Forecasting Industrial Production Using Models with Business Cycle Asymmetry

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This paper exploits an observed business cycle asymmetry, namely, a systematic shift in the dynamic relationship between output growth and an index for financial market conditions across expansionary and contractionary periods, to forecast monthly growth in industrial production. A bivariate model of monthly industrial production and the spread between the yield on 10-year Treasury notes and the federal funds rate is used as an example. This paper's method does not require a forecaster to make an exact ex ante determination of turning points in the output series being forecasted. A comparison of the forecast performance of various two-regime nonlinear and conventional linear models suggests that a measurable gain can be made by considering models which explicitly incorporate asymmetry in data.

There has been ongoing interest in forecasting turning points of business cycle phases (Fels and Hinshaw 1968, Zarnowitz 1972, Zarnowitz and Moore 1982, Wecker 1979, Kling 1987). One method of detecting turning points which has received considerable attention is credited to Neftci (1982). This method uses changes in the Department of Commerce's index of leading indicators, which exhibits different behavior over expansion and contraction periods, as a signal of imminent change in business cycle phases. The methodology has been extended further by Diebold and Rudebusch (1989, 1991). The basic idea behind their methodology has been further elaborated by many researchers (Neftci 1984, Hamilton 1989, Boldin 1992, French and Sichel 1993, Potter 1992, Sichel 1993, and Filardo 1994).

Despite much interest and effort in predicting turning points, there has been little work that extends and applies the methodological innovations and findings on business cycle asymmetry to a conventional multivariate forecasting exercise.[1] This paper offers such an application. The basic idea is that if information about asymmetry in business cycle variables is useful in predicting turning points, then models incorporating that information should produce more accurate forecasts.

In this paper, a bivariate model of the monthly industrial production (IP) series and the spread between the yield on 10-year Treasury notes and the federal funds rate is used as an example.[2] The exercise compares the one-month-ahead

1. A notable exception is Granger, Terasvirta, and Anderson (1993). They consider bivariate regression models of real GNP and the Department of Commerce's leading indicator, whose coefficients change smoothly between expansion and contraction regimes. However, these nonlinear models' out-of-sample performances are noticeably worse than an alternative linear model. In addition, the economic motivation for positing a shift in the bivariate relationship (real GNP-leading index) is not clear (see Harvey (1993) in the same volume).

2. For reference on the usefulness of interest rate and spread variables, see Stock and Watson (1989), Bernanke (1990), Bernanke and Blinder (1992), and Friedman and Kuttner (1992). The choice of the model is based on an earlier work (Huh 1994) that found evidence of asymmetry in the bivariate relationship over expansionary and contractionary business cycle phases.

forecast performance of two-regime nonlinear models and a conventional single-regime linear model. The method employed to generate forecasts from the nonlinear models does not require the exact placement of actual turning points in the IP series, which are always determined ex post. Rather, an ex ante rule is estimated from the data on when to anticipate lower growth in output, which in turn determines how best to combine forecasts from the contraction and expansion models to yield a single forecast. The nonlinear models are found to outperform the conventional models for both in-sample and out-of-sample forecasting exercises; in some cases, the improvement in forecast accuracy is statistically significant.

The nonlinear model is based on the switching regression model of Goldfeld and Quandt (1972), and consists of two regressions, one specific to an expansion and one specific to a contraction. They are initially estimated from the sample period 1956–1974, using NBER business cycle dates. To make an out-of-sample forecast with such a model, one has to determine the regime in place at any given time. Two alternative approaches are employed.

The first relies on the recent behavior of an economically relevant variable. I use information on the recent growth of IP. For example, the contraction regime is likely to be in place if the IP growth rate over the most recent three months is less than a certain value and if it is significantly less than the average IP growth rate during the actual previous contractionary periods. Methodologically, this is analogous to determining an index variable that regulates the way different regimes in nonlinear models come into play (e.g., the transition variable of smooth transition regression (STR) models (Granger, Terasvirta, and Anderson 1993) and the threshold and delay parameters for the self-exciting threshold (SETAR) models (Potter 1992)).

Once the likely regime is determined, the nonlinear model's forecast is constructed by taking a probability-weighted average of the forecasts from the two-regime regressions. The probability weights are calculated by comparing a phase-specific model's recent forecast errors to the known past forecast error distributions of the model in different business cycle phases. It can be thought of as an approximate measure of a conditional transition probability.

The second approach employs a Markov regime-switching (MS) model (à la Hamilton 1989). The MS model of univariate IP is estimated, as in Boldin (1992). This type of model provides probabilistic information about the likelihood that a particular regime, which is unobservable, is in place. Furthermore, the MS model provides estimates of transition probabilities for the 2×2 transition matrix between two regimes. Once these probabilities are obtained, an unconditional forecast of the nonlinear model is constructed by taking a probability-weighted average of the forecasts from the different phase-specific regressions. This is identical to the second step of the first approach except that the probabilities have a more direct and transparent interpretation.

The sample period from 1975:01 to 1989:12 is used as an intermediate period during which various optimal decision rules of the two approaches are estimated. The period from 1990:01 to 1993:03 is then used to gauge the out-of-sample forecast performance of the various models.[3]

The rest of the paper is organized as follows. Section I provides the results of the nonlinearity diagnostic tests, as well as a description of the various linear and nonlinear models. Section II describes how the optimal combining rules for the nonlinear models are estimated. Section III offers a comparison of the performances of the various models. Section IV concludes.

I. Estimation

Motivation and Diagnostic Tests

Intuitively, a systematic shift over expansionary and contractionary periods in a bivariate relationship between output and financial market prices (i.e., interest rates) is plausible. For example, the interest elasticity of investment might be smaller when overall economic activity is sluggish because heightened short-run uncertainty makes postponing new projects economically justifiable. Models in which investment is irreversible give rise to such a prediction (e.g., Pindyck 1990). Indeed, Huh (1994) provides evidence of a systematic change across expansions and contractions in the dynamic cross-variable patterns between the growth rate in aggregate IP and various interest rates and rate spreads. They include the spread between the yield on 10-year Treasury notes and the federal funds rate (T10–FF) used in this exercise. However, whether such shifts in the bivariate relationships can be exploited to improve forecasts is an open question.

To characterize the nature of the shift further, two diagnostic tests are carried out using a full-sample bivariate model of the growth rate of IP and the interest rate spread

3. Sample periods are divided so that there are approximately the same number of business cycles in the subsamples for the initial estimate of each model and for fine-tuning decision rules. The out-of-sample period was chosen to contain the most recent recession period. The sample period ends in March 1993 because rebenchmarking made data after that date less compatible with data before that date; for more details about the data revision, see Raddock 1993.

(denoted as ΔIP and R, respectively). The first is the CUSUM linearity test proposed by Ploberger and Kramer (1992), based on the OLS residuals (also known as the CUSUM-O test). Though not designed for any particular nonlinear models, it is a useful linearity test against an alternative such as switching regressions with two regimes, which is the type to be considered in this paper (Granger and Terasvirta 1993). The second test is based on exclusion tests of business cycle phase-specific dummy variables.

Tables 1 and 2 present the results for both types of diagnostic tests. They strongly suggest the presence of nonlinear dynamics in the bivariate relationship between IP and the interest rate spread. First, the CUSUM-O test rejects the null hypothesis of linearity at a significance level of less than 5 percent for both four-lag and twelve-lag specifications. Thus, considering regression models with two regimes is well justified.[4]

The results of the exclusion tests of the NBER dummy variables also indicate a systematic shift in the dynamic relationship between output and the interest rate spread. Interestingly, the exclusion test results suggest the possibility of a non-trivial shift in the *cross-variable* dynamics across the expansion and contraction periods. That is, a strong rejection of the coefficient dummies for R in the ΔIP equation indicates that there is a systematic shift in the relationship between the two variables, in addition to that in

4. The test result is somewhat sensitive to changes in the sample period. For example, the CUSUM result weakens when data from the 1950s are added.

TABLE 1

CUSUM-O TEST OF LINEARITY BASED ON THE OLS RESIDUALS (1961:01–1992:12)

$$\Delta IP_t = \alpha + \sum_{i=1}^{m} \beta_i \Delta IP_{t-i} + \sum_{i=1}^{m} \gamma_i R_{t-i} + \varepsilon_t$$

SPECIFICATION	TEST STATISTICS (u)	CRITICAL VALUES
$m = 12$	1.5757 **	$\alpha = 1\%$ $u = 1.63$
		$\alpha = 5\%$ $u = 1.36$
$m = 4$	1.4498 **	$\alpha = 10\%$ $u = 1.22$

NOTE: The test statistics are calculated as follows:

Let $B_{rT} = \dfrac{\sum_{j=1/T}^{r} \hat{\varepsilon}_{jT}}{\hat{\sigma}}$

where $\hat{\varepsilon}_{jT}$ is the OLS residual, and σ is the standard error of the residuals.

Then the test statistic is $U_T = \max_{1/T \le r \le 1} \left| T^{-1/2} B_{rT} \right|$.

Asymptotically, the following holds:

$\lim_{T\to\infty} Pr(U_T > u) = 2\sum_{k=0}^{\infty}(-1)^{k+1}\exp(-2k^2u^2) = 1 - p(u)$.

The test is carried out by computing the above expression for $u = U_T$. If $p(U_T) < \alpha$, the null hypothesis of linearity is rejected at the significance level of α, as shown above. For more detail, see Ploberger and Kramer (1992), or Granger and Terasvirta (1993), pp. 86–87.

** denotes significant cases at the 5 percent level.

TABLE 2

DUMMY VARIABLE EXCLUSION TEST RESULTS

$$\Delta IP_t = \alpha + \theta^{con}\mathrm{dum}_t + \sum_{i=1}^{m}(\beta_i + \theta_i^{\Delta IP}\mathrm{dum}_t)\Delta IP_{t-i} + \sum_{i=1}^{m}(\gamma_i + \theta_i^{R}\mathrm{dum}_t)R_{t-i} + \varepsilon_t$$

R = FYGT10 – FYFF	4 LAGS ($m = 4$)	12 LAGS ($m = 12$)
$H_0 : \theta^{con} = \theta_i^{\Delta IP} = \theta_i^{R} = 0$, for all i	8.143 ***	4.815 ***
$H_0 : \theta_i^{\Delta IP} = \theta_i^{R} = 0$, for all i	3.855 ***	3.082 ***
$H_0 : \theta_i^{\Delta IP} = 0$, for all i	2.991**	3.733 ***
$H_0 : \theta_i^{R} = 0$, for all i	3.986 ***	2.940 ***

Note: Monthly data for the sample period from 1961:1 to 1992:12 were used. The dummies (dum_t) take a value of one during the NBER contractionary period and zero otherwise. The numbers denote the F test statistics.

***, ** denote significant cases at 1 and 5 percent, respectively.

the univariate autoregressive structure of the ΔIP series over different phases of business cycles. The joint exclusion restriction is strongly rejected. The individual exclusion restrictions are significant for both lagged IP and the interest rate spread. Thus, the shift in the bivariate dynamic pattern is due to a combined effect of the changes in both the autoregressive component and the dynamic cross-variable component.[5] Based on the results of the diagnostic tests together, I proceed to consider two-regime regression models with two business cycle regimes.

The Model

The basic model consists of the monthly growth rate in IP (i.e., first difference of the log of IP) and the spread between the yield on the 10-year Treasury note and the federal funds rate. The level of the spread is denoted as R. The following equation (1) describes the model:

$$(1) \qquad \Delta IP_t^j = \alpha^j + \sum_{i=1}^{m(j)} \beta_{t-i}^j \Delta IP_{t-i}^j + \sum_{i=1}^{m(j)} \gamma_{t-i}^j R_{t-i}^j + \varepsilon_t^j .$$

Here j is the index for the different types of models to be estimated.[6] A linear model based on a single regime is indexed by f. The two-regime model consists of two separate equations, each estimated from the expansion and contraction samples and indexed by e and c. The lag length for each model is determined by the index m. For example, the linear model with a lag length of 12 is denoted as $m(f) = 12$. The last term, ε_t, denotes white noise errors.

In the following analysis, various combinations of model specifications are used. Two linear single-regime models are considered as benchmark cases. The two are different in the lag length specifications. Lag lengths of 4 and 12 are used (i.e., $m(f) = 4$ and 12). These will be denoted as linear 1 and linear 2 models.

For phase-specific equations of the two-regime models, two different lag specifications are considered. In one, a uniform lag length of 4 is used for both models (i.e., $m(e) = m(c) = 4$), and uneven lag lengths of 12 and 4 are used for expansion and contraction models in the other (i.e., $m(e) = 12$, $m(c) = 4$). The nonlinear model based on the first and the second set of equations will be denoted as nonlinear 1 and nonlinear 2. The uneven lag specification reflects the difference in the average durations of postwar expansions and contractions. An estimation of the initial two phase-specific models requires an explicit breakdown of the historical data into business cycle phases. For this purpose, the NBER business cycle dating is used.

Forecast Strategy and Benchmark Linear Model

The strategy for the forecasting exercise is as follows: First, the data period is partitioned into three subperiods: 1956:02–1974:12, 1975:01–1989:12, and 1990:01–1993:03. The first period is used for an initial estimation of the linear full-sample model, as well as of expansion and contraction regime equations. It includes five episodes each of recessions and expansions according to NBER dating. There are 42 and 185 monthly observations for the contractionary and expansionary observations, respectively.

The second period is used to estimate decision rules for various models' forecasts. Once the three initial models *(m(f), m(e), m(c))* are estimated, they are used to generate a one-period-ahead forecast for the second period; for brevity, only the one-month-ahead forecasting horizon is considered. So, the goal is how best to forecast the growth in monthly IP over the current and the next month. The forecast error statistics of the two full-sample linear models for the sample period of 1975:01–1989:12 are given in Table 3.

The third sample period from 1990:01 to 1993:03 is then used for out-of-sample forecast comparisons.

II. DESIGNING AND IMPLEMENTING A FORECASTING RULE

Given the forecasts generated from the two-regime models described above, the next question is how to devise a rule that combines the forecasts from the distinct models in an optimal way. This, in turn, raises two questions. One is how to determine the regime in place at any given time. The other is how to determine the weights for the two distinct forecasts in generating a combined forecast. If a significant business cycle asymmetry exists in the data, then matching forecasts from the contraction (expansion) model with contractionary (expansionary) periods should provide an improvement in forecasting accuracy over using a conven-

5. Another reason to prefer the bivariate system of output and the interest rate to a univariate output equation in a forecasting context is the practical consideration about the timing of data availability. That is, contemporaneous information on almost all interest rate variables is available at any given time, while the IP series is released with a lag of about one month. Even though the current exercise does not incorporate this point, adding contemporaneous interest rates would likely enhance the forecast accuracy of all the models considered here.

6. This specification is different from that of Table 2 in that it allows the error terms in the two regressions to behave differently. Using the specification given in Table 2 would amount to imposing that restriction. A shift in the behavior of the residual terms across different business cycle phases is potentially important in light of findings that suggest a possible heteroskedasticity in the error term (e.g., French and Sichel 1993).

TABLE 3

ONE-PERIOD-AHEAD INDUSTRIAL PRODUCTION GROWTH RATE
FORECAST ERROR STATISTICS FOR LINEAR MODELS
(FROM 1975:01 TO 1989:12, 180 OBSERVATIONS)

MODEL	MEAN ERROR	MEAN ABS. ERROR	R.M.S. ERROR	THEIL U
Linear 1 ($m(f) = 4$)	–0.069	0.655	0.875	0.956
Linear 2 ($m(f) = 12$)	–0.089	0.717	1.016	1.110

Note: All statistics except Theil U need to be multiplied by 10^{-2} to convert them to growth rates.

tional single-regime model. However, it is difficult to tell on a real-time basis which phase the economy is in, because there always is a considerable lag between the time of the initial release of data and the NBER dating of the business cycle phase of the series. Thus, it is necessary for any forecasting procedure based on a two-phase model to take such uncertainty into consideration.

The strategy followed here in incorporating this uncertainty is to calculate the combination forecast by taking a probability-weighted average of the two forecasts of the expansion and contraction models at any given time. The probability weight is calculated by comparing a phase-specific model's recent forecast errors to the known, past forecast error distributions of the model. It can be thought of as an approximate measure of a conditional transition probability. A more detailed description will be given later.

The first method is in the two traditions of combining forecasts from alternative models (e.g., Bates and Granger 1969, Engel, Granger, and Kraft 1984) and fitting regime-switching regression models to data (e.g., Goldfeld and Quandt 1972). Deutsch, Granger, and Terasvirta (1992) is one recent example that mixes features of the two methodologies. They alternatively consider information on both the lagged forecast errors and a pattern of relevant economic variables to determine the relative weights on the alternative forecasts in approximating the current regime. I use both types of information jointly in constructing forecasts from both nonlinear 1 and nonlinear 2 models.

To be specific, I use monthly IP growth over the past several months to judge which of the two (contraction and expansion) regimes will be in place in the next month. If the output growth has been noticeably sluggish in recent months, it is more likely that the next period's growth would be sluggish also. Forecasts from each of the contraction and expansion models are multiplied by relative weights which are based on past forecast errors of the respective models.

The second approach is directly linked to the Markov regime-switching models developed by Hamilton (1989). To implement this approach, a univariate equation of the growth in IP that switches between two regimes is estimated. The maximum likelihood estimation procedure of Boldin (1994) is followed.[7] This provides a set of probabilities that measure the likelihood that the current period is in a particular state, as well as 2×2 transition probabilities between states. Thus, these offer natural candidates as weights to be used in combining the forecasts of the contraction and expansion regime equations. The two-regime Markov switching model will be denoted as the MS model.

In devising these rules, the data from the intermediate period from 1975:01 to 1989:12 is used for testing and fine-tuning the candidate rules. Of particular interest is whether it is feasible to devise a simple rule that improves the fit of the combination model beyond that of the full-sample model given in Table 3.

A Model that Uses Information on Lagged Forecast Errors and Lagged IP Growth

Notation. It is necessary that the rules utilize only information available up to the time any particular forecast is made. In our case, the behavior of the models during the initial estimation period (1956–1974) is admissible information. To utilize such information, some relevant distributions and notations are defined as follows. First, let us denote an index variable I which equals c in a contraction and e in an expansion. For the initial sample period 1956:02–1974:12, we can pool the growth rates of IP into contraction and expansion groups, $\Delta IP(I = c|t = 1974{:}12)$ and $\Delta IP(I = e|t = 1974{:}12)$. The means and standard errors

7. For a detailed description, see Boldin (1994), pp. 128–129.

of each group as of time t are denoted as mean $(I = c|t)$, s.e. $(I = c|t)$ and mean $(I = e|t)$, s.e. $(I = e|t)$, respectively.

Next, the residuals from equation (1) of the contraction model during the initial sample period are pooled into two groups. The first group includes the contraction model's residuals during actual contractionary periods up to 1974, and it is denoted as $\varepsilon(c, I = c|1974{:}12)$. The second group includes the residuals of the contraction model during expansionary periods, and is denoted as $\varepsilon(c, I = e|1974{:}12)$. The corresponding notations for the residual pools of the expansion models are $\varepsilon(e, I = c|1974{:}12)$ and $\varepsilon(e, I = e|1974{:}12)$, respectively, for the contractionary and expansionary periods. Furthermore, let us denote the means and standard errors of each series as $\overline{\mu}_\varepsilon(x|I = y)$ and $\overline{\sigma}_\varepsilon(x|I = y)$ for each of the four residual pools $(\varepsilon(c, I = c), \varepsilon(c, I = e), \varepsilon(e, I = e)$, and $\varepsilon(e, I = c))$. Here x is the model index, that is, either c (contraction) or e (expansion), and y indicates the business cycle phase index from which the residual pool is drawn. Thus, for example, $\overline{\mu}_\varepsilon(c|I = e)$ and $\overline{\sigma}_\varepsilon(c|I = e)$, respectively, denote the mean and the standard error of the residuals of the contraction model during the expansionary period. Equivalently, they are the mean and standard error of the one-period forecast errors from using the contraction model during the expansionary period.

For further systematic application of this information, it is useful to fit normal distributions to these four pools of residuals with respective means and standard deviations. Let $CDF_\varepsilon(\cdot|x,y)$ denote the conditional density function for the forecast errors of type x model ($x = c$ or e) during a period y ($y = c$ or e). Then $CDF_\varepsilon(d|c,e)$ represents the conditional probability of observing a forecast error of size greater than or equal to d if the contraction model is used for forecasting when, in fact, the economy is in an expansionary phase.

The statistics and forecast error distributions described here are updated occasionally during the forecasting periods as ex post information on business cycle dating becomes available. For example, as of November 1983, which is one year after the last month (trough) of the 1982 recession, the actual data on the monthly growth in IP during the recessionary periods is added to the $\Delta IP(I = c|t = 1983{:}11)$ pool. Subsequently, mean $(I = c|\cdot)$ and s.e. $(I = c|\cdot)$ change values from those which were calculated using the actual contraction period data prior to 1975 to ones calculated from the newly expanded pool of $\Delta IP(I = e|\cdot)$ which includes the data from the 1981 and 1982 recessions. In all of the following procedures, such updating is carried out on four occasions (1976:07, 1983:11, 1989:12, and 1992:03).

Design of a Forecast Combination Rule. The conditional rule given below determines when to use the forecast based on the contraction model's forecast for period $t + 1$:

$$(2) \qquad [\Delta IP(t-2) + \Delta IP(t-1) + \Delta IP(t)] < [\text{mean}(I = c|t) + s.e.(I = c|t)] + \gamma\,,$$

and

$$\text{either} \quad \Delta IP(t) < \Delta IP(t-1),$$
$$\text{or} \quad \Delta IP(t) < \text{mean}(I = c|t) \times (1 + \theta)\,.$$

First, (2) utilizes information about recent growth trends in the IP series to determine whether the next period will be contractionary or not. The first part of (2) identifies a stretch of time during which output growth is sluggish. That is, the sum of output growth for three consecutive months is less than the average monthly output growth during the historical contractionary periods plus one standard deviation. The second part of the condition additionally requires that the most recent two periods be contracting, and/or that the contraction in the most recent period be significant based on history. The parameters γ and θ of (2) are free parameters that are used in fine-tuning the decision rule for the intermediate forecasting period from 1975:01 to 1989:12.

Although the motivation for the design of this rule is narrowly defined as the forecast accuracy of the model, it is conceptually closely related to other business cycle dating rules. Figure 1 compares the business cycle datings resulting from (2), with both γ and θ set equal to zero, with those from the NBER and from Romer (1992). The Romer dates are determined based solely on the levels of IP series around business cycles, whereas the NBER dates are based on examining cyclical patterns of a host of indicator variables of the aggregate economy. The periods selected by (2), shown in the middle panel, exhibit a pattern of general coherence with the recession dates of both the NBER and Romer, though they are noticeably more choppy. This divergence is due to the fact that (i) the rule is based on the behavior of the IP series over a relatively short duration (3 months) and (ii) the growth rate of IP is much less persistent than IP measured in levels.

When (2) is met, the economy is likely to be in a sluggish phase currently and is likely to remain in that phase in the next period. Thus, one could do better forecasting growth in IP next period by relying on the contraction model's forecast. However, there also is some non-negligible probability that the economy might switch to expansionary mode next period. Taking this into consideration, I adopt a forecast rule (3) which takes a probability-weighted average of the forecasts from the contraction and expansion models, with the contraction model forecast getting more weight than the expansion model forecast:

$$(3) \quad f\Delta IP(\text{comb},t+1) = f\Delta IP(c,t+1) \times P\cdot\text{weight}(c) + f\Delta IP(e,t+1) \times (1 - P\cdot\text{weight}(c))$$

where

$$P \cdot \text{weight}(c) = \frac{CDF_\varepsilon[\varepsilon_t(c,c)|c,c] + \sum_{I=e,c} CDF_\varepsilon[\varepsilon_{t-1}(c,I)|c,I]}{\sum_{I=e,c} CDF_\varepsilon[\varepsilon_t(c,I)|c,I] + \sum_{I=e,c} CDF_\varepsilon[\varepsilon_{t-1}(c,I)|c,I]}$$

and

$f\Delta IP(e,t+1)$, $f\Delta IP(c,t+1)$ denote the forecast from the $m(e)$ and $m(c)$ equations, respectively. Additionally,

$$\sum_{I=e,c} CDF_\varepsilon[\varepsilon_t(c,I)|c,I] \equiv CDF_\varepsilon[\varepsilon_t(c,e)|c,e] + CDF_\varepsilon[\varepsilon_t(c,c)|c,c]\,,$$

$$\sum_{I=e,c} CDF_\varepsilon[\varepsilon_{t-1}(c,I)|c,I] \equiv CDF_\varepsilon[\varepsilon_{t-1}(c,e)|c,e] + CDF_\varepsilon[\varepsilon_{t-1}(c,c)|c,c]\,.$$

$P\cdot$weight(c) is an approximate conditional transition probability of regime-switching. The calculation is based on the recent forecast errors from the contraction model. Each $CDF_\varepsilon(\cdot)$ measures the area under the forecast error density function as defined earlier. For example, $\varepsilon_t(c,c)$ denotes the actual forecast error of the contraction model (i.e., $m(c)$) in period t. Consequently, $CDF_\varepsilon[\varepsilon_t(c,c)|c,c]$ measures the conditional probability of making a forecast error that is the same size as or larger than $\varepsilon_t(c,c)$ during the actual contractionary period according to historical experience.

It is instructive to think in terms of the ratio of the first component of the numerator and denominator

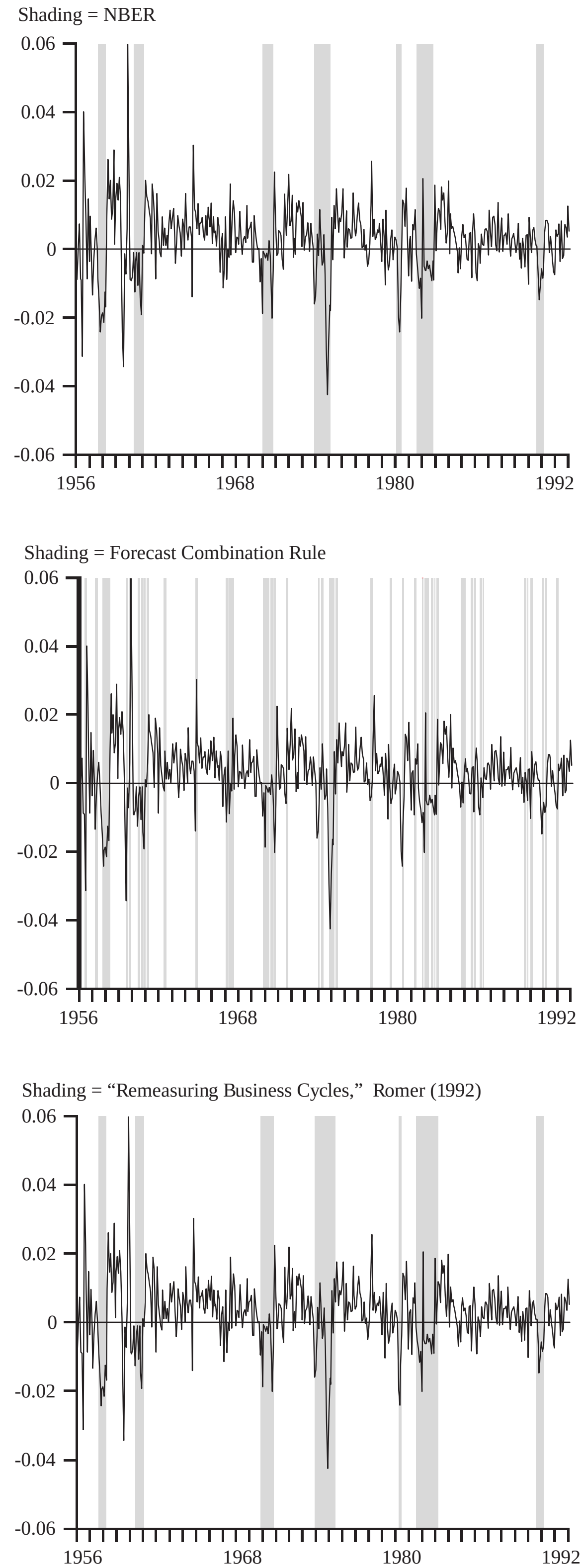
$$(CDF_\varepsilon[\varepsilon_t(c,c)|c,c] \text{ and } \sum_{I=e,c} CDF_\varepsilon[\varepsilon_t(c,I)|c,I]),$$

since the second component is common to the numerator and the denominator. The numerator term measures the probability of making a forecast error as large as, or larger than, that which is actually made in period t when the economy is indeed in a contraction. The denominator term is the sum of the same probability and the probability of related conditional complementary events. That is, the second part ($CDF_t[\varepsilon_t(c,e)|c,e]$) measures the probability that the current month is actually in an expansionary period, and the contraction model makes a forecast error of the observed size or larger. The second $\Sigma CDF_\varepsilon(\cdot)$ part which enters both the numerator and denominator commonly is the same measure for the previous period (i.e., $t - 1$). The key consideration for including the lagged CDFs is to make sure that the second weight ($1 - P\cdot$weight(c)) is smaller than the first. Together, the ratio measures a likelihood of the economy being in a contractionary period conditional on the forecast errors made by the contraction model.

Alternatively, if (2) is not true, that is, if the economy is more likely to be in an expansionary phase, (4) would be the forecast of the combination model instead:

FIGURE 1

GROWTH OF INDUSTRIAL PRODUCTION—IDENTIFYING CONTRACTIONS



$$(4)\quad f\Delta IP(\text{comb},t+1) = f\Delta IP(e,t+1)\times P\cdot\text{weight}(e) + f\Delta IP(c,t+1)\times(1-P\cdot\text{weight}(e))$$

where

$$P\cdot\text{weight}(e) = \frac{CDF_{\varepsilon}[\varepsilon_t(e,e)|e,e] + \sum_{I=e,c} CDF_{\varepsilon}[\varepsilon_{t-1}(e,I)|e,I]}{\sum_{I=e,c} CDF_{\varepsilon}[\varepsilon_t(e,I)|e,I] + \sum_{I=e,c} CDF_{\varepsilon}[\varepsilon_{t-1}(e,I)|e,I]}\ .$$

The explanation for the contractionary forecast of (3) given above applies symmetrically to the expansionary case.[8]

A Model that Uses Markov Transition Probabilities

Preliminaries. The second strategy is to use information that is more directly linked to the two-regime setup as posited in this exercise. A separate Markov switching model (MS) that includes four lags for ΔIP_t over the 1956–89 period is estimated with the maximum likelihood estimation method of Boldin (1994). The estimation yields two particularly useful sets of probabilities for the purpose of this exercise. One is a time series of the probability that any given period is in a contraction regime. To use the index I defined earlier, it can be written as $Pr(I_t = c|\Delta IP_k,\ k = t, t-1, \ldots, 2,1)$. Also available are two first-order transition probabilities that estimate the odds of switching from one regime to the other. Let Q_{ij} denote the probability of switching from regime i to regime j next period. As a result of the estimation, we obtain the four elements of the transition probabilities (i.e., Q_{ee}, Q_{ec}, Q_{cc}, and Q_{ce}).

Implementing MS Probabilities to the Forecasting Model. At any given period t, we have two distinct forecasts for the next period from the contraction and expansion regime models. Since we have information about the relative likelihood of which regime is going to be in place, one natural way of combining forecasts is to take a conditional expectation by taking a weighted average of the forecasts from the contraction and expansion regime models. Using the earlier notation, these conditional forecasts can be written as follows:

$$(5)\qquad f\Delta IP(\text{comb},t+1|I_t = e) = f\Delta IP(e,t+1)\times Q_{ee} + f\Delta IP(c,t+1)\times Q_{ec}$$

$$(6)\qquad f\Delta IP(\text{comb},t+1|I_t = c) = f\Delta IP(e,t+1)\times Q_{ce} + f\Delta IP(c,t+1)\times Q_{cc}\,.$$

Notice that both (5) and (6) are conditional on the unobservable regime of period t. Since the probabilities of each regime being in place are known, we could compute the unconditional forecast by further combining (5) and (6) in the same fashion. That is,

$$(7)\ f\Delta IP(\text{comb},t+1) = f\Delta IP(\text{comb},t+1|I_t = c)\times Pr(I_t = c) + f\Delta IP(\text{comb},t+1|I_t = e)\times Pr(I_t = e).$$

By substituting (5) and (6) into (7) and rearranging terms, it can be rewritten using $f\Delta IP(e,t{+}1)$ and $f\Delta IP(c,t{+}1)$ as follows:

$$(8)\ f\Delta IP(\text{comb},t+1) = f\Delta IP(e,t+1)\times[Pr(I_t = e)\times Q_{ee} + Pr(I_t = c)\times Q_{ce}] + f\Delta IP(c,t+1)\times[Pr(I_t = c)Q_{cc} + Pr(I_t = e)\times Q_{ec}]\ .$$

In addition to (8), I consider an alternative specification with a smoothing hyperparameter, ω. Namely, the first and the second terms are multiplied by $(1 + \omega)/2$, $(1 - \omega)/2$, respectively. Thus (8) can be rewritten as follows:

$$(9)\ f\Delta IP(\text{comb},t+1) = f\Delta IP(e,t+1)\times[Pr(I_t = e)\times Q_{ee} + Pr(I_t = c)\times Q_{ce}]\frac{1+\omega}{2} + f\Delta IP(c,t+1)\times[Pr(I_t = c)\times Q_{cc} + Pr(I_t = e)\times Q_{ec}]\frac{1-\omega}{2}\ .$$

There are two justifications for this. First, this allows an additional lever for the MS model to improve the forecast performance, as was done in the earlier nonlinear cases. Second, Markov regime-switching models of monthly IP tend to produce quite jumpy and discontinuous regime switches. Such properties translate into the terms $Pr(I_t = c)$ and $Pr(I_t = e)$, switching from values close to 1 to near zero, both Q_{cc} and Q_{ee} being close to one in terms of the formula.[9]

8. In actual implementation of the estimation, a minor change was made in how the two phase model forecasts were combined. In formula (3), $f\Delta IP(e,t)$ is used in place of $f\Delta IP(e,t+1)$, the second term of the equation. It turns out that the contemporaneous forecast errors of the two phase models (i.e., $\Delta IP_t - f\Delta IP(c,t)$ and $\Delta IP - f\Delta IP(e,t)$) have a high positive correlation. However, the correlation between forecast errors of the two models becomes negligible or negative when a one-period lagged forecast is used (i.e., $\Delta IP_t - f\Delta IP(c,t)$ and $\Delta IP - f\Delta IP(e,t{-}1)$). Hence, the substitution is made in the formula to reduce the forecast error variance. The second term of expression (4) was similarly replaced (i.e., $f\Delta IP(c,t)$ instead of $f\Delta IP(c,t+1)$) for the same reason.

9. The forecast accuracy (in terms of the RMSE) of the MS model is better than either the linear 1 or linear 2 model even without the hyperparameter. However, it is further enhanced with the introduction of the hyperparameter. Hence, only results from the specification with the hyperparameter will be considered in the rest of the paper.

Determination of the Parameters of the Decision Rules

There are three parameters to be determined: γ and θ for the forecast error combination models (nonlinear 1 and nonlinear 2) and for the MS model, to be determined. This is done by minimizing the metric of the sum of the square of the one-period forecast errors (i.e., $\Delta IP_t - f\Delta IP(\text{comb},t)$) for each model for the intermediate sample period from 1975:01 to 1989:12.

The grid search is carried out for the 1,000 × 1,000 equally spaced points spanning the parameter space that includes the (0, 0) point for γ and θ. For the forecast error combination models, the grid search yielded –0.0415 (for γ) and 0.32 (for θ) for the nonlinear 1, and –0.081 (for γ) and 0.9 (for θ) for the nonlinear 2.

In the MS case, the model based on the $m(e) = m(c) = 4$ specification is considered. A similar grid search is carried out for 3,000 points for the interval [–0.5, 0.5], and the parameter ω is set equal to 0.223. For the out-of-sample forecast exercise, the MS model of the ΔIP_t is reestimated at each date, and the resulting estimates of probabilities are used for each new date.

III. FORECAST PERFORMANCE OF THE MODELS

The Forecast Accuracy for 1975:01–1989:12

The forecast error statistics of the forecasts based on two-regime models for the intermediate period are shown in Table 4. The improvement in the forecast accuracy is quite obvious when compared to the results in Table 3. The use of the rule and the associated ΔIP_t improves the accuracy measured in terms of root mean square errors (RMSE) between 12 percent (MS model over the linear 1 model) and 19 percent (nonlinear 2 over linear 2). The improvement is statistically significant according to a formal statistical comparison of forecast accuracy in terms of the RMSEs of different models.[10] For example, the test statistic for the null hypothesis that the variance of the forecast errors of the nonlinear 1 model (RMSE of 0.741) is greater than that of the linear 1 (RMSE of 0.875) is –4.813 (with 167 degrees of freedom). The corresponding one-sided marginal significance level is 0.15×10^{-5}; thus it can be rejected at a 1 percent significance level. In other words, the improvement in the forecast accuracy of using the nonlinear 1 model over the linear 1 model is statistically highly significant.

In most pair-wise comparisons between the nonlinear and the conventional linear models, the former improves the forecast accuracy of the latter models at a significance level of 5 percent or less. The only exception is the case between the nonlinear 2 and the linear 1 model. The difference in the RMSEs of the respective models (0.875 vs. 0.823) is not statistically significant at the conventional levels.

10. The test assumes that the forecast errors have zero-mean, and are serially uncorrelated and normally distributed. Suppose $\{\varepsilon_1\}$ and $\{\varepsilon_2\}$ are the forecast error series with length T from the two models 1 and 2, which meet these conditions. Define two transformed error terms which are orthogonal as $\nu_{1t} = \varepsilon_{1t} - \varepsilon_{2t}$ and $\nu_{2t} = \varepsilon_{1t} + \varepsilon_{2t}$. Then the following test statistic is distributed as Student's t with T–1 degrees of freedom: $\rho(T-1)^{1/2}/(1-\rho^2)^{1/2}$, where ρ is the correlation coefficient between ν_{1t} and ν_{2t}. See, for example, Meese and Rogoff (1988) and Diebold and Mariano (1991). The forecast errors of the models examined here generally satisfy these conditions.

TABLE 4

ONE-PERIOD-AHEAD INDUSTRIAL PRODUCTION GROWTH RATE FORECAST ERROR STATISTICS FOR TWO-REGIME MODELS (FROM 1975:01 TO 1989:12, 180 OBSERVATIONS)

MODEL	MEAN ERROR	MEAN ABS. ERROR	R.M.S. ERROR	THEIL U
TWO-REGIME MODELS WITH THE LAGGED FORECAST ERROR RULE				
Nonlinear 1 ($m(e) = 4$, $m(c) = 4$)	–0.038	0.560	0.741	0.810
Nonlinear 2 ($m(e) = 12$, $m(c) = 4$)	–0.095	0.619	0.824	0.900
TWO-REGIME MODEL WITH THE MARKOV SWITCH TRANSITION PROBABILITY RULE				
MS nonlinear ($m(e) = 4$, $m(c) = 4$)	0.032	0.577	0.768	0.839

One interesting question is whether the source of the forecast improvement using the nonlinear models is concentrated in any particular business cycle phase. Table 5 shows the RMSEs for the business cycle phase samples for the linear and the two-regime models. A noticeable pattern across Tables 4 and 5 is that the fit of all the models worsens during contractionary periods. However, the forecasts from the two-regime models as a group do not deteriorate as much as those of the linear models. That is, the RMSEs during contractionary periods of the combination models are smaller than those for the full-sample models.

The pattern of relative improvement of nonlinear models over linear ones is not obviously concentrated. Using the nonlinear 2 over the linear 2 model brings a 22 percent reduction in the RMSE in the expansion sample compared to 12 percent for the contraction sample. The comparable figures for the MS and the linear 1 models are 14 percent for the expansion and 9 percent for the contraction samples. However, in the case of the nonlinear 1 and linear 1 models, the improvement for the contraction and the expansion sample are 25 and 12 percent, respectively. Thus, the nonlinear models improve forecast accuracy in both contractionary as well as expansionary periods.

Out-of-sample Forecast Accuracy: 1990:01–1993:03

The comparison in the previous section is not entirely fair, for the design of the forecast rule for the combination model hinges on the forecast performance itself. Thus, in this section the out-of-sample performance of the different models is examined. To this end, the same comparison of the previous section is applied to the 1990:01 to 1993:03 period (39 observations), which contains one recession in 1990–1991.

The linear models are reestimated using data up to 1989:12, and these estimates in turn are used for one-month-ahead forecasts from 1990:01 to 1993:03. The nonlinear models are also reestimated using all available data on the expansion and contraction episodes up to 1989:12, and the decision rule with the parameter values found with the earlier grid searches is used to generate the combination forecasts. The MS model is updated by repeatedly reestimating the MS model of IP for each period beyond 1990:01, in a truly real-time updating fashion.

Table 6 compares various forecast error statistics for the one period forecasts from all three types of models for the period 1990–1993. As a group, the nonlinear models unmistakably improve upon the linear models. In terms of the RMSE, the improvement is 4 and 5 percent for the lagged forecast error combination models (i.e., nonlinear 1 and nonlinear 2). For the MS model, it ranges from 9 to 11 percent over the linear models.

TABLE 5

RMSEs for the NBER Business Cycle Phase-Specific Samples (1975:01-1989:12)

Models	RMSE	
	Expansion (155 obs.)	Contraction (25 obs.)
Linear 1	0.805	1.222
Linear 2	0.906	1.529
Nonlinear 1	0.709	0.917
Nonlinear 2	0.706	1.338
MS Nonlinear	0.696	1.113

It is interesting to note that the forecast performance of the nonlinear models does not deteriorate in the out-of-sample period. This can be seen by comparing Table 4 to Table 6. For example, measured in terms of Theil's U, forecasts from the nonlinear 2 and MS perform better in the second period (out-of-sample) than the in-sample.

However, the improvement is not as significant as in the case of the 1975–1989 sample results. The most significant improvement is obtained when the forecasts from the MS model are compared to those of the linear models. The marginal significance level is 6 and 9 percent in the linear 1 and linear 2 cases, respectively.

Dynamic Comparison of Forecast Accuracy of Different Models

Since the forecast accuracy measures of Tables 3 through 6 are static, they provide little information regarding the stability of the relative fit of single-regime versus multiple-regime models over time. For this information, the dynamic changes in the forecast accuracy of selected linear and nonlinear models over time are examined. Such an examination could also offer an opportunity to see how "unusual" the output and interest rate bivariate behavior was near and during the most recent recession in the context of the historically observed pattern of forecast performance.

Figure 2A compares the relative forecast accuracy of the linear 1 and linear 2 models. The former outperforms the latter in the RMSE sense for the fixed sample periods 1975:01–1989:12 and 1990:01–1993:03. However, the figure shows

TABLE 6

OUT-OF-SAMPLE INDUSTRIAL PRODUCTION GROWTH RATE FORECAST ERROR STATISTICS
(FROM 1990:01 TO 1992:12, 39 OBSERVATIONS)

MODEL	MEAN ERROR	MEAN ABS. ERROR	R.M.S. ERROR	THEIL U
LINEAR MODELS				
Linear 1	–0.326	0.529	0.662	0.917
Linear 2	–0.357	0.544	0.678	0.940
TWO-REGIME MODELS WITH THE LAGGED FORECAST ERROR RULE				
Nonlinear 1	–0.294	0.512	0.638	0.884
Nonlinear 2	–0.323	0.520	0.646	0.895
TWO-REGIME MODEL WITH THE MARKOV SWITCH TRANSITION PROBABILITY RULE				
MS nonlinear	–0.164	0.496	0.602	0.835

the evolution of the statistical measure of relative forecast accuracy. The procedure is as follows: a rolling forecast accuracy *t*-test for an interval of 36 months is carried out from 1978:01 to 1993:03. For example, the *t*-test is applied to the two groups of 36 one-month-ahead forecast errors of the linear 1 and linear 2 models for the sample interval from 1975:01 to 1977:12, and the resulting marginal significance level (for H_0:$\sigma^2_{\text{linear 1}} \geq \sigma^2_{\text{linear 2}}$, where σ^2_i is the forecast error variance of model *i*) is 0.213. That value is plotted for the horizontal coordinate of 1978:01 in Figure 2A. Next, the observation for 1975:01 is dropped, and that for 1978:01 is added to the pool of 36 one-month-ahead forecasts (now 1975:02–1978:01) and the test is repeated. This procedure is repeatedly applied up to 1993:03, which is the last date for the last 36-month interval (i.e., 1991:04–1993:03) to give rise to Figure 2A. It shows that the linear 1 was significantly more accurate than the linear 2 model for the sample periods straddling the 1981–1982 recession, but otherwise the improvement is not significant. One possible reason for the improvement is that the linear 1 model, with a 4-lag specification, is more flexible and quicker to adjust to shifts than the linear 2 model with 12 lags. Thus, to focus on forecast accuracy of the nonlinear model exclusively, I compare the linear 1 model with the nonlinear 1 model, since both are based on four-lag specifications.

Figure 2B shows the marginal significance levels for the rolling 36-month interval as in the earlier case. Until about 1988, the forecast from the nonlinear 1 model is significantly more accurate than that of the linear 1 model. Especially compared to Figure 2A, the improvement is quite noticeable for the period leading up to and throughout the 1980 recession.

In contrast, no comparable gain in terms of improvement in the forecast accuracy is obtained near the most recent 1990–1991 recession, as in the earlier case. Though not shown, a similar pattern was seen when the nonlinear 2 model's forecast was compared to that of the linear 2 for the most recent recession. This suggests that it is unclear how much improvement could have been gained by using the nonlinear 1 and nonlinear 2 models during the sample period that includes the most recent recession. Thus, in this context, the comovement pattern between the growth in IP and the interest rate spread has become unusual near the recent recession.

However, the next figure conveys quite a different impression with regard to the gain of using the nonlinear model during the most recent recession. Figure 2C shows the comparison between the MS and the linear 1 models. The MS appears to increase the significance of the forecast accuracy even more. Furthermore, there is no visible deterioration in the relative forecast performance of the MS model compared to the linear 1 model in the period leading up to and through the 1990–1991 recession. The nonlinear model's performance appears to have deteriorated during the period that immediately followed the recent recession. Hence, in the context of the MS model, the usual bivariate comovement pattern was clearly observed for the period leading up to the 1990–1991 recession. Thus, it could

FIGURE 2A

Relative Forecast Fit of Linear 1 and Linear 2 Models

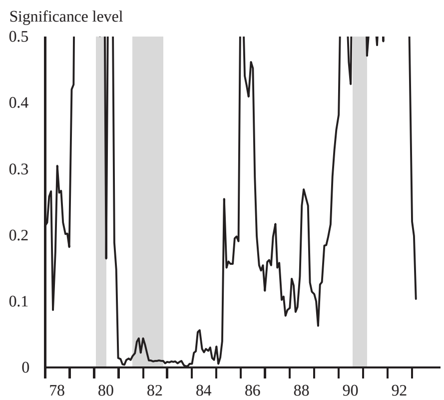


FIGURE 2B

Relative Forecast Fit of Nonlinear 1 and Linear 1 Models

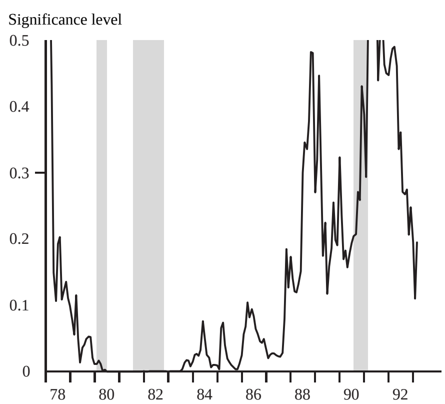
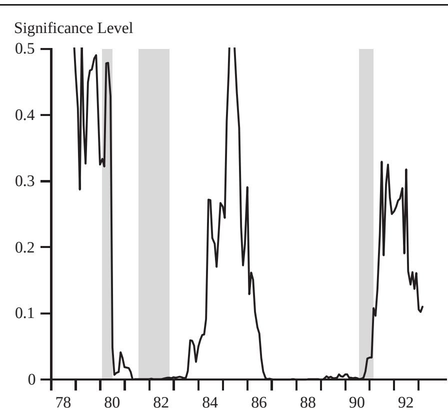


FIGURE 2C

Relative Forecast Fit of MS Nonlinear and Linear 1 Models



be the failure of a single-regime model to account for the asymmetry in the bivariate pattern which underlies the observation that the behavior of financial variables vis-à-vis output was "unusual" before the most recent recession.[11]

IV. Conclusion

This paper demonstrates a practical forecasting application of a modeling exercise that posits multiple regimes. An important advantage of this approach is that it does not require a forecaster to make an explicit ex ante determination of a turning point in the series that is being predicted. Both the static and dynamic results indicate that a noticeable improvement in the forecast fit can be obtained by using such a model compared to more conventional single-regime forecasting equations.

The main conclusion from this exercise is that there are measurable gains to be made by considering models that explicitly incorporate asymmetry in the data. Also this result is supporting evidence for the existence of business cycle phase-related asymmetry in the bivariate relationship between output and interest rates.

11. It is noteworthy that the design of the decision rules for the forecast error nonlinear models was taken from a previous exercise based on a different interest rate variable (i.e., 6-month commercial paper and the federal funds rate spread). The overall results were very similar. However, compared to the current case, the improvement in forecast performance using the nonlinear models was more concentrated in the contractionary periods.

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