Has the predictability of the yield spread changed?

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Abstract This paper examines the stability of the predictive power of the yield spread for future GDP growth. We find that the ability of the spread to predict to future GDP growth has weakened since 1984 (the beginning of the Great Moderation). As the existing literature has pointed out that the predictability of the spread could be decomposed into the expectation component and the term premium component, we investigate the change in the predictability of both components and find that that the term premium component appears to have lost the predictive power significantly while the predictive power of the expectation component has remained. In order to examine the change in the cyclical movement of the term premium, we take a look at the Expectations Hypothesis and find that since the 1984, the Expectations Hypothesis appears to be rejected less than before, implying that the time-varying movement of the term premium seems to have been weaker than before.

1. Introduction

A large literature has shown that the yield spread between the long- and short-term interest rates is useful for forecasting future economic activity. Examples include Harvey (1988, 1989), Estrella and Hardouvelis (1991), Plosser and Rouwenhorst (1994), Haubrich and Dombrosky (1996), Dueker (1997), Estrella and Mishkin (1998), Hamilton and Kim (2002), Estrella, Rodrigues, and Schich (2003), Estrella (2005) and among others.

Recently, however, there were some evidence on the instability of the predictive relationships. Chauvet and Potter (2002, 2005), provide an evidence that there was a break in 1984 in the stability of recession forecasts of the yield spread and Bordo and Haubrich(2008) find that the predictive ability of the yield spread was less accurate during 1985 - 1997 than before. Nevertheless, Estrella et al. (2003) show that the predictive relationships between the yield curve and subsequent real activity are stable in both Germany and the United States. Thus, there is controversial on the stability of the predictive power of the yield spread for future real economic activity.

The purposes of this paper are twofold. First of all, we examine whether the predictive ability has weakened along with rigorous methodology for the structural break test. Secondly, if so, we try to explain why the predictability changed. We find using Bai-Perron(1998)'s multiple structural break test that the predictive power of the yield spread for future real GDP growth has declined since 1984 at all forecasting horizons. Following Hamilton and Kim (2002), we decompose the spread into the expectation component and the term premium and find that the term premium component appears to have lost the predictive power significantly while the predictive power of the expectation component has remained. In order to examine the change in the cyclical movement of the term premium, we take a look at the Expectations Hypothesis and find that as the time-varying movement of the term premium has been weak since 1984, the Expectations hypothesis appears to be rejected less than before. We conjecture that the significant reduction in the volatility of US real GDP since 1984 may have contributed to the reduction in the cyclical movement of the time-varying term premium.

The structure of this paper is as follows. In section 2, we briefly explain Bai-Perron(1998)'s methodology and present estimation results. In section 3, we estimate the change in the predictive power of both the expectation component and the term premium over the subsample. In section 4, we provide the explanation for the weakened predictability of the spread in the context of Expectations Hypothesis. The concluding remark is provided in Section 5.

2. Structural Break Test

2.1 Predictive regression

In this paper, we use 10-year Treasury bond rate, 3-month Treasury bill rate and real GDP growth rate from 1962:Q1 to 2015:Q4. Real GDP growth rate data are from FRB of St Louis FRED database and interest rates are zero-coupon yield for maturities 1 and 40 quarters from Gurkaynak et al.(2007). Figure 1 displays the spread between 10-year bond yield and 3-month bill rate and 4-quarter real GDP growth rate. The Shaded areas indicate NBER recession dates. The figure indicates that the significant decrease in the yield spread appears to have preceded every recessions although the magnitude and the timing in the decrease of the yield spread seem to be different among different recessions.

Insert figure 1

However, we cannot clearly identify that the predictive power of the yield spread has changed only using this figure. In order to investigate the change in the statistical correlation between the yield spread and future real GDP growth rate, we consider the predictive regression as follows:

$$
\begin{aligned}
y_t^k &= \alpha_0 + \alpha_1 spread_t + \varepsilon_t, && (1)\\
y_t^k &= (\frac{400}{k}) \times (\ln Y_{t+k} - \ln Y_t), && (2)\\
spread_t &= i_t^n - i_t^1, && (3)
\end{aligned}
$$

where Y_{t+k} is real GDP in quarter $t+k$, y_t^k is the annualized real GDP growth over the next k quarters, i_t^n, i_t^1 are the ten-year Treasury bond rate and the three-month Treasury bill rate at time t. We use equation (1) to test whether the predictive power of the yield spread changed based on the coefficient α_1.

2.2 Methodology

Following Bai and Perron (1998), we consider the following equation:

$$
\begin{aligned}
y_t &= \mathbf{x}_t'\boldsymbol{\beta} + \mathbf{z}_t'\boldsymbol{\gamma}_j + u_t, && (4)\\
j &= 1, ..., m, m+1, \;\; t = T_{j-1}+1, ..., T_j,
\end{aligned}
$$

where y_t is observed dependent variable at time t, $\mathbf{x}_t$, and $\mathbf{z}_t$ are $(p \times 1)$ and $(q \times 1)$ independent vectors of covariates, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}_j$ are corresponding vector of coefficients. The equation (4) indicates that there are m unknown break points and our objective is to estimate unknown m break points $(T_1, T_2, ..., T_m)$ and coefficients $\boldsymbol{\gamma}_j$. This case is called as partial structural break test and if $\mathbf{x}_t$ are zero vector, we call a pure structural break test.

The estimation strategy is based on least-squares. For each m-partitioned $(T_1, T_2, ..., T_m)$, the associated least-square estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}_j$ are obtained by minimizing the sum of square residuals as follows:

$$S_T(T_1, ..., T_m) = \sum_{i=1}^{m+1} \sum_{t=T_{i-1}+1}^{T_{m+1}} (y_t - \mathbf{x}_t'\boldsymbol{\beta} - \mathbf{z}_t'\gamma_i)^2. \tag{5}$$

We can estimate the break points minimizing the $S_T(T_1, ..., T_m)$, namely:

$$(\widehat{T}_1, ..., \widehat{T}_m) = \arg \min_{T_1,...,T_m} S_T(T_1, ..., T_m). \tag{6}$$

Then, we apply this methodology to equation (1) in order to detect how many breaks are. Bai and perron(1998) propose a test that the null hypothesis of l breaks against the alternative $(l+1)$ breaks. The test is applied to each segment containing the observations $(\widehat{T}_0, ..., \widehat{T}_{l+1})$. We conclude for a rejection in favor of a model with $(l+1)$ breaks if the overall minimal value of the sum of residuals is sufficiently smaller than the sum of squared residuals from the l breaks model. More specifically, the test is defined as follows:

$$\begin{aligned} F_T(l+1|l) &= \\ & \{S_T(\widehat{T}_1, ..., \widehat{T}_l) - \min_{1 \leq i \leq l+1} \inf_{\tau \in \Delta_{i,\eta}} S_T(\widehat{T}_1, ..., \widehat{T}_{i-1}, \tau, \widehat{T}_i, ..., \widehat{T}_l)\}/\widehat{\sigma}^2 \end{aligned} \tag{7}$$

where $\Delta_{i,\eta} = \{\tau; \widehat{T}_{i-1} - (\widehat{T}_i - \widehat{T}_{i-1})\tau \leq \tau \leq \widehat{T}_i - (\widehat{T}_i - \widehat{T}_{i-1})\tau\}$.

2.3 Break test results

We estimate equation (1) for the full sample of 1962 - 2015 and investigate the stability of the coefficient on the spread, α_1 by using Bai-Perron(1998)'s multiple structural break test. We set the trimming value that means a minimal length of a segment as 0.2 and the maximum break point l as 3.[1] Estimation results are shown in the Table 1.

[1] Bai and Perron(2003a) recommend to set the trimming value as 0.2 if error is serially correlated. The critiacal values for this test can be obtained from Bai and Perron(2003b)

Insert table 1

The estimation results show that the estimated coefficient on the spread is statistically significant over 1 - 8 quarters forecasting horizons confirming the results of existing literature such as Estrella and Mishkin (1998) and Hamilton and Kim (2002). The predictive ability of the yield spread, however, appears to be weak as the values of $\bar{R}^2$ are lower in most forecasting horizons than those of Hamilton and Kim (2002).

The fifth and sixth columns of the Table 1 show the estimated break date and the test statistics respectively. At each forecasting horizon, the number of breaks is estimated *one* break and the break date is the first quarter in 1984 (1984:Q1) at 1% significant level. The simple break test indicates that the predictive power of the yield spread has changed since 1984.

Based on the break test result, we divide the full sample into two sub-samples according to the estimated break date and estimate equation (1) for two subsamples. The estimation results are reported in Table 2.

Insert table 2

The estimated coefficients on the yield spread over $1-8$ quarters forecasting horizons in the pre-break sample (1962:Q1 - 1983:Q4) are all statistically significant and $\bar{R}^{2\prime}s$ are much higher than those of the full sample whereas those in the post-break sample (1984:Q1 - 2015:Q4) are statistically significant only over $6-8$ quarters forecasting horizons and $\bar{R}^{2\prime}s$ are substantially lower than the pre-break sample. For example, the highest value of $\bar{R}^2$ is above 49% in 4 quarters ahead forecasting horizon in the pre-break sample while that is 10% in 8 quarters ahead forecasting horizon in the post-break sample.

Therefore, we interpret that the predictive power of the yield spread for future real economic activity has weakened significantly since 1984. Why has the forecastability of the spread declined? Following Hamilton and Kim (2002), we investigate the reason.

3. Decomposition of the yield spread

Hamilton and Kim (2002) decompose the yield spread into the expectation component and the term premium component and derive the predictive regression as follows:

$$y_t^k = \beta_0 + \beta_1(\frac{1}{n}\sum_{j=0}^{n-1} i_{t+j}^1 - i_t^1) + \beta_2(i_t^n - \frac{1}{n}\sum_{j=0}^{n-1} i_{t+j}^1) + \varepsilon_t, \tag{8}$$

$$EP = \frac{1}{n}\sum_{j=0}^{n-1} i_{t+j}^1 - i_t^1, \tag{9}$$

$$TP = i_t^n - \frac{1}{n}\sum_{j=0}^{n-1} i_{t+j}^1, \tag{10}$$

where EP in equation (9) is the difference between short-term interest rates over the next n periods and the current short rate and is called the expectations component, and TP in equation (10) is the time-varying term premium. From equations (1) and (8), if a fall in the spread predicts U.S. recessions, it could be either be because (1) a temporarily high short-term rate suggests a coming recession, or (2) a fall in the term premium on long-term bonds relative to short-term bonds suggests an economic recession. Hamilton and Kim (2002) interpret equation (8) as the question that given that the short rate rises relative to the long rate prior to a recession, to what extent this is because future short rates are rationally expected to fall, and to what extent it is because the forecastable excess yield from holding long-term bonds has fallen.

We estimate Equation (8) using instrumental variable estimation along with constant, i_t^n and i_t^1 as instruments. The estimation results are shown in the Table 3.

Insert table 3

The estimation coefficients on the EP component ($\hat{\beta}_1$) and the TP component ($\hat{\beta}_2$) are statistically significant most of $1-8$ quarters ahead forecasting horizons in the pre-break sample whereas the estimated coefficients on the EP component are only statistically significant over $7-8$ quarters ahead forecasting horizon in the post-break sample. In particular, none of the coefficients on the TP components is not statistically significant in the post-break sample. In Hamilton and Kim (2002), the TP component was helpful for forecasting future real economic activity over $1-8$ quarters ahead.

These estimation results imply that the decrease in the predictive power of the yield spread for the future real economic activity mainly results from the significant reduction of the forecasting power of the TP component although the predictive power of EP component also appears to be weak. In other words, since 1984, the TP component has not shown cyclical movement before the business cycle as before.[2] Why did the TP component lose its predictive power since 1984? For investigating this issue, we consider the Expectations Hypothesis.

4. Revival of Expectations Hypothesis

In above section, we confirm that the term premium loses its predictive power since 1984. In terms of existing literature, we may link the cyclical movement of the term premium with the Great Moderation. Kim and Nelson(1999) and McConell and Quiros(2000) find that the US GDP was more stable since 1984 which is called as "Great Moderation". We conjecture that the significant reduction in the volatility of US GDP may result in less cyclical movement in the term premium. In line with this conjecture, Rudebusch and Wu(2007) argue similar claim that the stability of overall macroeconomics conditions affect the term premium. Bulkley et al.(2011) argue that the development of financial system reduce the arbitrage opportunity

[2] Rudebusch and Wu (2007) and Dewatcher et al. (2014) show the similar results in the macro-finance model framework. In contrast, Favero et al. (2005) still emphasize the role of the term premium to predict future economic growth.

and thus the variability of the term premium. Although it is not clear why the variability of the term premium has been weak since 1984, we infer that the decrease in the variability of the term premium may have contributed to the reduction in the predictive power of the term premium for future economic activity.

In order to investigate the reduction of the variability of the term premium, we consider the Expectations Hypothesis(hereafter EH). If the EH holds, the term premium is not time-varying and constant. In other words, as the term premium is more stable, it is more plausible for the EH to hold. More specifically, the EH implies the following relation:

$$i_t^n = \frac{1}{n} E_t \sum_{j=0}^{n-1} i_{t+j}^1 + \theta, \tag{11}$$

where θ is the term premium (TP) and a constant under the EH. If θ is a cyclical time-varying component, the EH does not hold and such time-varying term premium helps the spread forecast real economic activity. Conversely, if θ is constant, the EH hypothesis holds and the TP component does not contribute to the predictability of the spread.

In order to evidence this inference, we consider the EH test of Campbell and Shiller (1991) and Bekaert and Hodrick (2001) as in the following $p-th$ order VAR framework:

$$(\mathbf{I} - \Theta(L))\mathbf{y}_t = \boldsymbol{\epsilon}_t, \tag{12}$$

where $\mathbf{I}$ is the $k \times k$ identity matrix, $\Theta(L)$ is a lag polynomial, and the $\boldsymbol{\epsilon}_t$ is a vector of error terms. This $p-th$ order VAR can be written in companion form as follows:

$$\mathbf{Z}_t = \mathbf{A}\mathbf{Z}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{13}$$

where $\mathbf{Z}_t = [\mathbf{y}_t', \mathbf{y}_{t-1}', ..., \mathbf{y}_{t-p+1}']'$ and $\boldsymbol{\varepsilon}_t = (\boldsymbol{\epsilon}_t', \mathbf{0}', ..., \mathbf{0}')'$.

In Bekaert and Hodrick(2001), $y_t \equiv (i_t^1,\ i_t^n)'$ and the constraints that satisfy the EH can be written as follows:

$$\mathbf{a}_T(\theta) \equiv \mathbf{e}_2' - \frac{1}{n}\sum_{i=0}^{n-1} \mathbf{e}_2'\mathbf{A}^i = 0 \tag{14}$$

where $\mathbf{e}_i$ is a choice vector that all elements are zero except for $i - th$ element that is one. Bekaert and Hodrick(2001) derive the asymptotic distribution of LM statistics for the null hypothesis that the EH is valid. The LM statistics are asymptotically distributed as $\chi^2(\ell)$, where ℓ is the number of the constraints.

In the similar framework, Campbell and Shiller(1991) takes for $y_t \equiv (\Delta i_t^1,\ s_t^n)$, where s_t^n is the spread between i_t^n and i_t^1. Then we can calculate the expected value of the spread and the change in the short yield, $E_t(\mathbf{Z}_{t+i}) = \mathbf{A}^i\mathbf{Z}_t$. Using the EH condition, we can define the 'theoretical spread', $\widetilde{s_t^n}$, and $\widetilde{s_t^n}$ can be written as follows:

$$\widetilde{s_t^n} = \mathbf{e}_1'\mathbf{A}[\mathbf{I} - (1/n)(\mathbf{I} - \mathbf{A}^n)(\mathbf{I} - \mathbf{A})^{-1}](\mathbf{I} - \mathbf{A})^{-1}\mathbf{Z}_t. \tag{15}$$

If the EH is valid, the theoretical spread, $\widetilde{s_t^n}$, should be equal to the actual spread, s_t^n and this restriction can be tested in the VAR estimate. Since the restriction is highly polynomial in the parameter vector, Campbell and Shiller(1991) suggest the test that calculate the correlation and standard deviation ratio between the theoretical spread and the actual spread. Under the null hypothesis of the EH, these two values should be unity.

Table 4 reports these two type of EH test results for the pre-break sample (1962-1983) and the post-break sample B(1984-2015).[2]

Insert table 4

The estimates of LM statistics by Bekaert and Hodrick(2001) in the second and fifth columns show that the EH is rejected in all long-term maturities in the pre-break sample, but the test statistics in the post-break sample substantially decrease and the EH is not rejected in the

[2] All maturities yield data are quarterly zero-coupon yield from Gurkaynak et al.(2007) and we choose the VAR lag length, p, is 1 by BIC and AIC.

long-term maturities, $n = 12, 16$, and 20 at the 5% level. In terms of Campbell and Shiller (1991)'s test, the estimated ratios of the standard deviations of the theoretical spread and the actual spread are between 0.19 - 0.54 in the pre-break sample which are very far from the unity, whereas they are between 0.76 - 0.88 in the post-break sample which are not far from the unity. In the case of the correlation between two spreads, however, there seems not to be much difference between two subsamples. Overall, the estimation results indicate that the EH is rejected in most cases in the pre-break sample but the rejection of the EH significantly reduces in the post-break sample. These test results indicate that since 1984, the cyclical variation of the term premium has significantly reduced and thus the predictive power of the TP decreased substantially.

5. Concluding remarks

In this paper, we investigate the stability of the predictive power of the spread for future real economic activity by employing the rigorous structural break test and find that there is an evidence on the break in 1984. Furthermore, the predictive power of the spread was strong in the pre-break subsample whereas the predictability decreased significantly in the post-break subsample.

Following the decomposition of the spread into the EP component and the TP component as in Hamilton and Kim (2002), we find that main reason of why the predictive ability of the yield spread decreased since 1984 results from the significant reduction in the predictive power of the TP component.

In order to address whether the cyclical variation of the TP component decreased in the post-break sample, we consider the EH and we find that the EH appeared to be rejected less in the post-break sample than in the pre-break sample, implying that the cyclical variability of the term premium substantially reduced since 1984, resulting in the reduction of the contribution of the TP component to the predictive power of the yield spread. We interpret that the less variation of the term premium resulted from the significant reduction in the volatility of US GDP since 1984. We leave more rigorous investigation in this interpretation for future research.

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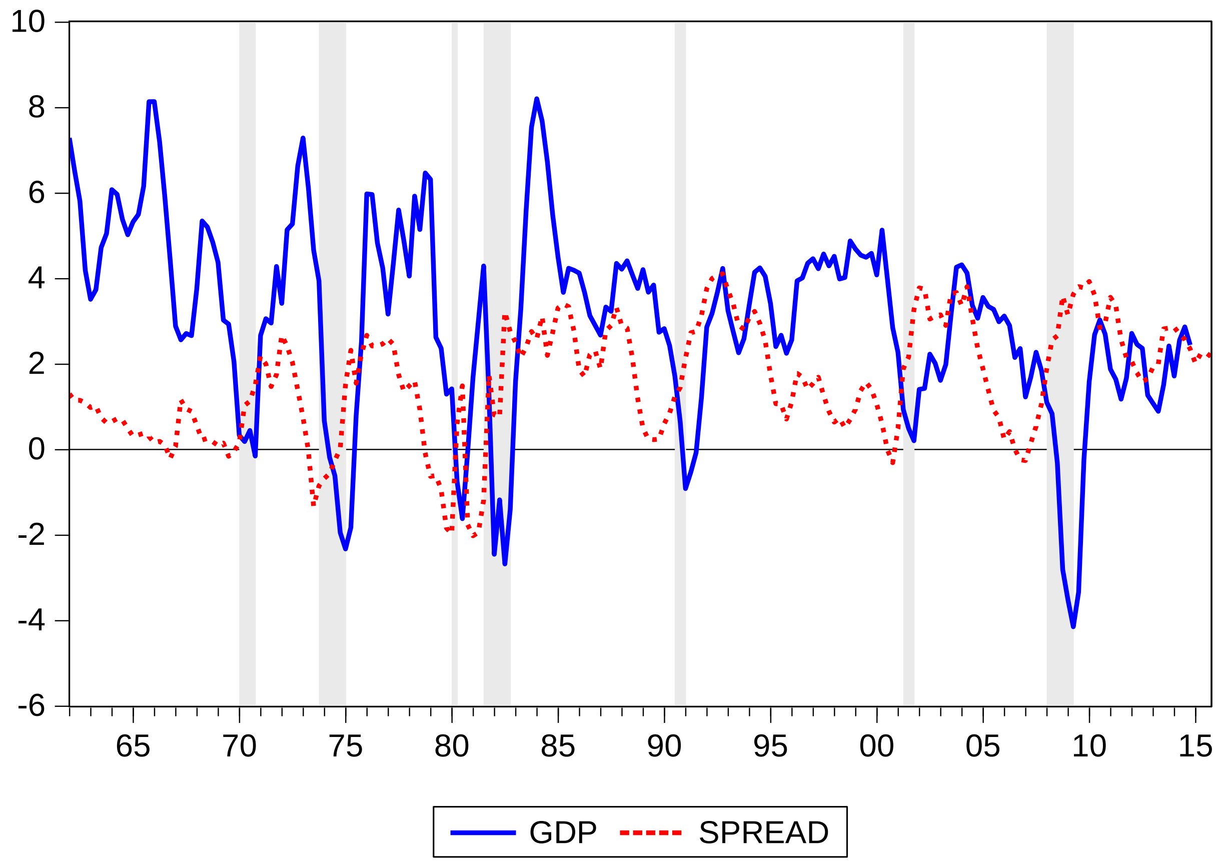
Figure 1. The growth rate of real GDP and the yield spread



Note: The solid line denotes the US GDP growth rate, the dash line denotes the yield spread between the 10-year Treasury bond rate and the 3-month Treasury bill rate and the shaded are NBER recession dates.

Table 1
The predictive power of the yield spread and the structural break test

$$y_t^k = \alpha_0 + \alpha_1 spread_t + \varepsilon_t$$

k(quarters ahead)	α_0	α_1	$\bar{R}^2$	estimated break dates	F(ℓ+1| ℓ) statistic
1	2.382*** (0.488)	0.367* (0.218)	0.018	1983:4	F(1|0) = 24.471*** F(2|1) = 4.5135
2	2.236*** (0.485)	0.461** (0.217)	0.050	1983:4	F(1|0) = 43.164*** F(2|1) = 2.577
3	2.215*** (0.465)	0.475** (0.202)	0.067	1983:4	F(1|0) = 37.307*** F(2|1) = 2.515
4	2.209*** (0.448)	0.480*** (0.189)	0.081	1983:4	F(1|0) = 39.856*** F(2|1) = 7.152
5	2.224** (0.433)	0.473*** (0.179)	0.090	1983:3	F(1|0) = 53.038*** F(2|1) = 6.956
6	2.267*** (0.415)	0.448*** (0.166)	0.091	1983:4 2004:3	F(1|0) = 29.1194*** F(2|1) = 11.899**
7	2.311*** (0.396)	0.418*** (0.154)	0.089	1983:4 2003:2	F(1|0) = 14.151*** F(2|1) = 8.534*
8	2.374*** (0.381)	0.377*** (0.145)	0.080	1983:4	F(1|0) = 12.238*** F(2|1) = 7.955
12	2.638*** (0.348)	0.201 (0.132)	0.030	-	F(1|0) = 3.215
16	2.826*** (0.287)	0.068 (0.104)	0.001	-	F(1|0) = 2.832

Note: a. In parentheses are Newey and West (1987) HAC standard errors.

b. ***, ** and * denote statistically significant at the 1%, 5%, and 10% levels respectively.

c. Row *k* is based on estimation for t = 1962:Q1 through 2015:Q4 – k.

Table 2 The predictive power of the spread pre- and post-break sample

$$y_t^k = \alpha_0 + \alpha_1 spread_t + \varepsilon_t$$

k(quarters ahead)	pre-break(1962:1983)			post-break(1984-2015)		
	α_0	α_1	$\bar{R}^2$	α_0	α_1	$\bar{R}^2$
1	2.279*** (0.568)	1.418*** (0.313)	0.165	2.439*** (0.524)	0.088 (0.209)	0
2	2.110*** (0.507)	1.639*** (0.258)	0.354	2.319*** (0.534)	0.140 (0.196)	0
3	2.142*** (0.456)	1.607*** (0.217)	0.434	2.196*** (0.557)	0.195 (0.190)	0.008
4	2.191*** (0.419)	1.557*** (0.192)	0.491	2.072*** (0.583)	0.250 (0.189)	0.022
5	2.263*** (0.396)	1.475*** (0.172)	0.509	1.970*** (0.608)	0.297 (0.194)	0.039
6	2,376*** (0.377)	1.339*** (0.156)	0.487	1.873*** (0.626)	0.342* (0.202)	0.061
7	2.484*** (0.349)	1.205*** (0.126)	0.452	1.796*** (0.638)	0.375* (0.2092)	0.083
8	2.605*** (0.328)	1.057*** (0.114)	0.398	1.747*** (0.637)	0.395* (0.213)	0.102

Note: a. In parentheses are Newey and West(1987) HAC standard errors.

b. *** and * denote statistically significant at the 1% and 10% levels respectively.

Table 3 The predictive power of the expectation component and the term premium

$$y_t^k = \beta_0 + \beta_1\left(\frac{1}{n}\sum_{j=0}^{n-1} i_{t+j}^1 + i_t^1\right) + \beta_2\left(i_t^n - \frac{1}{n}\sum_{j=0}^{n-1} i_{t+j}^1\right) + \varepsilon_t$$

(Using as Instruments a constant, i_t^{40} and i_t^1)

k(quarters ahead)	pre-break(1962-1983)				post-break(1984-2015)			
	β_0	β_1	β_2	$\bar{R}^2$	β_0	β_1	β_2	$\bar{R}^2$
1	2.421*** (0.632)	1.335*** (0.440)	0.742 (0.582)	0.167	2.478** (0.132)	0.212 (0.219)	0.310 (0.344)	0
2	2.242*** (0.553)	1.563*** (0.382)	1.013* (0.523)	0.349	2.611** (1.073)	0.250 (0.227)	0.262 (0.330)	0.010
3	2.258*** (0.502)	1.540*** (0.340)	1.054** (0.481)	0.409	2.693** (1.033)	0.272 (0.231)	0.240 (0.322)	0.036
4	2.297*** (0.464)	1.496*** (0.302)	1.054** (0.443)	0.447	2.730** (1.048)	0.295 (0.224)	0.228 (0.326)	0.070
5	2.359*** (0.437)	1.419*** (0.271)	1.018*** (0.412)	0.446	2.519*** (0.945)	0.310 (0.215)	0.299 (0.293)	0.071
6	2.460*** (0.414)	1.290*** (0.243)	0.940** (0.387)	0.404	2.472*** (0.893)	0.321 (0.201)	0.315 (0.275)	0.089
7	2.555*** (0.382)	1.164*** (0.204)	0.869** (0.353)	0.356	2.480*** (0.835)	0.325* (0.189)	0.309 (0.189)	0.109
8	2.666*** (0.358)	1.021*** (0.183)	0.765** (0.328)	0.291	2.417*** (0.784)	0.324* (0.177)	0.322 (0.237)	0.115

Note : a. In parentheses are Newey and West(1987) HAC standard errors.

b. ***, ** and * denote statistically significant at the 1%, 5%, and 10% levels respectively

Table 4 The expectation hypothesis test

	subsample A(1962-1983)			subsample B(1984-2015)		
n	LM statistics	std_ratio	corr.	LM statistics	std_ratio	corr.
4	64.4482 (0)	0.1937 (0.0023)	-0.2661 (0.0723)	13.9486 (0.001)	0.8403 (0.0606)	0.4991 (0.088)
8	67.0607 (0)	0.2268 (0.0214)	0.7209 (0.0573)	7.1260 (0.0284)	0.8750 (0.0790)	0.6908 (0.0572)
12	38.3222 (0)	0.3650 (0.0440)	0.9307 (0.0178)	5.9096 (0.0521)	0.8393 (0.0738)	0.8102 (0.0366)
16	32.5228 (0)	0.4694 (0.0597)	0.9680 (0.0084)	5.8578 (0.0535)	0.8091 (0.0782)	0.8793 (0.0242)
20	33.7817 (0)	0.5378 (0.0705)	0.9795 (0.0056)	5.9270 (0.0518)	0.7905 (0.0831)	0.9192 (0.0171)
40	20.769 (0)	0.5217 (0.0528)	0.9814 (0.0039)	6.4122 (0.0405)	0.7674 (0.0987)	0.9803 (0.0049)

Note: a. In parentheses that below LM statistics are P-value.

b. Figures in parentheses of std_ratio and correlation are estimated standard errors.