

TERM PREMIUM DETERMINANTS, RETURN ENHANCEMENT AND INTEREST RATE PREDICTABILITY

RICHARD DEAVES*

INTRODUCTION

Theories of the term structure have been subjected to a plethora of empirical studies. The evidence is now quite strong that the data reject the expectations hypothesis, or, synonymously, that term premia embodied in the yield curve are time-invariant. Much research has been devoted to what variables have an impact on these term premia. Despite much controversy and some contradictory empirical work, several tendencies seem to emerge. It is apparent that premia are positively related to the long-short spread, where the spread can either be viewed in terms of a long-term interest rate versus the short rate (e.g. Shiller, 1979) or a distant forward rate of interest versus the short rate (e.g. Fama, 1984; and Fama and Bliss, 1987). Evidence also exists that the current level of interest rates (e.g. Kessel, 1965; and Friedman, 1979);¹ and interest rate volatility (e.g. Shiller, Campbell and Schoenholtz, 1983; Jones and Roley, 1983; and Engle, Lilien, and Robins, 1987) are positively correlated with term premia.

This paper's purpose is a pragmatic one. Using this empirical literature as a point of departure, I consider whether an ability to estimate term premia opens up scope for return enhancement and interest rate forecastability, potentialities that no financial market participant or observer of the macroeconomy can view with indifference. For this purpose, quarterly sampled three-month and six-month US *T*-bill rates are utilized for a 1959–93 sample.² In this case, the two principal definitions of term premia — the gap between a forward rate and a corresponding expected future spot rate, and, second, an anticipated holding period return net of the short rate of interest — coalesce.³

One potential use of the ability to identify term premia is return enhancement. A well-known fixed income strategy is known as riding the yield curve. This is the act of purchasing fixed income securities with the intention of selling them prior to their maturity dates, as opposed to buying and holding

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Address for correspondence: Richard Deaves, Michael G. DeGroote School of Business, McMaster University, Hamilton, Ontario, Canada, L8S 4M4.
e-mail: deavesr@mcmaster.ca

shorter-dated instruments. Since the expected incremental return on this ride strategy versus staying with shorter instruments is equivalent to the term premium, given the fact that the average ex post term premium (from three to six months) is in the neighborhood of 50 basis points, it is not surprising that riding the yield curve is effective at the short end of the maturity spectrum (Dyl and Joehnk, 1981; and Grieves and Marcus, 1992).⁴ They argue that filters based on the magnitude of the (local) slope of the yield curve provide somewhat stronger results. Since such filters do not take into account time-variation of premia, I explore whether there is some scope for additional return enhancement by utilizing the predictable component of premia.

Recent studies abound on the relative efficacy of other interest rate forecasting methodologies using US data (see Fama, 1984; Hegde and McDonald, 1986; Belongia, 1987; Fama and Bliss, 1987; Hardouvelis, 1988; MacDonald and Hein, 1989; Hafer and Hein, 1989; Fama, 1990; Hafer, Hein and MacDonald, 1992; Bradley and Lumpkin, 1992; Hall, Anderson and Granger, 1992; and McNees, 1992). Such studies typically evaluate various time series models, approaches based on (implicit or explicit) market prices (i.e. forwards and futures), and survey responses. It is difficult to compare these studies since they use different methodologies and sample periods. Nevertheless, for the most part, it is fair to say that the various approaches are usually unable to surpass that most obvious of benchmarks, the naive no-change prediction. Unless term premia alone account for the slope of the yield curve and no other variables matter, knowledge of the term premium may also provide information on the direction of future interest rate movements. I test here a simple interest rate forecasting model, based on the direct extraction of estimated time-varying term premia from forward rates — a methodology which is to my knowledge a novel one. Comparison is made to previous methodologies, as well as to the naive no-change prediction.

In the next section, after some brief theoretical background, an attempt is made to explain the variability of the term premium spanning the three-month and six-month *T*-bill rates. In preview, the term premium identification equations estimated here are largely but not entirely consistent with previous work. The third section investigates whether return enhancement incremental to naively riding the yield curve is possible. The fourth section then examines the ability of a term premium estimation methodology to forecast changes in short-term interest rates. The final section concludes.

TERM PREMIUM DETERMINANTS

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TERM PREMIUM DETERMINANTS

Holding period returns for pure discount instruments over horizons less than maturity can be written, using continuously compounded interest rates, as:

$$h_{t+j,j,k} = \frac{k}{j} r_{t,k} - \frac{k-j}{j} r_{t+j,k-j} \tag{1}$$

where $h_{t+j,j,k}$ is the j -period holding period return from t to $t+j$ based on buying a k -period bond ($k > j$), and $r_{t,i}$ is the i -period spot rate observed at t .⁵ Noting that the i -period forward rate observed at t for j periods ahead can be decomposed into the market's expectation of the future spot rate and the corresponding term premium ($P_{t,i,j}$), one can straightforwardly express a long rate in terms of single-period expected yields and premia:

$$r_{t,i} = (1/i)[r_{t,1} + E_t r_{t+1,1} + \dots + E_t r_{t+i-1,1}] + (1/i)[P_{t,1,1} + \dots + P_{t,1,i-1}]. \tag{2}$$

Substituting (2) into (1), rearranging, and taking expectations, it is apparent that an anticipated j -period holding period return can be expressed as the j -period spot rate plus some terms involving term premia:

$$E_t h_{t+j,j,k} = r_{t,j} + \frac{1}{j} \left[\sum_{z=j}^{k-1} P_{t,1,z} - \sum_{m=1}^{k-j-1} P_{t,1,m} - \sum_{m=1}^{k-j-1} E_t \nabla^j P_{t+j,1,m} \right] \tag{3}$$

where $\nabla^j x_{t+j} = x_{t+j} - x_t$. This expression indicates that the ability to identify term premia inherent in the current term structure of interest rates, along with the ability to predict future changes in term premia, allows one to predict holding period returns. Thus return predictability can either be viewed in terms of interest rate predictability (the ex ante version of equation (1)) or (ex post) term premium predictability (equation (3)).

Of course, using (1) and (3), it is clear that the ability to estimate term premia (present and future) also allows one to extract expected future interest rates:

$$E_t r_{t+j,k-j} = f_{t,k-j} - \frac{1}{k-j} \left[\sum_{z=j}^{k-1} P_{t,1,z} - \sum_{m=1}^{k-j-1} P_{t,1,m} - \sum_{m=1}^{k-j-1} E_t \nabla^j P_{t+j,1,m} \right]. \tag{4}$$

Theories of the term structure have something to say about the nature of term premia. On the traditional side, the liquidity premium theory of Hicks (1946) argues that premia should, given the established empirical regularity that long-term instruments are more price-volatile than short-term, be positive and increase in magnitude with their dating. The preferred habitat hypothesis of Modigliani and Sutch (1966) allows for a non-monotonic path of term premia due to the fact that premia are a function of unobservable maturity preferences, which need not themselves be monotonic.⁶ In fact, negative ones are a possibility, as Fama and Bliss (1987) argue and illustrate empirically. More modern term structure theory is less ad hoc in that it takes an arbitrage-free or equilibrium perspective (e.g. Cox, Ingersoll and Ross, 1985; Ho and Lee, 1986; Longstaff and Schwartz, 1992; and Heath, Jarrow and Morton, 1992). If one assumes that a small number of state variables following continuous diffusion processes are sufficient to determine fixed

income security values, then one can impose restrictions on term premia. For example, in Longstaff and Schwartz (1992), both the short-term interest rate and volatility are determinants of premia (in the sense of expected returns net of the short rate).⁷ The present paper, however, takes a more practical bent, and focuses on empirical regularities without considering their consistency to specific pricing models.⁸

As mentioned earlier, the prime empirical regularities seem to be a positive correlation between premia and the long-short spread, the current overall level of interest rates and interest rate volatility. To first focus on the spread, it is straightforward to show that, by construction, the spread between a forward rate and a non-overlapping spot rate of the same length can be decomposed into a holding period return net of the short rate, and a change in the interest rate. This suggests the following regression approach for predicting excess returns and ex post term premia (Fama and Bliss, 1987):

$$\begin{aligned} j(h_{t+j,j+k} - r_{t,j}) &= a + b(k-j)(f_{t,k-j} - r_{t,k-j}) + e_{t+j} \\ (k-j)(r_{t+j,k-j} - r_{t,k-j}) &= -a + (1-b)(k-j)(f_{t,k-j} - r_{t,k-j}) + u_{t+j}. \end{aligned} \quad (5)$$

Thus, barring the issue of statistical significance, the slope of the term structure must be useful for predicting one or the other (if not both).

Other variables potentially having an impact on premia and interest rate movements can easily be incorporated into equation (5):

$$\begin{aligned} j(r_{t+j,j+k} - r_{t,j}) &= a + b(k-j)(f_{t,k-j} - r_{t,k-j}) + \sum_{i=1}^n c_i X_{t,i} + e_{t+j} \\ j(r_{t+j,k-j} - r_{t,k-j}) &= -a + (1-b)(k-j)(f_{t,k-j} - r_{t,k-j}) - \sum_{i=1}^n c_i X_{t,i} + u_{t+j}. \end{aligned} \quad (6)$$

Note that if one inserts additional right hand side variables into this pair of regressions, then it must be the case that the sum of their coefficients is zero. This implies that, if a variable is useful in predicting interest rate changes, it must *also* be useful in identifying term premium variability.

Recalling that instruments with three-month and six-month maturities are being investigated, the (rearranged) ex post versions of equations (3) and (4), and equation (6), can be simplified to:

$$h_{t+1,1,2} - r_{t,1} = P_{t,1,1} + e_{t+1}, \quad (3a)$$

$$r_{t+1,1} - r_{t,1} = f_{t,1,1} - P_{t,1,1} - r_{t,1} + u_{t+1}, \quad (4a)$$

$$h_{t+1,1,2} - r_{t,1} = a + b[f_{t,1,1} - r_{t,1}] + \sum_{i=1}^n c_i X_{t,i} + e_{t+1}, \quad (5a)$$

$$r_{t+1,1} - r_{t,1} = -a + (1-b)[f_{t,1,1} - r_{t,1}] - \sum_{i=1}^n c_i X_{t,i} + u_{t+1}. \quad (6a)$$

Table 1a provides results from OLS regressions of ex post term premia on likely determinants for a sample of quarterly observations for 1959–1993.

Table 1

Term Premium Estimations
1a: OLS Term Premium Regressions

$$hr_{t+1,1,2} - r_{t,1} = a + b[f_{t,1,1} - r_{t,1}] + c_1 r_{t,1} + c_2 VOL_t + e_{t+1}$$

Eqn.	a	b	c ₁	c ₂	R ²	White p-value	ARCH p-value	DW
(1)	-0.00076 0.51633	1.13841 3.71846	-	-	0.19	0.03	0.00	2.40
(2)	0.00002 0.00384	-	0.08495 1.09296	-	0.04	0.00	0.00	2.09
(3)	0.00216 0.77617	-	-	0.21286 0.87696	0.02	0.00	0.00	2.18
(4)	-0.00594 1.36054	1.13518 3.84821	0.08362 1.28438	-	0.23	0.00	0.00	2.30
(5)	-0.00564 1.29823	1.14572 3.91727	0.10975 1.48900	-0.13453 0.73632	0.23	0.00	0.00	2.26

Notes:

Heteroscedasticity-consistent *t*-statistics are provided below coefficient estimates; White *p*-value is probability value of White test-statistic for heteroscedasticity related to values of regressors or interactions between them; ARCH *p*-value is probability value of LM test statistic for first order autoregressive heteroscedasticity distributed as $\chi^2(1)$.

1b: ARCH Model Estimations

$$hr_{t+1,1,2} - r_{t,1} = b_0 + b_1[f_{t,1,1} - r_{t,1}] + b_2 r_{t,1} + b_3 \log(\sigma_{t+1}^2) + e_{t+1}$$

$$\sigma_{t+1}^2 = a_0 + a_1 \sum_{i=1}^3 w_i e_{t+1-i}^2 + a_2 r_{t,1} + a_3 [f_{t,1,1} - r_{t,1}], w_1 = \frac{1}{2}, w_2 = \frac{1}{3}, w_3 = \frac{1}{6}$$

Eqn. No.	b ₀	b ₁	b ₂	b ₃	a ₀	a ₁	a ₂	a ₃	L
(1)	0.003 7.120	-	-	-	0.000 2.359	1.451 7.015	-	-	575.1
(2)	0.000 0.115	0.998 7.137	-	-	0.000 3.973	1.093 5.514	-	-	599.1
(3)	-0.004 2.022	0.901 7.257	0.086 3.922	-	0.000 4.088	1.004 4.295	-	-	608.2
(4)	0.012 1.082	0.861 7.545	0.054 1.909	0.001 1.449	0.000 2.982	1.054 4.037	-	-	609.7
(5)	-0.002 2.319	0.589 5.299	0.083 4.399	-	-0.000 3.423	0.597 3.393	0.001 4.128	-	622.5
(6)	-0.001 3.602	0.682 6.378	0.072 3.686	0.000 1.248	-0.000 3.976	0.580 3.746	0.001 3.969	-	624.0
(7)	-0.003 1.579	0.534 6.141	0.071 3.263	-	-0.000 6.027	0.599 4.289	0.001 6.522	0.000 1.117	623.5

Notes:

Asymptotic *t*-statistics are presented below coefficient estimates; *L* = log of likelihood function.

The variables considered are the forward-spot spread, the current three-month *T*-bill rate, and interest rate volatility as proxied by a (past) 20-month moving window of the standard deviation of the three-month *T*-bill rate.⁹

The salient result is the importance of the slope for identifying premia. When the slope is the only explanatory variable, it cannot be rejected that the difference between the forward rate and the spot rate is *entirely* the market's best guess for the term premium.¹⁰ As for the other two possible term premium determinants, in the simple regressions both the level and volatility coefficients have the anticipated sign, but are statistically insignificant. The fourth and fifth multiple regressions only reinforce these observations.

Several tests for heteroscedasticity are conducted. The White (1980) test is for heteroscedasticity related to the regressors or interactions between them;¹¹ in addition, a test for first order autoregressive conditional heteroscedasticity (ARCH) is conducted.¹² On the basis of the *p*-values displayed in the table, one is able to safely reject homoscedasticity in all cases. Because of this evidence, the *t*-statistics presented above are based on White's standard errors that are consistent in the presence of heteroscedasticity.¹³

Given the above results, it was decided to conduct further empirical investigation using the ARCH methodology of Engle (1982) and the related ARCH-M methodology of Engle, Lilien, and Robins (1987). The reason for the choice was the clear evidence of an ARCH effect; other potential determinants of holding period return variance can easily be incorporated. The general ARCH-M model — adapted to the present purpose — is as follows:

$$h_{t+1,1,2} - r_{t,1} = b_0 + b_1[f_{t,1,1} - r_{t,1}] + b_2r_{t,1} + b_3f(\sigma_{t+1}^2) + e_{t+1}$$

$$\sigma_{t+1}^2 = a_0 + a_1 \sum_{i=1}^n w_i e_{t+1-i}^2 + a_2r_{t,1} + a_3[f_{t,1,1} - r_{t,1}] \quad (7)$$

where $f(\sigma_{t+1}^2)$ is some function of the variance.

The three variables investigated previously are included as possible determinants of term premia, as well as possible factors influencing variance. Table 1b provides the key model runs. First, it was necessary to arrive at the appropriate ARCH order. On the basis of LR tests,¹⁴ a third order ARCH effect was apparent; since the unrestricted estimation indicated declining weights, for parametric parsimony it was decided to use a third order linearly declining weighted average of past squared residuals. Equation (1) shows the result. Equations (2) to (4) reveal the impact of including potential term premium determinants sequentially from most important to least important according to OLS. Reasonable inferences are that the slope continues to occupy center stage, and the inclusion of volatility as an explanatory variable in the term premium equation is not accepted by the data. There is no theoretically correct functional form for the variance: several were experimented with, but the estimations presented are based on the log of the

variance.¹⁵ Note that the inability to accept volatility as a factor is in marked contrast to Engle, Lilien and Robins (1987) who find, for a 1960-84 sample period, that volatility was the predominant (in terms of statistical significance) determinant of premia, with the slope only playing a secondary role.¹⁶

In going from (3) to (5), I have allowed for the level of interest rates as a determinant of volatility, as is consistent with the highly significant White test statistic in equation (2) of Table 1a. Clearly, the results are strongly in favor of the importance of this factor. Note that a reintroduction of the ARCH-M factor (going from (5) to (6)) is safely rejected; as is the use of the slope as a determinant of volatility (from (5) to (7)). Thus ARCH model (5) is the preferred term premium model, and I designate it the TPI (term premium identification) model. In the next two sections, this TPI model will be used first as a mechanism for deciding when to ride the yield curve and second as an interest rate prediction strategy.

IS RETURN ENHANCEMENT POSSIBLE?

Could return enhancement have been accomplished by utilizing the knowledge on term premium determinants acquired above? To investigate, the procedure is to estimate the TPI model first using data up to the end of 1963. Based on the estimated coefficients, term premia are estimated for the next period (for the first quarter of 1964). The decision to ride the yield curve is made when the predicted holding period return net of the three-month *T*-bill rate (or, synonymously, the estimated term premium) is above a critical level. Several progressively more stringent filters are used in each case. Every period re-estimation is done so that all publicly available information is utilized.¹⁷

Table 2 provides the relevant information. In the top panel of the table a few useful benchmarks are provided. Always riding the yield curve boosted return by about 53 basis points over the three-month bill buy and hold — at the cost of increased risk or standard deviation. Another obvious benchmark is to ride the yield curve when its slope (here using the forward-short spread) is above some critical value. Filters up to 100 basis points are used. Selective riding can be viewed in two ways: investing long when riding is called for but otherwise investing short (a 'ride-short mix'); or only investing long when riding is called for (the 'just rides' case). In the former case, average returns actually decline as more stringent filters are applied. Using the just rides strategy, mean returns do increase with the filter, as do incremental mean returns (mean returns net of the short rate), albeit at a slower rate. Once again the cost is an increase in risk.

The TPI model, shown in the lower panel, leads to qualitatively similar results. That is, mean holding period returns do not increase with filter for

Table 2

Holding Period Returns (in Percent) for Different Strategies and Filters

<i>Benchmark Strategies</i>							
<i>Strategy</i>	<i>Mean Return</i>		<i>SD</i>		<i>No.</i>		
3-month T-bills	6.763		2.740		120		
Always ride	7.294		3.317		120		
<i>Ride When Slope is Above a Critical Level</i>							
<i>Filter</i>	<i>Ride-short Mix</i>		<i>Just Rides</i>		<i>Incr. Mean</i>	<i>No. of Rides</i>	<i>Per. Success</i>
	<i>Mean Return</i>	<i>SD</i>	<i>Mean Return</i>	<i>SD</i>			
0 BPs	7.307	3.342	7.121	3.289	0.578*	112	0.732
25 BPs	7.129	3.121	7.071	3.192	0.522*	83	0.711
50 BPs	7.064 ^{sd}	3.095	7.854 ^{sd}	3.569	0.740*	48	0.771
75 BPs	6.979	3.086	8.577 ^{sd-1}	4.350	0.941*	27	0.815
100 BPs	6.933	3.046	9.343	4.846	1.104*	18	0.833
<i>TPI Strategy</i>							
<i>Filter</i>	<i>Ride-short Mix</i>		<i>Just Rides</i>		<i>Incr. Mean</i>	<i>No. of Rides</i>	<i>Per. Success</i>
	<i>Mean Return</i>	<i>SD</i>	<i>Mean Return</i>	<i>SD</i>			
0 BPs	7.294	3.317	7.294	3.317	0.526*	120	0.725
25 BPs	7.256	3.393	7.567	3.336	0.569*	105	0.733
50 BPs	7.210	3.474	8.214 ^{sd-1}	3.714	0.894*	58	0.741
75 BPs	7.193	3.485	10.249 ^{sd-1}	4.536	1.579*	26	0.808
100 BPs	7.095	3.497	14.188 ^{sd-1}	5.628	3.353*	8	0.875

Notes:

SD = standard deviation; No. is number of occasions when strategy is performed; BPs = basis points; TPI is term premium identification methodology as described in the text; Incr. mean is incremental mean of strategy's return over and above mean short rate for the identical set of observations; Per. success is percentage of times strategy yields higher return than the short rate; * indicates statistically different from zero at 5%; 'sd' superscript indicates stochastic dominance and 'sd-1' indicates near stochastic dominance (i.e. two distributions intersections at one point).

the ride-short mix, but do increase in the just rides case. The principal difference between the TPI method and an approach based on the slope of the yield curve is greater scope for return enhancement using the TPI method in the just rides case. Using a 75 basis point filter, the additional boost is over 60 basis points, while at a 100 basis point filter, the gap is even more substantial (though the number of observations is somewhat sparse). Thus, allowing for time-variation of premia does provide a small payoff, even after the additional transaction costs of riding are taken into account.¹⁸

Several issues need to be addressed. First, is the ride-short mix or the just rides perspective the more appropriate vantage point? If a hypothetical

investor must maintain his/her funds in the money market, then the ride-short mix is the appropriate perspective; on the other hand, if other repositories of wealth can be considered, then the just rides strategy is the better benchmark. It was seen above that, in the former case, there is no value added in selectively riding: mean holding period returns are always below the always ride strategy, but, when one calculates the average return for *only* those cases where riding is done, then ever more stringent filters provide increasingly enhanced return. It is interesting to observe what is causing this effect. Typically the decision to ride is taken when the current short rate is high, as can be seen by noting that incremental mean returns do not increase one for one with mean returns. This explains why, when the strategy of always keeping your money in the money market is employed, no scope for return enhancement is evident: when riding is not done, short rates tend to be lower than average.

Second, it is clear that selective riding (for the just rides case) not only leads to higher returns but also higher risk. Grieves and Marcus (1992) however showed that riding when the yield curve has a positive slope stochastically dominates always maintaining funds in three-month instruments for three of four 10-year subperiods examined. The existence of stochastic dominance is investigated here for the *full* sample. When the yield curve slope is used as the filter, stochastic dominance holds with a 50 basis point filter both for the ride-short mix and the just rides case. Stochastic dominance also nearly holds (i.e., the distributions intersect at a single point) for a 75 basis point filter. Using the TPI methodology, in the just rides case stochastic dominance nearly holds for 50, 75 and 100 basis point filters.

CAN SHORT-TERM CHANGES IN INTEREST RATES BE PREDICTED?

Recalling that equation (4) suggests that the ability to identify term premia implies potential to forecast interest rates, I now turn to this issue. As in the previous section, one must have benchmarks. In addition to the naive no-change approach or martingale, two time series models as well as two approaches based on the use of market prices are used.

As for the former, a VEC (VAR error correction) model is an obvious choice, given the promising results of Bradley and Lumpkin (1992) and Hall, Anderson, and Granger (1992). Unit root tests for both the three-month and six-month rates suggest that one cannot reject nonstationarity, so a model in differences is appropriate.¹⁹ The problem with using differenced data is that important information on long-run equilibrium relationships may be lost — hence the appropriateness of including an error correction term, which serves to link the levels of the three- and six-month rates. This term is the lagged residual from a regression of short rates on a constant and long rates. Estimation of the model is done by full information maximum likelihood (FIML) (Johansen, 1988).²⁰ Likelihood ratio tests of cointegration can be

applied directly in this framework. Estimation is first done before the first forecast (at 1963:4) and model re-estimation is conducted every five years (1968:4, 1973:4, ..., 1988:4).²¹

In addition to the VEC time series model, a simple first order autoregressive (or AR1) model (using undifferenced data) is used: it too is re-estimated every five years and used with the latest value of the three-month rate.

Another obvious benchmark that is used here is the forward interest rate: in effect one is assuming the validity of the unbiased expectations theory of the term structure which sets term premia identical to zero. *T*-bill futures provide another approach based on market prices.²² Somewhat promising evidence for this methodology has been claimed by Hegde and MacDonald (1986), Santoni (1987), MacDonald and Hein (1989) and Hafer, Hein and MacDonald (1992). To operationalize, quotes were taken for each nearby contract on the last trading day of the previous quarter. Since the delivery date is actually several days prior to the end of the quarter, this method is put at a slight disadvantage, although, according to the findings of Hafer, Hein and MacDonald (1992), in practice the problem seems inconsequential.

Table 3 provides evidence on forecasting performance for these six methodologies for the full 1964–1993 sample, as well as for 1964:1–1979:3, 1979:4–1982:3 and 1983:4–1993:4 subsamples.²³ The breakpoints have been chosen to correspond to major changes in US monetary regimes.²⁴ In October 1979, the Federal Reserve replaced the federal funds rate with non-borrowed reserves as its operating instrument, while signalling a move to closer M1 targeting in an effort to combat high inflation. With the battle largely successful by October 1982, the Fed replaced non-borrowed reserves with borrowed reserves as its operating instrument and simultaneously de-emphasized strict monetary targeting.²⁵

Mean errors (MEs) provide information on bias. The obvious offender is the forward rate method which assumes term premia are zero, and thus persistently overpredicts short-term rates.²⁶ Results of a more rigorous test for bias are presented in the second column of the table. Regressions of actual three-month rates on a constant and the relevant set of forecasts are run, and the *p*-values of the Wald statistic testing the null hypothesis that the constant is zero and the slope unity are presented. For the full sample, as well as for the first and third subperiods, the martingale and TPI approaches are the only two that allow for safe acceptance of the null of unbiasedness. During the second subperiod, all methodologies exhibit bias. This is perhaps not surprising, given the small number of observations and the unprecedented interest rate volatility that was experienced.

As for overall performance, a brief look at mean absolute errors (MAEs) and root mean squared errors (RMSEs) reveals that the naive no-change prediction is not surpassed by any other methodology for the full sample. It has the lowest MAE, followed closely by TPI; in addition, it has the lowest

Table 3
Forecast Performance of Various Methodologies

<i>Methodology</i>	<i>ME</i>	<i>Bias p-value</i>	<i>MAE</i>	<i>RMSE</i>
<i>Full Sample</i>				
Naive	-0.00004	0.141	0.00788	0.01247
AR	0.00126	0.011	0.00840	0.01248
VEC	-0.00003	0.051	0.00932	0.01368
TPI	0.00046	0.209	0.00795	0.01274
Forwards	-0.00526	0.000	0.00908	0.01474
<i>1964:1-1979:3</i>				
Naive	0.00108	0.136	0.00606	0.00756
AR	0.00286	0.000	0.00689	0.00813
VEC	0.00248	0.000	0.00739	0.00931
TPI	0.00048	0.378	0.00588	0.00759
Forwards	-0.00501	0.000	0.00719	0.00936
<i>1979:4-1982:3</i>				
Naive	-0.00216	0.000	0.02759	0.03281
AR	0.00083	0.000	0.02752	0.03211
VEC	-0.00114	0.000	0.02814	0.03349
TPI	0.00111	0.000	0.02852	0.03388
Forwards	-0.00718	0.000	0.02888	0.03750
Futures	0.00091	0.000	0.02920	0.03475
<i>1982:4-1993:4</i>				
Naive	-0.00105	0.580	0.00517	0.00689
AR	-0.00087	0.241	0.00541	0.00689
VEC	-0.00326	0.015	0.00700	0.00887
TPI	0.00026	0.915	0.00535	0.00680
Forwards	-0.00510	0.000	0.00644	0.00905
Futures	-0.00168	0.220	0.00539	0.00746

Notes:

AR is first order autoregressive prediction methodology; VEC is vector autoregressive error correction methodology as described in text; TPI is term premium identification methodology described in text; ME = mean error; MAE = mean absolute error; RMSE = root mean squared error; Bias *p*-value is probability value of Wald test statistic from regression of actuals on forecasts where null is that intercept is zero and slope is one.

RMSE, followed closely by AR1 and TPI. The VEC model (rather unexpectedly) and forwards (not unexpectedly) fall well behind.

During the 1964:1-1979:3 subperiod, the TPI methodology performs about as well as the martingale — surpassing it in MAE but falling short in RMSE. It is fair to say that the two time series models and the use of forwards are not in

