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Abstract

We reassess the predictability of U.S. recessions at horizons from three months to two years ahead for a large number of previously proposed leading-indicator variables. We employ an efficient probit estimator for partially missing data and assess relative model performance based on the receiver operating characteristic (ROC) curve. While the Treasury term spread has the highest predictive power at horizons four to six quarters ahead, adding lagged observations of the term spread significantly improves the predictability of recessions at shorter horizons. Moreover, balances in broker-dealer margin accounts significantly improve the precision of recession predictions, especially at horizons further out than one year.

Key words: recession predictability, ROC, term spread, leading indicators, efficient probit estimator

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1 Introduction

Accurately predicting business cycle turning points, and in particular impending economic recessions, is of great importance to households, businesses, investors and policy makers alike. Prior research has documented that a variety of economic and financial variables contain predictive information about future recessions in the United States. Most prominently, Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998) have documented that the slope of the term structure of Treasury yields has strong predictive power for US output growth and US recessions at horizons up to eight quarters into the future. Other variables that have been considered as leading recession indicators include stock prices (Estrella and Mishkin (1998)), the index of Leading Economic Indicators (Stock and Watson (1989), Berge and Jordà (2011)), credit market activity (Levanon, Manini, Ozyildirim, Schaitkin, and Tanchua (2011)), as well as various employment and interest rate measures (Ng (2014)).

In this paper, we reassess the predictability of US recessions since 1959 using a wide variety of leading indicator variables that have been considered in the academic and practitioner literature. Consistent with most of the prior literature, we use the business cycle dating chronology provided by the National Bureau of Economic Research (NBER) as the benchmark series of business cycle turning points. While the NBER recession indicator is a binary variable, most leading indicators have continuous distributions. Thus, much of the empirical literature has used the nonlinear *probit* model to map changes in predictor variables into recession forecasts, and we follow this tradition.

The probability of a recession implied by the probit model is rarely exactly zero or one. Thus, a cutoff is usually adopted such that a predicted probability above the cutoff is classified as a recession. In order to objectively evaluate the model's ability to categorize future time periods into recessions versus expansions over an entire spectrum of different cutoffs, one needs to complement the probit model with a classification scheme. A classification scheme that has long been used in the statistics literature but has only recently found its way into economic research is the receiver operating characteristic (ROC) curve (see, for example, Khandani, Kim, and Lo (2010), Jordà and Taylor (2011), Jordà and Taylor (2012)). The ROC curve is computed in several steps. First, for a given grid of cutoff values of the implied recession probability, one calculates the percentage of true positives and false positives for classifying all periods in the sample. One then plots the percentage of true and false positives against one another for the entire grid to create the receiver operating curve. One method of comparing the predictive ability of classifiers across a spectrum of cutoff values is to integrate the area under the ROC curve, creating the AUROC. A model which delivers a perfect classification of all time periods into recession and expansion would only have true positives and no false positives and an AUROC equal to one. In contrast, a model which is the equivalent of a random guess would have on average an equal number of true and false positives, which corresponds to an AUROC equal to 0.5. Hanley and McNeil (1983) derive a t-test for the hypothesis that the predictive ability of two different classifiers are equal by using their AUROC's. We use their test in order to discriminate between the predictive ability of different recession indicators considered in the literature.

Our main findings can be summarized as follows. The Treasury term spread predicts best at horizons of one year and more. That said, some indicators add to the predictive ability of the term spread at these horizons. In particular, margin debit at NYSE brokers and dealers, a measure of leverage in the financial sector, significantly improves the in-sample and out-of-sample predictive power of the probit model when considered jointly with the term spread at these longer horizons. This highlights the importance of financial intermediary balance sheet conditions in the transmission of economic shocks (see, for example, Adrian and Shin (2010) and Adrian, Moench, and Shin (2010)). While the importance of financial intermediary leverage for the pricing of risk has been empirically documented by Adrian, Etula, and Muir (2012) and Adrian, Moench, and Shin (2013), to the best of our knowledge, its usefulness for the predictability of recessions has not previously been studied.

At horizons shorter than one year ahead, we find that adding six-month lagged observations of the Treasury term spread significantly improves the predictive power of the probit model to predict recessions. This suggests that at these shorter horizons there is predictive information not only in the contemporaneous steepness of the Treasury yield curve, but also in the lagged term structure slope. The negative sign on the coefficient of lagged spread has two implications: persistence and change. First, if spreads were negative six-months ago, then there is a higher probability of recession in the future. Second, given the same starting value of spread six-months ago, a sharper drop in the spread since then leads to a higher probability of recession in the future. In addition to the contemporaneous and lagged Treasury term spreads, a number of other variables also contain predictive information about future recessions at horizons less than one year ahead. In particular, the annual return on the S&P500 stock market index, the Michigan survey of consumer expectations, and again the margin debit at NYSE brokers and dealers significantly increase the predictive power of the probit model when added to the Treasury term spread.

Our paper is related to a large literature on predicting real output growth and recessions using financial and macroeconomic leading indicators. Estrella and Hardouvelis (1991) first popularized the Treasury term spread as a predictor of future output growth and recessions. They found that it has greater predictive power than the Leading Indicator Index and outperforms survey forecasts both in- and out-of-sample. Estrella and Mishkin (1996) and Estrella and Mishkin (1998) considered the out-of-sample performance of a range of macroeconomic and financial variables both one-at-a-time and in combination. Their findings suggest that in the short run, stock returns are a valuable leading indicator. However, at horizons of one year ahead or more, the Treasury term spread is still the single best performing predictor. Dueker (1997) revisited the term spread as a leading indicator within the context of the probit model studied in our paper. Confirming earlier results, he found the term spread to be the single best recession predictor when compared to other leading economic indicators and financial variables, and showed that this finding is robust to augmentation of the probit model with lagged dependent variables and Markov switching. Chauvet and Potter (2005) examine further extensions of the yield curve probit model, including a business cycle dependent model, a model with autocorrelated errors, and combinations of these extensions. They conclude that the more sophisticated models capture the predictive instability of the yield curve better by allowing for breakpoints.

While all of the above cited papers have studied the predictive power of the term spread for output growth and recessions in the U.S., some authors have documented similarly strong predictive power of government bond yield spreads in other countries. For example, Duarte, Venetis, and Payà (2005) find that yield spreads predict recessions in the European Monetary Union. Moreover, examining both the U.S. and Germany, Nyberg (2010) concludes that the domestic term spread remains the best recession predictor.

Recently, Rudebusch and Williams (2009) have found that the term spread consistently outperforms even professional forecastors in predicting recessions. This is surprising as these forecasters have a wealth of information and many other indicators available to them. Croushore and Marsten (2014) confirm that Rudebusch and Williams' findings are robust across several dimensions including the sample choice, the use of rolling regression windows, and various measures of real output. Moreover, Lahiri, Monokroussos, and Zhao (2013) report that the result remains valid even after further augmenting the model with factors extracted from a large macroeconomic dataset. These papers' findings highlight the singular importance of the Treasury term spread as a predictor of recessions and justify our use of this indicator as the benchmark predictor variable.

Methodologically, our paper borrows from Berge and Jordà (2011), who use the AUROC to both validate the NBER's business cycle chronology as well as investigate which leading indices work best as a classification mechanism for recessions. They find no support for statistically significant improvements of the parametric models over the NBER dates. Hence, their results also support our use of the NBER business cycle chronology as reference for the recession classification ability of the various probit models that we consider.

Our paper is organized as follows. Section 2 discusses the empirical methodology used to predict recession probabilities and evaluate the classification of future recession and expansion periods. Section 3 provides a description of the various recession indicators used in our analysis. Section 4 summarizes the in-sample and out-of-sample recession prediction results. Finally, Section 5 provides a discussion of the empirical findings.

2 Methodology

In this section, we briefly describe the empirical methods used in the paper. We start by revisiting the standard probit model which we use to estimate the recession probabilities as functions of observable predictor variables. We then briefly discuss an extension which allows for the inclusion of partially unobserved predictor variables. Finally, we describe the AUROC measure and related statistical tests which we employ to discriminate between models.

2.1 Predicting Recessions

The state of the business cycle is a binary variable, taking on the value of one during a recession and zero during an expansion. On the other hand, most leading indicators are continuous variables. In order to account for this, a common tool to predict recessions is the probit model (see Estrella and Hardouvelis (1991), Estrella and Mishkin (1996), Estrella and Trubin (2006),Wright (2006)) which allows a mapping from a set of continuous explanatory variables into a binary dependent variable. While other methods are available for predicting binary response variables, we restrict ourselves to this popular class of models for its simplicity and ease of use.

The model is characterized by the simple equation

$$P\left(REC_{t+k}=1\right)=\Phi\left(\alpha_0+\alpha_1' X_t\right), \tag{1}$$

where REC is a binary variable which takes on values of one in recessions and zero in expansions, X_t is a $n \times 1$ vector of predictor variables observed in period t, and Φ denotes the cumulative density function of the standard normal distribution. Letting $\alpha = (\alpha_0, \alpha_1')'$, the probit model maximizes the log likelihood function

$$\ln \ell(\alpha) = \sum_{t=1}^{T} \left[REC_{t+k} \ln \Phi(\alpha_0 + \alpha_1' X_t) + (1 - REC_{t+k}) \ln(1 - \Phi(\alpha_0 + \alpha_1' X_t)) \right] \quad (2)$$

Hence, given time series observations for the predictor variables X and the response variable REC, one can numerically solve for the maximum likelihood estimates α.
Some of the predictor variables we will consider in our empirical analysis are not observed over the full sample period. We therefore need to adjust the probit model to allow for missing observations. One commonly used method of handling missing data is to disregard the dates on which any variables are missing, but this method inefficiently discards potentially useful data. Instead, we employ the efficient "probitmiss" estimator, recently proposed by Conniffe and O'Neill (2011), which allows us to incorporate all relevant data.
Building off of Chesher (1984), Conniffe and O'Neill's model assumes that there exists one underlying unobservable, continuous latent variable Y_i and an observed binary variable Z_i which follows the relationship:

$$\begin{aligned} Z_i &= 1 \text{ if } Y_i > 0 \\ Z_i &= 0 \text{ if } Y_i < 0. \end{aligned}$$

The regressors are grouped into two categories, denoted in vector form: X_i (complete) and W_i (incomplete). There are k number of X's, and l number of W's. We observe the complete sample of observations $\{X_i, W_i, Z_i\}$ for i =1,2,... r. This leaves $(n-r)$ observations on which $\{X_i, Z_i\}$ alone are measured. They follow the relationship:

$$Y_i = X_i' B_x + W_i' B_w + \varepsilon_i. \quad (3)$$

To make use of the $n - r$ non-missing observations, assume:

$$W_i^{'} = X_i^{'} C + u_i^{'}, \tag{4}$$

where C is a $(k \text{ x } l)$ matrix of parameters and $u_i \sim MVN(0, \Sigma)$. Then, combining (3) and (4), one obtains:

$$Y_i = X_i^{'}(B_x + CB_w) + e_{y_i}, \tag{5}$$

where, conditional on X_i, (e_{y_i}, W_i) are multivariate normally distributed. The assumption of conditional joint normality is analytically convenient and allows for efficient estimation. Conniffe and O'Neill (2011) show that their proposed estimator is robust to various departures from the parametric assumptions in (4).

Rather than explicitly restating the estimator and its asymptotic variance derived by Conniffe and O'Neill (2011), we simply summarize the various estimation steps:[1]

1. Run an OLS regression of X on W for the sample with r complete observations.

2. Run a standard probit of Y on X and W for the sample with r complete observations.

3. Run a probit of Y on X for just the sample with $n - r$ missing observations

4. Calculate the coefficients and standard errors for the probitmiss estimator using as inputs the estimation outputs from steps(1)-(3).

It is important to point out that in addition to the assumption of conditional multinormality, the efficient probit estimator requires that the missing data for W are missing at random (MAR). In other words, the reason for the data's absence should not be related to an omitted variable that is correlated with recessions, such as the state of the business cycle. Since our missing data are only missing at the beginning of the dataset due to limitations of our database, the MAR assumption is naturally satisfied.

[1]For further details, we refer the interested reader to the paper by Conniffe and O'Neill (2011).

2.2 Model Selection

Previous research has used various different metrics to evaluate the fit of recession prediction models. For example, Moore and Shiskin (1967) present an explicit scoring system for business cycle indicators, focusing on the length of lead before business cycles turns, smoothness of the series, clarity of cyclical movements, and relationship to general business activity, among other criterion. Estrella and Mishkin (1996) and Estrella and Mishkin (1998) use the pseudo R-squared to evaluate the fits of probit models. Finally, Wright (2006) employs the BIC criterion to measure the fit of his model in-sample and root mean squared forecast errors to evaluate the fit of his out-of-sample forecasts.

However, all of these evaluation measures focus on model fit and not specifically classification ability, which is the object of interest in our application. Berge and Jordà (2011) have recently used the Receiver Operating Characteristic (ROC) curve to assess the recession classification ability of various leading indicators. The ROC curve is a useful measure, because it precisely captures the ability of each model to accurately categorize recessions and expansions. In particular, by using the area under the ROC curve (AUROC), one can evaluate the categorization ability of the model over an entire spectrum of different cut-offs for determining a recession, instead of evaluating predictive power at any one arbitrary threshold.

In a seminal paper, Peterson and Birdsall (1953) first developed the basic ROC methodology. The procedure has been widely used in statistics and other fields, but it has only recently found its way into the economics literature (see, for example, Khandani, Kim, and Lo (2010), Jordà and Taylor (2011), and Jordà and Taylor (2012)). Applied to the context of predicting recessions, it can be summarized as follows:

1. Let

$$X_t = \begin{cases} 1, & \text{if in recession} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

denote the true, observed state of the economy. Let P_t be the prediction of X_t, or the probability of recession, given by the probit model, where $0 \leq P_t \leq 1$.

2. Define evenly spaced thresholds (denoted C^*) along the interval [0,1]. A larger number of thresholds leads to a smoother ROC curve with more points. For example, a potential set with 50 thresholds would be: C_i^*={0,0.05,... 0.95,1}.

3. For each given threshold, C_i^*, record the model's predicted categories. More specifically, define the predicted categorization of X_t,or $\hat{X}_t$, in the following way:

$$\hat{X}_t = \begin{cases} 1, & \text{if } \; P_t \geq C_i^* \\ 0, & \text{if } \; P_t < C_i^* \end{cases} \tag{7}$$

4. Comparing the true X_t to predicted categorizations $\hat{X}_t$, calculate the percentage of true positives (PTP) and percentage of false positives (PFP). More specifically, they can be defined using the sum of two indicator variables:

$$PTP = \frac{1}{n_R} \sum_{t=1}^{N} I_t^{tp}; \;\; \text{where} \;\; I_t^{tp} = \begin{cases} 1, \text{if} \;\; X_t = 1 \;\; \text{and} \;\; \hat{X}_t = 1 \\ 0, \text{otherwise} \end{cases} \tag{8}$$

$$PFP = \frac{1}{n_E} \sum_{t=1}^{N} I_t^{fp}; \;\; \text{where} \;\; I_t^{fp} = \begin{cases} 1, \text{if} \;\; X_t = 0 \;\; \text{and} \;\; \hat{X}_t = 1 \\ 0, \text{otherwise} \end{cases} \tag{9}$$

and where n_R is the number of times the true X_t was in a recession and n_E is the number of times the true X_t was not in a recession, such that n_R+n_E=N, where N is the total number of observations in our sample.

5. For each C_i^*, create a set of coordinates: (PFP_i,PTP_i).

6. After a coordinate is created for each threshold, plot the coordinates across all thresholds where the false positive rate is on the x-axis and the true positive rate is on the y-axis. Connect these coordinates to trace out the ROC curve.

In summary, the ROC curve pinpoints the percent of false negatives one would have to trade for one additional percent of true positives. A model with 100% accuracy would draw a ROC curve hugging the top left corner. A model which is the equivalent of a random guess would follow a 45% diagonal that runs from the bottom-left corner to the top-right corner. By construction, if we defined X_t in terms of expansions (i.e. let X_t equal one during expansions and zero otherwise) instead of recessions, the new curve would look symmetric to the old curve about a 45 degree line from the bottom-right corner to the top-left corner. The area under the curve, by geometry, would then remain exactly the same as before.
Due to its ease of application and intuitive visual interpretation, the area under the ROC curve (AUROC) is a popular measure of classification ability for a given model. In our empirical analysis in Section 4, we will therefore compare the recession classification ability of various different probit models using their implied AUROC's. As discussed in Berge and Jordà (2011), a simple nonparametric estimate of the AUROC is given by

$$\widehat{\text{AUROC}} = \frac{1}{n_R n_E} \sum_{i=1}^{n_E} \sum_{j=1}^{n_R} \left\{ I(Z_i > X_j) + \frac{1}{2} I(Z_i = X_j) \right\}, \tag{10}$$

where $I(\cdot)$ is the indicator function, X are the observations classified to be a recessionary period and Z are the observations classified to be an expansionary period. n_R and n_E are the true numbers of recessionary and expansionary periods, respectively.

We can assess the statistical significance of a model-implied AUROC using the asymptotic standard error derived by Hanley and McNeil (1982). The variance is given by:

$$\sigma^2 = \frac{1}{n_R n_E} \left[\text{AUROC}(1 - \text{AUROC}) + (n_R - 1)(Q_1 - \text{AUROC}^2) + (n_E - 1)(Q_2 - \text{AUROC}^2) \right]^{1/2},$$

where $Q_1 = \frac{\text{AUROC}}{(2-\text{AUROC})}$, and $Q_2 = \frac{2\text{AUROC}^2}{(1+\text{AUROC})}$, see again Hanley and McNeil (1982).

Hanley and McNeil (1983) extend this estimator further by developing a t-statistic for comparing AUROCs across multiple models, taking into account the correlation between the two areas being compared. The t-statistic is given by:

$$t = \frac{\text{AUROC}_1 - \text{AUROC}_2}{\sqrt{\sigma_1^2 + \sigma_2^2 - 2r\sigma_1\sigma_2}}. \tag{11}$$

Here, AUROC_1 and AUROC_2 are the areas under the curve for models 1 and 2 which are being compared. Similarly, σ_1^2 and σ_2^2 refer to the variances of the AUROCs for model 1 and model 2, respectively. Finally, r is the correlation between the two AUROCs. To obtain r, one needs to compute two intermediate parameters r_E and r_R, which are the correlations for the expansionary observations and recessionary observations, respectively, across the two models. These correlations can be calculated using either Pearson product-moment correlation or the Kendall tau rank correlation coefficient. In our paper, we choose to use the latter. See Hanley and McNeil (1983) and Jordà and Taylor (2011) for more details on the test statistic and its implementation.

3 Data

We use monthly U.S. data for the sample period January 1959 to December 2011. The dependent variable is a binary recession indicator which takes on the value of one during a recession and zero during an expansion, both as defined by the NBER business cycle dating committee. The committee meets periodically to judge whether a peak or trough in economic activity has occurred, taking into account a variety of economic activity indicators, including real GDP measured on the product and income sides, economy-wide employment, real income, as well as indicators covering real parts of the economy, such as retail sales and industrial production.[2] The NBER's dating rules are widely regarded as the benchmark for

[2]See `http://www.nber.org/cycles/recessions.html`.

US business cycles. Moreover, as discussed in the introduction, Berge and Jordà (2011) find no improvement of a number of sophisticated parametric models over the recession classification ability of the NBER.

For in-sample recession prediction, our sample runs from 1959 to 2011 and covers a total of seven recessions, which range in duration from six to 18 months. We also conduct out-of-sample forecasts, using the period of January 1959 to August 1985 (which covers a total of four recessions) as our training sample, and the period from September 1985 through December 2011 (covering three recessions) as our forecasting sample. Our explanatory variables are taken from Haver Analytics, with the exception of real-time macroeconmic indicators, which come from the ArchivaL Federal Reserve Economic Database (ALFRED). Following Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), and others, we use the term spread, precisely defined as the difference between the ten-year and the three-month Treasury yield ("10y- 3m spd "), as our benchmark predictor variable. We then assess whether additional lags of the term spread as well as other candidate predictor variables add predictive power to the benchmark model.

Based on prior research, we consider the following list of additional predictor variables. First, following Estrella and Mishkin (1998), we add several financial indicators including returns on the S&P500 common stock price index ("S&P 500, 1y% change", "S&P 500, 3y % change") and the interest rates of the 3-month ("3m rate") and 10-year Treasuries ("10y rate"). Second, we include each component of the Conference Board's Leading Economic Index (LEI) (see Levanon, Manini, Ozyildirim, Schaitkin, and Tanchua (2011)). These indicators have been selected for their ability to signal peaks and troughs in the business cycle, and the aggregate index has been shown to drop ahead of recessions and rise before expansions. The individual factors consist of: average weekly hours of manufacturing ("Avg wkly hrs (manufacturing)"); average weekly initial claims for unemployment insurance ("Avg initial claims"); manufacturer's new orders, goods, and materials ("New orders, goods, materials"); the ISM index of new orders ("ISM new orders index"); manufacturers' new orders, nondefense capital goods excluding aircraft ("New orders, non-defense"); building permits, new private housing units ("Building permits"); the rate of the 10-year Treasury note less federal funds ("10yr-FF spread"); average consumer expectations ("Michigan consumer survey"); and the Leading Credit Index.

The latter was introduced by the Conference Board to supplement the Leading Economic Index and reflect potential structural changes in the changing credit and financial markets. Its components were selected in the spirit of financial intermediation models as laid out by Adrian and Shin (2010) and are tested for their ability to signal business cycle changes using a Markov Switching model (see Levanon, Manini, Ozyildirim, Schaitkin, and Tanchua (2011)). We include each of the LCI's components offered at a monthly frequency or greater going back to at least 1985: the LIBOR 3-month less 3-month Treasury bill yield spread ("LIBOR 3 month"), balances in Broker-Dealer margin accounts ("Debit margins (BD)"), and the AAII Sentiment Survey's Market Survey of the spread between bearish and bullish sentiments ("Bear less bull").

Finally, we add a number of predictor variables following the recent findings of Ng (2014). In her paper, Ng examines a comprehensive list of 132 different real and financial indicators and assesses their relevance for predicting recessions. We include all of the 14 unique variables found to be most important using cross-validation boosting techniques as well as the 4 additional unique variables found through a rolling window exercise. This list includes the spreads between the yields of several constant maturity Treasuries with the fed funds (FF) rate ("3m/6m/1yr/2yr/5yr/30yr- FF spread"); employment hours for total non-farm, government, manufacturing, and mining ("Emp: total/govt/mfg/mining"); NAMP index of consumer commodity prices ("NAPM com price"); NAPM vendor deliveries ("NAPM vendor del"); NAPM inventories index ("NAPM invent"); and the US$-Yen exchange rate ("Ex rate: Japan").

Table 1 provides a list of all the predictor variables that we consider, their available time span, the database from which they originate, and the transformations that we used to render the series stationary. These transformations directly follow those used in the papers cited above. Since macroeconomic variables are often revised after their release dates and these revisions are not available to the economist for out-of-sample forecasting, we use real-time, or the first-release, indicators whenever possible. When available, the real-time data is collected from the ALFRED database. For several macroeconomic variables, real-time data do not exist before 1985. These variables are marked with an asterisk in Table 1 and are excluded from our out-of-sample analysis.

4 Results

In this section, we describe our results from comparing various probit model specifications at different horizons. We divide our analysis into in-sample versus out-of-sample forecasts. In-sample forecasts are estimated over the entire sample from January 1959 to December 2011. Out-of-sample forecasts are estimated using the first half of the sample, from January 1959 to August 1985, and then evaluated using the second half of the sample, from September 1985 to December 2011. In both exercises, we consider forecasts at the 3-, 6-, 12-, 18-, and 24-months ahead horizons. At each horizon, we begin by estimating a baseline probit model using just the term spread as explanatory variable (Estrella and Hardouvelis (1991)). Then, we augment the benchmark model with the six-month lagged term spread as an additional explanatory variable. We do so in order to assess whether it is the contemporaneous level or the change in the spread that is important for predicting recessions. Moreover, this allows us to test whether the added leading indicators contain predictive information over and above that captured in the term spread.

Finally, one at a time, we add each of the variables shown in Table 1 to the spread and lagged spread models. We use the AUROC to evaluate the performance of each model and also to compare their forecasting abilities to the two baseline models using the t-statistic presented in Section 2.

4.1 In-sample Analysis

The results of our in-sample probit regressions are summarized in Table 2. The table is broken down into panels A through E, corresponding to 3-, 6-, 12-, 18-, and 24-months ahead forecast horizons, respectively. Each panel reports results from the spread-only model, a spread and six-month lagged spread model, and three additional models. These three additional models use the term spread, the lagged term spread, and one of three best-performing additional indicators as determined by the AUROC metric. For each model, we report its AUROC as well as its t-statistic when compared to the two baseline models: spread-only and spread augmented with six-month lagged spread.

Figures 1 - 3 summarize the findings in Table 2 visually. In these figures, the plots are paired by forecast horizon. The top graph shows the predicted probability of recession over time, with actual recessions shown as shaded grey areas. The second graph shows the corresponding ROC curves calculated as described in Section 2. In each graph, the three lines shown represent the estimates from the spread-only model (blue line), the spread and lagged spread model (green line), and one additional model with best performance as determined by the AUROC (red line).

At the three-months ahead horizon, we find that we can significantly improve the spread-only model by simply adding a six-month lag of the term spread. In fact, doing so increases the AUROC from 0.67, which is only slightly better than a random guess, to 0.85, which is quite accurate. The two AUROC's are significantly different at the 1% level, with a t-statistic of 5.5. Furthermore, we can improve the spread and lagged-spread model by including one of many additional indicators. The best one is the annual return on the S&P 500 index, which has a near-perfect AUROC of 0.95 and a t-statistic of 4.1 when compared to the spread and lagged spread model. The other two best-performing additional indicators are the Michigan consumer confidence survey and debit balances at margin accounts at broker dealers, which have AUROC's of 0.929 and 0.927 respectively.

At the six-months ahead horizon, we again see that adding a six-month lagged spread significantly improves the recession classification ability of the probit model, raising the AUROC from 0.78 to 0.87. In addition, the Michigan consumer survey continues to be one of the top additional indicators. The other two are the 5-year Treasury yield - fed funds rate spread and building permits. Again, we find that one can significantly improve upon a model with spread and lagged spread by adding any of these three additional indicators. Hence, there is predictive information in these other variables beyond that captured by the Treasury term spread.

At the twelve-months ahead horizon, the spread-only model performs remarkably better than at the shorter horizons with an AUROC of 0.87. While adding the lagged spread improves the predictive ability somewhat, it does not do so significantly. Similar to the six-months horizon, we find that the model with the 5-year Treasury-FF spread performs the best, improving upon the spread-only model with an AUROC of 0.90 and a only a t-statistic of 2.08. The two next best models use the 1-year Treasury-FF spread and the NAPM commodity price index, respectively.

Turning to the 18-months ahead forecast horizon, we see that the predictive ability of the spread-only model with an AUROC of 0.81 is slightly worse than at the twelve-months ahead horizon but better than the three- and six-months ahead horizons. Given these results we find that, not surprisingly, adding a six-month lagged spread actually marginally hurts the predictive ability of the model instead of improving it. Similar to the twelve-months ahead horizon, the NAPM commodity price index is among the top three additional predictor variables. It is outperformed only by the model using margin debit at broker-dealers as an additional predictor. In fact, broker dealer margin debit is the only predictor variable that significantly increases the AUROC when added to the two baseline models. This is intriguing given that the previous literature is generally in consensus that at the twelve- and eighteen-months ahead horizon, the spread-only model performs the best.

Finally, at the 24-months ahead horizon, we see that predictive ability is generally much lower for all models although still quite a bit better than a simple random guess model. The spread-only model has an AUROC of 0.69, which makes it comparable to its counterpart at the three-months ahead horizon (0.67). Adding the lagged spread improves the prediction ability but only marginally so. On the other hand, we also find that the addition of margin debit at broker-dealers, new non-defense orders, or the NAPM commodity price index significantly improves the two baseline models. All three perform about equally well with AUROC's ranging from 0.79 to 0.77. While these are not strong predictive abilities, they are higher than similar models estimated just using components of the LEI, which are considered the benchmark leading indicators (see Berge and Jordà (2011)).

Importantly, the probitmiss estimator by Conniffe and O'Neill (2011) allows us to find strong and significant forecasting value in variables which have missing observations and which may have been excluded from our analysis otherwise. More specifically, the broker-dealer margin debit variable and the Michigan survey of consumer expectations both start later than January 1959 which marks the beginning of our sample, yet we find that they are often useful in improving the in-sample recession forecasting ability.

4.2 Out-of-sample Analysis

The results of our baseline and best performing out-of-sample probit regressions are summarized in Table 3. As before, the table is organized in five panels corresponding to the five different forecast horizons. Each panel shows the AUROC for the spread-only model, the spread and lagged-spread model, and the three best models obtained by adding a third predictor variable to the spread and lagged spread baseline model. For each model, we report its AUROC as well as its t-statistic when compared to both baseline models.

Figures 1-3 summarize the findings in Table 3 visually. Again, the plots are grouped by pairs depending on the forecast horizon, where the first graph shows the predicted probability of recession over time and the second graph shows the corresponding ROC graphs calculated by comparing the predicted probability with the NBER business cycle chronology. In each of the latter graphs, the three lines represent the estimates from the spread-only model (blue line), the spread and lagged spread model (green line), and the best performing model which augments the spread and lagged spread model with an additional predictor variable (red line).

At the three-months ahead horizon, we see that the spread-only model is little better than a random guess, with an AUROC of only 0.56. This performance is notably worse than the in-sample model, which has an AUROC of 0.67. One possible interpretation of this finding is a shift in the predictive power of the term spread for recessions around the end of our training sample in 1985. This is consistent with prior evidence for structural change in the predictive relationship between the term spread and future output growth (see, for example, Schrimpf and Wang (2010)). That said, adding a six-month lag of the term spread improves the AUROC dramatically to 0.77 with an accompanying t-statistic of 4.34. In line with the in-sample analysis, we find that the annual return on the S&P 500 index, the Michigan survey of consumer sentiment, and margin debit at broker-dealers are the three best performing additional variables. They also significantly improve upon the spread and lagged spread model. The best model, using the annual return on the S&P 500 index, has a near-perfect predictive ability and an AUROC of 0.96.

Next, at the six-months ahead horizon, we find that the spread-only model performs worse than its in-sample counterpart with an AUROC of 0.67. Again, adding the six-months lagged spread significantly improves the model's predictive ability, raising its AUROC to 0.79. Similar to the three-months ahead horizon, we find that the annual return on the S&P 500 index and margin debit at broker-dealers are useful leading indicators. Moreover, in line with the in-sample analysis at this horizon, the remaining selected indicator is the 5-year Treasury yield-fed funds rate spread. While the best additional indicator is the annual return on the S&P 500 index, with a sizable AUROC of 0.90, all of the top three models with additional indicators significantly outperform the spread and lagged spread model.

At the 12-months ahead horizon, the spread-only model has an AUROC of 0.86. This is very similar to its in-sample counterpart, which has an AUROC of 0.87. Adding a six-month lag of the term spread slightly increases the AUROC to 0.88 but the difference is not found to be statistically significant. Consistent with the in-sample analysis, we find that the best three additional indicators ranked by decreasing importance are the 5-year Treasury yield - fed funds rate spread, the 1-year Treasury yield - fed funds rate spread, and the NAPM commodity price index. These models' AUROC's are also very similar to their in-sample counterparts, and, again, we find that we can significantly improve upon the spread-only model by adding the 5- or 1-year Treasury yield - fed funds rate spreads.

At the 18-months ahead horizon, the spread-only model performs quite well with an AUROC of 0.91, even better than at the 12-months ahead horizon. This is also remarkably better than its in-sample counterpart, which only has an AUROC of 0.81. While other models perform better than the spread-only model, we find their improvement to be statistically insignificant at conventional levels. Unlike the shorter forecast horizons, we find that adding the lagged spread actually decreases the AUROC to 0.88. However, adding margin debit at broker-dealers, the ISM new orders index, or average initial claims slightly improves the AUROC to 0.93, 0.91, and 0.90 respectively. That said, only the broker-dealer variable is found to significantly improve the predictive power of the model with respect to the spread and lagged spread model. However, when compared to the spread-only model the improvement is statistically insignificant.

Finally, at the 24-months ahead horizon, we find that the spread-only model has an impressive AUROC of 0.85. In fact, no other model performs better. Adding the lagged spread decreases the AUROC to 0.81. The best model with an additional predictor is the NAPM inventories index, which delivers an AUROC of 0.85. Comparing to the in-sample analysis, we find that the out-of-sample forecasts perform even better than their in-sample counterparts at the 24-months ahead horizon. In fact, the best model in the in-sample analysis has an AUROC of 0.79, which is lower than the corresponding out-of-sample estimation.

5 Summary of Findings and Concluding Remarks

In sum, our results imply the following main takeaways. First, consistent with the past literature, we find that our ability to improve upon the spread-only model drops at longer horizons of twelve months or greater. However, adding the 5-year Treasury - fed funds rate spread significantly improves both the in- and out-of-sample forecasts at the twelve-months ahead horizon. Moreover, our results indicate that adding the lagged term spread and margin debits at broker-dealers significantly improve both 18- and 24-months ahead in-sample forecasts.

Second, there is valuable information not only in the contemporaneous Treasury term spread but also in its dynamics. More specifically, one can drastically increase the recession prediction ability for out-of-sample forecasts by adding lagged observations of the Treasury term spread at short forecast horizons. In fact, adding six-months lagged observations of the Treasury term spread essentially moves the model from one that is little better than a random guess to a very accurate one. At longer horizons, the forecasting ability is generally worse across model specifications. For instance, in the out-of-sample forecast analyses at horizons longer than twelve months, the predictive ability decreases when the lagged spread is added to the probit model.

Third, we find that margin debit at broker-dealers is a useful leading indicator. To the best of our knowledge, this has not been appreciated in the previous academic literature. Models which add the margin debit variable consistently rank among the top three models for the three-, 18-, and 24-months ahead in-sample estimations, always significantly outperforming the spread-only model. In addition, we find that models with this variable rank among the top three for the thee-, six-, and 18-month ahead horizons for the out-of-sample estimations. As margin debit at broker-dealers is typically considered to be a measure of leverage in the financial system, its importance in predicting recessions highlights the role of financial intermediary balance sheet management in the transmission of economic shocks.

Table 1: **Summary of Key Variables** This table reports all of the predictor variables considered in our analysis. For each indicator, we report the series' name, the transformation we performed before using it in our analyses, the data source, and the time span for which the series is available. Transformation codes 1-6 correspond to levels, monthly log difference, annual log difference, annual difference, 6-months moving average smoother, and 12-months moving average smoother, respectively. The data sources USECON, BCI, and ALFRED refer to the U.S. Economics Statistics database in Haver Analytics, the Business Cycle Indicators database in Haver Analytics, and the online ArchivaL Federal Reserve Economic Database at the St. Louis Fed, respectively. * denotes macroeconomic indicators for which we real-time data extending past 1985 are not available and which are thus excluded from our out-of-sample analysis.

Series Name	**Code**	**Source**	**Time Span**
10y- 3m spd	1	USECON	Jan 1959-Dec 2011
10y rate	1	USECON	Jan 1959-Dec 2011
3m rate	1	USECON	Jan 1959-Dec 2011
S&P 500, 1y % change	1	USECON	Jan 1959-Dec 2011
S&P 500, 3y % change	1	USECON	Jan 1959-Dec 2011
Leading credit index	1	BCI	Jan 1959-Dec 2011
Michigan consumer survey	1	BCI	Jan 1978-Dec 2011
Debit margins (BD)	1	BCI	Jan 1960-Dec 2011
Bear less bull	4	BCI	Jul 1987-Dec 2011
LIBOR 3 month	1	USECON	Jan 1963-Dec 2011
Baa-Aaa spread	1	USECON	Jan 1959-Dec 2011
Aaa-FF spread	1	USECON	Jan 1959-Dec 2011
Baa-FF spread	1	USECON	Jan 1959-Dec 2011
3mo-FF spread	1	USECON	Jan 1959-Dec 2011
6m-FF spread	1	USECON	Jan 1959-Dec 2011
1yr-FF spread	1	USECON	Jan 1959-Dec 2011
2yr-FF spread	1	USECON	Jun 1976-Dec 2011
5yr-FF spread	1	USECON	Jan 1959-Dec 2011
10yr-FF spread	1	USECON	Jan 1959-Dec 2011
30yr-FF spread	1	USECON	Mar 1977-Dec 2011
Ex rate: Japan	2	USECON	Jan 1959-Dec 2011
Avg wkly hrs (manufacturing)	1	ALFRED	Jan 1959-Dec 2011
Avg initial claims *	3	BCI	Jan 1959-Dec 2011
New orders, goods, materials *	3	BCI	Jan 1959-Dec 2011
New orders, non-defense *	3	BCI	Jan 1959-Dec 2011
ISM new order index *	1	BCI	Jan 1959-Dec 2011
Building permits *	3	BCI	Jan 1959-Dec 2011
Emp: total	5	ALFRED	Jan 1959-Sep 2010
Emp: govt	5	ALFRED	Jan 1959-Dec 2011
Emp: mfg	6	ALFRED	Jan 1959-Dec 2011
Emp: mining	5	ALFRED	Jan 1959-Dec 2011
NAPM com price	1	ALFRED	Jan 1959-Dec 2011
NAPM vendor del *	1	USECON	Jan 1959-Dec 2011
NAPM invent *	1	USECON	Jan 1959-Dec 2011

Table 2: **In-sample summary of AUROCs.** The table below shows, for each forecast horizon, the resulting area of the ROC curve for the in-sample models using spread-only and spread-with-lagged-spread models. The remaining three models show the top performing variables when added to a spread and lagged spread model. Two sample t-statistics comparing current model to the model with spread only ("T-test 1") and to the model with spread and lagged spread ("T-test 2") are reported in the last two columns. The sample period is January 1959 to December 2011. ***, **, and * denote significance at the 1, 5, and 10% confidence levels, respectively.

Model	AUROC	T-test 1	T-test 2
Panel A: 3 months ahead			
Spread(t) only	0.672	—	—
Spread(t) + spread(t-6)	0.848	5.518***	—
S&P 500, 1y % chg	0.947	8.679***	4.137***
Michigan consumer survey	0.929	7.959***	3.523***
Debit margins (BD)	0.927	7.927***	3.335***
Panel B: 6 months ahead			
Spread(t) only	0.775	—	—
Spread(t)+spread(t-6)	0.867	3.484***	—
5 yr-FF spread	0.924	5.239***	2.754***
Michigan consumer survey	0.919	5.220***	2.582***
Building permits	0.917	5.137***	2.461**
Panel C: 12 months ahead			
Spread(t) only	0.865	—	—
Spread(t) + spread(t-6)	0.882	1.038	—
5 yr-FF spread	0.902	2.077**	1.577
1 yr-FF spread	0.898	1.862*	1.281
NAPM com price	0.896	1.619	0.848
Panel D: 18 months ahead			
Spread(t) only	0.811	—	—
Spread(t) + spread(t-6)	0.811	-0.005	—
Debit margins (BD)	0.862	2.054**	2.056**
NAPM com price	0.834	1.183	1.187
ISM new order index	0.826	0.811	0.796
Panel E: 24 months ahead			
Spread(t) only	0.693	—	—
Spread(t) + spread(t-6)	0.694	0.039	—
Debit margins (BD)	0.786	2.849***	2.829***
New orders, non-defense	0.771	2.519**	2.497**
NAPM com price	0.768	2.290**	2.316**

Table 3: **Out-of-sample summary of AUROCs.** The table below shows, for each forecast horizon, the resulting area of the ROC curve for the out-of-sample models using spread-only and spread-with-lagged-spread models. The remaining three models show the top performing variables when added to a spread and lagged spread model. Two sample t-statistics comparing current model to the model with spread only ("T-test 1") and to the model with spread and lagged spread ("T-test 2") are reported in the last two columns. The estimation sample is from January 1959 to August 1985 and the forecasting sample from September 1985 to December 2011. ***, **, and * denote significance at the 1, 5, and 10% confidence levels, respectively.

Model	**AUROC**	**T-test 1**	**T-test 2**
Panel A: 3 months ahead			
Spread(t) only	0.562	—	—
Spread(t)+spread(t-6)	0.765	4.341***	—
S&P 500, 1y % chg	0.963	12.830***	7.743***
Michigan consumer survey	0.941	12.706***	7.320***
Debit margins (BD)	0.933	11.920***	6.458***
Panel B: 6 months ahead			
Spread(t) only	0.674	—	—
Spread(t)+spread(t-6)	0.794	3.219***	—
S&P 500, 1y % chg	0.900	8.069***	4.658***
Debit margins (BD)	0.862	6.826***	3.407***
5 yr-FF spread	0.859	6.168***	2.667***
Panel C: 12 months ahead			
Spread(t) only	0.858	—	—
Spread(t)+spread(t-6)	0.883	1.152	—
5 yr-FF spread	0.902	2.785***	1.365
1 yr-FF spread	0.897	2.669***	1.102
NAPM com price	0.897	1.555	0.610
Panel D: 18 months ahead			
Spread(t) only	0.906	—	—
Spread(t)+spread(t-6)	0.881	-1.014	—
Debit margins (BD)	0.934	1.423	2.615***
2 yr-FF spread	0.897	-0.661	1.188
30 yr-FF spread	0.894	-1.022	0.907
Panel E: 24 months ahead			
Spread(t) only	0.853	—	—
Spread(t)+spread(t-6)	0.808	-1.214	—
1 yr-FF spread	0.846	-0.613	1.762*
2 yr-FF spread	0.827	-0.995	1.227
Baa-Aaa spread	0.801	-1.906	-0.298

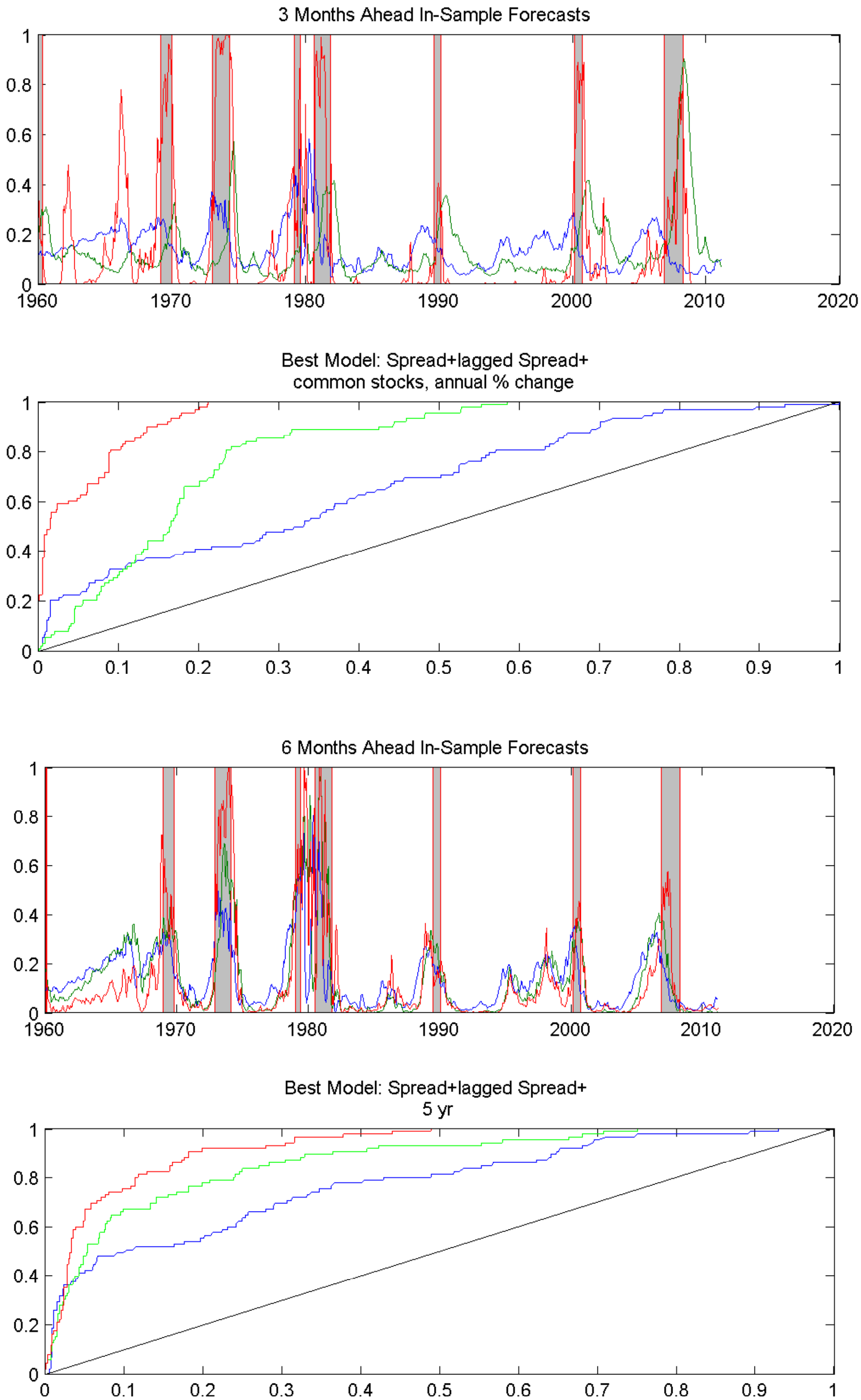


Figure 1: **3m and 6m In-sample Probabilities and ROC Curves.** For more information, see Figure 3 below.

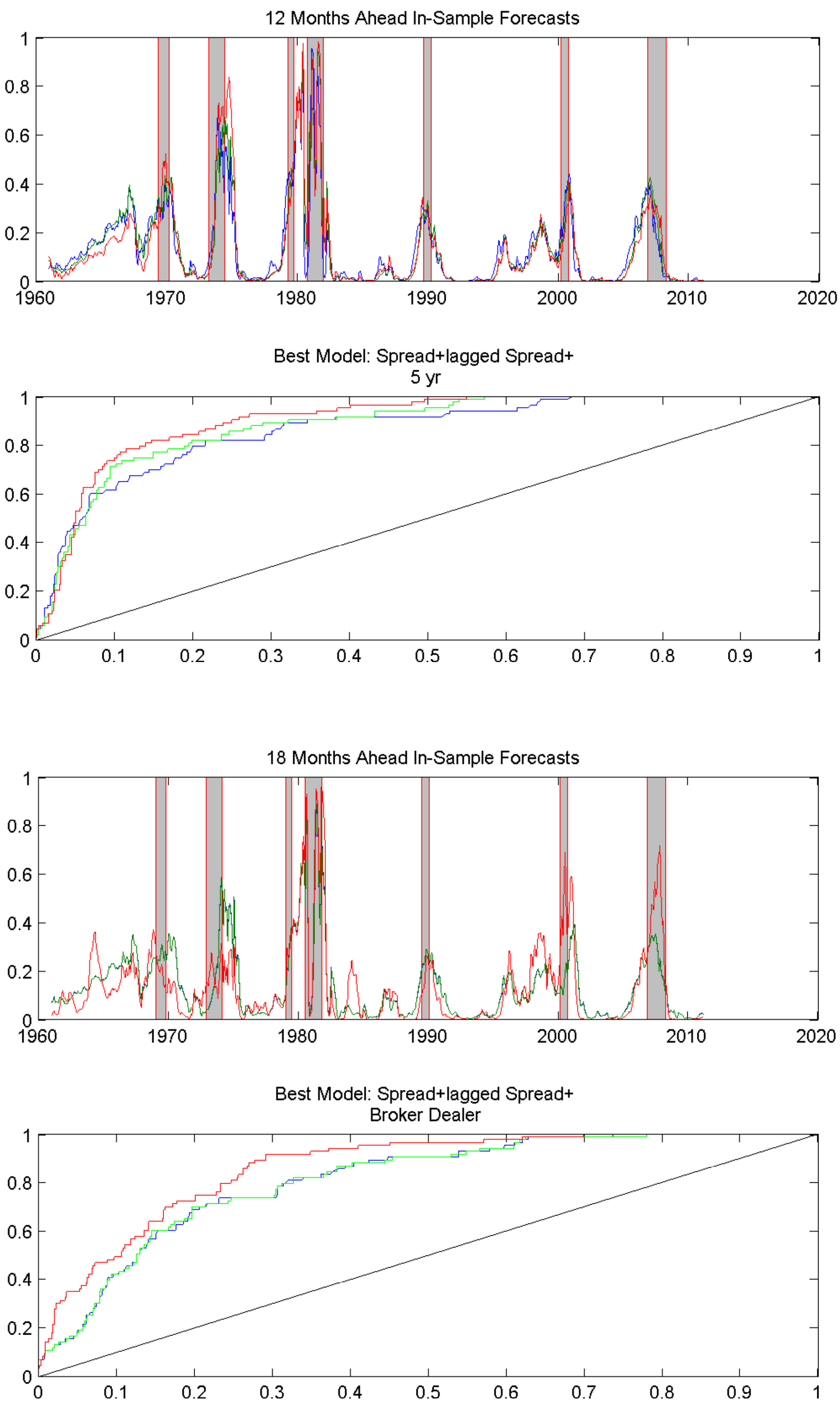
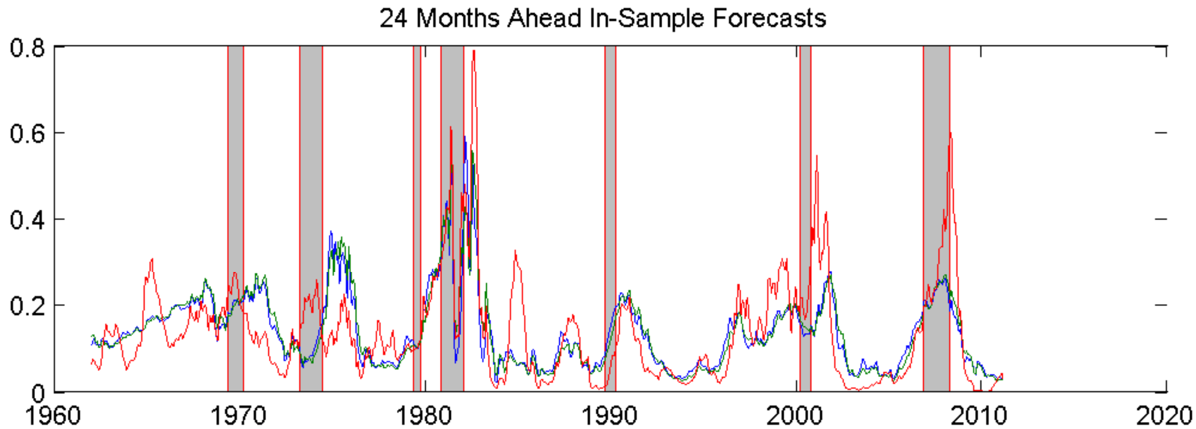


Figure 2: **12m and 18m In-sample Probabilities and ROC Curves.** For more details, see Figure 3 below.



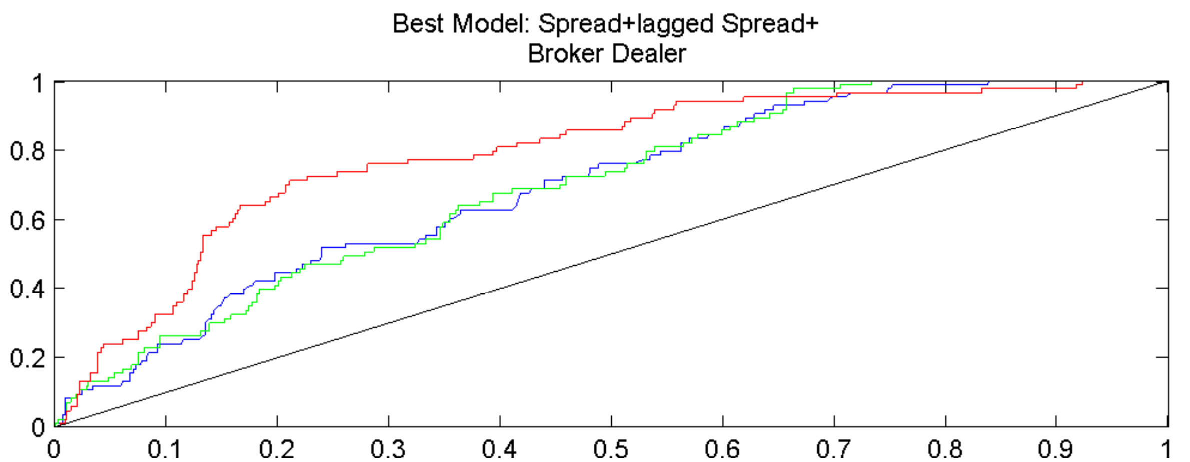


Figure 3: **24m In-sample Probabilities and ROC Curves.** The figures above show, at the 24-month forecast horizon, the probability of recession and the corresponding ROC curve for the spread-only model (blue line), the spread and lagged spread model (green line), and one additional model with best performance as determined by the AUROC (red line). Each model is estimated using monthly data from January 1959 to December 2011. In the first char, we show the probability of recession expressed as a decimal over our sample period, with the actual recession periods shaded in grey. Following this chart is a ROC curve that plots, for each model, the tradeoff between false positive rates (x-axis) and true positive rates (y-axis).

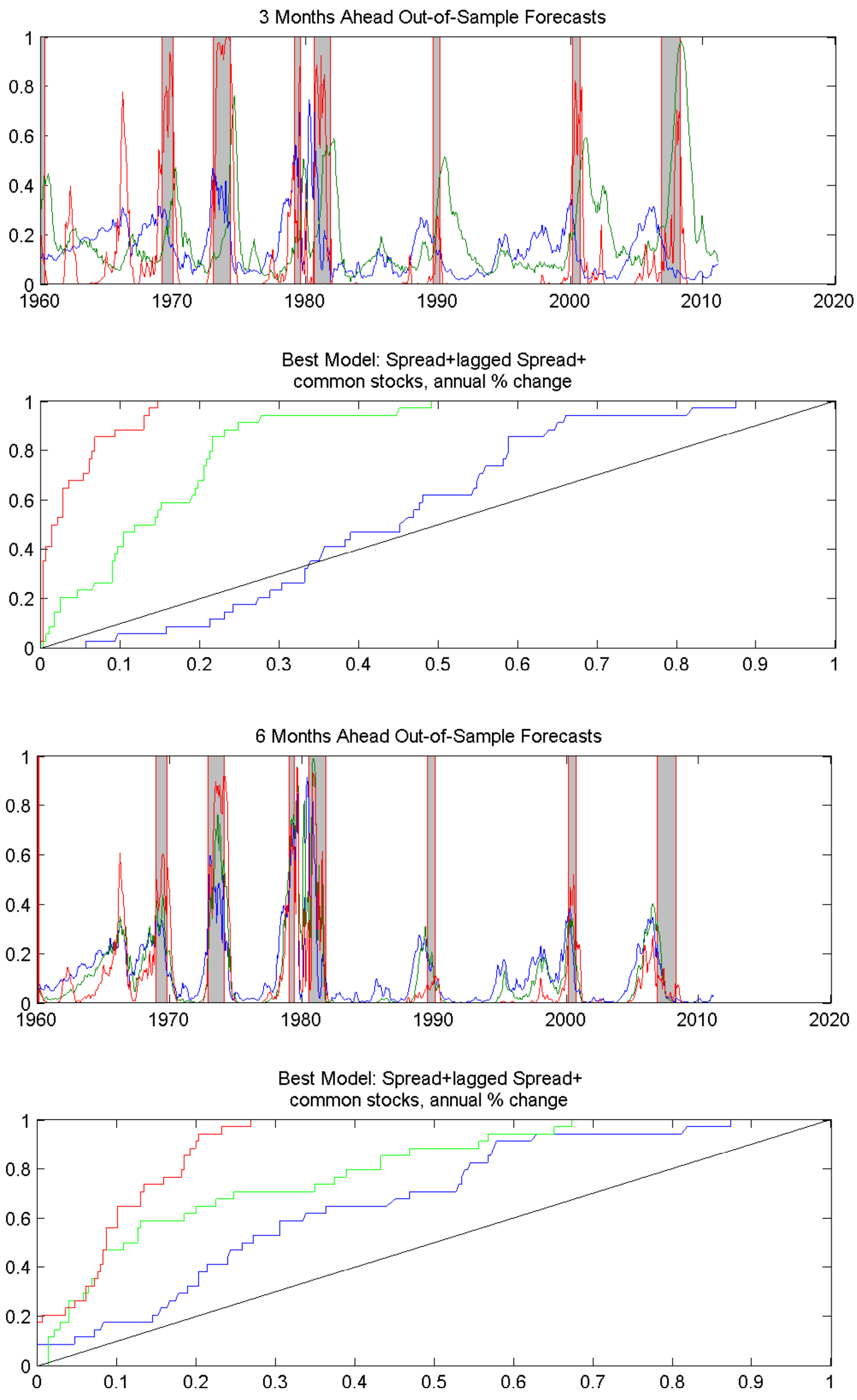


Figure 4: **3m and 6m Out-of-sample Probabilities and ROC Curves.** For more information, see Figure 6 below.

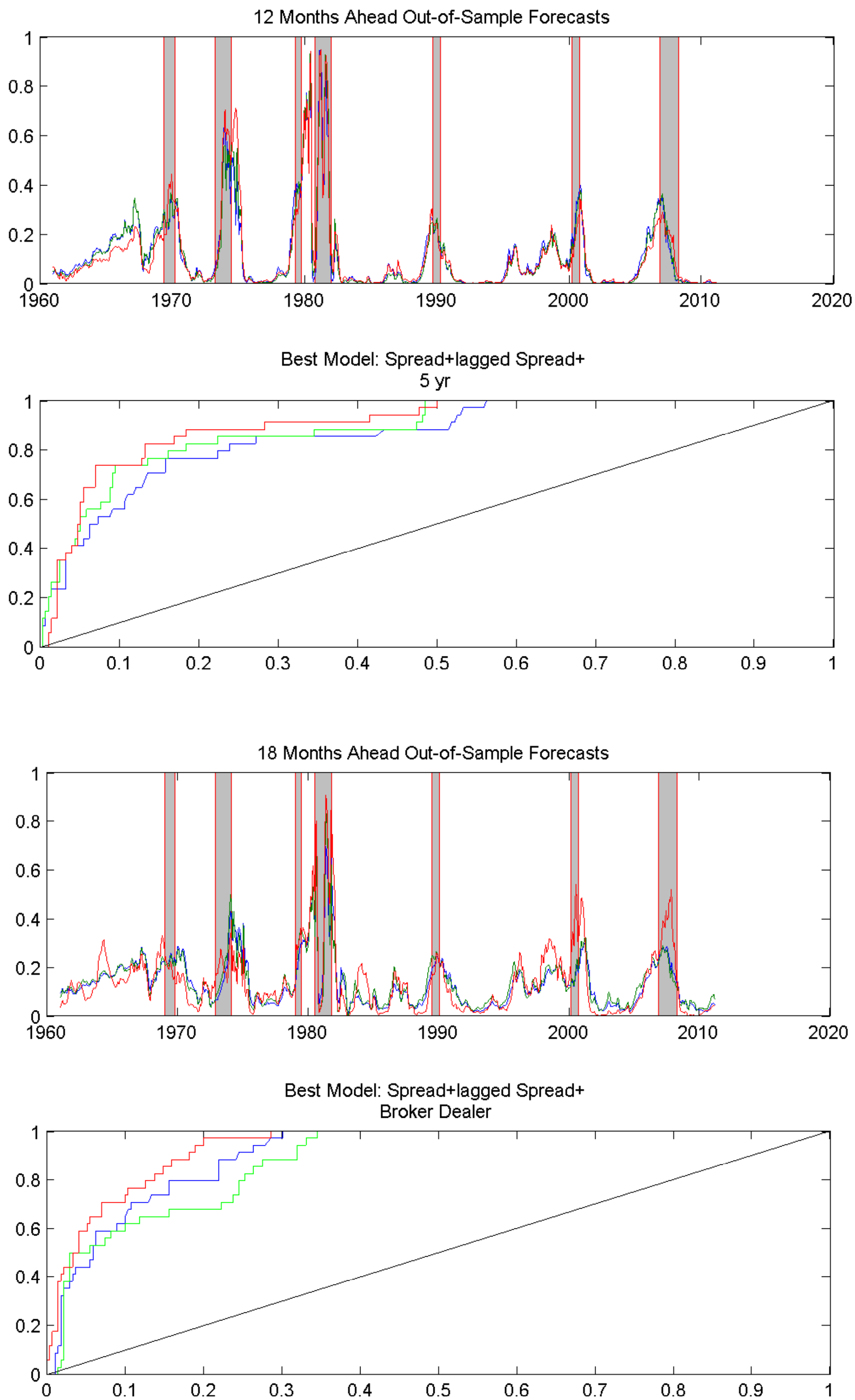
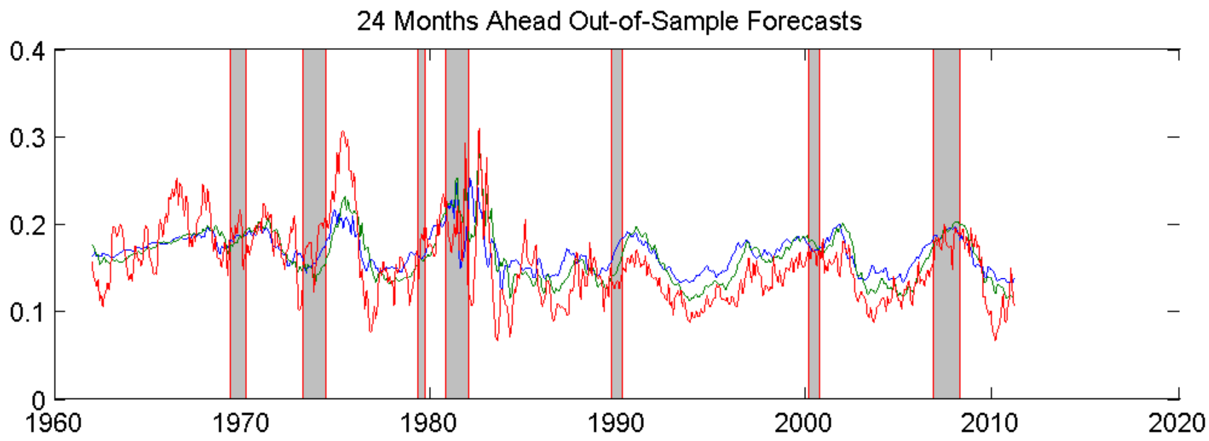


Figure 5: **12m and 18m Out-of-sample Probabilities and ROC Curves.** For more information, see Figure 6 below.



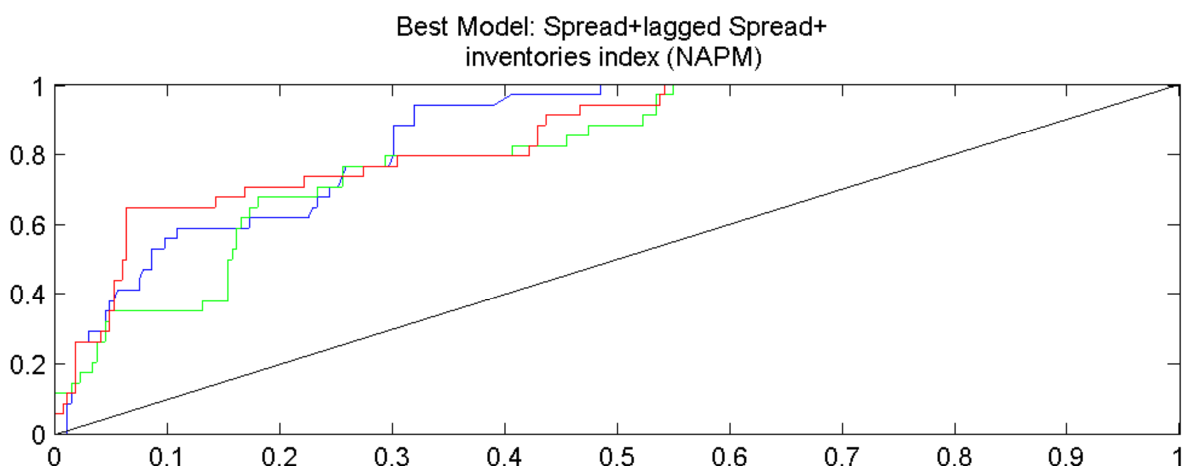


Figure 6: **24m Out-of-sample Probabilities and ROC Curves.** The figures above show, at the 24-month forecast horizon, the probability of recession and the corresponding ROC curve for the spread-only model (blue line), the spread and lagged spread model (green line), and one additional model with best performance as determined by the AUROC (red line). The model is estimated over the period of January 1959 to August 1985, and the calculation of forecast accuracy is estimated over the period of September 1985 to December 2011. In the first chart, we show the probability of recession as a decimal over our sample period, with the actual recession periods shaded in grey. Following this chart is a ROC curve that plots, for each model, the tradeoff between false positive rates (x-axis) and true positive rates (y-axis).

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