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Predicting Korean Recessions with Time-Varying Predictors*

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This study examines the predictive ability of a wide set of variables to predict Korean recessions based on probit models. In doing so, we extend probit-based recession forecasting models in several important and novel ways. First, in addition to commonly used financial variables, we incorporate several macro leading variables as potential predictors of recessions. Second, our forecasts use the algorithm of dynamic model selection/averaging (DMS/DMA), which allows for specific predictors to switch over time in a data-based manner.

Our main findings are as follows. First, in terms of both in-sample fits and out-of-sample forecasts, while financial indicators (such as interest rate spreads) are good predictors over short-horizons (i.e., one or three months ahead), some macro leading variables (such as commodity price index and job opening-to-application ratio) turn out to be useful over longer horizons. Second, forecasting using time-varying predictors (i.e., DMS/DMA models) performs well, beating individual best predictors for each forecast horizon. In addition, we show that forecasting using switching predictors outperforms the models that employ fixed predictors and the composite leading index, in most cases, especially in terms of the mean squared error (MSE). Third, we find strong evidence for predictor switching and illustrate how the performance of the key predictors has evolved over time.

JEL Classification: C35, C52, C53

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1. INTRODUCTION

Predicting the future state of an economy is a challenging, but important task for both private agents and policymakers. Households, firms, and investors make their decisions on consumption, production, and investment, respectively, based on their assessment of the outlook of the economy; policymakers need accurate and reliable economic forecasts to design and implement appropriate and preemptive polices.

While much of the previous research focuses on time series models where the dependent variable is continuous (such as the growth rate of real GDP), in the econometric literature, forecasting the values of the discrete recession indicator has attracted attention in recent years. A common approach to forecasting recessions in this line of research is to use the probit regression models, in which recessions are modeled as a binary indicator (Dueker, 1997; Estrella and Mishkin, 1998; Chauvet and Potter, 2005; Kauppi and Saikkonen, 2008). Under this approach, the probability of a recession is modeled as a function of the lagged values of potential predictors.

Although earlier studies focused on evaluating the predictive ability of a single variable, such as the interest term spread or equity market index, several recent studies have extended the probit models using multiple explanatory variables, including domestic and foreign yield spreads, stock market returns, credit spread, housing prices, and the composite macro leading index (Nyberg, 2010; Ng, 2012). In general, findings have shown that while the interest rate spread (between 10-year treasury bonds and three-month treasury bills) is the most statistically significant predictor of U.S. recessions (for two- to six-quarter forecast horizons), incorporating other financial variables and the composite macro leading index can help generate more accurate forecasts.

With regard to the Korean economy, a few studies have examined recession forecasting based on probit models (Ji and Park, 2002; Song and Choi, 2008; Lee, 2013), and those that have are limited to the predictive ability of financial variables or an analysis of their in-sample fit.

Even when we are able to identify a single predictor or set of good predictors of recessions, it remains unclear whether we should rely solely on such a model. This is because each recession is, in principle, unique. Thus, it is unlikely that a single predictor or model will be consistently superior, and what may seem to be a poor predictor could provide accurate forecasts on other occasions. For example, an indicator may accurately forecast recessions driven by shocks originating from financial sectors, but not other recessions. And when the economy undergoes a turbulent period due to abrupt changes in other countries, another predictor may turn out to be more useful. In fact, there is evidence that the predictive power of the yield spread, one of the key predictors of recessions, is not stable over time (Chauvet and Potter, 2002; 2005).[1)]

This study examines the predictive ability of a wide set of variables in predicting Korean recessions using probit-based regression models. In doing so, we extend the existing probit recession forecasting models in several important and novel ways. First, in addition to commonly used financial variables (including interest rate spreads, stock price index, and exchange rate), we incorporate several macro leading variables as potential predictors of recessions. In particular, these macro leading variables include most components used in constructing the composite leading index. Using disaggregated individual leading variables, rather than the aggregated leading index, allows us to incorporate more detailed information and thus may provide richer insight and flexibility in forecasting.

Second, rather than rely on a forecast model with fixed predictors, we use a forecast model that allows for specific predictors to switch over time in a data-based manner. Specifically, we implement this predictor switching using an algorithm developed by Raftery *et al*. (2010) and extended by Koop and Korobilis (2012, 2013), referred to as dynamic model selection/averaging (DMS/DMA). In this algorithm, by examining all possible combinations of predictors from a pool of candidate variables, the

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[1)] In a more general context, many studies show that forecasting models or useful regressors change over time (e.g., Pesaran and Timmermann, 2005; Stock and Watson, 2008).

best forecast model among them is updated at each time in a Bayesian fashion through a prediction-updating algorithm similar to Kalman filtering, and the algorithm allocates a higher probability to models that have forecasted well in the past.

Compared with standard forecasting methods that employ a model with fixed predictors, forecasting with predictor-switching probit models provides several practical benefits and important implications. First, with multiple predictors available, the properties of some predictors (even when they are, on average, poor predictors) may be of particular use in some phases over business cycles, because the nature of each is generally different. DMS/DMA, in which multiple models/predictors are allowed to compete and each of their information is efficiently weighed in a time-varying manner, enables us to better utilize multiple predictors at each time point and, thus, may yield improved forecasts. Second, with multiple models available and the best of them not fixed a priori, allowing for switches between different models can better accommodate various types of structural changes and is likely to be more robust to model misspecification. Because structural breaks are often attributed to one of the primary sources in forecasting failures, DMS/DMA is a potentially useful approach in this regard.

In fact, the DMS/DMA approach has proven to be flexible and competitive in several applications to linear regression models (e.g., Koop and Korobilis, 2012, 2013; Koop, 2014; Bork and Moller, 2015). However, there seems to be no previous study that adopts this approach in probit model-based recession forecasting. Hence, one of this paper’s contributions is an extension of the DMS/DMA framework to nonlinear time-series forecasting models and an illustration of its usefulness.

In the literature, there are a few alternative approaches to predicting binary indicator variables, including regime-switching models and qualitative VAR models. A handful of studies that use regime-switching models to forecast recessions include Lahiri and Wang (1994), Krolzig (2000), and Layton and Katsuura (2001). A notable study among them is Layton and Katsuura (2001), in which they ran horse races between regime-switching and probit models to predict recessions. Using the leading indicators as predictors, they found that regime switching models with time-varying transition probabilities perform better than the probit specifications. While this study is interesting, it is difficult to draw a general conclusion from their study regarding relative predictive abilities between competitor models. Since the forecast horizon considered in their paper is only one month ahead, each model's performance at longer horizons remains unknown. In addition, with only one predictor employed and fixed throughout the sample period, it fails to fully consider potential time-varying features of forecasting model, which is a focus of this paper.[2)]

Another alternative to recession forecasting is to use qualitative VARs, in which information from qualitative and/or discrete variables is incorporated into a standard VAR model framework. For example, Dueker and Assenmacher-Wesche (2010) compared simple probit forecasts with qualitative VARs, in which binary recession indictors are modelled as one of regressors in VAR system. They have found that the qualitative VAR produces overall less accurate forecasts than a standard VAR.

Our main findings are as follows. First, in terms of both in-sample fits and out-of-sample forecast results, while commonly used financial indicators (such as interest rate spreads) are good predictors over short horizons (i.e., one to three months ahead), some macro leading variables (such as commodity price index and job opening-to-application ratio) turn out to be useful over longer horizons. Second, forecasting using time-varying predictors (i.e., DMS/DMA models) demonstrates good performance, beating individual best predictors at each forecast horizon. In addition, we show that forecasting using switching predictors outperforms the models that employ fixed predictors and the composite leading index in most cases, especially in terms of the mean squared error (MSE). This result remains robust in the case of asymmetric loss in which forecast errors for recessions

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[2)] Although regime-switching models (Hamilton, 1989) have enjoyed great success in characterizing nonlinear dynamics inherent in many economic time series with good in-sample fit, their forecasts have been generally poor (see, for instance, Dacco and Satchell, 1999; Bessec and Bouabdallah, 2005).

are more heavily penalized. Third, we find strong evidence of substantial model (or predictor) switching over time. In so doing, we illustrate how each of main predictors' forecast performance has evolved over time.

The rest of this paper is structured as follows. Section 2 describes the probit model specification and forecast strategy. Section 3 presents the in-sample and out-of-sample results for individual predictors. Section 4 explains the key idea of DMS/DMA and the associated computation algorithm and discusses the forecast results. Finally, section 5 concludes the paper.

2. PROBIT MODEL FOR FORECASTING RECESSIONS

The main goal of this study is to evaluate the (time-varying) predictive power of various variables in forecasting the probability of a recession several months ahead. We assume the recession indicator, y_t, is a binary variable that takes on two possible values, depending on the state of the economy:

$$y_t = \begin{cases} 1 & \text{if the economy is in a recessionary state at time } t \\ 0 & \text{if the economy is in an expansionary state at time } t. \end{cases}$$

The standard probit model implies that the probability of recession at time *t*, with a forecast horizon of *h* periods (that is, the probability of $y_t = 1$, given the information up to *t*–*h*) is:

$$P_{t-h}(y_t = 1) = \Phi(X_{t-h}\beta) = \Phi(\pi_t) = \hat{y}_t, \tag{1}$$

where $P_{t-h}(\cdot)$ denotes the conditional probability given the information at time $t-h$ (i.e., data on predictors, X_{t-h}, which include a constant term) and β is a vector of parameters. Here, π_t is a linear function of explanatory variables $(\pi_t = X_{t-h}\beta)$ and links the continuous values with the forecast of the binary variable, y_t, through the cumulative standard normal distribution, $\Phi(\cdot)$, given as:[3)]

$$\Phi(\pi_t) = \int_{-\infty}^{\pi_t} \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz. \tag{2}$$

The parameters of the probit model can be estimated by the usual numerical methods to maximize the log likelihood, defined as:

$$\log L = \sum_{t=1}^{T} [y_t \log \Phi(X_{t-h}\beta) + (1-y_t)\log(1-\Phi(X_{t-h}\beta))]. \tag{3}$$

In the probit forecasting literature, a popular statistic used to evaluate the goodness-of-fit is the pseudo-R^2 (Estrella, 1998), defined as 1– $(\log(L^u)/\log(L^c))^{2\log(L^c)/T}$, where L^u is the unconstrained maximum value of the likelihood function, L^c is the corresponding maximum value under the constraint that all coefficients are 0 except for the constant, and T denotes the sample size. A higher pseudo-R^2 suggests that the inclusion of explanatory variables can increase the likelihood of the estimated model.

Pseudo-R^2 is an intuitive and attractive measure in that it is based on the objective function used for in-sample estimation and the likelihood represents the joint probability that the observed values are consistent with the estimated models. However, it suffers from several drawbacks. First, in out-of-sample forecasts, pseudo-R^2 may not lie between 0 and 1 and can be negative.[4)] Second, statistical tests of the significance for the predictive

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3) In terms of a modeling framework, several recent papers have extended the static probit model and adopted more general specifications by including a lagged recession indicator or forecasted recession probability, or both, as regressors (i.e., in the form of $\pi_t = \alpha y_{t-1} + \gamma\pi_{t-1} + X_{t-h}\beta$), referred to as dynamic, autoregressive, and dynamic autoregressive probit models, respectively (Kauppi and Saikkonen, 2008; Nyberg, 2010; Ng, 2012). However, the forecast performance of these specifications turns out to be (slightly) worse for many variables considered in this paper, especially over longer horizons. Moreover, given that one of the goals of this study is to investigate the (time-varying) predictive performance of individual indicators, these specifications may hinder this task.

4) While pseudo-R^2 is analogous to R^2 in linear regression and has values ranging from 0 to 1

abilities of the variables no longer exist in a strict sense.

An alternative measure commonly used in the literature to assess out-of-sample forecast accuracy is the mean squared error (MSE), or the quadratic probability score (QPS), the probability-forecast analog of the mean squared error (see, Diebold and Rudebusch, 1989). In fact, Estrella and Mishkin (1998) report that pseudo-R^2 does not always outperform the quadratic probability score if the forecast of the dependent indicator variable is very close to one-half and the fit of the model is poor. Hence, we use the MSE as a primary measure of predictive performance, but also report pseudo-R^2 as a supplementary statistic.

The data we use are monthly series running from 1995:4 to 2011:8, covering 4 recessions (as of September of 2015, 2011:8 is the latest business cycle turning point, announced as a peak by the National Statistics Office (NSO)). The binary time series for Korean recession periods is obtained from the NSO business cycle reference dates. A recession period starts from a peak month and lasts until the month of the subsequent trough. All months not included in a recession period are classified as expansion months.

In selecting candidate recession predictors, we follow the literature (e.g., Nyberg (2010), Ng (2012), and, in particular, Lee (2013), who considered an extensive set of financial variables in predicting Korean recessions using probit models). For the ease of discussion, we divide candidate predictors into the three groups: domestic financial variables, foreign financial variables, and macro leading variables. Table 1 contains the descriptions,

in in-sample results, out-of-sample pseudo-R^2 can be less than 0 if the model is worse than a constant term by itself. As noted by Estrella and Mishkin (1998), this problem is not a consequence of the probit form, for it applies to the predictions based on other linear regressions. In this case, the negative pseudo-R^2 can be interpreted as a very poor forecast. In fact, pseudo-R^2 can be a very large negative number (in magnitude) in the case of a completely false signal. For example, suppose that the true value of y_t is 1, but the forecast turns out to be (very close to) 0. Then, while the (squared) error is just one, the pseudo-R^2 associated with this episode would be a large negative number. Hence, even when the overall performance of a forecast model is reasonably good, the average pseudo-R^2 can be poor, or even negative. In presenting our results, we report only non-negative pseudo-R^2. In fact, in most cases reported below, a negative pseudo-R^2 occurs because of a few such episodes associated with bad forecasts.

Table 1 List of Individual Predictor Variables

Description	Mnemonic	Remark
I. Domestic Financial Variables		
Three-year treasury bill yield less call rate	SP3-CALL	
Three-year treasury bill yield less commercial paper yield	SP3-CP	
Five-year treasury bill yield less call rate	SP5-CALL	
Five-year treasury bill yield less commercial paper yield	SP5-CP	
Korea Composite Stock Price Index	KOSPI	GR
II. Foreign Financial Variables		
KRW/USD nominal exchange rate	EXCH	GR
10-year U.S. treasury bill yield less call rate	SP10-CALL	
10-year U.S. treasury bill yield less commercial paper yield	SP10-CP	
Standard & Poor's 500 index	SP500	GR
III. Macro Leading Variables		
Nominal monetary aggregates of M1 and M2	M1 and M2	GR
Job opening-to-application ratio	JOB	
Construction orders received	COR	GR
Inventory circulation indicator	ICI	
Commodity price index	COMPI	GR
Net barter terms of trade	NBTOT	GR

Note: GR indicates the variable is transformed as the percentage change, i.e., growth rate.

mnemonics, and transformations (where applicable) of all the individual predictor variables.[5)]

[5)] The data are collected from the NSO, except for U.S. treasury bill yields (from the Federal Reserve Economic Data) and SP500 (from Yahoo Finance). In addition to these variables, we experimented with other possible predictor variables such as alternative interest rate spreads (using the three- or five-year treasury bill yield less CD rate), corporate bond yields, unemployment rate, and housing prices. It turns out that these all have lower predictive power and the results are not reported.

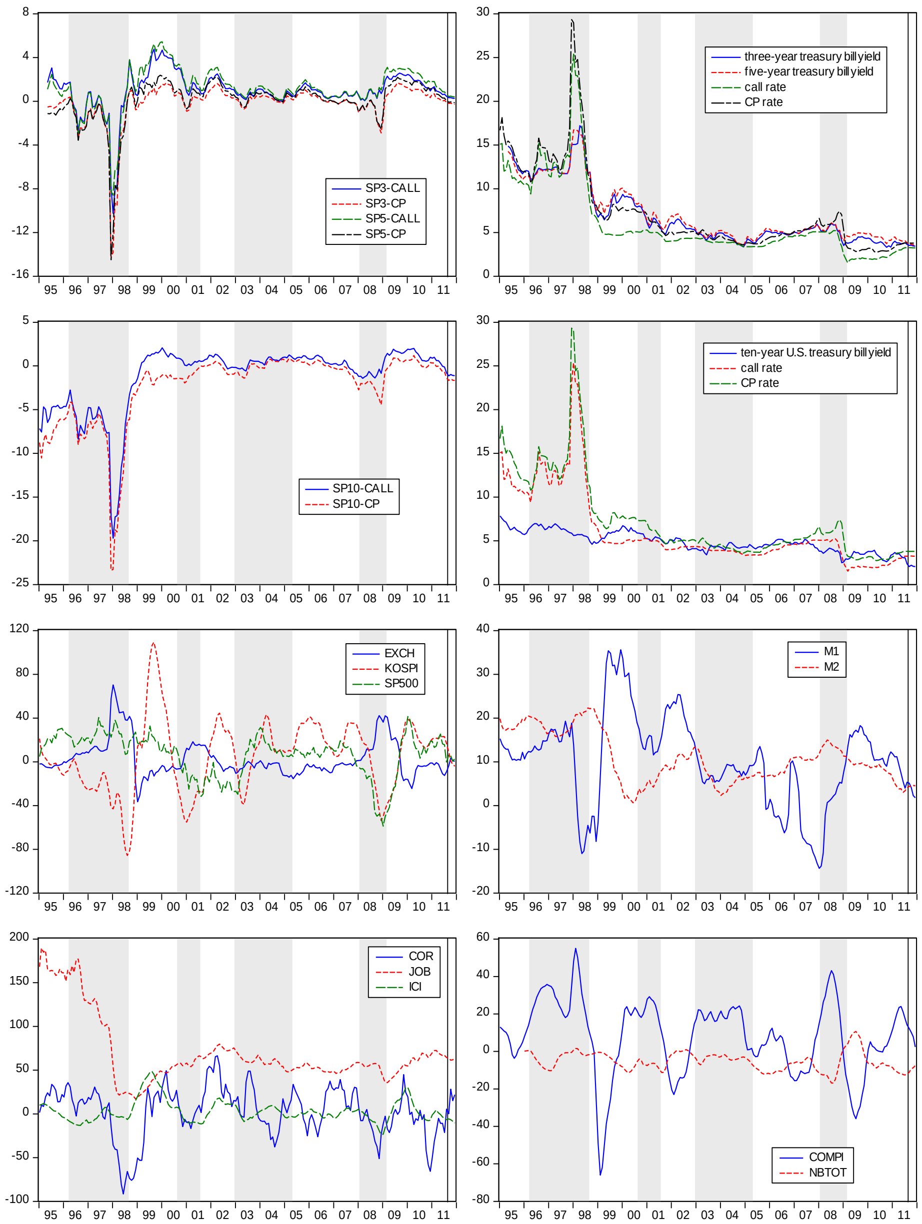
Note that the group of macro leading variables includes all indicators used in the construction of the composite leading index, except for the consumer expectation index and the producer shipment index. Because the data for these two series are available only from January of 1999, we exclude them to avoid a significant loss of sample observations. For KOSPI, SP500, EXCH, and all the macro leading variables (except for JOB and ICI) all of which exhibit apparent nonstationary behavior, we transform them and use their growth rates (percentage changes over previous year) in the forecast models.

Figure 1 presents the time series plot of these individual predictors (and their components for the interest spreads). While the detailed discussion on individual variables' performance is postponed until the forecast results are presented, it can be easily seen that their specific leading behaviors vary across individual variables. Furthermore, there appear to be several cases in which a predictor exhibits good leading properties over some periods, but it fails to do so other times. This suggests that the data used in this study make a good case of time-varying predictors in recession forecasting.

For all models, we use a rolling estimation window of size 72 observations (or six years) to produce pseudo out-of-sample forecasts for h=1, 3, 6, 12, and 24 step-ahead horizons.[6] Using the estimation sample from 1995:4 to 2001:3, the first available forecasts are for 2001: 3+h. We then proceed by

[6] One delicate, but practical issue in out-of-sample forecasting is 'publication lag'. Unlike financial variables (which are real-time data) and macro leading variables (available with just one or two months delay before the figures are officially published), the business cycle turning points are announced with a substantial time delay. For instance, the latest business cycle turning point (peak, August of 2011) was announced in June of 2014, and is still preliminary. This long publication lag implies a practical limitation on using current information of explanatory variables because most recent data on the explanatory variables (for the few past years) cannot be used for parameter estimation. However, several recent studies take a practical view that the public is reasonably certain of the near past or current state of the economy, although there is some uncertainty, so that we may make reasonable assumptions on whether a specific month in the recent past is in a recessionary state, even if the official announcement of the reference date is still pending (Kauppi, 2008; Kauppi and Saikkonen, 2008; Ng, 2012). Moreover, given that recent research offers various alternative procedures for dating business cycle turning points that work well in real time, even if they cannot forecast future turning points (see, for example, Chauvet and Hamilton, 2006; Chauvet and Piger, 2008; Camacho *et al*., 2012), it would not be too unreasonable to make such assumptions.

Figure 1 Time-series of Individual Predictors



Note: The recession periods are shaded.

moving the sample forward by a month and generate forecasts through 2011:8.[7] Forecast evaluation is done for the period 2004:1 to 2011:8.

3. RESULTS OF THE INDIVIDUAL PREDICTORS

Before presenting the forecast results of probit models with time-varying predictors, we briefly discuss individual predictors' performance concerning both their in-sample fits and out-of-sample forecast results.

3.1. In-sample Results

Tables 2A-2B and figure 2 provide the in-sample fit results for each of the individual variables considered. While domestic financial variables do a good job over short forecast horizons (i.e., $h=1$ and $h=3$), their predictive powers tend to deteriorate as the forecast horizon lengthens. In particular, the yield spreads show poor performance during the 2003-2004 recession with unclear signals. In contrast, over medium and longer forecast horizons, their roles seem to be replaced by some of the macro leading variables. In fact, although the overall performance of the macro leading variables is rather poor, some of them (e.g., COMPI and JOB) seem to perform fairly well over relatively longer horizons. COMPI, in particular, exhibits remarkable predictive power overall, and is ranked first for most of the forecast horizons considered by both accuracy measures. By and large, both the MSE and the pseudo-R^2 yield similar results.

This varying predictive ability of each group of variables over forecast horizons can be seen as follows. One of the key channels through which financial variables may work as predictors is via economic agents' expectations, which reflect developments of the economy in real-time.

[7] We also considered a recursive forecast by expanding the estimation sample as the forecast moves forward. However, the overall forecast results turn out to be worse and are not reported. This is presumably because potential structural changes in the economy during the forecast period are not properly addressed in the forecast scheme.

Table 2A MSE Measures of In-sample Results for Individual Predictors

Variable	h=1	h=3	h=6	h=12	h=24
SP3-CALL	0.181 [5]	0.195 [5]	0.230	0.243	0.238
SP3-CP	0.159 [3]	0.188 [4]	0.233	0.242	0.233 [4]
SP5-CALL	0.177 [4]	0.188 [3]	0.224 [3]	0.244	0.238
SP5-CP	0.157 [2]	0.181 [2]	0.226 [4]	0.243	0.235 [5]
KOSPI	0.193	0.222	0.243	0.230 [3]	0.243
EXCH	0.220	0.235	0.245	0.236 [4]	0.235
SP10-CALL	0.198	0.206	0.228 [5]	0.246	0.242
SP10-CP	0.204	0.213	0.232	0.246	0.241
SP500	0.243	0.244	0.243	0.242	0.241
M1	0.235	0.240	0.244	0.237 [5]	0.240
M2	0.243	0.245	0.247	0.247	0.229 [2]
COR	0.237	0.244	0.239	0.174 [1]	0.241
JOB	0.234	0.222	0.199 [2]	0.192 [2]	0.233 [3]
ICI	0.213	0.231	0.244	0.243	0.242
COMPI	0.096 [1]	0.098 [1]	0.165 [1]	0.243	0.214 [1]
NBTOT	0.245	0.244	0.243	0.244	0.236

Notes: The table reports the mean squared errors (MSEs) of individual predictors for the forecast horizons of h=1, 3, 6, 12 and 24. The numbers in brackets indicate the rank of the variable.

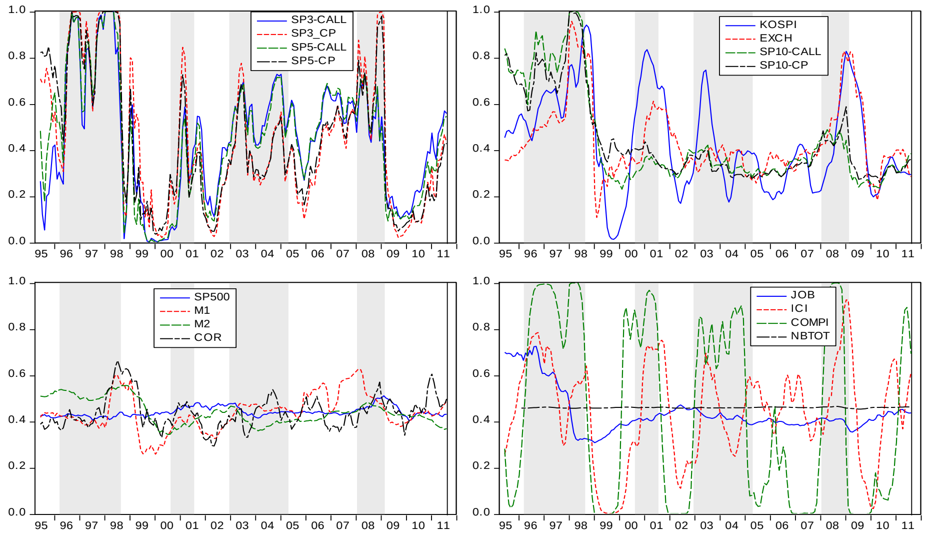
Table 2B Pseudo-R^2 Measures of In-sample Results for Individual Predictors

Variable	h=1	h=3	h=6	h=12	h=24
SP3-CALL	0.311 [5]	0.233 [5]	0.064	0.018	0.030
SP3-CP	0.386 [2]	0.233 [4]	0.050	0.014	0.055 [3]
SP5-CALL	0.327 [4]	0.269 [2]	0.098 [3]	0.004	0.026
SP5-CP	0.356 [3]	0.258 [3]	0.081 [4]	0.003	0.045 [4]
KOSPI	0.205	0.099	0.012	0.052 [4]	0.000
EXCH	0.112	0.043	0.000	0.052 [3]	0.039
SP10-CALL	0.188	0.166	0.078 [5]	0.005	0.009
SP10-CP	0.149	0.126	0.060	0.005	0.012
SP500	0.002	0.002	0.021	0.035 [5]	0.010
M1	0.025	0.013	0.000	0.029	0.013
M2	0.012	0.008	0.003	0.004	0.061 [2]
COR	0.020	0.000	0.032	0.357 [1]	0.009
JOB	0.039	0.086	0.190 [2]	0.323 [2]	0.041 [5]
ICI	0.214	0.120	0.028	0.004	0.006
COMPI	0.682 [1]	0.660 [1]	0.346 [1]	0.009	0.127 [1]
NBTOT	0.000	0.002	0.003	0.001	0.010

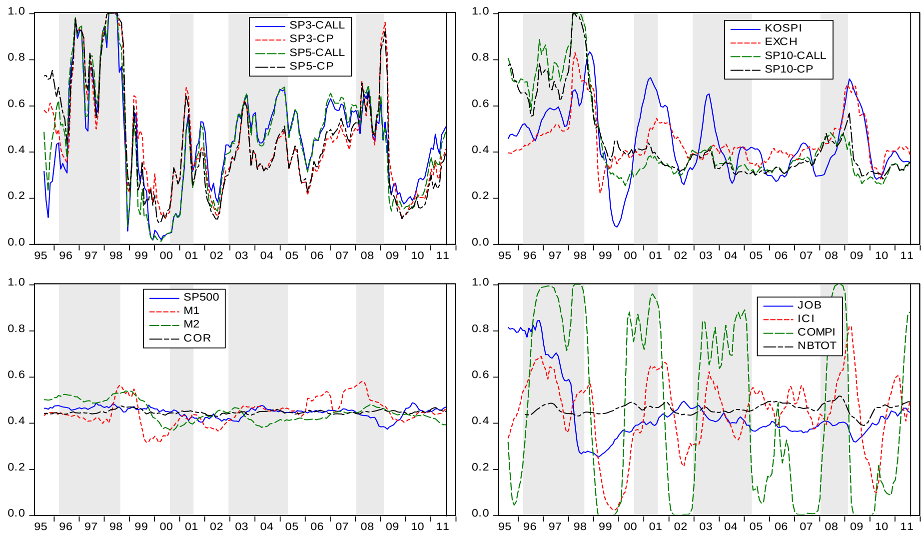
Notes: The table reports the pseudo-R^2 values of individual predictors for the forecast horizons of h=1, 3, 6, 12 and 24. The numbers in brackets indicate the rank of the variable.

Figure 2 In-sample Fits of Individual Predictors

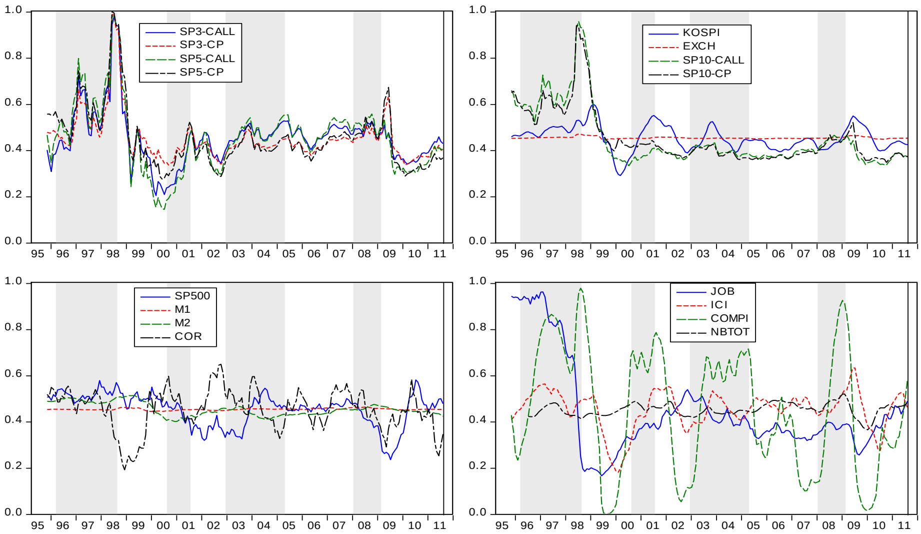
(*h*=1)



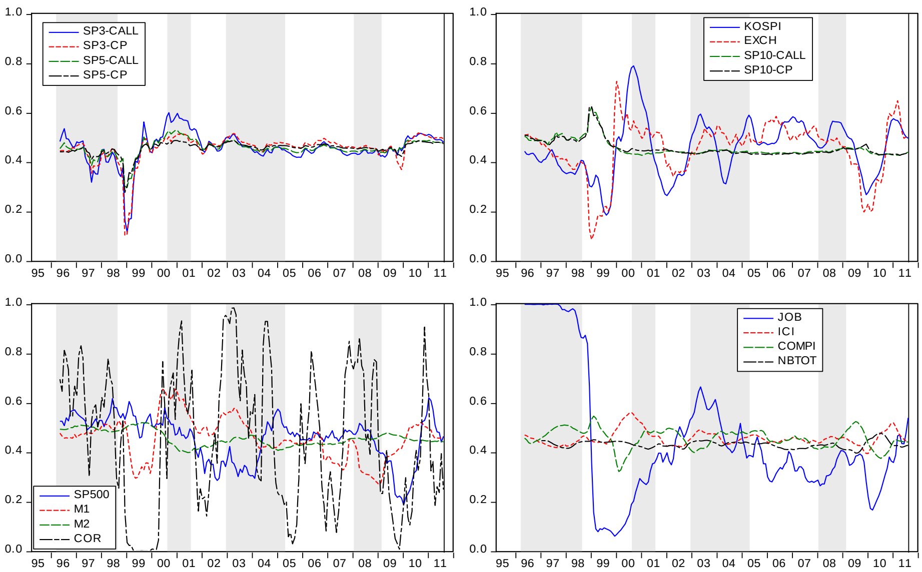
(*h*=3)



(*h*=6)



(*h*=12)



Note: The recession periods are shaded.

While this swiftness is a definite plus, it may also render some inherent pitfalls given its nature; more often than not, expectations are not too reliable and may not materialize in some cases (especially in the long term). For example, while stock prices are usually believed to precede the real side of economy, they are also notoriously volatile and noisy. Indeed, as figure 1 illustrates, although the equity prices tend to sharply decline prior to the crises, such tendency is not clearly visible before the other recessions and they also show equally substantial fluctuations within each regime.

The poor predictive performance of domestic yield spreads during the early to mid-2000's deserves some discussion. As shown in figure 1, the yield spreads do not show clear cyclical relationship with recessions and one explanation for this can be provided in terms of monetary policy conduct regarding expectations management. With the inflationary pressure and mild downturns during the period, the financial markets expected a tightening policy stance, which is reflected in several occasional upward movements (albeit overall downward trend) in the yields on the treasury bonds. However, the bank of Korea instead lowered the target rates, creating rather larger yield spreads over this time span. This indicates that the discrepancy between market expectations and the actual policy stance, resulting from the misconduct of monetary policy, can be a possible reason for poor performance of yield spreads during the period.[8)]

Unlike the financial variables, changes in individual macro leading variables are likely to have direct and real effects on the rest of the economy with some time lags. COMPI, the overall best predictor, shows a good example. As shown in figure 1 (where the figures are inverted), it exhibits a clear cyclical behavior leading peaks and troughs by several months; its growth rate turns negative prior to almost all of the peaks and positive before the trough dates. Given Korea's heavy dependence on oil and other imported raw materials, the result seems natural and intuitive; the increase in

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[8)] This result is largely in line with the recent findings that the bank's monetary policy stance towards inflation stabilization is relatively weaker than to output stabilization and its target rate changes are rather hard to predict (Hsing and Lee, 2004; Hwang, 2013; Kim, 2014).

international commodity prices is translated into domestic prices with some time lag (due to some rigidities by contracts). This, in turn, may serve as negative (supply) shocks. Roughly similar stories can be told about COR and JOB.[9)]

It is also interesting to observe the differences in horizons with the best fit among each group of variables. While the fit of financial variables tends to deteriorate as the forecast horizons grows, some of the macro leading variables (e.g., JOB and COR) turn out to have a relatively better fit over medium horizons (such as $h=6$ and $h=12$). This result contrasts with the case of U.S. recession forecasting, in which the yield spread tends to have higher predictive ability for medium- to long-term forecast horizons (6 to 12 months) (Kauppi and Saikkonen, 2008; Nyberg, 2010). Furthermore, the forecasting performance of the macro leading index worsens as the forecast horizon increases and it has virtually no predictive power beyond six months (Ng, 2012). Along with the discussion above, a few additional reasons behind this difference can be seen as follows. First, the maturities of the bonds considered in this study are much shorter, largely because of the under-development of the bond markets in Korea so that the expectation contents in yield spreads are largely short-horizoned. Second, the leading index, due to aggregation, may not properly reflect the actual time lag with which the changes in individual leading indicators propagate into the rest of the economy.

It turns out that foreign financial variables perform rather poorly and seem to do a reasonable job only over a few medium horizons. This is largely because only the two U.S. recessions are (roughly) synchronized with those of Korea during the sample span. Thus, the U.S. long-term interest rates and equity market index, while known to be good recession predictors for their own economy, may have limited use in predicting Korean recession.

[9)] The mediocre predictive power of the other macro leading variables is not straightforward to explain, but it may be because they in fact may not have good leading properties. Given the ever-changing nature of the Korean economy, it is suggested that the role of individual components of the leading index and their weights need to be constantly monitored and updated with the consideration of their time-varying importance.

Note that a good in-sample fit for a variable does not necessarily indicate that it is a good predictor. In fact, it is not uncommon for some of the best in-sample predictors to perform quite poorly out-of-sample (and vice versa), particularly in terms of the pseudo-R^2. Furthermore, in out-of-sample forecasts, the results may be altered substantially because the in-sample estimation results are based on the whole sample observations and thus they may not properly address potential structural changes of the Korean economy in the forecast sample.

3.2. Out-of-sample Results

In the out-of-sample results contained in tables 3A-3B and figure 3, several interesting differences emerge. In contrast to the in-sample results, foreign financial variables (in particular, SP10-CALL and SP10-CP) turn out to be useful over short horizons and tend to, in part, replace the role of domestic financial indicators. This is partly because the forecast sample period includes the global financial crisis of 2008, when the shocks essentially originated from the U.S.

In addition, macro leading variables exhibit relatively better out-of-sample performance and some now have a high rank over medium and long horizons. It is striking that COMPI continues to forecast consistently well. On the contrary, JOB has relatively worse out-of-sample performance. As shown in figure 1, JOB shows clear cyclical patterns up until early 2000's, but its movement does not seem to be tightly linked to recessions afterwards. This loose link is in line with the assertions that some labor market indicators do not appropriately reflect the actual labor market conditions for the past decade or so, largely owing to the issues associated with the increasing duality in labor market (e.g., increase in non-regular jobs) and the prevalence of discouraged workers.

It is noteworthy that, perhaps not surprisingly, the forecast performance of individual variables is not fixed in many cases; several indicators show varying predictive power over time. For example, as shown in figure 3,

Table 3A MSE Measures of Out-of-sample Fits for Individual Predictors

Variable	h=1	h=3	h=6	h=12	h=24
SP3-CALL	0.204 [5]	0.207 [4]	0.214 [5]	0.225 [3]	0.256
SP3-CP	0.203 [4]	0.226	0.241	0.260	0.211 [2]
SP5-CALL	0.210	0.213 [5]	0.222	0.226 [4]	0.249
SP5-CP	0.213	0.240	0.250	0.249	0.211 [3]
KOSPI	0.224	0.239	0.249	0.306	0.239
EXCH	0.227	0.237	0.261	0.271	0.225 [5]
SP10-CALL	0.184 [3]	0.185 [3]	0.196 [3]	0.240	0.223 [4]
SP10-CP	0.181 [2]	0.179 [2]	0.191 [2]	0.240	0.246
SP500	0.252	0.256	0.255	0.259	0.242
M1	0.304	0.281	0.247	0.258	0.248
M2	0.219	0.213	0.210 [4]	0.234 [5]	0.284
COR	0.253	0.257	0.246	0.191 [1]	0.251
JOB	0.273	0.264	0.236	0.220 [2]	0.294
ICI	0.236	0.257	0.270	0.243	0.239
COMPI	0.103 [1]	0.080 [1]	0.158 [1]	0.248	0.207 [1]
NBTOT	0.248	0.246	0.254	0.256	0.225

Notes: The table reports the mean squared errors (MSEs) of individual predictors for the forecast horizons of h=1, 3, 6, 12 and 24. The numbers in brackets indicate the rank of the variable.

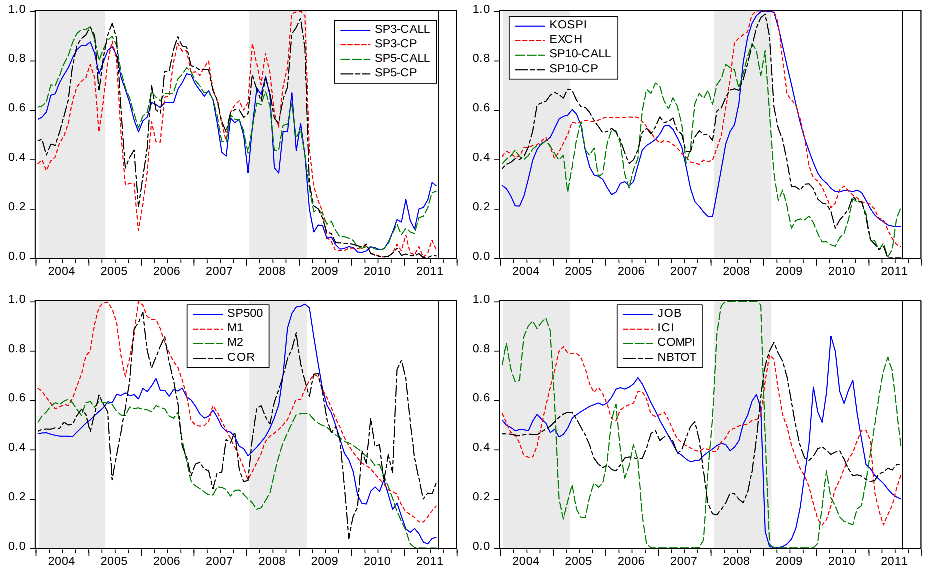
Table 3B Pseudo-R^2 Measures of Out-of-sample Results for Individual Predictor

Variable	h=1	h=3	h=6	h=12	h=24
SP3-CALL	0.418 [3]	0.391 [3]	0.236 [3]	0.119 [3]	0.010
SP3-CP	0.327 [5]	–	0.214 [4]	–	0.098 [2]
SP5-CALL	0.443 [2]	0.416 [1]	0.272 [1]	0.096 [4]	0.031
SP5-CP	0.104	0.065	0.062	–	0.082 [4]
KOSPI	–		–	–	–
EXCH			–	–	–
SP10-CALL	0.473 [1]	0.289 [5]	–	–	0.041 [5]
SP10-CP	0.143	–	–	–	–
SP500	–	–	–	–	–
M1	–	–	–	–	–
M2	0.186	–	0.159 [5]	–	0.088 [3]
COR	–	–	–	0.082 [5]	–
JOB	0.387 [4]	0.292 [4]	0.252 [2]	0.288 [1]	–
ICI	–	–	–	–	–
COMPI	0.288	0.399 [2]	0.044	–	0.122 [1]
NBTOT	0.005	0.048	0.133	0.243 [2]	–

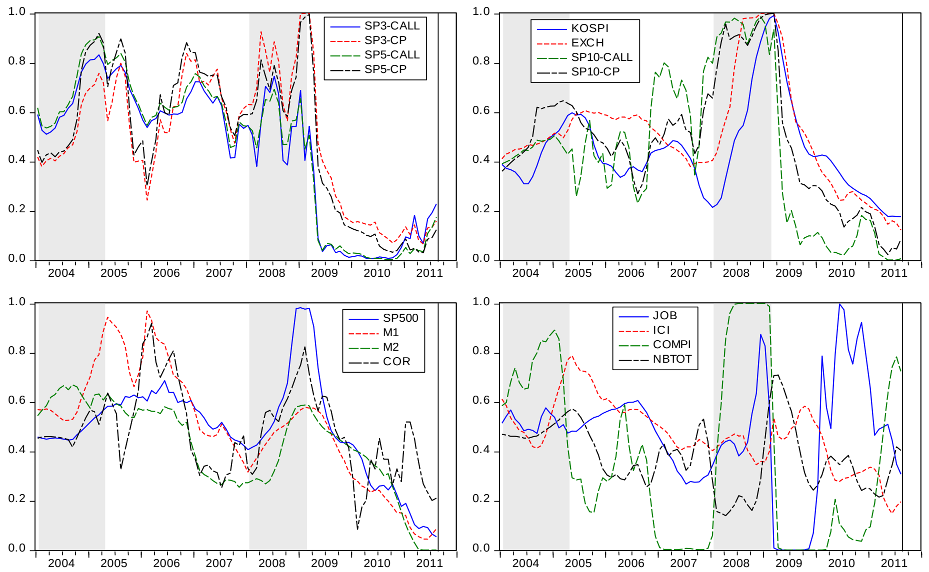
Notes: The table reports the pseudo-R^2 values of individual predictors for the forecast horizons of h=1, 3, 6, 12 and 24. The numbers in brackets indicate the rank of the variable.

Figure 3 Out-of-sample Forecasts of Individual Predictors

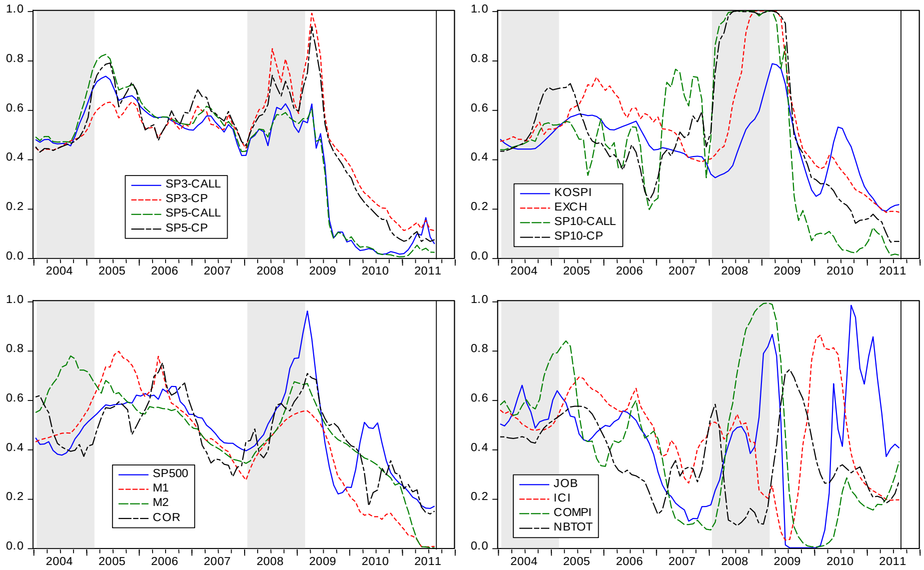
(*h*=1)



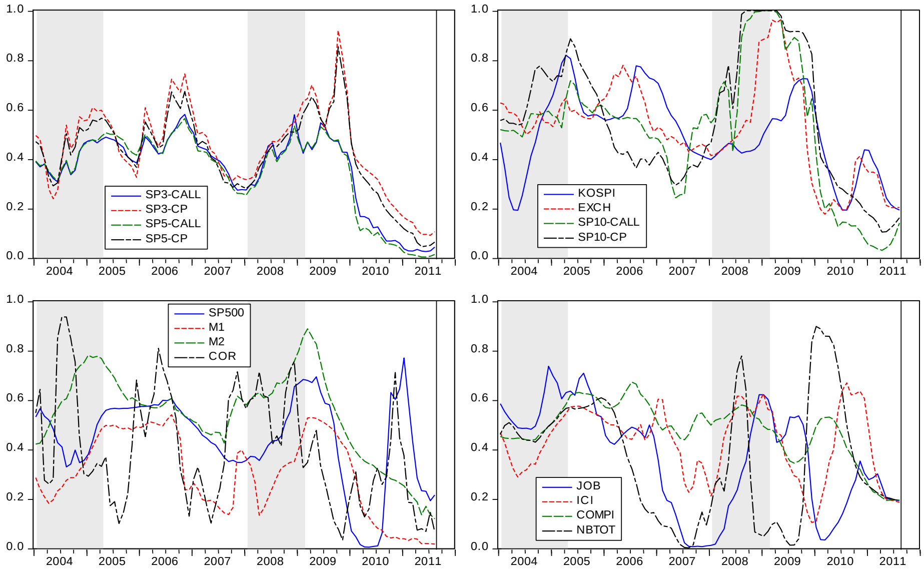
(*h*=3)



(*h*=6)



(*h*=12)



Note: The recession periods are shaded.

while foreign financial variables do a good job in predicting the recession associated with the global financial crisis, they perform rather poorly in forecasting the 2003-2004 recession, when domestic financial variables do a relatively better job. In another example, M1 shows good predictive power for the 2003-2004 recession (over short horizons), but its predictive ability is rather poor at other times. This result reflects the changes in composition of private short-term liquidity (from RP and demand deposits to CD and mutual funds) during the recent years.

4. FORECASTING WITH TIME-VARYING PREDICTORS

The discussion in the previous sections provides good motivation for forecasting models allowing for switching or time-varying predictors. This section first briefly describes the key idea of the DMS/DMA algorithm and then presents the forecast results.[10)]

4.1. DMS/DMA Algorithm

Suppose we have a set of N predictors available. There are then a total of $K = 2^N$ possible combinations of predictors (or models) in each time period t, depending on whether each predictor is included or not. The DMS/DMA algorithm computes the probability that model $k \in \{1, 2, \ldots, K\}$ should be used for forecasting at each time t, which is done using Kalman filtering methods. In fact, the DMS/DMA is a recursive algorithm in which the recursions are analogous to the prediction and updating equations of the Kalman filter. Although the algorithm sounds computationally challenging unless the number of models is small, Raftery *et al*. (2010) developed a fast recursive algorithm of the DMS/DMA to calculate the predicted probability

[10)] Raftery *et al*. (2010) and Koop and Korobilis (2012) provide a full derivation of the DMS/DMA algorithm and discuss its advantages. The reader is referred to their papers and references therein.

under an approximation involving the so-called ‘forgetting factor’ parameter.

The specific algorithm proceeds as follows. One of the key components of the DMS/DMA algorithm is the predicted probability, $\pi_{t|t-h,\,k}$. This is the probability that model k is the forecasting model for time t, given the data available at time $t-h$. Given an initial probability, $\pi_{0|0,\,k}$, at each point in time t, before observing the data, the predicted probability of model k is calculated using the following equation:

$$\pi_{t|t-h,\,k} = \frac{\pi^{\eta}_{t-1|t-h,\,k}}{\sum_{n=1}^{N} \pi^{\eta}_{t-1|t-h,\,n}}, \tag{4}$$

where η is a forgetting factor. Equation (4) approximately, but effectively summarizes the model’s past performance, which is reflected in $\pi_{t-1|t-h,\,k}$. The DMS selects the model with the highest predicted probability and forecasts using it, while the DMA uses these probabilities as model weights to compute the averages of the forecasts across models.

Once the data (of time t) are realized, each model’s probability is updated using the following equation:

$$\pi_{t|t-h+1,\,k} = \frac{\pi_{t|t-h,\,k}\, p_k(y_t \,|\, \tilde{X}_{t-h})}{\sum_{n=1}^{N} \pi_{t|t-h,\,n}\, p_n(y_t \,|\, \tilde{X}_{t-h})}, \tag{5}$$

where $p_k(y_t \,|\, \tilde{X}_{t-h})$ is the likelihood evaluated at the actual realization of the state, y_t, given the history of past data, $\tilde{X}_{t-h} = (y_1,\ \ldots,\ y_{t-h};\ X_1,\ \ldots,\ X_{t-h})$. Note that equation (5) is a standard application of the Bayes theorem, where $\pi_{t|t-h,\,k}$ and $p_k(y_t \,|\, \tilde{X}_{t-h})$ are the prior probability and likelihood, respectively. This updated probability is carried over to the next time period, and is used to calculate the predicted probability in that period.

To sum in words, the algorithm allocates a higher probability to models that have forecast well (as measured by the likelihood) in the past, and these probabilities are updated over time in a Bayesian fashion. This is a simple filtering algorithm and is computationally fast and efficient.

The forgetting factor, η, controls the rate at which the past forecasting performance is weighted or discounted, and is usually fixed to a value slightly below one. To better see the implication of the forgetting factor, note that through repeated substitutions, the predicted probability can be written as (in the case of h=1):

$$\pi_{t|t-1,\,k} \propto [\pi_{t-1|t-2,\,k}\, p_k(y_{t-1} \,|\, \tilde{X}^{t-2})]^{\eta} = \cdots = \sum_{i=1}^{t-1} [p_k(y_{t-i} \,|\, \tilde{X}^{t-i-1})]^{\eta^i}. \qquad (6)$$

Thus, a larger (smaller) value indicates that the recent data receive more (less) weight and, accordingly, relatively slow (fast) model switching. For example, with $\eta = 0.99$ and at a monthly frequency, observations five years ago receive about $(0.99)^{60}$, or 55% as much weight as the previous period's observation. As the range of values for the forgetting factor commonly used with quarterly data is 0.95 to 0.99, we consider three values: $\eta = 1.00$, $\eta = 0.99$, and $\eta = 0.98$.[11] The first is consistent with fairly stable models in which change is gradual, while the last allows for rapid change in the forecasting model over time.

There are also a few special cases of interest. If $\eta = 1$, the prediction rule will be equivalent to (static) Bayesian model averaging (BMA), in which the forecasting performance from all past periods is weighted equally. On the other hand, the case with $\eta = 0$ leads to the equal weighting of all models in forecast averaging in all time periods. Since equal weight forecasts are popular in many contexts and seem to forecast well, this is also a useful benchmark to consider in our set of models.

4.2. Forecast Results with Time-Varying Predictors

This subsection presents the forecast results of the DMS/DMA. One important decision in the DMS/DMA models is the selection of candidate

[11] We also tried even lower values of η, but found no notable benefits.

predictors. While it is tempting to include as many variables in the forecast model pool as possible, the issue is rather subtle.

With a larger number of predictors, a forecast model is naturally more flexible and may enjoy greater degrees of freedom in selecting/averaging models (or predictors). However, at the same time, it is likely to contain combinations of relatively poor predictors (note that even when a single variable is a good predictor, there is no guarantee that its predictive power will remain so when combined with other variables). Of course, if a sufficiently small weight is attached to such poor models in model averaging, it can avoid such over-fitting problems. However, in a particular empirical application, it is a priori unclear whether this would work, and the issue is an empirical matter. An obvious downside of forecast models with fewer predictors is that their predictive ability can be limited, because they may not capture other potential risk factors for recessions. However, as relatively less competitive predictors can be ruled out, the forecasts can be conservative in the sense that the risk of over-fitting or having a negative pseudo-R^2 is likely to be small.

Considering these points, we examine two groups of predicators, namely, set A (four predictors) and set B (eight predictors).[12] In creating the small group, we use the following rule: a series is included if it is ranked in the top five three or more times. Because each evaluation metric identifies different predictors, with only one in common, we also consider an additional sub-group, A1. Thus, we have:

· A (by MSE): SP3-CALL, SP10-CALL, SP10-CP, and COMPI.
· A1 (by pseudo-R^2): SP3-CALL, SP3-CP, SP5-CALL, and JOB.

For the large set, we use the following selection rule: a variable is included if it is listed in the top five two or more times by either measure:

[12] Owing to the memory constraint of the computer, the maximum number of variables that the algorithm can handle seems to be nine, which implies the total number of models (or predictor combinations) we consider at each time point is still quite large (2^9=512).

Table 4A DMS/DMA Results Using Predictor Set A

	h=1	h=3	h=6	h=12	h=24
Individual Best	0.103 (0.473)	0.080 (0.416)	0.158 (0.272)	0.191 (0.288)	0.207 (0.122)
$\eta = 1.00$					
DMS	0.106 (0.177)	0.059^{*} (0.683)	0.085^{***} (–)	$0.186_{\dagger\dagger}$ (–)	$0.216_{\dagger\dagger\dagger}$ (0.123)
DMA	0.099 (0.106)	0.057^{**} (0.649)	0.092^{***} (–)	$0.165_{\dagger\dagger}$ (–)	$0.214_{\dagger\dagger\dagger}$ (0.118)
$\eta = 0.99$					
DMS	0.099 (0.169)	0.058^{*} (0.683)	0.085^{***} (–)	$0.178_{\dagger\dagger}$ (–)	$0.212_{\dagger\dagger\dagger}$ (0.144)
DMA	0.094 (–)	0.057^{**} (0.626)	0.092^{***} (–)	$0.159_{\dagger\dagger}$ (–)	$0.205_{\dagger\dagger\dagger}$ (0.118)
$\eta = 0.98$					
DMS	0.099 (0.169)	0.058^{*} (0.683)	0.086^{***} (0.527)	$0.171_{\dagger\dagger}$ (–)	$0.208_{\dagger\dagger\dagger}$ (0.145)
DMA	0.091 (–)	0.056^{**} (0.097)	0.092^{***} (–)	$0.157_{\dagger\dagger\dagger}$ (–)	$0.189_{\dagger\dagger\dagger}$ (0.114)
$\eta = 0$	0.097 (–)	0.078 (0.437)	0.120 (–)	0.207 (–)	0.220 (0.023)
All Predictors	0.101 (–)	0.054 (0.729)	0.071 (–)	0.243 (–)	0.273 (0.175)

Notes: The table reports the MSE and pseudo-R^2 (in parentheses) of DMS/DMA models using the predictor set A. The figures for 'all predictors' are the results of the probit model that uses all four variables at each point in time. – indicate negative values. *, **, and *** indicate the significance of the predictive ability test of Diebold and Mariano (1995) against the individual best predictor for each horizon at the 0.10, 0.05, and 0.01 levels, respectively. Improvements over the individual best are marked in bold. $_{\dagger}$, $_{\dagger\dagger}$, and $_{\dagger\dagger\dagger}$ indicate the significance of the test against the all-predictor model at the 0.10, 0.05, and 0.01 levels, respectively.

· Set B: SP3-CALL, SP3-CP, SP5-CALL, SP10-CALL, SP10-CP, M2, JOB, and COMPI.

Tables 4A-4C contain the forecast results by the DMS/DMA using these three sets of predictors, along with the equal-weighted average forecasts

Table 4B DMS/DMA Results Using Predictor Set A1

	h=1	h=3	h=6	h=12	h=24
Individual Best	0.103 (0.473)	0.080 (0.416)	0.158 (0.272)	0.191 (0.288)	0.207 (0.122)
$\eta = 1.00$					
DMS	$0.180_{\dagger\dagger}$ (0.552)	$0.180_{\dagger\dagger}$ (0.483)	$0.127^{*}_{\dagger\dagger}$ (0.312)	$0.181_{\dagger}$ (–)	$0.224_{\dagger}$ (0.048)
DMA	$0.189_{\dagger\dagger}$ (0.569)	$0.176_{\dagger\dagger}$ (0.513)	$0.127_{\dagger}$ (0.301)	$0.164_{\dagger\dagger}$ (–)	$0.218_{\dagger\dagger}$ (0.001)
$\eta = 0.99$					
DMS	$0.177_{\dagger\dagger}$ (0.540)	$0.178_{\dagger\dagger}$ (0.434)	$0.133_{\dagger}$ (0.298)	$0.172_{\dagger}$ (–)	$0.224_{\dagger}$ (0.038)
DMA	$0.188_{\dagger\dagger}$ (0.556)	$0.172_{\dagger\dagger\dagger}$ (0.451)	$0.141_{\dagger}$ (0.215)	$0.159^{*}_{\dagger\dagger}$ (–)	$0.205_{\dagger\dagger}$ (–)
$\eta = 0.98$					
DMS	$0.168_{\dagger\dagger}$ (0.529)	$0.168_{\dagger\dagger\dagger}$ (0.407)	$0.129^{*}_{\dagger\dagger}$ (0.263)	$0.170_{\dagger}$ (–)	$0.215_{\dagger\dagger}$ (0.039)
DMA	$0.181_{\dagger\dagger}$ (0.548)	$0.166_{\dagger\dagger\dagger}$ (0.416)	$0.136_{\dagger\dagger}$ (0.213)	$0.170^{*}_{\dagger\dagger}$ (–)	$0.199_{\dagger\dagger}$ (–)
$\eta = 0$	0.191 (0.386)	0.173 (0.365)	0.156 (–)	0.203 (–)	0.247 (0.044)
All Predictors	0.244 (0.361)	0.245 (0.368)	0.166 (–)	0.228 (0.369)	0.271 (0.216)

Notes: The table reports the MSE and pseudo-R^2 (in parentheses) of the DMS/DMA models using the predictor set A1. See also the notes to table 3A.

(with $\eta = 0$) and all-predictor models (i.e., fixed models that employ all the variables in each set all the time). To indicate the statistical significance of the differences in forecasting performance, we provide the result of the predictive ability test of Diebold and Mariano (1995) for the DMS/DMA models against the individual best predictors for each forecast horizon and all-predictor models.

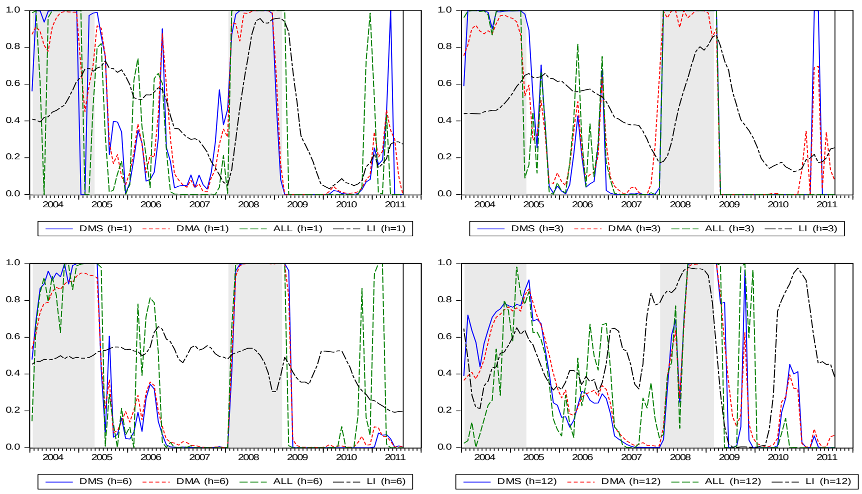
Table 4C DMS/DMA Results Using Predictor Set B

	h=1	h=3	h=6	h=12	h=24
Individual Best	0.103 (0.473)	0.080 (0.416)	0.158 (0.272)	0.191 (0.288)	0.207 (0.122)
$\eta = 1.00$					
DMS	0.127 (0.497)	0.089 (0.443)	$0.081^{***}_{\dagger\dagger}$ (–)	$0.175_{\dagger}$ (0.141)	0.210 (–)
DMA	$0.094_{\dagger}$ (–)	0.062 (–)	$0.070^{***}_{\dagger\dagger}$ (–)	$0.186_{\dagger}$ (–)	0.212 (–)
$\eta = 0.99$					
DMS	0.130 (0.508)	0.072 (0.454)	$0.071^{***}_{\dagger\dagger}$ (–)	$0.162_{\dagger\dagger}$ (0.202)	0.185 (–)
DMA	$0.094_{\dagger\dagger}$ (–)	0.061 (–)	$0.070^{***}_{\dagger\dagger}$ (–)	$0.168_{\dagger\dagger}$ (–)	0.189 (–)
$\eta = 0.98$					
DMS	0.114 (0.555)	0.081 (0.433)	$0.074^{***}_{\dagger\dagger}$ (–)	$0.147^{*}_{\dagger\dagger}$ (–)	$0.167^{*}_{\dagger}$ (–)
DMA	$0.092_{\dagger\dagger}$ (–)	0.060^{*} (–)	$0.070^{***}_{\dagger\dagger}$ (–)	$0.156_{\dagger\dagger}$ (–)	$0.173^{*}_{\dagger}$ (–)
$\eta = 0$	0.095 (–)	0.069 (–)	0.097 (–)	0.201 (–)	0.216 (–)
All Predictors	0.144 (0.580)	0.069 (0.466)	0.159 (–)	0.243 (0.291)	0.207 (–)
Leading Index	0.196 (0.663)	0.230 (0.610)	0.247 (0.325)	0.233 (0.337)	0.278 (0.420)

Notes: The table reports the MSE and pseudo-R^2 (in parentheses) of DMS/DMA models using the predictor set B. See also the notes to table 3A.

We see that forecasts allowing for time-varying predictors show good performance overall, beating the individual best predictors for each horizon in most cases, particularly in terms of the MSE. Furthermore, these improvements are often accompanied by good statistical significances. The

Figure 4 Out-of-sample Forecasts of DMS/DMA Models



Note: The recession periods are shaded.

overall best forecast fits are found at $h=6$, indicating that the included macro leading variables (which also show the best performance over this horizon) play an important role. Figure 4 demonstrates that the performance of the DMS/DMA models (with forgetting factor of $\eta=0.98$) is successful in that they reasonably predict the two recessions in the out-of-sample forecast sample. While the all-predictor models (ALL in the figures) seem to perform reasonably well and their performances are superior to those of the individual best predictors for some horizons, they perform worse than the DMS/DMA, especially over longer horizons, indicating the possibility of an over-fitting problem.

By and large, the DMA models yield slightly better results than do the DMS models, although the pseudo-R^2 values associated with the former turn out to be negative in many cases. This implies that some predictor combinations are potentially poor (in terms of pseudo-R^2; recall the discussion in section 2). With regard to the degree of discounting in the past data used in the forecasting, smaller values of the forgetting factor seem to yield better results overall, suggesting that the predictor/model switching is fairly fast. And when it comes to the size of the predictor pool, the overall results seem to be better for the large set of predictors (set B), although the small set seems to yield similar or slightly better results over short forecast horizons. Interestingly, the set of predictors selected by the MSE criteria (set A) shows better pseudo-R^2 values than the other small set (set A1, by the pseudo-R^2 criteria) does over some horizons.

Given the good forecasting performance of the DMS/DMA model, one interesting exercise is to compare its predictive power with that of the composite leading index. The last row in table 4C shows that, while the leading index produces impressive results in terms of the pseudo-R^2, it is substantially outperformed by the DMS/DMA in terms of the MSE. As shown in figure 4, the forecasts using the leading index (LI in the figure) change gradually (with monotonic behavior within each regime), and do not move too far from one-half in many cases. That is, although the composite leading index can provide relatively conservative predictions in the sense that this predictor is not likely to generate extreme forecast errors (i.e., yielding reasonable pseudo-R^2 values overall), this indicator may not be appropriate in predicting discrete, or regime-switching type changes in business cycles (recall the discussion in section 2).

One caveat with the MSE criterion is that the loss associated with this metric is essentially symmetric. That is, forecast errors for each business cycle regime are penalized equally. However, it is not clear that symmetric loss is always appropriate. Instead, a forecaster may be more concerned with missing one regime than the other. Thus, we also consider a generalized loss function of the following form (e.g., Elliott *et al*., 2005):

$$\text{loss} = \frac{1}{T}\sum_{t=1}^{T}[qy_t(1-\hat{y}_t)^2 + (1-q)(1-y_t)\hat{y}_t^{\,2}], \tag{7}$$

where q (and $1-q$) is the weight of the loss associated with the forecast errors for recession (and expansion) periods and represents the degree of asymmetry of the loss function. With the value of $q=0.5$, the loss function reduces to a symmetric loss, while $q > 0.5$ (and $q < 0.5$) indicates that forecast errors for recessions (and expansions) are more heavily penalized. In practice, as forecasters are more likely to be concerned about missing a recession call than signaling a false alarm of a recession, the plausible range for q is $q > 0.5$. Thus, we consider three values of q, with varying degrees of asymmetry: $q = 0.6$, $q = 0.75$, and $q = 0.9$.

The forecast results of the DMS/DMA (using the large predictor set, set B) under asymmetric loss are provided in table 5.[13] Here, the superiority of the DMS/DMA models remains robust under symmetric loss. For each of the three values of q, the losses of the DMS/DMA models are smaller than those of the individual bests in most cases, and occasionally they generate slightly better results in terms of the statistical significances of the tests (than under symmetric loss). Furthermore, they also outperform the all-predictor models, which are competitive only at $h = 3$. This result illustrates that DMS/DMA models will also be useful when one is particularly concerned with predicting upcoming recessions.

A useful by-product of DMS/DMA forecasts is that the method allows us to identify which predictors are useful at each point in time. That is, from the predicted probability of each model, $\pi_{t|t-h,\,k}$, we can easily calculate the probability that an individual predictor is included in the forecast model at each time. These probabilities can be interpreted as weights used by the DMA attached to models which include a particular predictor and, thus, indicate the importance of the predicator in forecasting a future recession.

Figure 5 plots the inclusion probabilities of individual predictors and we find strong evidence for changing predictors. That is, the inclusion probabilities associated with individual predictors in the forecast model change substantially over time (either gradually or abruptly, and sometimes from near zero to near one, or vice versa). The interested reader can examine the figure for any particular variable of interest. Here, we discuss only a few notable and interesting findings.

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[13] Because the loss function here uses different weights for each regime, the figures in table 5 are not directly compatible to those in table 4C.

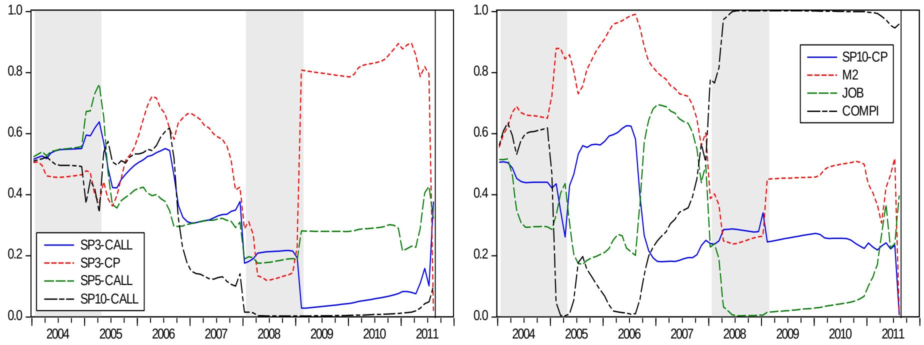
Table 5 MSE under Asymmetric Loss

	h=1	h=3	h=6	h=12	h=24
$q=0.6$					
Individual Best	0.051	0.039	0.076	0.095	0.095
DMS ($\eta=1.00$)	0.063	0.042	$0.040^{***}_{\dagger\dagger}$	0.087	0.093
DMA ($\eta=1.00$)	0.047	0.028^{*}	$0.034^{***}_{\dagger\dagger}$	0.090	0.094
DMS ($\eta=0.99$)	0.064	0.038	$0.031^{***}_{\dagger\dagger}$	$0.078^{*}_{\dagger}$	0.083^{*}
DMA ($\eta=0.99$)	0.045	0.029^{*}	$0.034^{***}_{\dagger\dagger}$	0.083	0.085
DMS ($\eta=0.98$)	0.053	0.038	$0.035^{***}_{\dagger\dagger}$	$0.072^{**}_{\dagger\dagger}$	0.076^{**}
DMA ($\eta=0.98$)	0.044	0.027^{*}	$0.034^{***}_{\dagger\dagger}$	$0.077^{*}_{\dagger}$	0.079^{**}
All Predictors	0.065	0.027	0.066	0.120	0.093
$q=0.75$					
Individual Best	0.051	0.036	0.072	0.093	0.081
DMS ($\eta=1.00$)	0.062	0.039	$0.036^{***}_{\dagger\dagger}$	$0.083_{\dagger}$	0.077
DMA ($\eta=1.00$)	0.044	0.024^{**}	$0.033^{***}_{\dagger\dagger}$	0.087	0.076
DMS ($\eta=0.99$)	0.062	0.032^{*}	$0.030^{***}_{\dagger\dagger}$	$0.075^{*}_{\dagger\dagger}$	0.070^{*}
DMA ($\eta=0.99$)	0.042	0.024^{*}	$0.033^{***}_{\dagger\dagger}$	$0.081^{*}_{\dagger}$	0.070
DMS ($\eta=0.98$)	0.048	0.032^{*}	$0.033^{***}_{\dagger\dagger}$	$0.070^{**}_{\dagger\dagger}$	0.066^{**}
DMA ($\eta=0.98$)	0.040	0.023^{**}	$0.033^{***}_{\dagger\dagger}$	$0.077^{**}_{\dagger\dagger}$	0.067^{**}
All Predictors	0.063	0.023	0.060	0.125	0.080
$q=0.9$					
Individual Best	0.050	0.034	0.067	0.092	0.068
DMS ($\eta=1.00$)	0.061	0.036	$0.032^{***}_{\dagger\dagger}$	$0.078_{\dagger\dagger}$	0.060
DMA ($\eta=1.00$)	$0.040_{\dagger}$	0.020^{**}	$0.031^{***}_{\dagger\dagger}$	$0.083_{\dagger}$	0.058
DMS ($\eta=0.99$)	0.060	0.027^{*}	$0.030^{***}_{\dagger\dagger}$	$0.071^{*}_{\dagger\dagger}$	0.057
DMA ($\eta=0.99$)	$0.038_{\dagger}$	0.019^{**}	$0.032^{***}_{\dagger\dagger}$	$0.080_{\dagger\dagger}$	0.056
DMS ($\eta=0.98$)	0.043	0.027^{*}	$0.031^{***}_{\dagger\dagger}$	$0.068^{**}_{\dagger\dagger}$	0.055^{*}
DMA ($\eta=0.98$)	$0.036^{*}_{\dagger}$	0.018^{**}	$0.032^{***}_{\dagger\dagger}$	$0.076^{*}_{\dagger\dagger}$	0.055^{*}
All Predictors	0.060	0.019	0.055	0.130	0.067

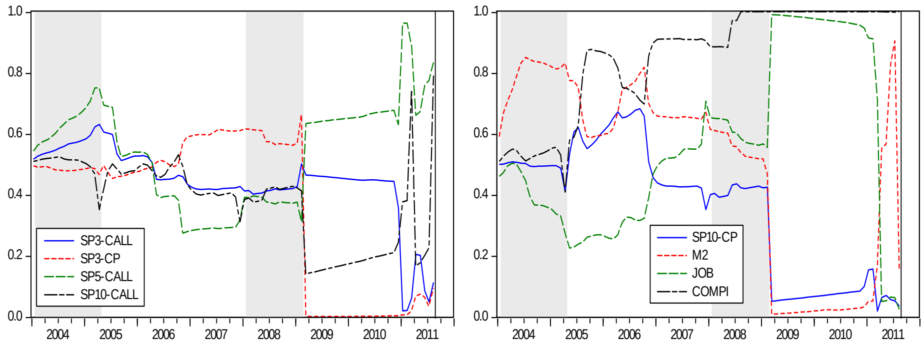
Notes: The table reports the asymmetric mean squared errors of the DMS/DMA models using the large predictor set. See also the notes to table 3A.

Figure 5 Inclusion Probabilities of Individual Predictors

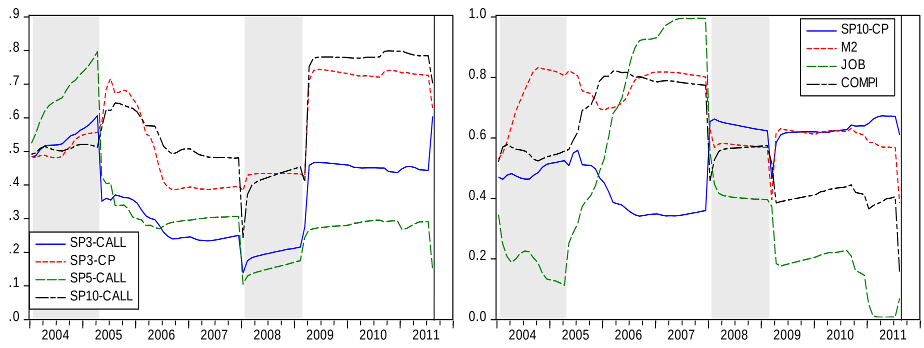
(*h*=1)



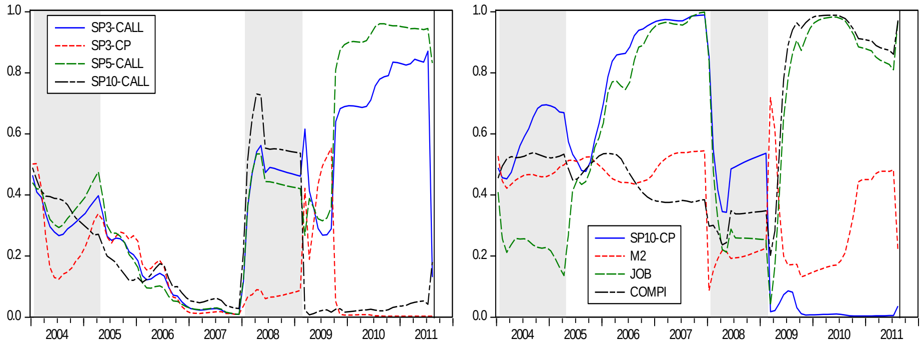
(*h*=3)



(*h*=6)



(*h*=12)



Note: The recession periods are shaded.

Several major switchings (between predictors and/or over forecast horizons) seem to be associated with the business cycle turning points of the 2008 global financial crisis. For example, while M2 played an important role prior to the global financial crisis, its importance subsequently declined substantially, especially over short horizons. In addition, in the case of COMPI, which was quite useful in predicting the crisis over short horizons, its role appears to have been replaced by other variables over longer horizons. On the contrary, interest rate spreads, although poor predictors early in the sample or for short-term forecasts overall, have become relatively more useful in predicting the 2008 recession and in later periods over longer horizons. These overall results suggest that, in the wake of the global financial crisis, the low interest regime and increased global uncertainty (reflected in term premium) have become primary factors to gauge prospects of the economy.

Another interesting observation is that some predictors exhibit distinctive behavior across the business cycle regimes. For example, the predictive power of JOB and M2 seems to lessen during recession periods. It is also intriguing to note that, while a few variables seem to dominate for short-term forecasts of recessions (e.g., M2 for the 2003-2004 recession and COMPI for the 2008 recession), variables tend to receive relatively more equal weights over longer horizons. This result reflects the DMS/DMA algorithm's internal attempt to diversify the predictor pool to hedge against the increased forecast uncertainty due to longer forecast horizons, which can be argued as one of the model's advantages.

Given that the forecast model employed is not structural, one must be cautious in interpreting these results with too many economic stories. However, it seems clear that the overall results provide strong evidence for predictor/model switching during the forecast period, and illustrate an important benefit of DMS and DMA, namely that they will pick up good predictors automatically as the forecasting model evolves over time.

5. CONCLUDING REMARKS

This study examines the predictive ability of a wide set of variables in forecasting Korean recessions, based on probit models. In doing so, we extend the probit recession forecasting models using the DMS/DMA algorithm, which allows for specific predictors to switch over time in a data-based manner.

It is shown that, in addition to commonly used financial indicators, several macro leading variables exhibit good predictive power, particularly over medium- and long-term forecast horizons. When we incorporate predictor switching over time in the forecasting using the DMS/DMA algorithm, the predictive performance improved substantially, outperforming individual best predictors and models with fixed predictors. Moreover, we show there is strong evidence for predictor switching in forecasting recessions, and illustrate how the key predictors' performance evolves over time.

A few policy implications can be drawn from this study. First, while policy-makers generally tend to rely on a set of fixed forecasting models, this study raises a warning signal to such practice. Since the nature of the economy is ever-changing, and, accordingly, the roles of individual predictors are likely to vary over time, forecast models need to be flexible and have to be updated in a timely manner. The DMS/DMA approach discussed in this study makes a good example of such. Second, it is increasingly standard for central bankers, financial market participants, and academic researchers to describe management of expectations as central to monetary policy. However, as the episode of the early 2000's exemplifies, a central bank's poor expectations management may not only do harm to its credibility, but also weaken the predictive power of key recession predictors such as yield spreads. The overall forecast result suggests that the transparent communication of policy stance with the private agents should be important policy-makers' agenda, which will help then attain the goal of stabilization.

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