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Econometrics of yield spreads in the money market: a note

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The literature on bond markets and interest rates has focused largely on the term structure of interest rates, specifically, on the so-called expectations hypothesis. At the same time, little is known about the nature of the spread of the interest rates in the money market beyond the fact that such spreads are generally unstable. However, with the evolution of complex financial instruments, it has become imperative to identify the time series process that can help one accurately forecast such spreads into the future. This article explores the nature of the time series process underlying the spread between three-month and one-year US rates, and concludes that the movements in this spread over time is best captured by a GARCH(1,1) process. It also suggests the use of a relatively long term measure of interest rate volatility as an explanatory variable. This exercise has gained added importance in view of the revelation that GARCH based estimates of option prices consistently outperform the corresponding estimates based on the stylized Black–Scholes algorithm.

I. INTRODUCTION

The most debated explanation for the stylized upward sloping term structure of interest rates lies in the so-called expectations hypothesis. The 'pure' version of this hypothesis suggests that the slope and the shape of the term structure depend on the market participants' expectations about the forward rates. More specifically, according to the pure expectations hypothesis, an upward sloping yield curve implies that the market expects the short term interest rates to increase in the future. However, this implication of the pure version has been questioned by several economists (Fabozzi, 1996).[1]

Critics of the expectations hypothesis argue that by assuming that the forward rates are perfect predictors of future short term rates, the hypothesis ignores the price and reinvestment risks that are associated with future bond prices (for example, see Cox *et al.*, 1981). In the absence of such risks, an investor who wants to hold a security for a five-year period, say, has options other than holding a five-year bond. For example, she can hold a two-year bond face value of which they can reinvest in a six-year bond after two years, or hold a 10-year bond of the same credit quality. In case of the first alternative, they can sell the six-year bond after three years, and, in case of the second, she can sell the 10-year bond after five years. But, in reality, this is often not the case, implying that there are some risks associated with the future prices of the bonds, such that the two alternatives may not offer the same return, with certainty, as the option where the investor buys and holds a five-year bond.[2]

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[1] Indeed, the expectations hypothesis is one of the most tested hypothesis of finance theory. For details, see Bekaert *et al*. (1996).

[2] For example, using US data, Campbell and Shiller (1991) found that the expectations hypothesis cannot accurately predict the direction of movement of long term rates, but is fairly good at predicting the direction of movement of the future short term rates. Note that this finding is in harmony with the argument that in order to predict long term rates, the forward rates should reflect *both* the future short-term rates and the risk premia. If the risk premia are not taken into account, the predictions about the long-term rates will have a downward bias.

Given the uncertainty regarding future bond prices, it would be reasonable to assume that, in reality, the forward rates reflect not only the expectations about the future short-term rates but also the risk premia associated with uncertainty about the prices of long-term bonds. This variation of the expectations hypothesis, known as the liquidity theory of term structure of interest rates, implies that a yield curve can be upward sloping irrespective of whether the short-term rates are expected to rise in the future. Indeed, even if short-term rates are expected to decline in the future, the yield curve can be upward sloping if the risk premia more than compensate for the drop in the expected future rates (Sharpe *et al.*, 1998). In other words, since the n-period spot rate is generated using the $(n-1)$ period spot rate and the corresponding forward rate, the former spot rate too should reflect expectations about future short-term rates, and the aforementioned risk premium. Hence, the difference between the n-period spot rate and the $(n-1)$ period spot rate should reflect the expected difference between the present short term rate and the future short term rate, and the associated risk premium. Unfortunately, it is has thus far proved difficult to move beyond this basic understanding of the nature of the spread, and relationships between spot rates at the short end of the term structure has proved to be very unstable (Fama and Bliss, 1987).

However, given the rising sophistication of the financial derivatives and other financial instruments, spreads at the short end of the yield curve have assumed significant importance. For example, it is not uncommon for hedge funds to speculate on the spreads between any two interest rates. While the usual vehicle of such speculation is the spread between interest rates of two different countries having similar maturities, the nature of the speculation highlights the importance of accurate forecasts about various kinds of spreads into the future. Further, recent research indicates that GARCH based estimation of option prices for financial variables consistently outperform the stylized Black–Scholes algorithm based estimation of such prices (Heston and Nandi, 1997). This has serious implications for financial structures involving knock out options on interest rate spreads. In other words, there is a need to identify the time series processes that underlie the movement of the interest rates in the short end of the term structure, namely, the money market. However, the empirical literature on interest rates has largely ignored this issue, and this paper contributes towards filling this void.

This article identifies the process underlying the spread between spot rates of USA government securities with residual lives of three months and one year.[3] This spread has been modelled as being determined by interest rate volatility prevailing in the market. It was found that this movement follows a highly autoregressive process, and that, after being corrected for conditional heteroscedasticity, more than 97% of the variation in the spread can be explained by its previous value and the proxies for interest rate risk. Specifically, it suggests that a GARCH(1,1) process that takes into account interest rate volatility over a relatively long time period best explains the movements of the spread over time. The structure of the article is as follows: the next section describes the nature of the data and the research methodology used. The following section highlights the results and their implications. In the final section, the concluding views are presented.

II. DATA AND SPECIFICATION

The data set was downloaded from the web site of the Federal Reserve Bank of New York. It provides information on the daily yields on, among others, government securities with three-month and one-year maturity. The data set spans 30 years (1962–1992), and consists of 9871 observations. The data set covers three different eras in the macroeconomic history of the USA. The first third of the data, which covers most of the 1960s and the first half of the 1970s, was marked by macroeconomic stability characterized by a low inflation rate and relatively high levels of economic growth. The second third of the data spans much of the 1970s and the early 1980s. This was a period of significant macroeconomic instability in the USA marked by high inflation rates and periods of economic slowdown. The final third of the data, spanning much of the 1980s and the early 1990s was once again a period of relative prosperity and macroeconomic stability, albeit with systemic shocks like the one caused by the savings and loans crisis.

The differences in the macroeconomic regimes are amply reflected in the data set. The mean and the standard deviations of the spread for the first third of the data set are 0.43 and 0.28 respectively, while the values of these statistical moments for the second third are 0.81 and 0.60 respectively.[4] Presumably, higher inflation rate and the consequent (additional) uncertainty about the future nominal interest rates contributed to a higher average value of the spread and greater interest rate volatility during the more unstable of the two macroeconomic eras.[5] As relative

[3] Two short horizon securities were deliberately chosen for the econometric exercise, to avoid the problems associated with modelling the long horizon movements of short-term nominal rates. As shown by Kozicki and Tinsley (1997), forecasts from such models are highly sensitive to endpoint specifications.

[4] Throughout this paper, 'the spread' refers to the spread/difference between yields on the three-month and one-year securities.

[5] Note that the volatility of the spread can increase only if the volatility of the three-month yield, or the volatility of the one-year yield, or both increases. In other words, the volatility of the spread is a reasonably good proxy for interest rate volatility in general.

stability returned to the US economy after 1982, the interest rate volatility fell by about 50% and the standard deviation of the spread for the final third of the data recorded a value of 0.40. However, possibly in keeping with the tight-money policy of the Federal Reserve Board during the Volcker years, the average value of the spread, at 0.71, remained higher than that during the 1960s and early 1970s.[6] To summarize, therefore, the three macroeconomic regimes seem to have sufficiently different impacts on the spread, and hence it is imperative to identify specifications and models that fit each of these three regimes well.

Let us now turn to the problem of identifying the initial specification that can form the starting point of the subsequent econometric exercise. To recapitulate, it is proposed that the movements of the spread should, in principle, be significantly explained by the interest rate risk prevailing in the market. It is also argued that, to the extent volatility is an adequate measure of risk, the volatility of the spread is a reasonably good proxy for the volatility of interest rates in the money market. The basic model specification can, therefore, be the linear regression model:

$$SPRD = \mu_0 + \mu_1 STDDEV + u \tag{1}$$

where *SPRD* and *STDDEV* denote the spread and its standard deviation at any point of time, μ_0, μ_1 and ε being the regression parameters and the equation disturbance term, respectively.

Given the nature of the specification, we have had to identify the number of past values of the spread that the investors take into account when they estimate the aforementioned variance/volatility. There is no theoretical basis for choosing a unique number of trading days that can constitute the appropriate number of observations for the implicit distributions of the spread. Hence, the choice of the number of periods would have to be ad hoc, and that gives rise to the possibility of the estimates being sensitive to this choice. We, therefore, used three different spans of time – 90 days, 60 days and 30 days – for the generation of the distributions of spread. In other words, the STDDEV variable in Equation 2, for period t, are derived from the distribution of the spread over the period $(t-j, t-1)$ when j equals either 90, or 60 or 30.[7] The models with which we begin our estimation process, therefore, are given by:

$$\begin{aligned} SPRD &= \mu_0 + \mu_1 STDDEV_{90} + \varepsilon_1 \\ SPRD &= \mu_0 + \mu_1 STDDEV_{60} + \varepsilon_2 \\ SPRD &= \mu_0 + \mu_1 STDDEV_{30} + \varepsilon_3 \end{aligned} \tag{2}$$

where the number in the subscript of *STDDEV* refers to the number of (past) time periods defining the distribution from which these (square root of) second moments have been worked out.

III. MODEL SELECTION

Since macro-financial time series typically have unit roots, the exercise began with testing for unit roots of the dependent and independent variables using the Phillips–Perron test for stationarity[8] (Table 1).[9] The values of the test statistic suggest that the null hypothesis of unit root was rejected for all variables and for all tests, for most at the 1% level of significance and for some at the 5% level of significance. In other words, the dependent and independent variables are stationary for all the three subsamples described in the previous section. The same conclusion was reached after estimating the corresponding values of the adjusted Dickey–Fuller statistic, not reported in the table.[10] Hence, one can estimate Equation 2 using ordinary least squares (OLS), without recourse to differencing of the variables, and tests of cointegration between the dependent and independent variables.

However, the OLS estimates suggest that STDDEV can explain less than 7% of the variation in the spread, for all subsamples, and for all n-day measures of standard deviation, when n equals 30, 60 and 90. Moreover, the values of the Durbin–Watson statistic indicate that the equation disturbance terms may be autocorrelated.

To improve the explanatory power of the regression model, let us temporarily ignore the phenomenon of autocorrelation of the equation disturbance term and look for

[6] Such a conjecture implicitly assumes that the liquidity crunch affected the yield of one-year securities more than the yield of three-month securities. While, this is plausible, there is no obvious reason as to why this would necessarily happen. However, the relative impact of monetary policy on different spot rates does not affect our analysis, and is not the focus of this paper. Hence, this relationship is not explored in the remainder of the article.

[7] Note that this is somewhat similar to taking a j-period moving average of a variable. For example, the underlying distribution of the spread for period $t+1$ is dependent on the values of the spread for the period $(t-j+1, t)$.

[8] In keeping with Schwert (1989), the number of lags used for the Phillips–Perron and the adjusted Dickey–Fuller tests were estimated using the formula $k = \text{int}\{12(T/100)^{0.25}\}$ when k is the number of lags. The number of lags used for each of the sub-samples roughly equal 27.

[9] In the table, *SP_3M1Y* refers to the spread. The $STDDEV_j$ variables highlighted in Equation 2 are given by *SD_90D*, *SD_60D* and *SD_30D* respectively.

[10] In view of the discussion in Maddala and Kim (1998), it is prudent to check for stationarity using both the augmented Dickey–Fuller and Phillips–Perron tests.

Table 1. *Phillips–Perron statistics*

Variable	Options	1st third	2nd third	3rd third
SP_3M1Y	Intercept	−3.750	−4.682	−3.130
	Intercept & trend	−5.031	−5.080	−3.908
SD_90D	Intercept	−4.709	−4.657	−5.050
	Intercept & trend	−5.823	−4.933	−5.226
SD_60D	Intercept	−5.154	−5.471	−6.040
	Intercept & trend	−6.422	−5.706	−6.280
SD_30D	Intercept	−6.924	−6.715	−8.626
	Intercept & trend	−8.275	−6.949	−9.151

additional explanatory variable(s). Thus, if it is assumed that the investors' behaviour is governed by adaptive expectations, the spread for the *i*th day should depend not only on the nature of the distribution of spread in previous days, but also on the absolute value of the spread on the $(i-1)$th day. Hence, we may modify the regression specifications as follows:

$$\begin{aligned} SPRD &= \mu_0 + \mu_1 SPRD(-1) + \mu_2 STDDEV_{90} + \varepsilon_1 \\ SPRD &= \mu_0 + \mu_1 SPRD(-1) + \mu_2 STDDEV_{60} + \varepsilon_2 \quad (3) \\ SPRD &= \mu_0 + \mu_1 SPRD(-1) + \mu_2 STDDEV_{30} + \varepsilon_3 \end{aligned}$$

The specifications (Equation 3) containing the lagged value of spread as an additional explanatory variable vastly improve the goodness of fit. Indeed this new specification explains 96–98% of the observed variations of the dependent variable. But the high values of the associated Durbin's h statistic for the first and the second samples suggest rejection of the null hypothesis of a white noise equation disturbance term for these samples (see Table 2). In other words, we have to use higher order lags of $SPRD$ as right hand side variables to eliminate the problem of autocorrelation of the disturbance terms.[11] At the same time, the movement of the spread over time indicates that we may have to correct for conditional heteroscedasticity (Figures 1–3). Therefore, we have to test for presence of conditional heteroscedasticity, and if it is present in the given data set (Greene, 1997), one would have to try a model that incorporates an ARCH or a GARCH process.

Table 2. *Ordinary least square estimates*

Variable	1st third	2nd third	3rd third
Constant	0.0046	0.0143	0.0042
	(0.010)	(0.000)	(0.062)
SP_3M1Y(-1)	0.9847	0.9833	0.9905
	(0.000)	(0.000)	(0.000)
SD_90D	0.0053	−0.0006	0.0051
	(0.048)	(0.758)	(0.081)
Adjusted R^2	0.9724	0.9666	0.9835
Durbin's h	5.6507	6.3510	−1.6084
	(0.000)	(0.000)	(0.105)
Ramsey RESET	2.2519	0.5491	1.0879
	(0.134)	(0.459)	(0.297)

Note: The numbers within parentheses are p-values of the test statistic.

The obvious next step is thus to decide on the nature of the conditional heteroscedasticity to specify. To recapitulate, an autoregressive time series y_t exhibiting conditional heteroscedasticity can be described by the following set of equations (Franses, 1998):

$$\begin{aligned} y_t | Y_{t-1} &= (h_t)^{0.5}\eta_t \\ \eta_t &\sim \mathrm{NID}(0,1) \quad (4) \\ h_t &= \alpha_0 + \alpha_1 y_{t-1}^2 \qquad \alpha_0 > 0, \alpha_1 \in (0,1) \end{aligned}$$

where Y_{t-1} is the information set containing information on y_t until time period $t-1$, and where NID means normal and identically distributed. In the above specification, since h_t depends on one period lagged value of y_t (i.e. on y_{t-1}), the y_t series is said to be ARCH of order 1. In general, for a time series variable y_t following an ARCH process of order q Equation 4 is of the form:

$$h_t = \alpha_0 + \alpha_1 y_{t-1}^2 + \ldots + \alpha_q y_{t-q}^2 \quad (5)$$

where the restrictions on the parameters are $\alpha_0 > 0$ and $\alpha_1 \in (0,1)$ If a variable obeys an ARCH(p) process where p is large, the pth order polynomial given in Equation 5 may be replaced by a rational polynomial of order (p, q),viz.:

$$h_t = \alpha_0 + \alpha_1 y_{t-1}^2 + \ldots + \alpha_q y_{t-q}^2 + \beta_1 h_{t-1} + \ldots + \beta_p h_{t-p} \quad (6)$$

The set of Equations 4–6 with the restrictions that α-s and β-s are greater than zero and $(\Sigma_{j-1}\alpha_j + \Sigma_{i-1}\beta_i)$ is less than unity defines the GARCH(p, q) process. The advantage of using a GARCH specification over a corresponding ARCH specification in a given empirical situation lies in the fact that compared to the latter the former is parametrically

[11] The resultant/final specifications are reported in Tables 5–7.

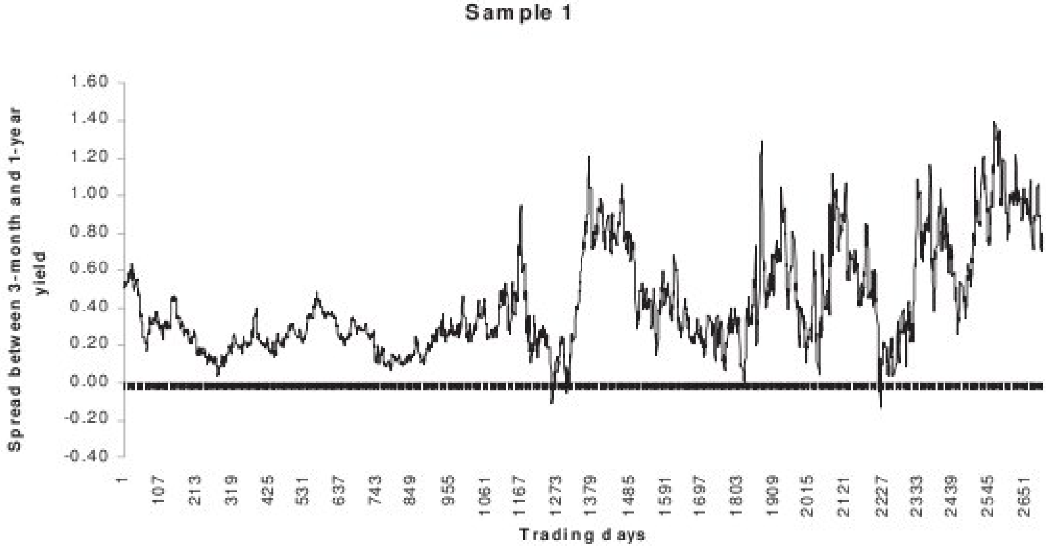

Fig. 1.

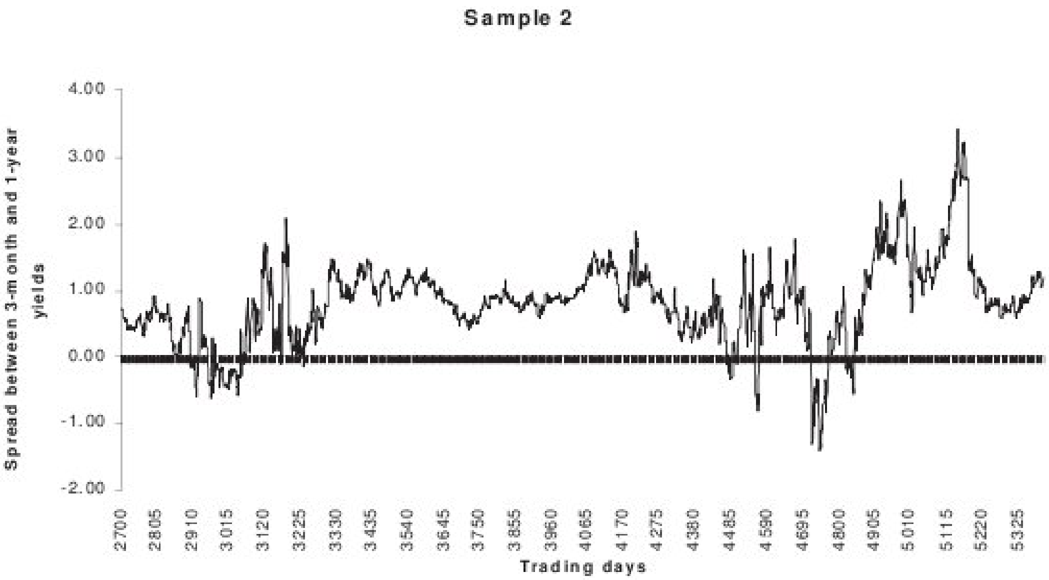

Fig. 2.

parsimonious in the sense that a high order ARCH process can be satisfactorily approximated by a GARCH process of sufficiently small order having very small values of p and q. In other words, a GARCH(1,1) process, say, may be capable of capturing the non-linearities implicit in an ARCH(n) process, when n is large.[12]

Given that one is fairly sure that the equation disturbances in Equation 3 are autoregressive, the first step in respecification should be to check for presence of conditional heteroscedasticity, i.e. whether or not a (G)ARCH specification of these equation disturbance terms would be adequate. One, therefore, estimated the model:

$$e_t^2 = \bar{\omega}_0 + \bar{\omega}_1 e_{t-1}^2 + \ldots + \bar{\omega}_q e_{t-q}^2 + \kappa_t \tag{7}$$

where e_t^2 are the squared residuals of the ARMA filtered time series *SPRD*. Under the null hypothesis of no ARCH (of order q), n times the R^2 value of the regression given by Equation 7 has an asymptotic $\chi^2(q)$ distribution. The values of the chi-squared test statistic obtained from the residuals of AR(1) filtered *SPRD* indicate the null hypothesis of no ARCH is rejected for $q = 1$ as well has for higher

[12] For a lucid description of the difference between an ARCH(1) and a GARCH(1,1) process, see Frances (1998).

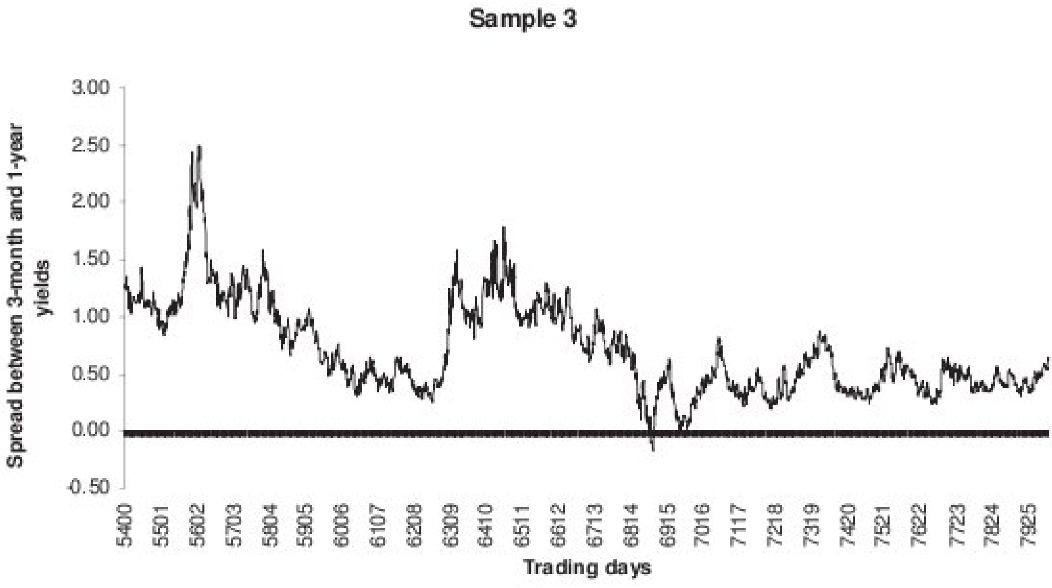

Fig. 3.

values of q (see Table 3). A similar conclusion is suggested by the F version of the test. Therefore, an ARCH(1) model was estimated next as well as GARCH(1,p) models with $p = 1$, 2, the latter models being proxies for higher order ARCH models.

IV. INTERPRETATION OF ESTIMATION RESULTS

Table 4 presents the results of the diagnostic tests (viz. the Ljung–Box statistic to judge whether the equation disturbance terms of the ARCH/GARCH specification were indeed white noise errors and the Jarque–Bera statistic to judge the normality of the conditional heteroscedasticity corrected equation disturbances). These tend to indicate that for the given data set GARCH(1,1) and GARCH(1,2) specifications are clearly superior to ARCH(1) specification. However, there is virtually little to choose between the GARCH(1,1) and GARCH(1,2) specifications. This is true for each of the three time periods under examination, and for all three different measures of (moving average) risk.[13] Interestingly, in all cases, the superiority of GARCH(1,p) specifications over ARCH(1) specification is based on lower autocorrelation of the corresponding residuals. Hence, keeping in view the parametric parsimony criterion of model selection, we choose the GARCH(1,1) model as the one that is best suited for explaining the observed intertemporal variations in the spread in the given data set.

Table 3. *LM test statistics for ARCH(q)*

Filtering	ARCH order	1st third	2nd third	3rd third
AR(1)	$q = 1$	110.96	111.52	142.04
	$q = 10$	435.86	278.54	352.99
AR(1) & SD_90D	$q = 1$	111.54	111.53	142.47
	$q = 10$	434.75	278.55	351.85
AR(1) & SD_60D	$q = 1$	121.76	108.11	142.54
	$q = 10$	450.69	290.98	350.25
AR(1) & SD_30D	$q = 1$	118.17	107.82	155.74
	$q = 10$	427.93	281.83	331.76

[13] Note, however, that the residuals from the estimations involving the data from the first and third subsamples are generally better behaved than the residuals from the estimations involving the second subsample. Since the second subsample includes data from the volatile 1970s and early 1980s, there is reason to believe that during periods of high and volatile inflation rates, finding the appropriate model for the prediction of yield spreads may be quite difficult. This premonition finds further support from the fact that the residuals from the estimations involving the low inflation-stable macroeconomy era of the third subsample are very well behaved.

Table 4.

Sample	ARCH(1)		GARCH(1,1)		GARCH(1,2)	
Model with 90-day moving standard deviation as measure of risk (SD_90D)						
1st third	LB:	38.905	LB:	6.9119	LB:	6.6607
	Kurt:	8.9650	Kurt:	9.6293	Kurt:	9.6269
	JB:	3890.3	JB:	4781.9	JB:	4778.4
	Adj. R^2:	0.972	Adj. R^2:	0.972	Adj. R^2:	0.972
2nd third	LB:	56.441	LB:	19.915	LB:	20.153
	Kurt:	9.8615	Kurt:	9.7321	Kurt:	9.7309
	JB:	5346.5	JB:	5146.9	JB:	5145.0
	Adj. R^2:	0.966	Adj. R^2:	0.966	Adj. R^2:	0.966
3rd third	LB:	1.6082	LB:	1.9477	LB:	1.9344
	Kurt:	8.5242	Kurt:	8.5119	Kurt:	8.5125
	JB:	3356.5	JB:	3332.4	JB:	3333.5
	Adj. R^2:	0.983	Adj. R^2:	0.983	Adj. R^2:	0.983
Model with 60-day moving standard deviation as measure of risk (SD_60D)						
1st sample	LB:	42.019	LB:	6.6249	LB:	6.3520
	Kurt:	8.9075	Kurt:	9.5881	Kurt:	9.5861
	JB:	3813.8	JB:	4271.4	JB:	4718.5
	Adj. R^2:	0.972	Adj. R^2:	0.972	Adj. R^2:	0.972
2nd sample	LB:	55.789	LB:	20.582	LB:	20.825
	Kurt:	9.7367	Kurt:	9.5750	Kurt:	9.5734
	JB:	5142.8	JB:	4893.8	JB:	4891.3
	Adj. R^2:	0.966	Adj. R^2:	0.966	Adj. R^2:	0.966
3rd sample	LB:	1.6389	LB:	1.9994	LB:	1.9849
	Kurt:	8.5340	Kurt:	8.5144	Kurt:	8.5154
	JB:	3363.3	JB:	3331.6	JB:	3333.2
	Adj. R^2:	0.983	Adj. R^2:	0.983	Adj. R^2:	0.983
Model with 30-day moving standard deviation as measure of risk (SD_30D)						
1st sample	LB:	43.193	LB:	6.8505	LB:	6.9851
	Kurt:	8.9391	Kurt:	9.6393	Kurt:	9.7954
	JB:	3852.7	JB:	4795.9	JB:	5024.2
	Adj. R^2:	0.972	Adj. R^2:	0.972	Adj. R^2:	0.972
2nd sample	LB:	56.122	LB:	19.782	LB:	19.982
	Kurt:	9.7341	Kurt:	9.7055	Kurt:	9.7049
	JB:	5132.8	JB:	5104.2	JB:	5103.1
	Adj. R^2:	0.966	Adj. R^2:	0.966	Adj. R^2:	0.966
3rd sample	LB:	1.6946	LB:	2.0104	LB:	1.9987
	Kurt:	8.5205	Kurt:	8.5046	Kurt:	8.5056
	JB:	3346.8	JB:	3319.5	JB:	3320.9
	Adj. R^2:	0.983	Adj. R^2:	0.983	Adj. R^2:	0.983

Notes: LB = Ljung–Box statistic, Kurt = kurtosis, JB = Jarque–Bera test statistic for normality.

The estimated coefficients of the GARCH(1,1) model (see, Tables 5–7 below) are along expected lines for all the three specifications: viz. those with 90-day, 60-day and 30-day moving standard deviation as proxies for interest rate risk. The coefficients of the $\alpha(0)\alpha(1)$, as well as $\beta(1)$ are significant at 1% level, justifying the adoption of the GARCH(1,1) model. The value of the constant term is, almost always, higher for the second third of the sample for all the specifications, indicating higher average spread during the 1970s and early 1980s, and this is in agreement with the descriptive statistics.

Perhaps the most interesting feature of the results presented above is that they suggest that while interest rate volatility over a relatively long period of time, namely, 90 days, affects the spread in the expected manner – the spread increases with increase in volatility (and hence risk) – shorter run volatility does not affect the spread at all. As such, neither the diagnostic tests nor the measures of goodness of fit suggest that one should choose one specification over the others. However, economic theory suggests that, more likely than not, interest rate volatility determines the three-month and one-year yields differently such that the spread between them would not completely be independent of the volatility. Hence, it would perhaps be prudent to use the specification of the GARCH(1,1) model which includes the 90-day moving standard deviation.

Table 5. *GARCH(1,1) with 90-day moving standard deviation*

Variable	1st third	2nd third	3rd third
Constant	0.002 (0.000)	0.011 (0.000)	0.004 (0.007)
SP_3M1Y(-1)	1.047 (0.000)	1.020 (0.000)	0.987 (0.000)
SP_3M1Y(-2)	−0.092 (0.002)	−0.076 (0.006)	
SP_3M1Y(-3)	0.031 (0.142)	0.039 (0.044)	
SD_90D	0.006 (0.005)	0.001 (0.536)	0.004 (0.095)
ALPHA_0	0.4E-05 (0.000)	0.3E-04 (0.536)	0.1E-04 (0.000)
ALPHA_1	0.089 (0.000)	0.119 (0.000)	0.062 (0.000)
BETA_1	0.915 (0.000)	0.890 (0.000)	0.931 (0.000)
H(0)	0.09E-04 (0.632)	0.001 (0.180)	0.004 (0.014)

Note: The numbers within parentheses are *p*-values of the test statistic.

Table 6. *GARCH(1,1) with 60-day moving standard deviation*

Variable	1st third	2nd third	3rd third
Constant	0.002 (0.003)	0.013 (0.000)	0.005 (0.003)
SP_3M1Y(-1)	1.048 (0.000)	1.020 (0.000)	0.987 (0.000)
SP_3M1Y(-2)	−0.093 (0.002)	−0.076 (0.006)	
SP_3M1Y(-3)	0.031 (0.139)	−0.004 (0.881)	
SP_3M1Y(-4)		0.044 (0.030)	
SD_60D	0.003 (0.233)	0.003 (0.118)	0.003 (0.224)
ALPHA_0	0.3E-05 (0.002)	0.3E-04 (0.000)	0.1E-04 (0.000)
ALPHA_1	0.088 (0.000)	0.119 (0.000)	0.063 (0.000)
BETA_1	0.916 (0.000)	0.889 (0.000)	0.930 (0.000)
H(0)	0.1E-03 (0.603)	0.001 (0.178)	0.004 (0.016)

Note: The numbers within parentheses are *p*-values of the test statistic.

V. CONCLUSION

The increasing degree of sophistication in the financial world demands a better understanding of not only interest rates per se, but also of co-movement between interest rates of different maturities. However, while the literature on bond markets and interest rates has focused on the nature of the term structure, little attention has been paid to the spread among money market interest rates. This article fills this lacuna in the literature, and concludes that a GARCH(1,1) model, which includes a moderately long-term measure of interest rate volatility in the specification, is best suited to forecast the spread between short term and long term money market rates in the USA between 1962 and 1992.

However, as with any empirical analysis, it is imprudent to make a definitive statement about the process underlying movements in interest rate spreads in general, given that the analysis includes data from only one country. This exercise should be repeated using data from other countries, initially from the developed countries of Western Europe, and later from emerging markets. The contrast between the macroeconomic conditions of the various countries would, we feel, broaden the understanding about interest rate movements in the money market.

Table 7. *GARCH(1,1) with 30-day moving standard deviation*

Variable	1st third	2nd third	3rd third
Constant	0.002 (0.002)	0.012 (0.000)	0.005 (0.001)
SP_3M1Y(-1)	1.048 (0.000)	1.020 (0.000)	0.987 (0.000)
SP_3M1Y(-2)	−0.093 (0.002)	−0.076 (0.006)	
SP_3M1Y(-3)	0.031 (0.041)	0.040 (0.044)	
SD_30D	0.006 (0.135)	0.3E-03 (0.908)	0.002 (0.525)
ALPHA_0	0.3E-05 (0.002)	0.3E-04 (0.000)	0.1E-04 (0.000)
ALPHA_1	0.089 (0.000)	0.118 (0.000)	0.063 (0.000)
BETA_1	0.916 (0.000)	0.890 (0.000)	0.930 (0.000)
H(0)	0.1E-03 (0.605)	0.001 (0.180)	0.004 (0.015)

Note: The numbers within parentheses are *p*-values of the test statistic.

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