainder of the paper is structured as follows. Section 2 introduces the list of predictors used to forecast bear markets. Section 3 explains the sources of data and the statistical properties of these time series. Section 4 presents a MS model and shows how this model identifies bear market periods. Sections 5 and 6 document our main findings on the predictability of bear markets. Section 7 provides the robustness checks, while Section 8 details the economic significance of predictions of bear markets. Finally, Section 9 offers some concluding remarks.

2. Potential Predictors

We consider 14 predictors of bear markets, including financial and macroeconomic variables and measures of the EFP. A brief explanation of these predictors follows.

Dividend–Price Ratio and Dividend Yield The log dividend–price ratio was first proposed by Campbell and Shiller (1988). They show that the log dividend–price ratio dp can be written as:

$$dp \equiv d_t - p_t = \overline{dp} + E_t \sum_{j=0}^{\infty} \rho^j [(r_{t+j} - \overline{r}) - (\Delta d_{t+j} - \overline{d})], \tag{1}$$

where d_t is the log dividends paid on the stock, p_t is the log of the stock price, and r_t is the log stock return at time t, and ρ denotes the discount factor. Finally, the mean of the log dividend–price ratio $\overline{dp}$ is a function of the growth rate of log dividends $\overline{d}$ and expected log return $\overline{r}$ in the steady state:

$$\overline{dp} = \log(\exp(\overline{r}) - \exp(\overline{d})) - \overline{d}.$$

According to equation (1), the dividend–price ratio is high when it is expected that the future log stock return r_t will be high or the future dividend growth rates Δd_t will be low.

In addition to the dividend–price ratio, we include a variant often used in the literature: namely, the log dividend–yield ratio. This is calculated by subtracting the log of the lagged stock price from the log dividend, i.e., $d_t - p_{t-1}$.

Earnings–Price Ratio Another valuation ratio often used in the literature is the earnings–price ratio (ep), as derived from a dynamic Gordon growth model. Assuming that companies pay out a constant proportion of earnings as dividends, the earnings–price ratio can be expressed as in equation (1), except that dividends are replaced by earnings. This assumption relies on the observation made by Lintner (1965) that corporations have a certain target payout ratio, and that variations in the earnings–price ratio should predict expected stock returns.

Dividend–Payout Ratio Lamont (1998) argues that the ratio of dividends to earnings is a good predictor of excess returns because high dividends typically forecast high returns, whereas high earnings typically forecast low returns. Hence, an increases in the dividend–payout ratio is associated with a high probability of a bear market.

Stock Variance Goyal and Welch (2008) and Guo (2006) show that the variance of stock returns predicts the future equity premium. That is, an increase in the variance of stock returns indicates an increase in the future volatility of the stock market and a high probability of bear markets.

Book-to-Market Ratio Lewellen (1999) and Kothari and Shanken (1997) show that an aggregate book-to-market ratio predicts stock returns. Pontiff and Schall (1998) argue that this is because the book value proxies for expected cash flows; i.e., the book-to-market ratio is the ratio of a cash flow proxy to the current price level. Holding expected cash flow constant, a decrease in market value leads to an increase in the book-to-market ratio. This explains the positive relation between the current book-to-market ratio and future stock returns.

Net Equity Expansion Net equity issuing activity refers to initial public offerings (IPOs), seasoned equity offerings (SEOs), and stock repurchases minus distributed dividends, which is closely related to the net payout yield proposed by Boudoukh et al. (2007) and Goyal and Welch (2008) as a predictor of future stock returns.

Inflation The inflation rate has been investigated extensively in empirical literature (Fama, 1981; Rapach et al., 2005). Chen (2009) also finds that the inflation rate, apart from the term spread, is useful in predicting bear markets.

Treasury Bill Rate Campbell (1991) and Hodrick (1992) show that the Treasury bill rate is able to forecast future stock returns. In this paper, we specify the three-month Treasury bill rate.

Long-Term Yield, Long-Term Return, and Term Spread We follow Goyal and Welch (2008) and Rapach and Zhou (2012) and also consider long-term government bond yields and long-term government bond returns as predictors. The difference between the long-term yield and the Treasury bill rate is the term spread, which has been widely used in stock return forecasting exercises (See, for example Ang and Bekaert, 2007; Campbell and Yogo, 2006; Fama and French, 1989; Keim and Stambaugh, 1986; Pontiff and Schall, 1998). In particular, Chen (2009) finds this to be significant in predicting bear markets.

Default Yield Spread and Default Return Spread Fama and French (1989) show that the default yield spread, which is the spread between the yields on low- and high-grade corporate bonds, is a good predictor of long-horizon stock returns. The intuition is that the default yield spread not only proxies the EFP required by outside investors but also serves as a good indicator of general business conditions, and hence should be able to capture any long-term business cycle variation in stock returns. In this paper, we also follow Goyal and Welch (2008) and include a similar predictor, namely the default return spread, which is defined as the difference in returns between a long-term corporate bond and a long-term government bond.

3. Data

The monthly data used in this paper spans the period from 1952M1 to 2011M12. We use CRSP value-weighted returns to proxy the aggregate stock returns. The CRSP Index (which includes the NYSE, AMEX, and NASDAQ markets) provides a better proxy for US stock market returns because it is a much broader measure of market behavior than the Standard & Poor (S&P) Index.[2]

The dividend–price ratio dp is calculated using the log of a 12-month moving sum of the CRSP dividends minus the log of the CRSP value-weighted (VW) stock index (imputed from the CRSP-VW returns, including dividends). For the dividend yield, we use the log of a 12-month moving sum of dividends minus the log of the lagged CRSP value-weighted stock index.

To calculate the earnings–price ratio ep, we use the log of a 12-month moving sum of

[2] The data on the stock return predictors are mostly available on Amit Goyal's Web page at `http://www.hec.unil.ch/agoyal/`, with the exception of some series obtained from the CRSP database and the Board of Governors of the US Federal Reserve. The data and their sources are described in detail in Goyal and Welch (2008).

earnings per share on the S&P 500 Index minus the log of the S&P Composite Index. The dividend–payout ratio *de* is also measured based on data from the S&P 500 Index. We use the log of a 12-month moving sum of dividends minus the log of a 12-month moving sum of earnings.

Stock variance *svar* is measured by the monthly sum of squared daily returns on the S&P 500 Index. The book-to-market ratio *bm* is the ratio of book value to market value for the Dow Jones Industrial Average (DJIA).

Net equity expansion *ntis* is the ratio of the 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks. The amount of net equity issues (IPOs, SEOs, and stock repurchases, less dividends) for NYSE-listed stocks is computed from the CRSP data as:

$$\text{net equity issues} = \text{MCAP}_t - \text{MCAP}_{t-1} \times (1 + \text{vwretx}_t),$$

where MCAP_t is the total market capitalization, and vwretx_t is the value-weighted return (excluding dividends) on the NYSE Index.

The inflation rate $infl$ is calculated using the Consumer Price Index (All Urban Consumers) from the Bureau of Labor Statistics. We use one-month lagged inflation to measure the inflation rate to account for any delays in the release of the CPI.

The three-month Treasury bill yield tbl is obtained from the Board of Governors of the US Federal Reserve. As constant maturity rates are available only from 1982 onward, we follow Estrella and Trubin (2006) and use the secondary market three-month rates (which is on a discount basis) and express these on a bond-equivalent basis. Specifically:

$$r = \frac{365 \times r^d/100}{360 - 91 \times r^d/100} \times 100,$$

where r^d is the three-month discount rate, and r is the bond-equivalent rate.

The long-term government bond yield lty is from Ibbotson's *Stocks, Bonds, Bills, and Inflation Yearbook*. The same source also provides long-term government bond returns ltr. The term spread tms is the difference between the ten-year yield on Treasury bonds and the three-month Treasury bill rate.

Finally, the default yield spread dfy is constructed using the difference between Moody's Baa-rated corporate bond rate and the Aaa-rated corporate bond rate, while the default return spread dfr is measured by the difference in returns between long-term corporate bonds and long-term government bonds.

Among the predictors investigated, the unit root test results indicate that the null hypotheses of nonstationarity are not rejected for dp, dy, bm, tbl, and lty. To avoid the problem of nonstationarity in tbl and lty, we follow the suggestions by Campbell (1991) and Hodrick (1992) and use interest rates minus their respective 12-month moving averages to obtain a "relative Treasury bill rate" ($rrel$) and a "relative long-term bond yield" ($rlty$), so as to remove the stochastic trends in tbl and lty. As for dp, dy, and bm, we follow Lettau and Van Nieuwerburgh (2008) and correct for structural breaks in the means of dp, dy, and bm, and use the deviations of dp, dy, and bm from their time-varying means to predict bear markets; we denote these deviations as $\widetilde{dp}$, $\widetilde{dy}$, and $\widetilde{bm}$, respectively, henceforth. The appendix provides details on the construction of $\widetilde{dp}$, $\widetilde{dy}$, and $\widetilde{bm}$ using the method suggested by Lettau and Van Nieuwerburgh (2008).

Finally, we run Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests on each of the time series we employ. The results are presented in Table 1. Clearly, the null hypothesis of a unit root process is rejected for all series.

4. Identifying Bull and Bear Markets

Following Maheu and McCurdy (2000), Frauendorfer et al. (2007), and Chen (2009), we identify busts (bears) and booms (bulls) in the stock market using an MS approach. We consider a two-state MS-AR model of stock returns with lag length p (MS-AR(p)) as follows:

$$R_t = \alpha_{S_t} + \phi_1(R_{t-1} - \alpha_{S_{t-1}}) + \cdots + \phi_p(R_{t-p} - \alpha_{S_{t-p}}) + u_t, u_t \sim N(0, \sigma^2_{S_t}), \qquad (2)$$

where

$$\alpha_{S_t} = \alpha_0(1 - S_t) + \alpha_1 S_t,$$

and

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

The unobserved state variable S_t is a latent dummy variable taking a value of either 0 or 1, indicating a bear or bull market in stock returns, respectively. α_{S_t} and σ_{S_t} are the state-dependent mean and standard deviation of R_t, respectively. That is, the mean and standard deviation are (α_0, σ_0) for bear markets and (α_1, σ_1) for bull markets. Finally, the parameters $(\phi_1, \ldots, \phi_p)$ capture the autoregressive components of stock returns.

Furthermore, the transition probability matrix of the MS model is assumed to be time invariant and is expressed as follows:

$$P = \begin{bmatrix} P_{00} & 1 - P_{11} \\ 1 - P_{00} & P_{11} \end{bmatrix},$$

where

$$P_{00} = P(S_t = 0 | S_t = 0) = \frac{\exp(\theta_0)}{1 + \exp(\theta_0)},$$

$$P_{11} = P(S_t = 1|S_t = 1) = \frac{\exp(\theta_1)}{1+\exp(\theta_1)}.$$

We use the information criterion proposed by Psaradakis and Spagnolo (2003) to determine the optimal lag length p of the MS-AR(p) model in equation (2). According to the Psaradakis–Spagnolo Akaike information criterion (AIC) and Bayesian information criterion (BIC) presented in Table 2, the lag length is taken to be $p = 1$. Moreover, although we specify a two-state MS model to identify the bear and bull markets, it is possible that a third market state (regime) may exist, such as a huge bear or bull market. Again we compute the information criterion proposed by Psaradakis and Spagnolo (2003) to determine the optimal number of states. The AIC and BIC are 4081.09 and 4140.55, respectively, for the three-state MS-AR(1) model, while the AIC and BIC are 4074.16 and 4106.18, respectively, for the two-state MS-AR(1) model. Clearly, the MS-AR(1) model with two regimes is chosen via the information criterion.

The estimation results using the MS-AR(1) model are presented in Table 3. The results indicate that the MS-AR(1) model identifies a regime with a higher mean ($\mu_1 = 1.327$) and lower standard deviation ($\sigma_1 = 3.101$) and a regime with a lower mean ($\mu_0 = 0.267$) and larger standard deviation ($\sigma_0 = 5.771$). We identify the former as a bull market and the latter as a bear market. This result resembles the findings in Maheu and McCurdy (2000) in their investigation of CRSP returns.

Once we have statistically identified the bear and bull markets, we calculate the filtered probabilities of each state as follows:

$$Q_{j,t} = P(S_t = j|\Omega^t), j = \{0,1\}, \tag{3}$$

where Ω^t denotes the information set at time t. For example, the filtered probability $Q_{0,t} = P(S_t = 0|y^t)$ is an estimate of the probability of a bear market at time t. Figure 1 displays the estimated filtered probabilities based on the MS-AR(1) model.

5. Predictive Regression and In-Sample Tests

After obtaining the filtered probability of a bear market from equation (2), we follow Chen (2009) and consider the following predictive regression:

$$Q_{0,t+k} = \alpha + \beta x_t + e_{t+k}, \tag{4}$$

where $Q_{0,t+k}$ is the bear market probability at a horizon k months ahead, and x_t is the predictor under investigation.

The in-sample test for the predictability of future bear markets investigates the forecasting power of x_t in equation (4). Table 4 reports the estimates of β, p-values based on Newey–West-corrected t-statistics, and the adjusted R^2 (denoted as $\overline{R}^2$). The in-sample predictive power is measured at horizons of 1, 3, 6, 12, and 24 months.

We summarize the empirical findings as follows. First, the valuation ratios, such as $\widetilde{dp}$, ep, and $\widetilde{bm}$, have no predictive power at any horizon. [3] Second, the estimates of equity risk, such as *svar*, predict bear markets at $k = 1,3,6,12$. Third, inflation also predicts bear markets at $k = 1,3,6,12$ months. This concurs with the finding in Chen (2009) that the inflation rate is a good leading indicator of bear markets. Finally, most of the interest rate spread variables predict bear markets. For instance, the default yield spread predicts bear markets at horizons of $k = 1,3,6,12$ months. The term spread predicts bear markets at long horizons, such as $k = 12,24$. According to the adjusted R^2, the default yield spread has better goodness-of-fit at short horizons, while the term spread is more powerful in forecasting future bear markets at long horizons.

[3] We also used the original series for the dividend–price ratio, dividend yield, and book-to-market ratio, and these results are also not significant.

It is worth noting that according to Table 4, the sign of the estimates of β also generally accords with the economic intuition. For instance, $svar$, dfy, and $infl$ are positively associated with future bear markets, implying that an increase in stock market volatility, default risk, or inflation raises the likelihood of a future recession in the stock market. On the other hand, tms is negatively correlated with future bear markets, [4] which implies that when the long-term bond supply increases due to expected future expansion in the stock market, long-term bond yields will rise and therefore the probability of a future bear market will decrease. Overall, our in-sample results show that most of our predictors, including stock variance, long-term government bond returns, default yield spread, and inflation, have good predictive power for bear markets.

6. Out-of-Sample Tests

6.1. Nested Forecast Comparisons

As a first step, we conduct out-of-sample tests by making forecast comparisons for the nested models. That is, we compare the mean squared prediction error (MSPE) from an unrestricted model that includes the predictor under investigation with that from a restricted benchmark model that excludes this same variable. Thus, the unrestricted model nests the benchmark model. Specifically, the nested models are as follows:

$$\text{restricted model: } Q_{0,t+k} = \alpha_1 + \varepsilon_{1t},$$

$$\text{unrestricted model: } Q_{0,t+k} = \alpha_2 + \beta x_t + \varepsilon_{2t}.$$

[4] In Chen (2009), the term spread is defined as the difference between the short- and long-term interest rates. Thus, the term spreads in Chen (2009) are positively correlated with future bear markets.

It is clear that the unrestricted model nests the restricted model under the no-predictability null, $\beta = 0$. We may conclude that x_t is a useful predictor in out-of-sample tests if the predictive ability of the unrestricted model is better than that of the restricted model. Let $MSPE_u$ be the error for the unrestricted model and let $MSPE_r$ be the error for the restricted model. Then $MSPE_u/MSPE_r < 1$ indicates that the unrestricted model performs better in forecasting $Q_{0,t+k}$; that is, x_t has predictive power for future bear markets.

To evaluate the out-of-sample forecasting performance, we conduct out-of-sample forecasts at horizons k months ahead. First, we divide the total sample of T observations into in-sample and out-of-sample periods. Let there be R in-sample and P out-of-sample observations. The out-of-sample forecasts of $Q_{0,t+k}$ for the restricted and unrestricted models are $\hat{Q}^1_{0,t+k}$ and $\hat{Q}^2_{0,t+k}$, respectively, and $\hat{e}^1_{t+k}$ and $\hat{e}^2_{t+k}$ are the corresponding forecast errors for these two models. To test whether the unrestricted model outperforms the restricted model, we compute the mean square error-adjusted statistic proposed by Clark and West (2007) as follows:

$$\text{CW} = \frac{\overline{f}}{\sqrt{V/P}},$$

where $\overline{f} = P^{-1}\sum_{t=R+1}^{T} \hat{f}_{t+k}$, $\hat{f}_{t+k} = (\hat{e}^1_{t+k})^2 - [(\hat{e}^2_{t+k})^2 - (\hat{Q}^1_{0,t+k} - \hat{Q}^2_{0,t+k})^2]$, and V is the sample variance of $\hat{f}_{t+k} - \overline{f}$. The Clark–West test is an approximately normal test for equal predictive accuracy in nested models. The null hypothesis specifies equal MSPEs for these two models, while the alternative is that the unrestricted model has a smaller MSPE than the restricted model.

We set the out-of-sample period to be 1965M1–2011M12, corresponding to a period when $P/R \approx 4$, as identified by Clark and West (2007) in their empirical analysis of the US stock market.[5] We then use recursive regressions to reestimate the forecasting model and calculate a series of forecasts k months ahead. Table 5 provides the results for the out-of-sample tests,

[5]We specified several different P/R ratios: P/R=3, 2, and 1. The results are not reported here but are available upon request.

including the Clark–West MSPE-adjusted statistics and the corresponding asymptotic p-values.

As shown in the table, $\widetilde{dp}$ and $\widetilde{dy}$ predict future bear markets one and three months ahead. For the other predictors, the out-of-sample test results are similar to those of the in-sample tests. The exception is *svar*, which shows no predictive power at any horizon. It is worth noting that the default yield spread displays statistically significant out-of-sample predictive power at short horizons (less than six months), whereas inflation and term spread deliver significant out-of-sample predictive power at short and medium ($k = 1, 6, 12$) and long horizons (12 months and longer). Overall, our empirical results show that among the tested predictors, the dividend–price ratio and default yield spread predict bear markets well in out-of-sample tests.

6.2. Non-Nested Forecast Comparisons

The out-of-sample Clark–West test results in the preceding section show that most financial variables are able to predict bear markets. It is of interest to see which predictors have smaller mean square errors at different forecasting horizons. In doing so, we test the equality of the MSPEs using the modified Diebold–Mariano (MDM) test proposed by Harvey et al. (1998), which is a version of the Diebold and Mariano (1995) test statistic modified to account for finite-sample bias. Let $\hat{e}^j_{t+k}$ denote the forecasting errors of the "competing model" j, and let $\hat{e}^i_{t+k}$ denote the forecasting errors of the "preferred model" i. We express the MDM test statistic as follows:

$$\text{MDM} = h \cdot \frac{\overline{d}}{\sqrt{\hat{\Omega}}},$$

where $h = [p + 1 - 2k + p^{-1}k(k-1)]^{1/2}$, k is the forecasting horizon, $\overline{d} = p^{-1}\sum_{t=R+1}^{T}\hat{d}_{t+k}$, $\hat{d}_{t+k} = (\hat{e}^j_{t+k})^2 - (\hat{e}^i_{t+k})^2$, and $\hat{\Omega}$ is a consistent estimator of the long-term variance of $d_t = (\hat{e}^j_t)^2 - (\hat{e}^i_t)^2$. The MDM statistic aims to evaluate whether the difference in prediction errors between the "competitive model" and "preferred model" is correlated with the prediction error of the model encompassed under the null, and the statistic is compared with the critical values from a t distribution with $p-1$ degrees of freedom.

For each forecasting horizon k, we select a combination of two models from $\{dfy, tms, infl\}$, so that in total there are three pairs of models for the non-nested tests. The reason for choosing $\{dfy, tms, infl\}$ is that dfy exhibits superior predictive power according to the Clark–West test, and therefore it is of interest to compare its forecasting performance with that of tms and $infl$, which are considered to be useful predictors of bear markets (Chen, 2009). For this purpose, we denote the model with the smaller MSPE as the "preferred model" (model i), such that the null hypothesis is that the "competitor model" (model j) encompasses the preferred model, and the alternative hypothesis is that the preferred model contains information that could have improved the forecasts of the competitor model. Specifically:

$$H_0: \text{ MSPE of model } i = \text{MSPE of model } j,$$

$$H_1: \text{ MSPE of model } j > \text{MSPE of model } i.$$

Therefore, a significantly positive MDM statistic implies that the preferred model has better predictive power.

We report the ratios of the MSPEs of models i and j, the MDM statistics, and the associated asymptotic p-values in Table 6. At k = 1 and 3, the tests indicate that dfy contains information that produces forecasts superior to those of tms and $infl$, and these findings are statistically significant at the 10% level.[6] This demonstrates that the default yield spread has superior predictive power for bear markets at short horizons. At $k = 12, 24$, tms produces the smallest MSPE, and this indicates that the term spread has superior predictive power at long horizons. However,

[6]We also considered other potential variables, such as $\widetilde{dp}$, as candidate competitor models. However, the MDM tests indicate that no predictors can encompass dfy at $k = 1$ and 3. The results are not reported here but are available upon request.

the MDM test statistics indicate that there is no significant difference between tms and dfy or between tms and $infl$. Overall, our out-of-sample non-nested test results suggest that using the default yield spread to forecast bear markets at short horizons would consistently yield forecasts superior to those delivered using other popular forecasting variables. Conversely, inflation and the term spread have better predictive power at medium and long horizons.

7. Robustness Checks

7.1. Smoothing Probability

To check for robustness, we also measure the probabilities of bear markets by computing the smoothing probabilities:

$$Q_{j,t} = \Pr(s_t = j|\Omega_T), j = \{1,2\},$$

where Ω_T denotes the information set at time T. That is, it is the posteriori probability given that all sample observations are available. The idea is that we compute the probability of being in a certain state of the economy from an *ex post* point of view, and thus the full set of information is utilized. The smoothing probability is plotted in Figure 2.

Tables 7 and 8 present the in-sample and out-sample results, respectively. The results presented closely resemble those obtained in Tables 4 and 5. Moreover, $infl$ has predictive power at all the horizons we investigated, and dfy has significant predictive power at horizons $k = 1,3,6,12$. The results of the non-nested out-of-sample tests are presented in Table 9, and as before, the default yield spread still stands out as the best predictor at $k = 1,3$, which suggests that our main empirical results are robust.

7.2. Other Stock Market Indicators

We use S&P 500 returns for an additional robustness check. First, we obtain the S&P 500 stock returns following Chen (2009):

$$R_t = 100 \times (p_t - p_{t-1}),$$

where p_t is the log of the S&P 500 Index. The in-sample and out-of-sample results for the S&P 500 stock returns are reported in Tables 10, 11, and 12. [7] As shown, our empirical results remain intact, and dfy continues to outperform the other predictors at short horizons. The only difference from our previous results is that the out-of-sample performance of $infl$ turns out to be insignificant in predicting bear markets.

7.3. Bootstrapping Out-of-Sample Statistics

Our benchmark out-of-sample Clark–West test results for predictive power are based on the asymptotic critical values assuming a normal distribution, as suggested by Clark and West (2007). However, Rogoff and Stavrakeva (2008) criticize the asymptotic Clark–West test on the grounds that it may yield overestimates when using a recursive scheme. We thus compute bootstrapped p-values.

We follow Rapach et al. (2005) and obtain the bootstrapped p-values of the Clark–West statistic. The data are generated by the following system under the null hypothesis of no predictive power for the bear market probabilities $Q_{0,t}$:

$$Q_{0,t} = a_0 + e_{1t}, \tag{5}$$

[7] We use the dividends paid on the S&P 500 Index to construct $\widetilde{dp}$ and $\widetilde{dy}$ here.

and the data-generating process of the predictor x_t:

$$x_t = b_0 + b_1 x_{1t} + \cdots + b_p x_{t-p} + e_{2t}, \tag{6}$$

where $(e_{1t}, e_{2t})'$ is i.i.d. with covariance matrix Ω. We first estimate equations (5) and (6) using ordinary least squares (OLS), where the lag order p in equation (6) is selected using the AIC. We then obtain the OLS residuals, $\{\hat{e}_{1t}, \hat{e}_{2t}\}_{t=1}^{t-p}$. In order to generate a series of disturbances for our pseudo-sample, we randomly draw (with replacement) $T+100$ times from the OLS residuals $\{\hat{e}_{1t}, \hat{e}_{2t}\}_{t=1}^{T-p}$, giving us a pseudo-series of disturbance terms $\{\hat{e}^*_{1t}, \hat{e}^*_{2t}\}_{t=1}^{T+100}$. Note that we draw from the OLS residuals in tandem, thus preserving the contemporaneous correlation between the disturbances in the original sample. We denote the OLS estimate of a_0 in equation (5) by $\hat{a}_0$ and denote the OLS estimate of in equation (6) by $\{\hat{b}_0, \hat{b}_1, \cdots \hat{b}_p\}$. Using $\{\hat{e}^*_{1t}, \hat{e}^*_{2t}\}_{t=1}^{T+100}$ and $\{\hat{a}_0, \hat{b}_0, \hat{b}_1, \cdots \hat{b}_p\}$ in equations (5) and (6), we can build up a bootstrapped sample of $T+100$ observations, $\{Q^*_t, x^*_t\}_{t=1}^{T+100}$. We drop the first 100 transient startup observations, which leaves us with a bootstrapped sample of T observations, matching the original sample size. Finally, we calculate the out-of-sample Clark–West statistics for each bootstrapped sample.

The out-of-sample Clark–West test results based on the bootstrapped p-values are reported in Table 13. Clearly, the results do not change our conclusions about significance when we apply the bootstrapping method in calculating the p-values. This indicates that our benchmark out-of-sample Clark–West test results are robust with respect to the bootstrapped distribution. We also apply a similar bootstrapping procedure to the MDM statistics for the non-nested out-of-sample tests. The results are reported in Table 14. Clearly, the bootstrapped p-values yield similar conclusions, which suggests that our main results concerning the out-of-sample predictability tests are robust with respect to the bootstrapping method.

7.4. Multivariate Regression

In the previous sections, we examined the predictive power of the predictors individually, and the out-of-sample test results indicate that dfy strongly predicts bear markets at short horizons while tms predicts bear markets at long horizons. It is of interest to question whether a regression including many predictors could improve the accuracy of forecasts at the different horizons. For this purpose, we consider a multivariate regression that includes several predictors as explanatory variables to see whether we can improve the accuracy.

Table 15 provides the out-of-sample results from multivariate predictive regressions that include a number of variables discussed in Section 4 thought to have predictive power for bear markets. Specifically, the upper panel presents the results based on the multivariate regression models specifying dfy as an explanatory variable. We consider three sets of predictors: $\{dfy, tms\}$, $\{dfy, tms, infl\}$, and $\{dfy, tms, infl, ntis, \widetilde{dp}\}$. The lower panel shows the empirical results of the models excluding dfy as an explanatory variable, and in this case we consider $\{tms, infl\}$ and $\{tms, infl, ntis, \widetilde{dp}\}$.

Clearly, the MSPEs of the models including dfy are always lower than those of the restricted model at $k = 1, 3, 6, 12$. Moreover, the results indicate that the multivariate regressions including dfy predict bear markets at $k = 1, 3, 6, 12, 24$ based on the Clark–West test. For the models excluding dfy, predictive power is insignificant at $k = 3, 6$. Our results thus demonstrate that including dfy as a predictor can significantly improve the out-of-sample predictability of bear markets, especially at short horizons.

7.5. Nonparametric Approach to Dating Bear Markets

We follow Candelon et al. (2008) and Chen (2009) and use an alternative nonparametric approach to identify bull and bear markets. Candelon et al. (2008) and Chen (2009) use a Bry–

Boschan dating algorithm to identify the local maxima and minima of the log of the stock price index as peaks and troughs, and then a bull (bear) market period is identified as the period between the trough (peak) and the next peak (trough). This definition implies that the stock market has transitioned from a bull (bear) market to a bear (bull) market if prices have declined (increased) for a substantial period since their previous peak (trough).

We identify the (local) peaks and troughs by choosing a window of six months. Let p_t denote the log of stock prices. The peaks and troughs are identified as follows:

$$\text{Peak} = [p_{t-6}, \cdots p_{t-1}, < p_t > p_{t+1}, \cdots, p_{t+6}],$$

$$\text{Trough} = [p_{t-6}, \cdots p_{t-1}, > p_t < p_{t+1}, \cdots, p_{t+6}].$$

Once the peaks and troughs are obtained, let I_t be a binary dummy variable that indicates a bust or boom in the stock market, and then define the peak-to-trough and trough-to-peak periods as the bear ($I_t = 1$) and bull ($I_t = 0$) markets, respectively. We then employ the following probit model to evaluate the predictability of the bear market:

$$\Pr(I_{t+k} = 1) = F(\alpha + \beta x_t). \tag{7}$$

To measure the in-sample goodness-of-fit of the probit model, we follow Estrella and Mishkin (1998) and compute the pseudo-R^2 developed by Estrella (1998). Let L_u and L_r be the likelihoods yielded by the unrestricted model and the restricted model, respectively. The statistic is given by:

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

The in-sample results, including p-values based on the Newey–West-corrected t-statistics and pseudo-R^2,[8] are given in Table 16. As shown, dfy predicts bear markets at $k = 1$ and $k = 24$, while $infl$ predicts bear markets at $k = 1, 3, 6$. The only difference from our previous results is that tms becomes an insignificant predictor, as it has no particular predictive power when k is greater than one month.

To evaluate the out-of-sample forecasting performance of the probit model, we use the quadratic probability score (QPS) and log probability score (LPS) proposed by Diebold and Rudebusch (1989) as follows:

$$QPS = \frac{1}{P} \sum_{t=R+1}^{T} 2[\hat{\Pr}(I_{t+k} = 1) - I_{t+k}]^2,$$

$$LPS = \frac{1}{P} \sum_{t=R+1}^{T} [(1 - I_t)\ln(1 - \hat{\Pr}(I_{t+k})) + I_t \ln(\hat{\Pr}(I_{t+k} = 1))],$$

where $\hat{\Pr}(I_{t+k} = 1) = F(\hat{\alpha} + \hat{\beta} x_t)$ denotes the expected probability of a bear market. Notice that the QPS and LPS range from 0 to 2 and from 0 to ∞, respectively. A score of zero for both the QPS and LPS indicates that the probit model has perfect predictive accuracy. Lower values of QPS and LPS indicate the better predictability of the model.

Tables 17 and 18 report the QPS and LPS for different predictors. As shown, all of the scores are less than one, which suggests that the predictors under investigation have good predictive power. The results indicate that $rlty$ has the smallest QPS and LPS at $k = 1, 3, 24$.

It is worth noting that the values of the QPS and LPS are very close across the different predictors. Hence, we adopt the MDM test to compare the predictive accuracies of dfy, $infl$, and tms at $k = 1, 3, 24$ using $rlty$ as the benchmark, and the results are reported in Table 19. Clearly, we fail to reject the null hypothesis of equal forecasting accuracy at most horizons. Nevertheless, we could interpret the overall result as indicating no significant difference between

[8] The details of our calculations of the Newey–West standard errors in the probit model are discussed in Estrella and Mishkin (1998).

$\{dfy, infl, tms\}$ and $rlty$ in terms of out-of-sample predictive power when the bear market is dated using the Bry–Boschan method.

7.6. An Alternative Measure of the EFP: The TED Spread

So far, our empirical results indicate that the default yield spread has superior predictive power for bear markets, particularly at short horizons. In the literature, the default yield spread is closely related to the notion of the EFP, which is considered to be a measure of the default risk premium and hence a reflection of the credit market conditions faced by nonfinancial firms.

In this section, we consider an alternative measure of credit market conditions: the TED spread, TED. In general, TED reflects the credit market liquidity conditions faced by banks: a rising TED often indicates a tight credit market as liquidity is being withdrawn, and this is linked with a higher probability of a bear market.

We measure the TED spread by taking the difference between the interest rate for the three-month London Interbank Offering Rate (LIBOR) and the three-month US Treasury bill rates, from 1971M1 to 2011M12. The in-sample and out-of-sample prediction results, based on the filtered probabilities obtained from the CRSP-VW returns, are presented in Table 20. Clearly, both the in-sample and out-of-sample test results suggest that TED predicts bear markets at all the horizons investigated. To sum up, our empirical findings demonstrate that proxies for EFP are also useful for predicting bear markets.

8. Implementing the Regime-Switching Trading Strategy Based on Predicted Bear Markets

In this section, we further investigate whether predicting bear markets is useful for investors seeking profitable opportunities.

We consider the regime-switching investment strategy discussed in Pesaran and Timmermann (1995) and Chen (2009), by which investors invest all funds in three-month Treasury bonds if the probability of a bear market one month ahead is more than 30%; otherwise, they invest all funds in the S&P500 Index. This regime-switching strategy would be ideal for institutional investors, e.g., pension funds and mutual funds, which would like to exploit market conditions but at the same time prefer to trade in high-liquidity securities. The probabilities of bear markets are obtained by recursively forecasting the probability of a bear market at a horizon of one month based on the predictors we investigated. Table 21 shows the terminal values of a $1 investment over the period from 1965M1 to 2011M12 and the monthly compound returns. Investing $1 in the S&P500 Index (a buy-and-hold strategy) would yield $15.648 and a monthly compound return of 0.483%. On the other hand, a switching strategy based on bear market prediction models with different predictors would yield higher terminal wealth and compound returns in general, and the forecasts based on $svar$, dfy, and $infl$ yield much better results in terms of terminal wealth and compounded returns. This result demonstrates the usefulness of predicting bear markets, which in turn supports the economic significance of the identified predictors.

9. Conclusion

In this paper, we revisit bear market predictability using a number of financial variables widely employed in stock return forecasting. In particular, we focus on the forecasting power of the EFP, such as the default yield spread and the default return spread, as the EFP is the key indicator of the extent of credit market imperfections and should therefore be related to stock market dynamics. We find that the default yield spread has good predictive power for bear markets, particularly at short horizons. We find that these results are robust with respect to different specifications, including different measures of bear markets (such as the measures based on the S&P 500 Index), different econometric specifications (such as the probit model), and an alternative measure of the EFP (the TED spread). We have shown that it is important to consider measures of the credit market conditions in predicting stock markets, especially for investors implementing trading strategies and for monetary authorities responsible for financial market stabilization.

Appendix

This appendix details how we construct the adjusted series for the dividend–price ratio, dividend yields, and book-to-market ratio using the method proposed by Lettau and Van Nieuwerburgh (2008).

In equation (1), Lettau and Van Nieuwerburgh (2008) show evidence of the breaks in the constant mean $\overline{dp}$. That is, if either the steady-state growth rate $\overline{d}$ or expected return $\overline{r}$ were to change, the effects on the dividend–price ratio and their stochastic relationships with returns would be profound, and this means the dividend–price ratio becomes very persistent. For this reason, Lettau and Van Nieuwerburgh (2008) consider the dividend–price ratio with a time-varying mean as follows:

$$dp_t \equiv d_t - p_t = \overline{dp_t} + E_t \sum_{j=1}^{\infty} \rho_t^{j-1} [(r_{t+j} - \overline{r}_t) - (\Delta d_{t+j} - \overline{d}_t)], \tag{8}$$

where $\rho_t = (1 + \exp(\overline{dp}_t))^{-1}$. In equation (8), the dividend–price ratio varies over time and is nonstationary. For instance, when the steady-state growth rate permanently increases, the steady-state dividend–price ratio decreases, and the current dividend–price ratio declines permanently. However, even though the dividend–price ratio in equation (8) is nonstationary, Lettau and Van Nieuwerburgh (2008) show that deviations in $dp_t =$ from its time-varying steady state, $dp_t - \overline{dp}_t$, are stationary as long as the deviations in dividend growth and returns from their respective steady states are also stationary. Lettau and Van Nieuwerburgh (2008) then provide evidence that the deviations of dp_t from the time-varying mean have much stronger forecasting power for stock market returns than does the original dividend–price ratio given in equation (1).

To construct the adjusted dividend–price ratio $\widetilde{dp}_t = dp_t - \overline{dp}_t$, the adjusted dividend yield $\widetilde{dy} = dy_t - \overline{dy}_t$, and the book-to-market ratio $\widetilde{bm} = bm_t - \overline{bm}_t$, we first apply the structural break test proposed by Bai and Perron (1998) to dp, dy, and bm. By setting the maximum number of breaks to five, we obtain the test results based on the sup-F test statistics given in Table 22. It is worth noting that all the sup-F statistics in Table 22 are significant at the 1% level, which suggests that the null hypothesis of four breaks (against the alternative of five breaks) is rejected. However, the null of four breaks is not rejected (the data are not shown in the table but are available upon request), and we conclude that four breaks in the mean of dp, dy, and bm are statistically significant.

Given the break dates τ_1, τ_2, τ_3, and τ_4, we can construct the adjusted series by subtracting the mean in the corresponding subsamples. Using the dividend–price ratio as an illustration, the adjusted dividend–price ratio $\widetilde{dp}$ is:

$$\widetilde{dp} \equiv \widetilde{dp}_t = \begin{cases} dp_t - \overline{dp}_1, \text{ for } t = 1, \cdots, \tau_1 \\ dp_t - \overline{dp}_2, \text{ for } t = \tau_1 + 1, \cdots, \tau_2 \\ dp_t - \overline{dp}_3, \text{ for } t = \tau_2 + 1, \cdots, \tau_3 \\ dp_t - \overline{dp}_4, \text{ for } t = \tau_3 + 1, \cdots, \tau_4 \\ dp_t - \overline{dp}_5, \text{ for } t = \tau_4 + 1, \cdots, T, \end{cases}$$

where $\overline{dp}_i, i = 1, \ldots, 5$ are the sample means for the corresponding subsamples. The method described above can be applied to dy and bm, and the calculation is straightforward.

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Figure 1: Filtered Probabilities Based on the MS-AR(1) Model of CRSP Value-Weighted Returns

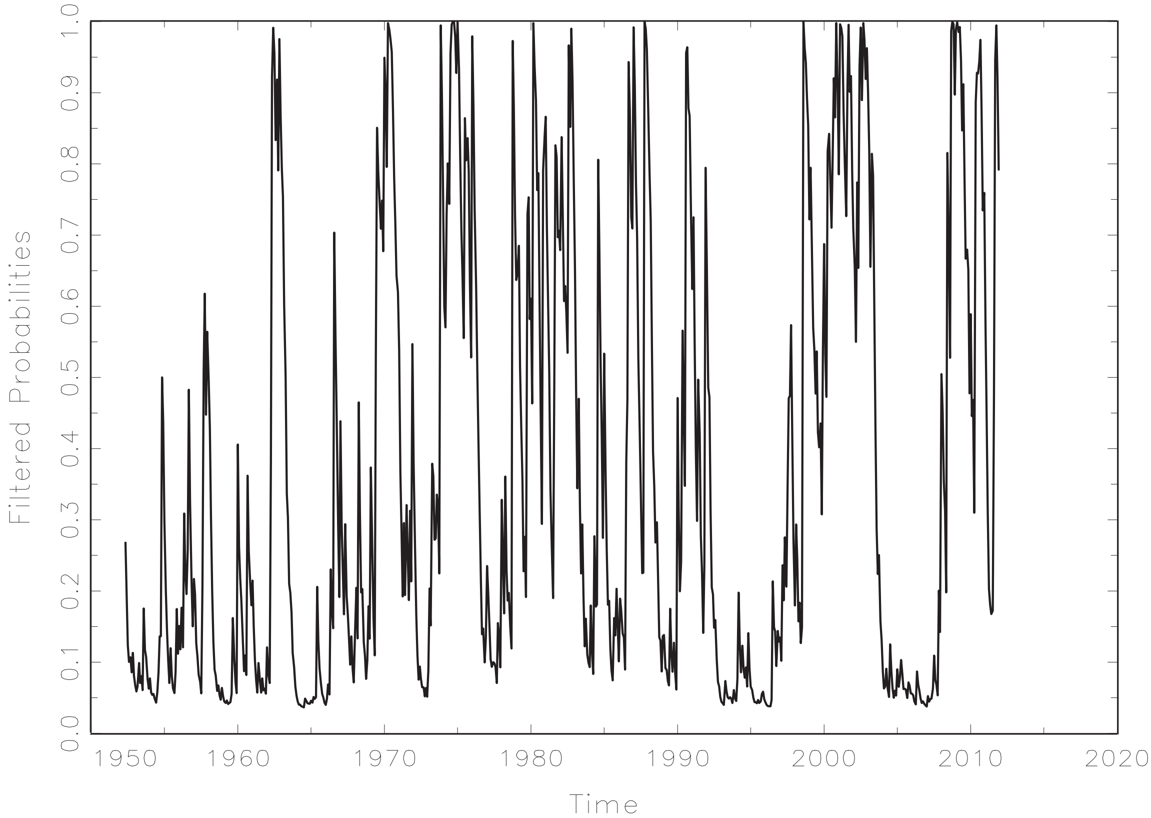

Figure 2: Smoothing Probabilities Based on the MS-AR(1) Model of CRSP Value-Weighted Returns

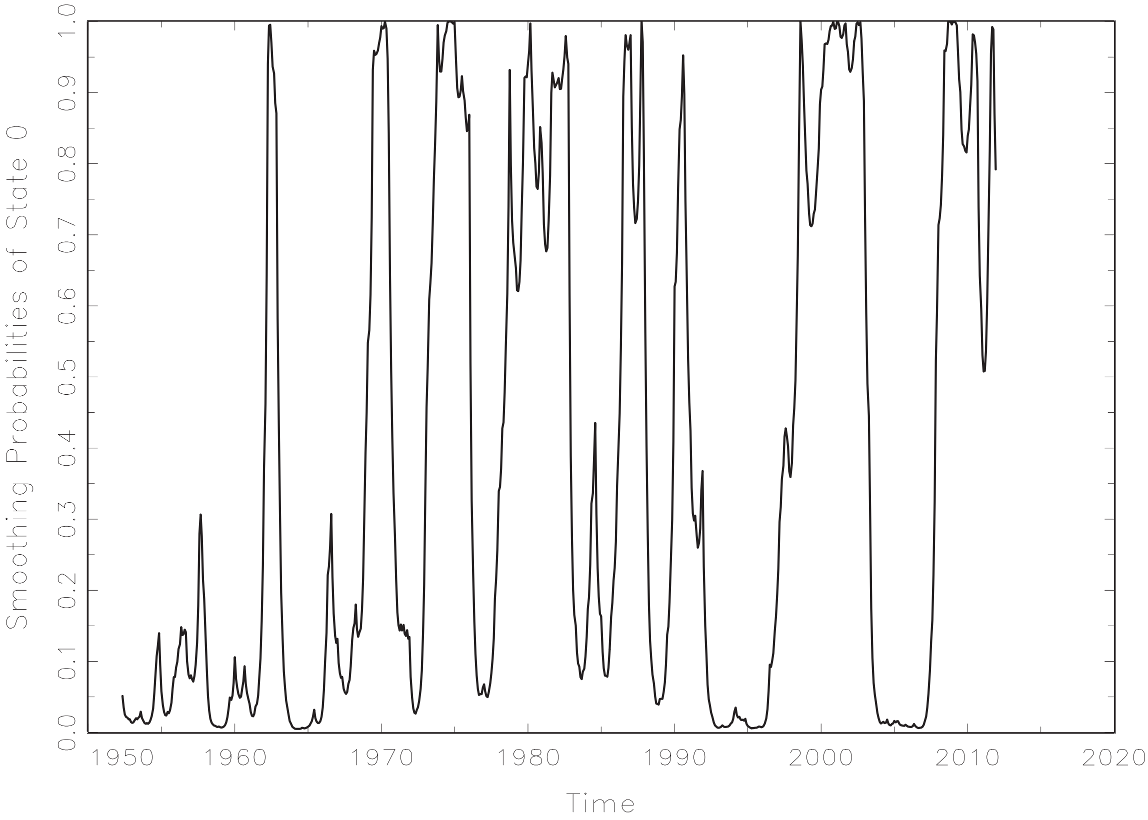

Table 1: Unit Root Tests

	ADF	PP
$\widetilde{dp}$	-4.249	-4.493
$\widetilde{dy}$	-4.291	-4.546
ep	-2.631	-3.408
de	-4.175	-4.349
$\widetilde{bm}$	-2.984	-4.245
$svar$	-4.590	-17.126
$ntis$	-3.142	-3.769
$infl$	-2.701	-15.089
$rrel$	-5.101	-6.005
$rlty$	-7.136	-7.513
ltr	-6.884	-25.602
tms	-3.237	-4.089
dfy	-3.117	-3.882
dfr	-29.196	-29.304

Note: All statistics are significant at the 10% level or above.

Table 2: AIC and BIC Values of Two-State Markov Switching Models

	Lag length				
	0	1	2	3	4
AIC	4096.44	**4074.16**	4075.36	4077.31	4078.93
BIC	4123.92	**4106.18**	4111.95	4118.47	4124.67

Note: Bold type indicates the smallest values among the MS-AR(p) models we investigated.

Table 3: Estimation Results for the MS-AR(1) Model

Parameters	μ_0	μ_1	σ_0	σ_1	ϕ_1	P_{00}	P_{11}	LogLik
	0.267	1.327	5.771	3.101	0.043	0.946	0.967	-2030.082
	(0.572)	(**0.000**)	(**0.000**)	(**0.000**)	(0.308)	(**0.000**)	(**0.000**)	

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above. *LokLik* indicates the likelihood values of MS-AR(1) model.

Table 4: In-Sample Predictability Results: Dependent Variable is Measured by the Filtered Probabilities Obtained from the Markov-Switching Autoregressive Model Based on CRSP Value-Weighted Returns

		k=1	k=3	k=6	k=12	k=24
$\widetilde{dp}$	$\hat{\beta}$	0.113	0.093	0.041	-0.020	-0.126
	p-value	(0.208)	(0.308)	(0.652)	(0.846)	(0.234)
	$\overline{R}^2$	[0.020]	[0.013]	[0.001]	[-0.001]	[0.026]
$\widetilde{dy}$	$\hat{\beta}$	0.098	0.077	0.027	-0.025	-0.122
	p-value	(0.271)	(0.395)	(0.764)	(0.807)	(0.247)
	$\overline{R}^2$	[0.015]	[0.009]	[0.000]	[0.000]	[0.024]
ep	$\hat{\beta}$	-0.075	-0.075	-0.077	-0.093	-0.009
	p-value	(0.566)	(0.553)	(0.531)	(0.434)	(0.931)
	$\overline{R}^2$	[0.009]	[0.009]	[0.009]	[0.014]	[-0.001]
de	$\hat{\beta}$	0.102	0.066	0.003	-0.050	-0.270
	p-value	(0.489)	(0.660)	(0.984)	(0.757)	(0.126)
	$\overline{R}^2$	[0.008]	[0.002]	[-0.001]	[0.001]	[0.060]
$\widetilde{bm}$	$\hat{\beta}$	0.007	-0.058	-0.164	-0.282	-0.265
	p-value	(0.980)	(0.830)	(0.503)	(0.178)	(0.151)
	$\overline{R}^2$	[-0.001]	[0.000]	[0.009]	[0.029]	[0.025]
$svar$	$\hat{\beta}$	31.848	28.508	22.423	11.005	6.492
	p-value	(**0.001**)	(**0.001**)	(**0.004**)	(**0.079**)	(0.239)
	$\overline{R}^2$	[0.168]	[0.134]	[0.080]	[0.018]	[0.006]
$ntis$	$\hat{\beta}$	-2.249	-2.333	-2.737	-3.860	-4.916
	p-value	(**0.001**)	(0.100)	(0.146)	(**0.030**)	(**0.000**)
	$\overline{R}^2$	[0.015]	[0.016]	[0.023]	[0.048]	[0.079]
$infl$	$\hat{\beta}$	15.448	19.476	22.338	19.586	9.536
	p-value	(**0.001**)	(**0.007**)	(**0.003**)	(**0.005**)	(0.186)
	$\overline{R}^2$	[0.026]	[0.043]	[0.056]	[0.043]	[0.009]
$rrel$	$\hat{\beta}$	-6.189	-4.331	-3.043	1.116	2.968
	p-value	(**0.076**)	(0.189)	(0.353)	(0.789)	(0.360)
	$\overline{R}^2$	[0.030]	[0.014]	[0.006]	[0.000]	[0.006]
$rlty$	$\hat{\beta}$	-0.058	4.418	9.359	7.500	-1.707
	p-value	(0.992)	(0.369)	(**0.060**)	(0.258)	(0.789)
	$\overline{R}^2$	[-0.001]	[0.004]	[0.021]	[0.013]	[-0.001]
ltr	$\hat{\beta}$	0.906	0.954	-0.346	-0.258	0.324
	p-value	(**0.066**)	(**0.045**)	(0.389)	(0.507)	(0.588)
	$\overline{R}^2$	[0.005]	[0.006]	[-0.001]	[-0.001]	[-0.001]
tms	$\hat{\beta}$	0.640	-0.424	-1.419	-4.601	-5.128
	p-value	(0.475)	(0.811)	(0.544)	(**0.068**)	(**0.032**)
	$\overline{R}^2$	[-0.001]	[-0.001]	[0.003]	[0.041]	[0.050]
dfy	$\hat{\beta}$	34.486	29.867	23.310	12.847	4.451
	p-value	(**0.000**)	(**0.000**)	(**0.000**)	(**0.031**)	(0.474)
	$\overline{R}^2$	[0.240]	[0.180]	[0.109]	[0.032]	[0.003]
dfr	$\hat{\beta}$	-0.330	-0.914	-1.023	-0.154	-1.315
	p-value	(0.776)	(0.379)	(0.234)	(0.881)	(0.146)
	$\overline{R}^2$	[-0.001]	[0.000]	[0.000]	[-0.001]	[0.002]

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above.

Table 5: Nested Out-of-Sample Predictability Test Results: Dependent Variable is Measured by the Filtered Probabilities Obtained from the Markov-Switching Autoregressive Model Based on CRSP Value-Weighted Returns

		k=1	k=3	k=6	k=12	k=24
$\widetilde{dp}$	$MSPE_u/MSPE_r$	0.979	0.991	1.008	1.025	1.022
	CW-stat	2.744	1.299	-1.502	-5.683	-0.934
	p-value	(**0.003**)	(**0.097**)	(0.934)	(1.000)	(0.825)
$\widetilde{dy}$	$MSPE_u/MSPE_r$	0.985	0.995	1.010	1.025	1.023
	CW-stat	2.272	0.892	-2.147	-5.300	-0.966
	p-value	(**0.012**)	(0.186)	(0.984)	(1.000)	(0.833)
ep	$MSPE_u/MSPE_r$	0.996	1.017	1.043	1.090	1.128
	CW-stat	0.210	-0.665	-2.295	-4.721	-6.839
	p-value	(0.417)	(0.747)	(0.989)	(1.000)	(1.000)
de	$MSPE_u/MSPE_r$	0.999	1.036	1.077	1.180	1.136
	CW-stat	0.991	-0.741	-2.362	-3.521	-1.321
	p-value	(0.161)	(0.771)	(0.991)	(1.000)	(0.907)
$\widetilde{bm}$	$MSPE_u/MSPE_r$	1.003	1.011	1.013	1.004	1.004
	CW-stat	-0.583	-1.405	-1.135	-0.074	-0.062
	p-value	(0.720)	(0.920)	(0.872)	(0.529)	(0.525)
$svar$	$MSPE_u/MSPE_r$	1.618	1.386	1.318	1.127	1.007
	CW-stat	-0.373	-0.364	-0.709	-0.906	-1.932
	p-value	(0.645)	(0.642)	(0.761)	(0.818)	(0.973)
$ntis$	$MSPE_u/MSPE_r$	0.991	1.017	1.037	1.025	0.954
	CW-stat	1.368	-0.763	-1.460	-1.052	2.947
	p-value	(**0.086**)	(0.777)	(0.928)	(0.854)	(**0.002**)
$infl$	$MSPE_u/MSPE_r$	0.975	0.968	0.955	0.981	1.013
	CW-stat	2.431	0.831	1.444	1.551	-0.221
	p-value	(**0.008**)	(0.203)	(**0.074**)	(**0.060**)	(0.587)
$rrel$	$MSPE_u/MSPE_r$	0.970	1.000	1.023	1.039	1.040
	CW-stat	4.563	0.052	-1.289	-1.540	-2.793
	p-value	(**0.000**)	(0.479)	(0.901)	(0.938)	(0.997)
$rlty$	$MSPE_u/MSPE_r$	1.014	1.021	1.023	1.037	1.104
	CW-stat	-0.721	0.409	-0.602	-1.045	-5.229
	p-value	(0.765)	(0.341)	(0.726)	(0.852)	(1.000)
ltr	$MSPE_u/MSPE_r$	1.001	0.999	1.002	1.03	1.010
	CW-stat	0.210	3.007	-0.278	-0.532	-1.502
	p-value	(0.417)	(**0.001**)	(0.610)	(0.702)	(0.934)
tms	$MSPE_u/MSPE_r$	1.006	1.017	1.021	0.967	0.979
	CW-stat	-0.248	-0.532	0.323	6.566	21.161
	p-value	(0.634)	(0.847)	(0.821)	(**0.000**)	(**0.000**)
dfy	$MSPE_u/MSPE_r$	0.740	0.812	0.900	0.996	1.048
	CW-stat	10.153	7.183	4.913	0.357	-3.169
	p-value	(**0.000**)	(**0.000**)	(**0.000**)	(0.360)	(0.999)
dfr	$MSPE_u/MSPE_r$	1.007	1.002	1.002	1.004	1.001
	CW-stat	-2.012	-0.247	-0.267	-0.827	1.072
	p-value	(0.978)	(0.597)	(0.605)	(0.796)	(0.142)

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above.

Table 6: Non-Nested Out-of-Sample Tests Comparison: Dependent Variable is Measured by the Filtered Probabilities Obtained from the Markov-Switching Autoregressive Model Based on CRSP Value-Weighted Returns

		$k=1$		
$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.745	dfy	tms	5.745	**0.000**
0.766	dfy	$infl$	5.301	**0.000**
0.973	$infl$	tms	0.814	0.208
		$k=3$		
$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.808	dfy	tms	2.069	**0.019**
0.845	dfy	$infl$	1.724	**0.043**
0.956	$infl$	tms	0.618	0.269
		$k=6$		
$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.889	dfy	tms	0.965	0.167
0.948	dfy	$infl$	0.503	0.308
0.938	$infl$	tms	0.716	0.237
		$k=12$		
$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.967	tms	dfy	0.313	0.377
0.988	$infl$	dfy	0.169	0.433
0.979	tms	$infl$	0.309	0.379
		$k=24$		
$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.935	tms	dfy	0.984	0.163
0.969	$infl$	dfy	0.579	0.282
0.965	tms	$infl$	0.549	0.291

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above.

Table 7: In-Sample Results: Dependent Variable is Measured by the Smoothing Probabilities Obtained from the Markov-Switching Autoregressive Model Based on CRSP Value-Weighted Returns

		k=1	k=3	k=6	k=12	k=24
$\widetilde{dp}$	$\hat{\beta}$	0.105	0.073	0.025	-0.022	-0.136
	p-value	(0.314)	(0.464)	(0.778)	(0.787)	(0.205)
	$\overline{R}^2$	[0.012]	[0.005]	[-0.001]	[-0.001]	[0.021]
$\widetilde{dy}$	$\hat{\beta}$	0.087	0.056	0.014	-0.025	-0.131
	p-value	(0.402)	(0.574)	(0.879)	(0.754)	(0.219)
	$\overline{R}^2$	[0.008]	[0.002]	[-0.001]	[-0.001]	[0.020]
ep	$\hat{\beta}$	-0.094	-0.101	-0.108	-0.098	-0.018
	p-value	(0.677)	(0.646)	(0.607)	(0.605)	(0.893)
	$\overline{R}^2$	[0.010]	[0.012]	[0.014]	[0.011]	[-0.001]
de	$\hat{\beta}$	0.001	-0.030	-0.078	-0.155	-0.330
	p-value	(0.995)	(0.887)	(0.733)	(0.561)	(0.226)
	$\overline{R}^2$	[-0.001]	[-0.001]	[0.002]	[0.013]	[0.064]
$\widetilde{bm}$	$\hat{\beta}$	-0.127	-0.199	-0.295	-0.332	-0.257
	p-value	(0.702)	(0.519)	(0.281)	(0.171)	(0.112)
	$\overline{R}^2$	[0.003]	[0.009]	[0.022]	[0.028]	[0.017]
$svar$	$\hat{\beta}$	33.168	27.735	21.153	14.173	6.446
	p-value	(**0.001**)	(**0.006**)	(**0.033**)	(0.101)	(0.238)
	$\overline{R}^2$	[0.130]	[0.090]	[0.051]	[0.022]	[0.003]
$ntis$	$\hat{\beta}$	-3.708	-4.120	-4.881	-6.459	-5.882
	p-value	(**0.044**)	(**0.037**)	(**0.026**)	(**0.004**)	(**0.010**)
	$\overline{R}^2$	[0.031]	[0.038]	[0.055]	[0.097]	[0.081]
$infl$	$\hat{\beta}$	29.737	30.726	30.498	26.522	17.109
	p-value	(**0.039**)	(**0.029**)	(**0.020**)	(**0.041**)	(**0.064**)
	$\overline{R}^2$	[0.072]	[0.077]	[0.076]	[0.057]	[0.023]
$rrel$	$\hat{\beta}$	-3.652	-1.895	-0.209	3.195	3.550
	p-value	(0.537)	(0.768)	(0.976)	(0.650)	(0.302)
	$\overline{R}^2$	[0.007]	[0.001]	[-0.001]	[0.005]	[0.006]
$rlty$	$\hat{\beta}$	8.817	11.191	10.584	4.344	1.697
	p-value	(0.296)	(0.175)	(0.221)	(0.631)	(0.666)
	$\overline{R}^2$	[0.013]	[0.022]	[0.019]	[0.002]	[-0.001]
ltr	$\hat{\beta}$	0.530	0.195	-0.271	-0.098	0.305
	p-value	(0.368)	(0.770)	(0.577)	(0.841)	(0.538)
	$\overline{R}^2$	[0.000]	[-0.001]	[-0.001]	[-0.001]	[-0.001]
tms	$\hat{\beta}$	-0.037	-0.052	-0.070	-0.095	-0.052
	p-value	(**0.001**)	(**0.031**)	(**0.025**)	(**0.005**)	(0.181)
	$\overline{R}^2$	[0.014]	[0.029]	[0.054]	[0.100]	[0.027]
dfy	$\hat{\beta}$	37.133	31.897	25.690	15.987	7.732
	p-value	(**0.000**)	(**0.000**)	(**0.000**)	(**0.095**)	(0.383)
	$\overline{R}^2$	[0.198]	[0.146]	[0.095]	[0.036]	[0.007]
dfr	$\hat{\beta}$	-1.056	-1.324	-1.144	-0.852	-0.625
	p-value	(**0.001**)	(**0.000**)	(**0.037**)	(0.219)	(0.385)
	$\overline{R}^2$	[0.000]	[0.001]	[0.000]	[0.000]	[-0.001]

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above.

Table 8: Nested Out-of-Sample Predictability Test Results: Dependent Variable is Measured by the Smoothing Probabilities Obtained from the Markov-Switching Autoregressive Model Based on CRSP Value-Weighted Returns

		k=1	k=3	k=6	k=12	k=24
$\widetilde{dp}$	$MSPE_u/MSPE_r$	0.990	1.003	1.018	1.037	1.049
	CW-stat	1.518	-0.390	-3.457	-5.866	-2.044
	p-value	(**0.065**)	(0.652)	(1.000)	(1.000)	(0.980)
$\widetilde{dy}$	$MSPE_u/MSPE_r$	0.994	1.005	1.019	1.038	1.049
	CW-stat	1.069	-0.791	-3.598	-5.748	-2.064
	p-value	(0.143)	(0.785)	(1.000)	(1.000)	(0.980)
ep	$MSPE_u/MSPE_r$	0.998	1.023	1.062	1.128	1.188
	CW-stat	0.123	-0.832	-2.763	-4.974	-7.822
	p-value	(0.451)	(0.797)	(0.997)	(1.000)	(1.000)
de	$MSPE_u/MSPE_r$	1.012	1.056	1.131	1.282	1.221
	CW-stat	-0.315	-1.310	-2.289	-2.554	-1.385
	p-value	(0.623)	(0.905)	(0.989)	(0.995)	(0.917)
$\widetilde{bm}$	$MSPE_u/MSPE_r$	1.001	1.004	1.003	1.013	1.019
	CW-stat	-0.020	0.085	-0.145	-0.579	-1.403
	p-value	(0.508)	(0.466)	(0.558)	(0.719)	(0.920)
$svar$	$MSPE_u/MSPE_r$	1.458	1.353	1.245	1.094	1.010
	CW-stat	-0.367	-0.485	-0.766	-1.005	-1.550
	p-value	(0.643)	(0.686)	(0.778)	(0.843)	(0.939)
$ntis$	$MSPE_u/MSPE_r$	0.975	0.993	1.007	0.975	1.008
	CW-stat	2.252	0.305	-0.185	1.530	-0.167
	p-value	(**0.012**)	(0.380)	(0.573)	(**0.063**)	(0.566)
$infl$	$MSPE_u/MSPE_r$	0.927	0.931	0.938	0.967	0.996
	CW-stat	4.979	1.549	1.814	1.855	0.999
	p-value	(**0.000**)	(**0.061**)	(**0.035**)	(**0.032**)	(0.159)
$rrel$	$MSPE_u/MSPE_r$	0.998	1.023	1.040	1.031	1.038
	CW-stat	0.089	-0.918	-1.311	-1.059	-2.832
	p-value	(0.465)	(0.821)	(0.905)	(0.855)	(0.998)
$rlty$	$MSPE_u/MSPE_r$	0.994	1.006	1.035	1.059	1.072
	CW-stat	1.558	3.220	-0.870	-1.790	-4.619
	p-value	(**0.060**)	(**0.001**)	(0.808)	(0.963)	(1.000)
ltr	$MSPE_u/MSPE_r$	1.007	1.005	1.003	1.003	1.007
	CW-stat	-1.813	-1.238	-0.542	-0.621	-0.730
	p-value	(0.965)	(0.892)	(0.706)	(0.733)	(0.767)
tms	$MSPE_u/MSPE_r$	0.989	0.990	0.983	0.969	1.046
	CW-stat	0.465	0.507	3.350	8.970	8.180
	p-value	(0.321)	(0.306)	(**0.000**)	(**0.000**)	(**0.000**)
dfy	$MSPE_u/MSPE_r$	0.790	0.859	0.935	1.021	1.088
	CW-stat	9.153	5.543	2.890	-1.013	-3.023
	p-value	(**0.000**)	(**0.000**)	(**0.002**)	(0.844)	(0.999)
dfr	$MSPE_u/MSPE_r$	1.005	1.001	1.003	1.002	1.001
	CW-stat	2.629	0.039	-0.448	0.988	1.079
	p-value	(**0.004**)	(0.484)	(0.673)	(0.162)	(0.140)

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above.

Table 9: Non-Nested Out-of-Sample Predictability Comparison: Dependent Variable is Measured by the Smoothing Probabilities Obtained from the Markov-Switching Autoregressive Model Based on CRSP Value-Weighted Returns

$k = 1$				
$\text{MSPE}_i/\text{MSPE}_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.808	dfy	tms	3.725	**0.000**
0.859	dfy	$infl$	2.698	**0.004**
0.941	$infl$	tms	1.271	0.102
$k = 3$				
$\text{MSPE}_i/\text{MSPE}_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.877	dfy	tms	1.142	0.127
0.929	dfy	$infl$	0.677	0.249
0.944	$infl$	tms	0.649	0.258
$k = 6$				
$\text{MSPE}_i/\text{MSPE}_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.960	dfy	tms	0.288	0.387
0.998	$infl$	dfy	0.014	0.495
0.958	$infl$	tms	0.429	0.334
$k = 12$				
$\text{MSPE}_i/\text{MSPE}_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.944	tms	dfy	0.451	0.326
0.948	$infl$	dfy	0.524	0.300
0.995	tms	$infl$	0.047	0.481
$k = 24$				
$\text{MSPE}_i/\text{MSPE}_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.962	tms	dfy	0.354	0.362
0.920	$infl$	dfy	0.912	0.181
0.957	$infl$	tms	0.538	0.296

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above.

Table 10: In-Sample Predictability Results: Dependent Variable is Measured by the Filtered Probabilities Obtained from the Markov-Switching Autoregressive Model Based on Changes in the S&P 500 Composite Index

		k=1	k=3	k=6	k=12	k=24
$\widetilde{dp}$	$\hat{\beta}$	0.339	0.172	0.021	-0.094	-0.209
	p-value	(**0.073**)	(0.348)	(0.898)	(0.547)	(0.171)
	$\overline{R}^2$	[0.057]	[0.014]	[-0.001]	[0.003]	[0.020]
$\widetilde{dy}$	$\hat{\beta}$	0.243	0.122	-0.004	-0.104	-0.187
	p-value	(0.186)	(0.495)	(0.979)	(0.510)	(0.218)
	$\overline{R}^2$	[0.029]	[0.006]	[-0.001]	[0.004]	[0.016]
ep	$\hat{\beta}$	-0.063	-0.064	-0.063	-0.088	-0.036
	p-value	(0.356)	(0.287)	(0.260)	(**0.074**)	(0.443)
	$\overline{R}^2$	[0.012]	[0.012]	[0.012]	[0.025]	[0.003]
de	$\hat{\beta}$	0.095	0.036	-0.036	-0.034	-0.157
	p-value	(0.263)	(0.629)	(0.560)	(0.679)	(0.128)
	$\overline{R}^2$	[0.013]	[0.001]	[0.001]	[0.000]	[0.036]
$\widetilde{bm}$	$\hat{\beta}$	0.122	-0.013	-0.140	-0.201	-0.194
	p-value	(0.431)	(0.924)	(0.185)	(**0.045**)	(**0.085**)
	$\overline{R}^2$	[0.009]	[-0.001]	[0.012]	[0.026]	[0.025]
$svar$	$\hat{\beta}$	28.444	20.287	11.736	2.208	1.503
	p-value	(**0.000**)	(**0.000**)	(**0.014**)	(0.466)	(0.529)
	$\overline{R}^2$	[0.247]	[0.124]	[0.040]	[0.000]	[-0.001]
$ntis$	$\hat{\beta}$	-1.704	-1.919	-2.394	-2.455	-2.734
	p-value	(0.251)	(0.198)	(0.103)	(**0.038**)	(**0.011**)
	$\overline{R}^2$	[0.016]	[0.021]	[0.033]	[0.035]	[0.044]
$infl$	$\hat{\beta}$	5.352	6.855	9.697	7.088	0.694
	p-value	(0.452)	(0.301)	(**0.066**)	(**0.082**)	(0.788)
	$\overline{R}^2$	[0.005]	[0.009]	[0.019]	[0.009]	[-0.001]
$rrel$	$\hat{\beta}$	-3.113	-1.970	-1.488	-0.123	1.519
	p-value	(0.133)	(0.312)	(0.498)	(0.962)	(0.301)
	$\overline{R}^2$	[0.013]	[0.005]	[0.002]	[-0.001]	[0.002]
$rlty$	$\hat{\beta}$	-0.632	2.309	4.957	0.670	-1.623
	p-value	(0.860)	(0.426)	(0.138)	(0.822)	(0.544)
	$\overline{R}^2$	[-0.001]	[0.001]	[0.010]	[-0.001]	[0.000]
ltr	$\hat{\beta}$	0.681	0.854	-0.571	-0.069	0.350
	p-value	(**0.056**)	(**0.018**)	(**0.029**)	(0.780)	(0.334)
	$\overline{R}^2$	[0.005]	[0.009]	[0.003]	[-0.001]	[0.000]
tms	$\hat{\beta}$	-0.004	-0.010	-0.016	-0.034	-0.026
	p-value	(0.578)	(0.482)	(0.369)	(**0.037**)	(0.153)
	$\overline{R}^2$	[-0.001]	[0.002]	[0.006]	[0.031]	[0.018]
dfy	$\hat{\beta}$	16.375	11.921	6.435	1.217	0.260
	p-value	(**0.001**)	(**0.011**)	(**0.081**)	(0.703)	(0.926)
	$\overline{R}^2$	[0.099]	[0.052]	[0.014]	[-0.001]	[-0.001]
dfr	$\hat{\beta}$	-1.386	-1.838	-1.316	0.283	-0.431
	p-value	(**0.021**)	(**0.001**)	(**0.032**)	(0.709)	(0.585)
	$\overline{R}^2$	[0.005]	[0.010]	[0.004]	[-0.001]	[-0.001]

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above.

Table 11: Out-of-Sample Predictability Test Results: Dependent Variable is Measured by the Filtered Probabilities Obtained from the Markov-Switching Autoregressive Model Based on Changes in the S&P 500 Composite Index

		k=1	k=3	k=6	k=12	k=24
$\widetilde{dp}$	$MSPE_u/MSPE_r$	0.940	0.998	1.021	1.019	1.013
	CW-stat	6.011	3.853	-3.459	-2.600	2.202
	p-value	(**0.000**)	(**0.000**)	(1.000)	(0.995)	(**0.014**)
$\widetilde{dy}$	$MSPE_u/MSPE_r$	0.971	1.006	1.021	1.017	1.017
	CW-stat	4.631	0.170	-3.389	-1.808	2.214
	p-value	(**0.000**)	(0.433)	(1.000)	(0.965)	(**0.013**)
ep	$MSPE_u/MSPE_r$	0.993	1.013	1.028	1.013	1.041
	CW-stat	0.376	-0.690	-2.814	-1.068	-4.762
	p-value	(0.354)	(0.755)	(0.998)	(0.857)	(1.000)
de	$MSPE_u/MSPE_r$	0.995	1.037	1.047	1.111	1.067
	CW-stat	1.648	-1.295	-2.200	-3.633	-1.156
	p-value	(**0.050**)	(0.902)	(0.986)	(1.000)	(0.876)
$\widetilde{bm}$	$MSPE_u/MSPE_r$	0.991	1.010	1.000	0.988	0.997
	CW-stat	2.167	-1.677	0.061	1.292	0.574
	p-value	(**0.015**)	(0.953)	(0.476)	(**0.098**)	(0.283)
$svar$	$MSPE_u/MSPE_r$	1.415	1.079	1.100	1.040	1.006
	CW-stat	-0.003	0.324	-0.654	-1.433	-1.718
	p-value	(0.501)	(0.373)	(0.743)	(0.924)	(0.957)
$ntis$	$MSPE_u/MSPE_r$	0.996	1.013	1.018	1.017	0.995
	CW-stat	1.429	-0.744	-0.820	-0.793	0.616
	p-value	(**0.077**)	(0.772)	(0.794)	(0.786)	(0.269)
$infl$	$MSPE_u/MSPE_r$	1.003	1.013	1.002	1.018	1.006
	CW-stat	0.335	-0.413	0.055	-0.889	-1.727
	p-value	(0.369)	(0.660)	(0.478)	(0.813)	(0.958)
$rrel$	$MSPE_u/MSPE_r$	0.988	1.004	1.017	1.036	1.030
	CW-stat	2.374	-0.414	-1.321	-1.857	-3.430
	p-value	(**0.009**)	(0.661)	(0.907)	(0.968)	(1.000)
$rlty$	$MSPE_u/MSPE_r$	1.009	1.013	1.030	1.027	1.043
	CW-stat	-0.485	0.169	-0.867	-1.514	-3.058
	p-value	(0.686)	(0.433)	(0.807)	(0.935)	(0.999)
ltr	$MSPE_u/MSPE_r$	1.000	0.995	1.000	1.002	1.011
	CW-stat	0.442	4.926	0.230	-0.692	-0.442
	p-value	(0.329)	(**0.000**)	(0.409)	(0.756)	(0.671)
tms	$MSPE_u/MSPE_r$	1.006	1.017	1.027	1.009	1.009
	CW-stat	-0.336	-0.627	-0.349	2.835	9.196
	p-value	(0.631)	(0.735)	(0.636)	(**0.002**)	(**0.000**)
dfy	$MSPE_u/MSPE_r$	0.897	0.959	1.002	1.011	1.034
	CW-stat	5.027	3.027	0.150	-5.368	-3.437
	p-value	(**0.000**)	(**0.001**)	(0.441)	(1.000)	(1.000)
dfr	$MSPE_u/MSPE_r$	1.002	0.994	1.000	1.005	1.006
	CW-stat	11.578	1.081	0.351	-1.193	-1.350
	p-value	(**0.000**)	(0.140)	(0.363)	(0.884)	(0.912)

Note: The numbers in parentheses are *p*-values. Bold type indicates significance at the 10% level or above.

Table 12: Non-Nested Out-of-Sample Predictability Comparison: Dependent Variable is Measured by the Filtered Probabilities Obtained from the Markov-Switching Autoregressive Model Based on the S&P 500 Composite Index

$k=1$				
$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.896	dfy	tms	3.194	**0.001**
0.901	dfy	$infl$	2.116	**0.017**
0.995	$infl$	tms	0.149	0.441
$k=3$				
$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.945	dfy	tms	1.066	0.143
0.952	dfy	$infl$	0.713	0.238
0.992	$infl$	tms	0.156	0.438
$k=6$				
$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.974	dfy	tms	0.485	0.314
0.993	$infl$	dfy	0.170	0.432
0.967	$infl$	tms	0.770	0.221
$k=12$				
$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.996	dfy	tms	0.112	0.455
0.993	dfy	$infl$	0.212	0.416
0.997	tms	$infl$	0.090	0.464
$k=24$				
$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
0.980	tms	dfy	0.659	0.255
0.978	$infl$	dfy	1.059	0.145
0.998	$infl$	tms	0.087	0.465

Note: Bold type indicates significance at the 10% level or above.

Table 13: Nested Out-of-Sample Predictability Test Results with Bootstrapped p-values: Dependent Variable is Measured by the Filtered Probabilities Obtained from the Markov-Switching Autoregressive Model Based on CRSP Value-Weighted Returns

		k=1	k=3	k=6	k=12	k=24
$\widetilde{dp}$	$MSPE_u/MSPE_r$	0.979	0.991	1.008	1.025	1.022
	CW-stat	2.744	1.299	-1.502	-5.683	-0.934
	p-value	(**0.015**)	(**0.055**)	(0.745)	(1.000)	(0.519)
$\widetilde{dy}$	$MSPE_u/MSPE_r$	0.985	0.995	1.010	1.025	1.023
	CW-stat	2.272	0.892	-2.147	-5.300	-0.966
	p-value	(**0.021**)	(**0.069**)	(0.943)	(1.000)	(0.521)
ep	$MSPE_u/MSPE_r$	0.996	1.017	1.043	1.090	1.128
	CW-stat	0.210	-0.665	-2.295	-4.721	-6.839
	p-value	(0.158)	(0.385)	(0.953)	(1.000)	(1.000)
de	$MSPE_u/MSPE_r$	0.999	1.036	1.077	1.180	1.136
	CW-stat	0.991	-0.741	-2.362	-3.521	-1.321
	p-value	(**0.063**)	(0.446)	(0.972)	(0.999)	(0.676)
$\widetilde{bm}$	$MSPE_u/MSPE_r$	1.003	1.011	1.013	1.004	1.004
	CW-stat	-0.583	-1.405	-1.135	-0.074	-0.062
	p-value	(0.396)	(0.767)	(0.638)	(0.218)	(0.221)
$svar$	$MSPE_u/MSPE_r$	1.618	1.386	1.318	1.127	1.007
	CW-stat	-0.373	-0.364	-0.709	-0.906	-1.932
	p-value	(0.246)	(0.243)	(0.411)	(0.515)	(0.940)
$ntis$	$MSPE_u/MSPE_r$	0.991	1.017	1.037	1.025	0.954
	CW-stat	1.368	-0.763	-1.460	-1.052	2.947
	p-value	(**0.050**)	(0.447)	(0.748)	(0.606)	(**0.013**)
$infl$	$MSPE_u/MSPE_r$	0.975	0.968	0.955	0.981	1.013
	CW-stat	2.431	0.831	1.444	1.551	-0.221
	p-value	(**0.072**)	(**0.073**)	(**0.032**)	(**0.054**)	(0.293)
$rrel$	$MSPE_u/MSPE_r$	0.970	1.000	1.023	1.039	1.040
	CW-stat	4.563	0.052	-1.289	-1.540	-2.793
	p-value	(**0.006**)	(0.222)	(0.714)	(0.818)	(0.989)
$rlty$	$MSPE_u/MSPE_r$	1.014	1.021	1.023	1.037	1.104
	CW-stat	-0.721	0.409	-0.602	-1.045	-5.229
	p-value	(0.462)	(0.157)	(0.423)	(0.612)	(1.000)
ltr	$MSPE_u/MSPE_r$	1.001	0.999	1.002	1.003	1.010
	CW-stat	0.210	3.007	-0.278	-0.532	-1.502
	p-value	(0.192)	(**0.018**)	(0.276)	(0.380)	(0.814)
tms	$MSPE_u/MSPE_r$	1.006	1.017	1.021	0.967	0.979
	CW-stat	-0.248	-0.532	0.323	6.566	21.161
	p-value	(0.286)	(0.377)	(0.211)	(**0.004**)	(**0.000**)
dfy	$MSPE_u/MSPE_r$	0.740	0.812	0.900	0.996	1.048
	CW-stat	10.153	7.183	4.913	0.357	-3.169
	p-value	(**0.001**)	(**0.001**)	(**0.005**)	(0.141)	(0.999)
dfr	$MSPE_u/MSPE_r$	1.007	1.002	1.002	1.004	1.001
	CW-stat	-2.012	-0.247	-0.267	-0.827	1.072
	p-value	(0.926)	(0.272)	(0.279)	(0.494)	(**0.069**)

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above.

Table 14: Non-Nested Out-of-Sample Predictability Comparison with Bootstrapped p-values: Dependent Variable is Measured by the Filtered Probabilities Obtained from the Markov-Switching Autoregressive Model Based on CRSP Value-Weighted Returns

$\text{MSPE}_i/\text{MSPE}_j$	Model i	Model j	MDM statistic	Bootstrapped PV
		$k=1$		
0.745	dfy	tms	5.745	**0.000**
0.766	dfy	$infl$	5.301	**0.000**
0.973	$infl$	tms	0.814	0.212
		$k=3$		
$\text{MSPE}_i/\text{MSPE}_j$	Model i	Model j	MDM statistic	Bootstrapped PV
0.808	dfy	tms	2.069	**0.026**
0.845	dfy	$infl$	1.724	**0.040**
0.956	$infl$	tms	0.618	0.280
		$k=6$		
$\text{MSPE}_i/\text{MSPE}_j$	Model i	Model j	MDM statistic	Bootstrapped PV
0.889	dfy	tms	0.965	0.180
0.948	dfy	$infl$	0.503	0.302
0.938	$infl$	tms	0.716	0.249
		$k=12$		
$\text{MSPE}_i/\text{MSPE}_j$	Model i	Model j	MDM statistic	Bootstrapped PV
0.967	tms	dfy	0.313	0.393
0.988	$infl$	dfy	0.169	0.436
0.979	tms	$infl$	0.309	0.376
		$k=24$		
$\text{MSPE}_i/\text{MSPE}_j$	Model i	Model j	MDM statistic	Bootstrapped PV
0.935	tms	dfy	0.984	0.198
0.969	$infl$	dfy	0.579	0.299
0.965	tms	$infl$	0.549	0.292

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above.

Table 15: Nested Out-of-Sample Predictability Test Results: Multivariate Regression

Models including dfy						
		k=1	k=3	k=6	k=12	k=24
dfy, tms	$MSPE_u/MSPE_r$	0.736	0.812	0.899	0.924	1.000
	CW-stat	7.804	4.427	6.349	8.071	15.004
	p-value	(**0.000**)	(**0.000**)	(**0.000**)	(**0.000**)	(**0.000**)
$dfy, tms, infl$	$MSPE_u/MSPE_r$	0.734	0.805	0.882	0.921	1.027
	CW-stat	7.038	4.804	5.309	8.557	12.142
	p-value	(**0.000**)	(**0.000**)	(**0.000**)	(**0.000**)	(**0.000**)
$dfy, tms, infl, ntis, \widetilde{dp}$	$MSPE_u/MSPE_r$	0.727	0.830	0.949	1.033	1.029
	CW-stat	6.346	3.818	3.539	3.809	8.343
	p-value	(**0.000**)	(**0.000**)	(**0.000**)	(**0.000**)	(**0.000**)
Models excluding dfy						
		k=1	k=3	k=6	k=12	k=24
$tms, infl$	$MSPE_u/MSPE_r$	0.983	0.988	0.982	0.957	0.998
	CW-stat	1.994	0.318	0.433	7.052	15.842
	p-value	(**0.023**)	(0.375)	(0.332)	(**0.000**)	(**0.000**)
$tms, infl, ntis, \widetilde{dp}$	$MSPE_u/MSPE_r$	0.956	0.999	1.027	1.030	0.963
	CW-stat	6.346	3.818	3.539	3.809	8.343
	p-value	(**0.021**)	(0.469)	(0.720)	(**0.000**)	(**0.000**)

Note: Bold type indicates significance at the 10% level or above.

Table 16: In-Sample Predictability Results: Dependent Variable is the Date of Bear Markets Identified by the Bry–Boschan Method

		k=1	k=3	k=6	k=12	k=24
$\widetilde{dp}$	$\hat{\beta}$	-0.716	-0.842	-0.928	-0.563	-0.224
	p-value	(**0.000**)	(**0.001**)	(**0.005**)	(0.190)	(0.491)
	pseudo-R^2	[0.047]	[0.064]	[0.075]	[0.029]	[0.005]
$\widetilde{dy}$	$\hat{\beta}$	-0.809	-0.910	-0.898	-0.552	-0.209
	p-value	(**0.000**)	(**0.001**)	(**0.013**)	(0.193)	(0.507)
	pseudo-R^2	[0.060]	[0.074]	[0.072]	[0.029]	[0.004]
ep	$\hat{\beta}$	0.165	0.080	-0.038	-0.067	-0.055
	p-value	(0.130)	(0.702)	(0.930)	(0.814)	(0.826)
	pseudo-R^2	[0.003]	[0.001]	[0.000]	[0.000]	[0.000]
de	$\hat{\beta}$	-0.250	-0.428	-0.510	-0.550	0.131
	p-value	(0.142)	(0.174)	(0.212)	(0.273)	(0.711)
	pseudo-R^2	[0.003]	[0.007]	[0.010]	[0.011]	[0.001]
$\widetilde{bm}$	$\hat{\beta}$	-0.137	-0.926	-1.916	-2.309	-0.352
	p-value	(0.598)	(**0.060**)	(**0.001**)	(**0.001**)	(0.617)
	pseudo-R^2	[0.000]	[0.017]	[0.063]	[0.083]	[0.003]
$svar$	$\hat{\beta}$	115.224	47.161	0.698	4.203	0.879
	p-value	(**0.000**)	(**0.030**)	(0.993)	(0.821)	(0.892)
	pseudo-R^2	[0.050]	[0.015]	[0.000]	[0.000]	[0.000]
$ntis$	$\hat{\beta}$	-6.159	-4.621	-2.753	-3.069	-5.144
	p-value	(**0.033**)	(0.442)	(0.737)	(0.702)	(0.454)
	pseudo-R^2	[0.008]	[0.004]	[0.002]	[0.002]	[0.005]
$infl$	$\hat{\beta}$	50.970	56.497	63.710	19.820	12.733
	p-value	(**0.003**)	(**0.031**)	(**0.023**)	(0.474)	(0.648)
	pseudo-R^2	[0.018]	[0.021]	[0.025]	[0.002]	[0.001]
$rrel$	$\hat{\beta}$	18.032	21.328	23.880	13.151	-11.818
	p-value	(**0.002**)	(**0.055**)	(**0.067**)	(0.345)	(0.324)
	pseudo-R^2	[0.015]	[0.021]	[0.026]	[0.009]	[0.007]
$rlty$	$\hat{\beta}$	57.565	64.260	51.176	11.726	-5.328
	p-value	(**0.000**)	(**0.001**)	(**0.019**)	(0.656)	(0.839)
	pseudo-R^2	[0.044]	[0.052]	[0.035]	[0.002]	[0.000]
ltr	$\hat{\beta}$	-0.050	-0.561	-4.429	-1.416	0.779
	p-value	(0.879)	(0.691)	(**0.009**)	(0.465)	(0.541)
	pseudo-R^2	[0.000]	[0.000]	[0.008]	[0.001]	[0.000]
tms	$\hat{\beta}$	-0.115	-0.110	-0.125	-0.083	-0.002
	p-value	(**0.004**)	(0.166)	(0.212)	(0.400)	(0.983)
	pseudo-R^2	[0.012]	[0.011]	[0.014]	[0.006]	[0.000]
dfy	$\hat{\beta}$	33.711	19.596	13.902	28.703	46.239
	p-value	(**0.014**)	(0.153)	(0.298)	(**0.043**)	(**0.002**)
	pseudo-R^2	[0.013]	[0.004]	[0.002]	[0.010]	[0.026]
dfr	$\hat{\beta}$	-8.024	-10.353	-0.567	0.689	4.547
	p-value	(**0.037**)	(**0.004**)	(0.860)	(0.843)	(0.262)
	pseudo-R^2	[0.007]	[0.011]	[0.000]	[0.000]	[0.002]

Note: The numbers in parentheses are p-values. Bold type indicates significance at the 10% level or above.

Table 17: Out-of-Sample Results of the Probit Model: QPS

	$k=1$	k=3	k=6	k=12	k=24
$\widetilde{dp}$	0.478	0.488	0.506	0.524	0.470
$\widetilde{dy}$	0.478	0.488	0.507	0.522	0.468
ep	0.435	0.444	0.457	0.486	0.443
de	0.440	0.439	0.438	0.446	0.441
$\widetilde{bm}$	0.444	0.443	0.426	0.434	0.431
$svar$	0.422	0.431	0.445	0.449	0.449
$ntis$	0.463	0.475	0.488	0.482	0.451
$infl$	0.424	0.420	**0.418**	0.435	0.427
$rrel$	0.416	0.424	0.440	0.435	0.442
$rlty$	**0.404**	**0.413**	0.430	0.444	**0.424**
ltr	0.434	0.433	0.424	0.437	0.429
tms	0.436	0.445	0.442	**0.424**	0.440
dfy	0.424	0.434	0.438	0.442	0.450
dfr	0.428	0.426	0.430	0.435	0.428

Note: Bold type indicates the smallest QPS among the predictors for a given k.

Table 18: Out-of-Sample Results of the Probit Model: LPS

	k=1	k=3	k=6	k=12	k=24
$\widetilde{dp}$	0.691	0.708	0.735	0.750	0.680
$\widetilde{dy}$	0.692	0.711	0.738	0.747	0.677
ep	0.629	0.641	0.654	0.687	0.641
de	0.629	0.630	0.631	0.645	0.641
$\widetilde{bm}$	0.640	0.646	0.622	0.621	0.625
$svar$	0.616	0.622	0.654	0.646	0.644
$ntis$	0.683	0.706	0.736	0.709	0.642
$infl$	0.623	0.612	**0.608**	0.629	0.622
$rrel$	0.608	0.618	0.645	0.636	0.637
$rlty$	**0.594**	**0.605**	0.639	0.653	**0.617**
ltr	0.627	0.626	0.616	0.632	0.622
tms	0.635	0.648	0.645	**0.618**	0.636
dfy	0.614	0.626	0.631	0.635	0.647
dfr	0.621	0.617	0.623	0.629	0.621

Note: Bold type indicates the smallest LPS among the predictors for a given k.

Table 19: Non-Nested Out-of-Sample Tests Comparison: Probit Model

$MSPE_i/MSPE_j$	Model i	Model j	MDM statistic	Asymptotic PV
$k=1$				
0.973	dfy	$rlty$	0.843	0.200
0.970	$infl$	$rlty$	1.059	0.145
0.937	tms	$rlty$	1.757	**0.040**
$k=3$				
0.959	dfy	$rlty$	0.864	0.194
0.986	$infl$	$rlty$	0.300	0.382
0.933	tms	$rlty$	1.033	0.151
$k=24$				
0.970	dfy	$rlty$	0.461	0.323
0.998	$infl$	$rlty$	0.149	0.441
0.961	tms	$rlty$	1.898	**0.029**

Note: Bold type indicates significance at the 10% level or above.

Table 20: Predictive Performance of the TED Spread: In-Sample and Out-of-Sample Results

Variable		k=1	k=3	k=6	k=12	k=24
In-sample results						
TED	$\hat{\beta}$	0.118	0.127	0.111	0.099	0.076
	p-value	(**0.013**)	(**0.007**)	(**0.014**)	(**0.031**)	(**0.098**)
	$\overline{R}^2$	[0.093]	[0.106]	[0.081]	[0.062]	[0.035]
Out-of-sample results						
TED	$MSPE_u/MSPE_r$	0.960	0.958	0.949	0.956	0.987
	CW-stat	6.494	6.760	6.598	7.292	1.609
	p-value	(**0.000**)	(**0.000**)	(**0.000**)	(**0.000**)	(**0.054**)

Note: Bold type indicates significance at the 10% level or above.

Table 21: Economic Value of a Regime-Switching Trading Strategy based on the Prediction of Bear Markets: Out-of-Sample Performance

Buy-and-hold strategy		
	Terminal wealth ($)	Monthly compounded return (%)
	15.648	0.483
Switching strategy		
Predictors	Terminal wealth ($)	Monthly compounded return (%)
$\widetilde{dp}$	13.957	0.463
$\widetilde{dy}$	11.756	0.433
ep	34.535	0.622
de	31.100	0.604
$\widetilde{bm}$	15.648	0.483
$svar$	280.639	0.992
$ntis$	15.971	0.486
$infl$	196.041	0.930
$rrel$	14.839	0.479
$rlty$	45.870	0.681
ltr	15.648	0.483
tms	31.664	0.607
dfy	192.884	0.926
dfr	15.648	0.483

Table 22: Tests for Changes in Mean of dp, dy, and bm

Test (H_0, H_1)	dp	dy	bm
sup-F(0,1)	1117.594	2642.417	2630.713
sup-F(1,2)	589.439	1518.679	1516.452
sup-F(2,3)	229.018	738.610	736.066
sup-F(3,4)	50.310	178.077	174.484

Note: All sup-F statistics are significant at the 1% level.