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# ZERO LOWER BOUND AND INDICATOR PROPERTIES OF INTEREST RATE SPREADS

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# Zero Lower Bound and Indicator Properties of Interest Rate Spreads*

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**Abstract**

This paper examines the predictive power of interest rate spreads when the zero lower bound restriction for monetary policy is binding. We show that this restriction has a major effect on the predictive content of some interest rate spreads. Most importantly, we find that the term spread outperforms the AR benchmark in real-time forecasting exercise when the short-term rate is at the zero lower bound, but not otherwise. On the other hand, our results indicate that the difference between the 30-year mortgage rate and ten-year Treasury bond rate is a robust predictor of future economic activity.

**Keywords**: business fluctuations, forecasting, interest rate spreads, monetary policy, zero lower bound

**JEL codes**: C53, E32, E44, E52, E58

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# 1. Introduction

The empirical literature focusing on forecasting U.S. real macroeconomic variables has found that interest rate spreads have substantial predictive power for future economic activity. In particular, the term spread i.e., the difference between the yields on long-term and short-term Treasury securities, has been identified as one of the most informative leading indicators (see, e.g., Stock and Watson, 2003). The previous literature has also found that the paper-bill spread (i.e., the difference between a commercial paper rate and a Treasury bill rate of the same maturity) and various credit spreads (i.e., either the difference between the yields on various corporate bonds and government bonds of comparable maturity or the difference between the yields on two private debt instruments differing with respect to their rating categories) contain significant information about the subsequent real activity (see, e.g., Bernanke, 1990; Bernanke and Blinder, 1992; Friedman and Kuttner, 1992, 1998; Gertler and Lown, 1999; Mody and Taylor, 2003; Gilchrist *et al.*, 2009; Faust *et al.*, 2012; Gilchrist and Zakrajšek, 2012).

However, the predictive power of interest rate spreads varies over time. For example, it is nowadays a well-known fact that the ability of the term spread to forecast future economic activity has diminished since the mid-1980s (Stock and Watson, 2003 and the references cited therein). The changes in the predictive content of the term spread often correspond quite closely to major changes in the conduct of monetary policy (Estrella *et al.*, 2003; Giacomini and Rossi, 2006). Therefore, regime shifts in monetary policy are potentially important for the predictive power of the term spread. Because the paper-bill spread and credit spreads are, at least to some extent, indicators of the stance of monetary policy and are thus informative leading indicators, changes in monetary policy may also affect their predictive ability.

The previous studies have examined the predictive power of interest rate spreads during time periods when the Fed has set the federal funds rate, more or less, according to the famous Taylor (1993) rule. When applying the Taylor rule, the Fed has set the federal funds rate — and thus the short-term interest rate — well above zero. The financial crisis in 2008 changed the Fed's behavioral pattern altogether. Since December 2008, the Fed has not applied the Taylor rule anymore, because it implies negative federal funds rate (Chung *et al.*, 2012; Clarida, 2012). Instead, the federal funds rate has been very close to zero i.e., at the zero lower bound (ZLB). Figure 1 demonstrates this fundamental change in monetary policy by plotting ten-year and one-year Treasury rates and the federal funds rate from 2000 through 2013. This change is potentially important for the predictive power of interest rate spreads, because regime shifts in monetary policy often affect the reliability of interest rate spreads as predictors of future economic activity. Thus, it is unclear whether interest rate spreads are still useful leading indicators when the federal funds rate is at the ZLB.

INSERT FIGURE 1 HERE

The short-term rates in the U.S. have been effectively constrained by the ZLB only in the 1930s and since 2008. Although very low interest rates have been rare, Bernanke *et al.* (2004) and Chung *et al.* (2012) argue that the ZLB restriction is nowadays much more likely to become binding than in the past. The primary reason for this is the change in the way central banks conduct monetary policy. Modern central banks have adopted an inflation target and thus committed to keeping inflation at a low level. Low and less volatile inflation has in turn allowed for lower interest rates. Low inflation and interest rates increase the probability that negative shocks will force the central bank to lower the short-term rate to the ZLB. As a consequence, we believe that empirical study of the leading indicator properties of interest rate spreads when the ZLB restriction is binding is highly worthwhile.

In this paper, we compare the predictive power of the term spread, the paper-bill spread and a set of widely used credit spreads for U.S. monthly industrial production when the ZLB restriction is binding. The main finding from this study is that the level of the short-term rate seems to matter for the predictive power of the term spread. We find that term spread models outperform the AR benchmark in real-time forecasting exercise when the short-term rate is at the ZLB, but not otherwise. Thus, our results provide further evidence supporting the view that fundamental changes in monetary policy affect the predictive ability of the term spread. We find that the effect of the ZLB restriction on the predictive content of credit spreads is mixed, probably due to the fact that they do not directly depend on the short-term rate. Hence, no consensus on how the ZLB restriction affects their predictive power emerges.

Our results indicate that the mortgage spread (i.e., the difference between the 30-year mortgage rate and ten-year Treasury bond rate) is a particularly informative leading indicator. It is a robust predictor of industrial production growth across a variety of sample periods and forecast horizons. The mortgage spread systematically outperforms the AR benchmark in our real-time out-of-sample forecasting exercise, regardless of whether the ZLB restriction is binding or not. The improvements over the AR model are typically large, ranging from 22 to 60%.

The remainder of the paper is organized as follows. In Section 2, we describe the econometric methodologies. Section 3 presents the empirical results. Section 4 contains concluding remarks.

# 2. Methodology

In this section, we briefly describe the econometric methodologies used in this paper. The purpose of this study is to examine whether different spreads forecast future economic activity when the ZLB restriction is binding.[1] In order to analyze this question, we estimate the following linear $h$-step ahead regression model:

$$Y_{t+h}^h = \beta_0 + \sum_{i=0}^{p} \beta_{1i} X_{t-3i} + \sum_{j=0}^{q} \beta_{2j} Y_{t-j} + u_{t+h}^h, \qquad t = 1, ..., T \tag{1}$$

where the dependent variable and the lagged dependent variable are

$Y_{t+h}^h = (1200/h)ln(IP_{t+h}/IP_t)$ and $Y_{t-j} = 400ln(IP_{t-3j-1}/IP_{t-3j-4})$ ($IP_t$ is the industrial production at month $t$)[2], $X_t$ is the candidate predictor and $u_{t+h}^h$ is an error term.[3] The forecast horizon $h$ is chosen such that we forecast economic activity one, two, three, and four quarters ahead (i.e., $h$ = 3,6,9,12). The forecasting regression (1) is estimated by OLS. For forecast horizons $h > 1$, the data are overlapping and thus the error term is autocorrelated. The MA ($h$-1) structure of the error term induced by overlapping observations is taken into account by computing Newey and West (1987) HAC covariance matrix.

We evaluate the forecasting performance of various interest rate spreads using a real-time out-of-sample forecasting exercise. We follow the procedure proposed by Stock and Watson (2003) and allow the lags of $Y_t$ to vary between zero and four and the lags of $X_t$ to vary between one and four in the forecasting model (1) (so we have 20 different models for each interest rate spread). At each forecast origin, the model with the lowest Bayesian information criteria (BIC) is chosen. Unlike Stock and Watson (2003), we

[1]Monthly industrial production is used to gauge the state of the economy. The most frequently used measure of economic activity in the previous literature is quarterly GDP. In our case, the number of observations is important, because the ZLB period is relatively short (running from December 2008 to April 2013). Therefore, monthly industrial production is more appropriate for our purposes.

[2]The one month publication lag in the industrial production series is taken into account. We use quarterly lags instead of monthly lags because we want to include information from the latest year to the forecasting regression and still keep the model relatively parsimonious.

[3]Alternatively, we could use univariate regression equations including only current and lagged values of the candidate predictor as regressors. However, this approach has an important shortcoming: the industrial production series is serially correlated and thus its own past values are themselves useful predictors. By including the lagged values of the dependent variable, we consider the marginal predictive power of the spreads, i.e., whether they have predictive content for $Y_{t+h}^h$ when its own past values $Y_t$ are already taken into account.

use a rolling estimation scheme. This estimation scheme is more appropriate for our purposes than a recursive scheme for two reasons. First, as Giacomini and White (2006) point out, when the forecasting model is misspecified, it is often the case that a limited memory estimator provides more reliable forecasts than an expanding-window estimator. Second, tests of equal predictive ability (discussed below) require limited memory estimators and thus rule out the recursive estimation scheme.

A standard way to quantify out-of-sample forecast performance is to compute the mean squared forecast error (MSFE) of a candidate forecast relative to a benchmark. Because the growth rate of industrial production is serially correlated and thus its own past values are themselves informative about future industrial production growth, it is natural to use an autoregressive (AR) model as a benchmark. The results from the previous literature indicate that it is relatively hard to outperform the AR benchmark (see, e.g., Stock and Watson, 2003; Rossi, 2012). For the benchmark model, we consider lags between one and four and again choose the optimal lag length at each forecast origin with the BIC. If the relative MSFE is less than one, the candidate predictor has produced more accurate forecasts than the benchmark. However, this does not necessarily mean that the difference in the predictive content is statistically significant. The relative MSFE could be less than one simply because of sampling variability. Thus, we need more formal test procedures for deciding which models are preferable relative to a simple AR model.

In our setting, forecast evaluation is complicated by the fact that both the candidate model and the benchmark model have a recursive BIC lag length selection. This implies that we might possibly use both nested and non-nested models when generating a sequence of out-of-sample forecasts. The Giacomini and White (2006) test of equal conditional predictive ability and test of equal unconditional predictive ability allow the comparison of both nested and non-nested models as well as models that change from time to time and are thus appropriate for our purposes.

The test of equal unconditional predictive ability tests the null hypothesis that the two forecasting methods are equally accurate on average over the out-of-sample period. Rejection of the null hypothesis implies that one of the two methods produces on average more accurate forecasts than the other method. Because the unconditional test focuses on average performance, it is suitable for analyzing which forecasting method should be used for generating a forecast for an unspecified future date. On the other hand, the test of equal conditional predictive ability examines whether some available information (above and beyond past average behavior) can be used to predict which forecast will be more accurate for a specified future date. Under the null hypothesis the two methods are equally accurate and thus one cannot predict which method will be more accurate using the information in the conditioning set. Rejection of the null hypothesis indicates that the conditioning information (e.g., some feature of the economy) can be used to decide which forecasting method is preferable at each forecast origin. Because we are interested in analyzing whether the ZLB restriction changes the predictive ability of different spreads, we condition the relative predictive ability on an indicator taking value of one when the ZLB restriction is binding and zero otherwise.[4] In our case, the null hypothesis states that the two forecasting methods have equal predictive ability regardless of whether the ZLB restriction is binding or not. If the null hypothesis is rejected, the information about whether the short-term rate is at the ZLB or not can be used to predict which method will yield more accurate forecasts.

Giacomini and Rossi (2010) point out that the relative forecasting performance may change over time in unstable environments. In such a case, average relative performance over the whole out-of-sample period may hide important information and even lead to incorrect conclusions. We analyze time-variations in the relative forecasting performance using methods developed by Giacomini and Rossi (2010). Their Fluctuation test is simply the Giacomini and White (2006) test of equal unconditional predictive

[4] In other words, we use the test function $h_t = (1, ZLB_t)'$, where $ZLB_t$ is a dummy variable that takes a value of one when the ZLB restriction is binding (2008:M12—2013:M4) and zero otherwise.

ability computed over a rolling out-of-sample window size of $m$. This Fluctuation test examines whether the local relative forecasting performance of the methods is equal at each point in time. Under the null hypothesis the two methods yield equally accurate forecasts at each point in time. If the null hypothesis is rejected, one of the methods outperformed its competitor at some point in time.

# 3. Empirical results

This section describes the data and summarizes our empirical results. The sample period runs from 1987:M9 to 2013:M4. Different vintages of industrial production series used in an out-of-sample forecasting exercise were obtained from Philadelphia Fed's real-time database. The monthly interest rate data were obtained from St. Louis Fed's FRED database.[5] Definitions of the alternative spreads used in this paper are given in Table 1. The first ten of these spreads have been frequently used in the previous literature. The inclusion of the last spread, namely the mortgage spread, can be motivated by the recent work of Hall (2011).

INSERT TABLE 1 HERE

We start our analysis by considering the whole out-of-sample period running from 2003:M6 to 2013:M4. The performance of the various interest rate spreads relative to the autoregressive benchmark over this whole out-of-sample period is summarized in Table 2. The first row provides the root MSFE of the benchmark AR model.[6] For the subsequent rows, the first line reports the MSFE of a candidate model relative

[5]The Merrill Lynch U.S. High-yield Master II index for the period 1986:M9—1996:M12 is taken from Mark Watson's webpage. During this period the high-yield index is the last daily observation of the month.

[6]Forecast errors are calculated using the latest available data i.e., the vintage of May 2013. The results are qualitatively similar if forecast errors are computed using the first available real-time vintages of data.

to the MSFE of the benchmark model. Values less (more) than one indicate that the candidate model has produced more (less) accurate forecasts than the benchmark. The p-value of the one-sided Giacomini and White (2006) test of equal unconditional predictive ability is reported in parenthesis. As discussed in Rossi (2012), the choice of the estimation window size is crucial since different window sizes may lead to different empirical results. In order to check the robustness of our results to the selection of the estimation window size, we consider three different window sizes. These window sizes are 120, 150 and 180.

INSERT TABLE 2 HERE

The results reported in Table 2 show that the mortgage spread is the best leading indicator among the eleven considered. Its ability to forecast future industrial production growth is superior to the AR benchmark and all other spreads — no matter which forecast horizon/window size combination we use. The p-values of the Giacomini and White (2006) test of equal unconditional predictive ability indicate that, with one exception, the mortgage spread produces forecasts that are statistically significantly more accurate at the 10% level than those produced by the AR benchmark. Our results suggest that the high-yield spreads are informative at the 3-month horizon, although we cannot reject the null of equal accuracy at conventional significance levels. The evidence for the rest of the spreads is mixed, but none of these spreads systematically beats the AR benchmark. Various measures of the term spread perform relatively poorly and they rarely improve upon the benchmark. This result is interesting because the previous literature has identified the term spread as one of the most informative leading indicators (see, e.g., Stock and Watson, 2003).

The results reported in Table 2 focus on average predictive power over the whole out-of-sample period. However, the purpose of this study is to examine whether the

ZLB restriction affects the predictive content of different spreads. In order to analyze this question, we divide the sample period into two parts. The first period runs from 2003:M6 to 2008:M11 and it characterizes a period with normal monetary policy. During this period, the Fed has applied, more or less, the famous Taylor rule and consequently interest rates have been well above zero. The second period runs from 2008:M12 to 2013:M4. During this second period, short-term interest rates have been very close to zero and thus the ZLB restriction has been binding. The results for these two subperiods are summarized in Table 3. The first row provides the root MSFE of the benchmark AR model in the two sample periods. In subsequent rows, the first line reports the MSFE of a candidate model relative to the MSFE of the benchmark model in the first subperiod; the second line reports the relative MSFE in the second period; and the third line reports the p-value of the Giacomini and White (2006) test of equal conditional predictive ability. This test is implemented by conditioning the relative predictive ability on an indicator taking value of one when the ZLB restriction is binding (2008:M12—2013:M4) and zero otherwise. Under the null hypothesis the candidate model and the benchmark model have equal predictive ability regardless of whether the ZLB restriction is binding or not. If the null is rejected, one can use the information about whether the ZLB is binding or not to predict which method will yield more accurate forecasts.

INSERT TABLE 3 HERE

The results in Table 3 suggest that the level of the short-term rate matters for the predictive power of the term spreads. These spreads do not improve upon the AR benchmark in the first period, but when the ZLB restriction is binding they perform much better and typically outperform the benchmark. However, the Giacomini and White (2006) test rejects the null hypothesis of equal conditional predictive ability at the 10% significance level in less than half of the cases. Note that our sample period is relatively short and turbulent. Therefore, it might be difficult to reject the null even if the conditional performance differs considerably. As a consequence, the high p-values of the Giacomini and White (2006) test should not be overemphasized.

In the cases where the null hypothesis is rejected, one can use the level of the short-term rate to predict which model will yield more accurate forecasts for a specified future date. In particular, our results suggest that forecasts should be based on the AR model if the short-term rate is not at the ZLB. On the other hand, the term spread models are preferable if the short-term rate is at the ZLB.

The results reported in Table 3 also indicate that the Aaa.10y-spread and the mortgage spread perform well in the second period, although the p-values indicate that the difference in the conditional predictive ability is not statistically significant in most of the cases. The mortgage spread is overwhelmingly the best leading indicator in the first period. It produces the most accurate forecasts in each of the twelve forecast horizon/estimation window combinations considered. In the second period, it produces the best forecasts in eleven of the twelve cases. The improvements over the AR model are typically very large. For instance, the 9-month-ahead forecast (window size = 150) based on the mortgage spread has a relative MSFE of 0.40, indicating a 60-percent improvement relative to the benchmark.

The effect of the ZLB restriction on the predictive content of the rest of the spreads is somewhat mixed. In general, however, our results indicate that these spreads perform quite well in the first period, but poorly in the second period when the ZLB restriction has been binding. Although the differences in the MSFE-values are large, we cannot reject the null of equal conditional predictive ability at conventional significance levels.

All in all, our findings support the view that the beginning of the ZLB era might have affected the predictive content of frequently used interest rate spreads. The effect is more pronounced for the term spread and the paper-bill spread, which depend directly on the short-term rate. Note that some credit spreads (e.g., the Baa-Aaa corporate bond spread) perform poorly when the ZLB restriction is binding, whereas some credit spreads (e.g., the Aaa.10y- and Mortgage-spreads) perform well when the short-term rate is at the zero level. Hence, no consensus on how the ZLB restriction affects the real-time predictive power of credit spreads emerges.

So far we have assumed that the relative forecasting ability either remains constant over time (Table 2) or depends on whether the short-term rate is at the ZLB or not (Table 3). However, Giacomini and Rossi (2010) point out that the relative forecasting performance may be time-varying. In such a case, average relative performance (either unconditional or conditional) over the whole out-of-sample period may hide important information and even lead to incorrect conclusions. Thus, we next consider the Giacomini and Rossi (2010) Fluctuation test robust to instabilities. The Fluctuation test is implemented by using a centered rolling window of 45 observations (i.e., $\mu$ = m / P is approximately 0.4). Optimally one would like to plot the test statistic for each forecast horizon/estimation window combination. However, this is infeasible due to space limitation. To save space, we focus on 3-month-ahead forecasts when the estimation window size is 150.[7] Figure 2 reports both the Fluctuation test statistic as well as the one-sided critical value at the 5% significance level (dashed horizontal line). Positive (negative) values of the Fluctuation test indicate that the interest rate spread model has produced more (less) accurate forecasts than the AR benchmark. If the value of the Fluctuation test exceeds the critical value, we can reject the null hypothesis of equal local predictive ability at each point in time.

INSERT FIGURE 2 HERE

Inspection of Figure 2 reveals that various measures of the term spread perform

[7]We focus on the shortest forecast horizon because we want to maximize the number of out-of-sample observations when the ZLB restriction is binding.

worse than the benchmark at the beginning of the out-of-sample period. Recently these spreads have outperformed the AR benchmark (with the exception being the TS1y.3m-spread). Hence, the Fluctuation test confirms the results from Table 3. However, note that we cannot reject the null of equal local predictive ability at each point in time. The evidence for the paper-bill spread and the Baa.10y- and Baa.Aaa-spreads is mixed, but in general they perform relatively poorly. The Aaa.10y-spread and high-yield spreads produce worse forecasts than the benchmark for all windows centered before the early 2007, but since then they have typically outperformed the benchmark. However, the most recent observations indicate that the high-yield spreads have lost their edge as predictors of industrial production growth. The Fluctuation test shows that the mortgage spread has systematically produced more accurate industrial production forecasts than the AR benchmark (the value of the Fluctuation test is always positive). The null is rejected at the 5% significance level for all windows centered at 2007:M7 through 2010:M6.

To sum up, the Fluctuation test and the results reported in Tables 2 and 3 suggest that the mortgage spread is overwhelmingly the best leading indicator in our real-time forecasting exercise. Our results indicate that the predictive power is not due to some specific subperiod but rather the spread produces fairly accurate forecasts over the whole out-of-sample period. This implies that whether the ZLB restriction is binding or not does not affect the predictive power of this spread.

# 4. Conclusions

This paper analyzes the leading indicator properties of various interest rate spreads when the short-term rate is at the ZLB. Our empirical analysis leads us to three main conclusions. First, and perhaps most importantly, our results suggest that the predictive content of the term spreads have changed with timing corresponding quite closely to the beginning of the ZLB era. In particular, we find that these spreads do not improve upon the AR benchmark in the period 2003:M6—2008:M11, but when the short-term rate is at the ZLB they perform much better and typically outperform the benchmark. Thus, our results are consistent with the view that fundamental changes in monetary policy change the predictive power of the term spreads. On the other hand, no consensus on how the ZLB restriction affects the real-time predictive power of credit spreads emerges. Second, the Giacomini and Rossi (2010) Fluctuation test detects widespread instability in predictive relationships. This finding of instability highlights the burdens associated with using interest rate spreads as business cycle indicators; predictors that perform well in one period may work poorly in another. Third, the mortgage spread is overwhelmingly the best leading indicator among the eleven considered. Its real-time predictive power is remarkable. The mortgage spread typically outperforms the AR benchmark and all other spreads regardless of the sample period under investigation. Importantly, our results suggest that whether the ZLB restriction is binding or not does not affect its predictive ability. Our results are important even to those who are skeptical about the ZLB discussion, because they emphasize the role of housing market frictions. These frictions are much more important for the future development of the economy than the frictions in the Treasury or corporate bond markets.

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# Tables

TABLE 1
*Definitions of the variables*

| *Series label* | *Definition* |
|---|---|
| TS10y.3m | Treasury bond (10 years) — Treasury bill (3 months) |
| TS10y.1y | Treasury bond (10 years) — Treasury bill (1 year) |
| TS10y.Ffs | Treasury bond (10 years) — Federal funds rate (overnight) |
| TS1y.3m | Treasury bill (1 year) — Treasury bill (3 months) |
| | |
| Paper.bill | Commercial paper (3 months) — Treasury bill (3 months) |
| Aaa.10y | Long-term corporate bond (Aaa rating) — Treasury bond (10 years) |
| Baa.10y | Long-term corporate bond (Baa rating) — Treasury bond (10 years) |
| Baa.Aaa | Long-term corporate bond (Baa rating) — long-term corporate bond (Aaa rating) |
| | |
| Hy.10y | High-yield bond — Treasury bond (10 years) |
| Hy.Aaa | High-yield bond — long-term corporate bond (Aaa rating) |
| | |
| Mortgage | Mortgage rate (30 years) — Treasury bond (10 years) |

Table 2

*Out-of-sample mean squared forecast errors*

| | *h*=3 | | | *h*=6 | | | *h*=9 | | | *h*=12 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Window size* | | | *Window size* | | | *Window size* | | | *Window size* | | |
| *Spread* | 120 | 150 | 180 | 120 | 150 | 180 | 120 | 150 | 180 | 120 | 150 | 180 |
| Uni. | 6.86 | 6.73 | 6.67 | 6.79 | 6.72 | 6.65 | 6.52 | 6.47 | 6.41 | 6.11 | 6.15 | 6.07 |
| TS10y.3m | 1.06 | 1.03 | 1.05 | 1.05 | 1.01 | 1.04 | 0.99 | 1.10 | 0.98 | 0.92 | 1.04 | 0.99 |
| | (0.96) | (0.80) | (0.85) | (0.90) | (0.60) | (0.85) | (0.41) | (0.81) | (0.25) | (0.15) | (0.67) | (0.45) |
| TS10y.1y | 1.05 | 1.00 | 1.04 | 1.06 | 0.99 | 1.08 | 1.02 | 0.98 | 0.96 | 1.01 | 1.01 | 0.99 |
| | (0.96) | (0.45) | (0.80) | (0.93) | (0.34) | (0.89) | (0.60) | (0.28) | (0.07) | (0.57) | (0.59) | (0.38) |
| TS10y.Ffs | 1.05 | 1.01 | 1.04 | 0.99 | 1.08 | 1.08 | 1.03 | 1.09 | 1.05 | 0.92 | 1.01 | 1.00 |
| | (0.92) | (0.61) | (0.82) | (0.41) | (0.76) | (0.89) | (0.59) | (0.73) | (0.68) | (0.29) | (0.55) | (0.47) |
| TS1y.3m | 1.17 | 1.19 | 1.11 | 1.23 | 1.17 | 1.10 | 1.13 | 1.09 | 1.03 | 1.02 | 1.01 | 0.97 |
| | (0.93) | (0.94) | (0.91) | (0.87) | (0.85) | (0.82) | (0.82) | (0.75) | (0.65) | (0.59) | (0.56) | (0.31) |
| Paper.bill | 0.92 | 0.97 | 1.04 | 0.94 | 1.09 | 1.14 | 0.92 | 1.04 | 1.10 | 0.82 | 1.04 | 1.17 |
| | (0.17) | (0.40) | (0.61) | (0.32) | (0.68) | (0.73) | (0.28) | (0.62) | (0.69) | (0.02) | (0.63) | (0.77) |
| Aaa.10y | 0.92 | 0.95 | 1.00 | 0.92 | 0.94 | 0.94 | 0.93 | 0.95 | 0.92 | 0.94 | 1.00 | 0.99 |
| | (0.18) | (0.23) | (0.48) | (0.18) | (0.20) | (0.21) | (0.26) | (0.30) | (0.21) | (0.33) | (0.51) | (0.44) |
| Baa.10y | 0.92 | 0.98 | 0.97 | 1.05 | 1.12 | 1.10 | 1.00 | 1.04 | 0.98 | 0.96 | 0.91 | 0.89 |
| | (0.20) | (0.43) | (0.42) | (0.62) | (0.69) | (0.66) | (0.51) | (0.65) | (0.41) | (0.35) | (0.22) | (0.18) |
| Baa.Aaa | 1.14 | 0.96 | 1.11 | 1.27 | 1.17 | 1.19 | 1.24 | 1.26 | 1.27 | 1.12 | 1.19 | 1.25 |
| | (0.81) | (0.35) | (0.68) | (0.91) | (0.75) | (0.75) | (0.86) | (0.80) | (0.79) | (0.87) | (0.77) | (0.78) |
| Hy.10y | 0.86 | 0.96 | 0.91 | 1.06 | 1.15 | 1.13 | 1.16 | 1.18 | 1.17 | 1.03 | 1.11 | 1.11 |
| | (0.13) | (0.36) | (0.25) | (0.64) | (0.75) | (0.72) | (0.93) | (0.93) | (0.89) | (0.62) | (0.93) | (0.93) |
| Hy.Aaa | 0.96 | 0.98 | 0.76 | 1.19 | 1.23 | 1.21 | 1.21 | 1.24 | 1.28 | 1.08 | 1.13 | 1.14 |
| | (0.37) | (0.44) | (0.04) | (0.84) | (0.82) | (0.77) | (0.93) | (0.93) | (0.89) | (0.80) | (0.96) | (0.97) |
| Mortgage | 0.70 | 0.68 | 0.69 | 0.74 | 0.61 | 0.64 | 0.71 | 0.62 | 0.65 | 0.78 | 0.67 | 0.67 |
| | (0.01) | (0.01) | (0.01) | (0.06) | (0.02) | (0.03) | (0.06) | (0.04) | (0.06) | (0.11) | (0.05) | (0.07) |

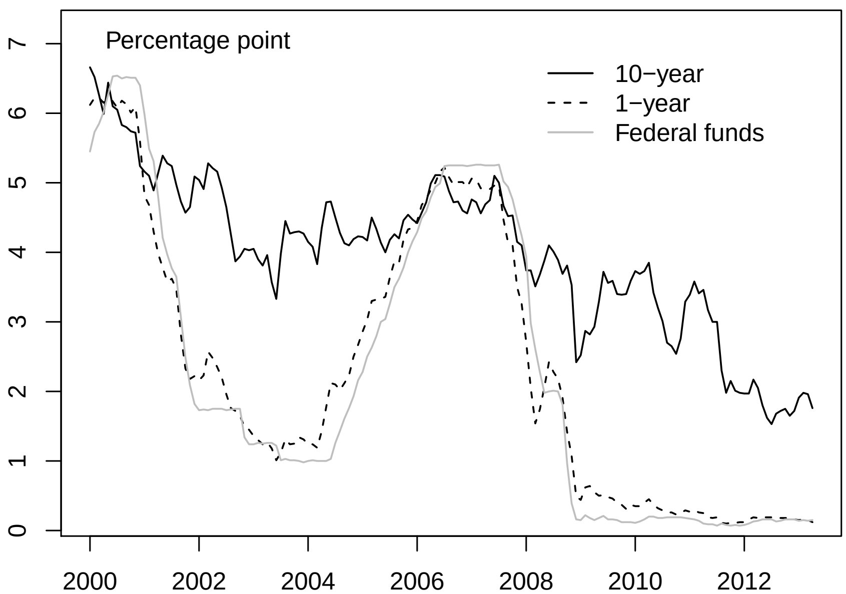
*Notes*: Sample period: Monthly data from 2003:M6 to 2013:M4. The first row shows the root mean squared forecast error for the univariate autoregression. In subsequent rows, the first line reports the ratio of the MSFE of a candidate model relative to the MSFE of the benchmark model; the p-value of the one-sided Giacomini and White (2006) test of equal unconditional predictive ability is reported in parenthesis. The truncation lag for the HAC estimator is $h$-1, where $h$ is the forecast horizon.

# Table 3
*Tests of equal conditional predictive ability*

| | *h*=3 | | | *h*=6 | | | *h*=9 | | | *h*=12 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Window size* | | | *Window size* | | | *Window size* | | | *Window size* | | |
| *Spread* | 120 | 150 | 180 | 120 | 150 | 180 | 120 | 150 | 180 | 120 | 150 | 180 |
| Uni. | 6.88 | 6.85 | 6.93 | 7.09 | 7.08 | 7.13 | 7.03 | 7.08 | 7.16 | 6.69 | 6.83 | 6.94 |
| | 6.82 | 6.58 | 6.31 | 6.34 | 6.20 | 5.91 | 5.69 | 5.44 | 5.08 | 5.03 | 4.86 | 4.35 |
| TS10y.3m | 1.10 | 1.08 | 1.04 | 1.10 | 1.07 | 1.06 | 1.07 | 1.19 | 1.02 | 1.05 | 1.12 | 1.05 |
| | 0.99 | 0.95 | 1.07 | 0.96 | 0.90 | 1.00 | 0.81 | 0.87 | 0.84 | 0.54 | 0.78 | 0.76 |
| | (0.08) | (0.08) | (0.38) | (0.08) | (0.00) | (0.51) | (0.05) | (0.07) | (0.22) | (0.09) | (0.08) | (0.20) |
| TS10y.1y | 1.08 | 1.03 | 1.02 | 1.09 | 1.03 | 1.02 | 1.13 | 1.02 | 1.00 | 1.11 | 1.06 | 1.01 |
| | 1.01 | 0.95 | 1.06 | 1.02 | 0.93 | 1.19 | 0.78 | 0.90 | 0.84 | 0.72 | 0.86 | 0.92 |
| | (0.09) | (0.24) | (0.35) | (0.17) | (0.07) | (0.34) | (0.04) | (0.33) | (0.28) | (0.01) | (0.19) | (0.83) |
| TS10y.Ffs | 1.10 | 1.07 | 1.04 | 1.08 | 1.21 | 1.05 | 1.19 | 1.23 | 1.15 | 1.13 | 1.11 | 1.04 |
| | 0.97 | 0.92 | 1.05 | 0.82 | 0.84 | 1.14 | 0.67 | 0.74 | 0.77 | 0.34 | 0.72 | 0.81 |
| | (0.08) | (0.02) | (0.49) | (0.01) | (0.02) | (0.44) | (0.03) | (0.05) | (0.19) | (0.05) | (0.10) | (0.33) |
| TS1y.3m | 1.28 | 1.29 | 1.16 | 1.38 | 1.29 | 1.16 | 1.23 | 1.19 | 1.09 | 1.10 | 1.11 | 1.03 |
| | 1.02 | 1.03 | 1.02 | 0.97 | 0.95 | 0.97 | 0.92 | 0.85 | 0.86 | 0.81 | 0.71 | 0.69 |
| | (0.30) | (0.29) | (0.37) | (0.16) | (0.31) | (0.47) | (0.35) | (0.40) | (0.54) | (0.57) | (0.55) | (0.66) |
| Paper.bill | 0.91 | 0.92 | 0.90 | 0.86 | 0.89 | 0.84 | 0.84 | 0.88 | 0.82 | 0.85 | 0.92 | 0.88 |
| | 0.92 | 1.05 | 1.26 | 1.08 | 1.46 | 1.76 | 1.11 | 1.43 | 1.94 | 0.72 | 1.42 | 2.38 |
| | (0.30) | (0.31) | (0.21) | (0.39) | (0.34) | (0.19) | (0.40) | (0.35) | (0.22) | (0.11) | (0.36) | (0.24) |
| Aaa.10y | 1.06 | 1.05 | 1.03 | 1.03 | 0.99 | 0.96 | 1.10 | 1.04 | 0.99 | 1.14 | 1.09 | 1.03 |
| | 0.74 | 0.81 | 0.95 | 0.72 | 0.84 | 0.92 | 0.55 | 0.74 | 0.73 | 0.38 | 0.72 | 0.79 |
| | (0.18) | (0.24) | (0.63) | (0.30) | (0.44) | (0.66) | (0.03) | (0.44) | (0.65) | (0.01) | (0.16) | (0.66) |
| Baa.10y | 0.94 | 0.88 | 0.84 | 0.89 | 0.84 | 0.80 | 0.95 | 0.88 | 0.86 | 0.99 | 0.93 | 0.91 |
| | 0.91 | 1.11 | 1.19 | 1.33 | 1.63 | 1.72 | 1.13 | 1.45 | 1.33 | 0.85 | 0.83 | 0.85 |
| | (0.69) | (0.47) | (0.22) | (0.52) | (0.33) | (0.23) | (0.74) | (0.37) | (0.42) | (0.92) | (0.74) | (0.64) |
| Baa.Aaa | 1.03 | 0.84 | 0.79 | 1.04 | 0.84 | 0.81 | 1.03 | 0.85 | 0.82 | 1.07 | 0.86 | 0.84 |
| | 1.29 | 1.12 | 1.62 | 1.67 | 1.76 | 1.95 | 1.72 | 2.32 | 2.62 | 1.27 | 2.24 | 2.95 |
| | (0.67) | (0.21) | (0.11) | (0.27) | (0.18) | (0.18) | (0.37) | (0.20) | (0.19) | (0.48) | (0.22) | (0.21) |
| Hy.10y | 0.89 | 0.92 | 0.84 | 0.97 | 0.92 | 0.87 | 1.07 | 1.04 | 0.99 | 1.09 | 1.11 | 1.08 |
| | 0.82 | 1.01 | 1.03 | 1.23 | 1.57 | 1.68 | 1.35 | 1.55 | 1.70 | 0.85 | 1.11 | 1.25 |
| | (0.37) | (0.86) | (0.60) | (0.83) | (0.56) | (0.44) | (0.26) | (0.31) | (0.45) | (0.42) | (0.27) | (0.31) |
| Hy.Aaa | 0.98 | 0.95 | 0.84 | 1.06 | 0.94 | 0.86 | 1.08 | 1.03 | 0.98 | 1.11 | 1.08 | 1.06 |
| | 0.94 | 1.04 | 0.64 | 1.43 | 1.78 | 1.93 | 1.51 | 1.77 | 2.16 | 0.98 | 1.29 | 1.48 |
| | (0.92) | (0.91) | (0.21) | (0.59) | (0.51) | (0.38) | (0.26) | (0.31) | (0.47) | (0.48) | (0.21) | (0.18) |
| Mortgage | 0.78 | 0.76 | 0.75 | 0.77 | 0.69 | 0.70 | 0.78 | 0.70 | 0.71 | 0.78 | 0.73 | 0.70 |
| | 0.59 | 0.58 | 0.59 | 0.68 | 0.45 | 0.51 | 0.55 | 0.40 | 0.46 | 0.79 | 0.47 | 0.58 |
| | (0.04) | (0.04) | (0.05) | (0.24) | (0.13) | (0.18) | (0.25) | (0.23) | (0.29) | (0.43) | (0.25) | (0.35) |

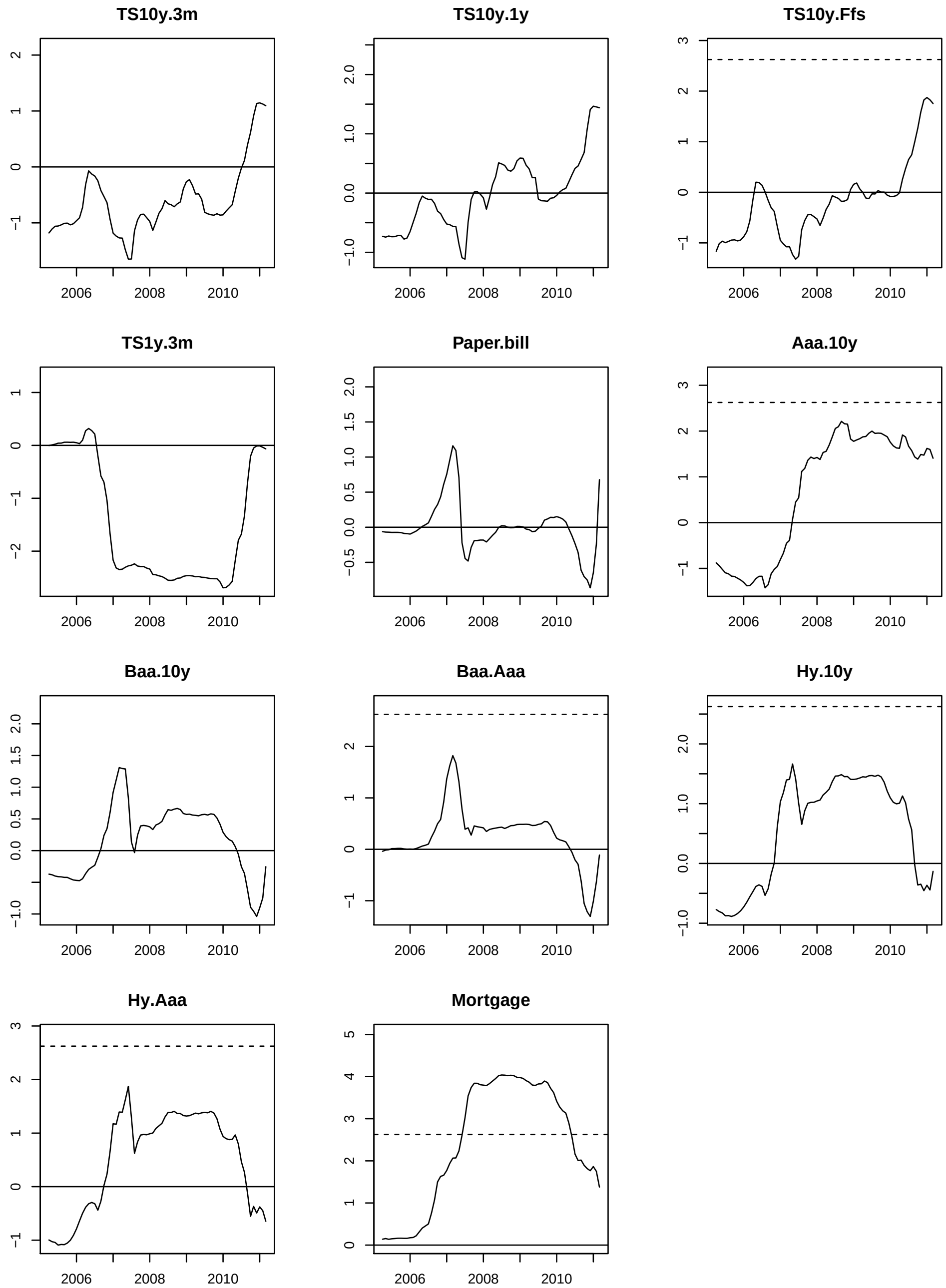
*Notes*: The first period runs from 2003:M6 to 2008:M11 and the second from 2008:M12 to 2013:M4. The first row provides the root MSFE for the univariate autoregression in the two sample periods. In subsequent rows, the first line reports the MSFE of a candidate model relative to the MSFE of the benchmark model in the first period; the second line reports the relative MSFE in the second period; the p-value of the Giacomini and White (2006) test of equal conditional predictive ability is reported in parenthesis. The test function is $h_t = (1, ZLB_t)'$, where $ZLB_t$ is a dummy variable taking value of one when the ZLB restriction is binding (2008:M12—2013:M4) and zero otherwise.

Figure 1. Treasury rates




*Notes*: Sample period 2000:M1—2013:M4. The data are extracted from the Federal Reserve Economic Data (FRED) (Federal Reserve Bank of St. Louis).

Figure 2. Fluctuation test for equal out-of-sample predictability ($h$ = 3 months)




*Notes*: The Figure plots the Giacomini and Rossi (2010) Fluctuation test based on sequences of the Giacomini and White (2006) (GW) unconditional test statistics. The Fluctuation test is implemented by using a centered rolling window of 45 observations (i.e., $\mu$ = m / P is approximately 0.4, where m is the size of the rolling window of the GW statistics and P is the number of out-of-sample observations). The sample period spans from 2003:M6 to 2013:M4. Positive (negative) values indicate that the interest rate spread model has produced more (less) accurate forecasts than the benchmark. The dashed line represents the critical value at 5% significance level. If the Fluctuation test statistic exceeds the critical value (2.770), the null that the two models have equal predictive ability at each point in time is rejected.