Modeling Fixed Income Excess Returns

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Abstract

Excess returns earned in fixed-income markets have been modeled using the ARCH-M model of Engle et al. and its variants. We investigate whether the empirical evidence obtained from an ARCH-M type model is sensitive to the definition of the holding period (ranging from 5 days to 90 days) or to the choice of data used to compute excess returns (coupon or zero-coupon bonds). There is robust support for the inclusion of a term spread in a model of excess returns, while the significance of the in-mean term depends on characteristics of the underlying data.

Keywords: term premium, excess returns, GARCH modeling

JEL: E43, C22, C52

1 Introduction

Excess returns or bond term premia have been studied extensively in the empirical finance literature. The excess return on a $k-$period bond is defined as the difference between the holding period return on the bond and the one-period interest rate.[1] The excess return represents the realized (or *ex post*) premium from holding the long maturity bond as compared to the one-period security and is commonly referred to as the *ex post* term or liquidity premium. One of the first studies to empirically model time variation in term premia is Engle, Lilien, and Robins (1987) where the authors introduced the autoregressive conditional heteroskedasticity-in-mean model (ARCH-M). In the ARCH-M model, the term premium depends on the conditional variance of the underlying interest rate process. A number of studies applying and extending this methodology followed (see Bollerslev, Chou and Kroner (1992) for a survey of the literature). More recently, Brunner and Simon (1996) find that the exponential generalized autoregressive conditional heteroskedasticity-in-mean model (EGARCH-M) is a good representation of weekly excess returns on ten-year Treasury notes and long-term Treasury bonds[2].

[1] For example, if a bond maturing in 5 years is held for one month, the (one-month) excess return on this bond is calculated as the difference between the return realized from holding the 5-year bond for one month and the interest rate on a one-month security.

[2] Other recent studies have analyzed the role of time-variation in term premia in a different setting. Tzavalis and Wickens (1997) find that when they account for a time-varying term premium by including excess returns in a regression of the change in the long term interest rate on the yield spread, their estimated coefficients are consistent with the predictions of the expectations theory. Using a discrete time approximation for the term premium which is derived in the continuous time CIR model, Klemosky and Pilotte (1992) estimate the *ex ante* term premium as a

Although conditional heteroskedasticity models have been widely applied to excess returns, there have been no studies on the robustness of empirical findings that are based on these models with respect to varying characteristics of the data that are used in calculating bond term premia. This paper attempts to fill this gap in the literature by providing evidence on the sensitivity of empirical results to the choice of holding period over which excess returns are measured, the data set which is used to calculate excess returns, and the bonds' term to maturity. This is a particularly interesting issue since the empirical literature has largely focused on modeling excess returns that are calculated from Treasury bills. We document and compare the time series characteristics of excess returns on medium to long-term Treasury securities for various sampling intervals which we set equal to the holding period. Using the class of conditional heteroskedasticity models which have been previously used in the literature, we analyze excess returns series for three holding periods: five days (one week), one month, and three months, and for a number of maturities. Our study contributes to the literature in two other respects. We employ a general conditional heteroskedasticity model which allows for the inclusion of in-mean effects, lagged returns, and a term spread variable which has been found to be significant in previous studies. In addition, the model allows for a general class of distributions for the error term rather than assuming that the errors are normal. Finally, we provide new evidence on modeling excess returns of medium-term zero coupon bonds and medium- to long-term coupon bonds which have not received attention in the literature.

Our findings can be summarized as follows. The model of excess returns presented here, incorporating the term spread, conditional heteroskedasticity, and a more flexible error distribution, appears to be quite robust to variations in tenor, holding period, and the form of the underlying data. This robust behavior holds up over a lengthy sample period encompassing structural changes in the behavior of the Federal Reserve as a dominant force in the Treasury markets, with concomitant fluctuations in the volatility of interest rates and returns from holding fixed-income securities. Alternative sampling intervals and holding periods, ranging from five days to 90 days, do not appear to have a qualitative impact on these findings. Explicit consideration of the conditional heteroskedasticity of excess returns series appears to be an essential component of a characterization of their stochastic properties. However, inclusion of an in-mean term in the conditional mean equation is not consistently supported by our findings.

The rest of the paper is constructed as follows. Section 2 presents the theoretical background

function of the level and the variability of the riskless interest rate process. They find that the term premium varies positively with the variability of the interest rate and negatively with its level.

and methodology underlying our investigation, while the data used in the analysis are described in Section 3. The following section presents our empirical results. Section 5 concludes with an outline of further research.

2 Theoretical background and methodology

Let R_t^k be the yield per period on a zero-coupon bond with k periods to maturity. The one period holding return on this k-period bond is given by:

$$H_t^{(k,1)} = kR_t^k - (k-1)R_{t+1}^{k-1} \tag{1}$$

According to the expectations theory, investors seek to equalize expected holding returns from all available investment strategies. Therefore, the expected return from holding any k-period bond for one period (say one month) is related to the yield on a one-period bond as shown in (2) below.

$$E_t H_t^{(k,1)} = R_t^1 + TP^k \tag{2}$$

E_t is the expectations operator conditional on information available at time t and TP^k is a constant term premium. The one-period excess holding return on a k-period bond (XR_t^k) is defined as the difference between the *ex post* holding return and the one-period yield which, assuming that expectations are rational, is equal to the unobservable term premium plus noise unforecastable at time t:

$$XR_t^k = H_t^{(k,1)} - R_t^1 = TP^k + \nu_t \tag{3}$$

Given the assumption of a constant term premium, the expectations hypothesis implies that excess returns are unforecastable using information available at time t. Equation (3) can be used to test this implication by regressing XR_t^k on observable and relevant variables and testing for their significance. Previous studies have found that excess returns are forecastable using variables such as the spread between the k-period and the one-period rates (see for example Campbell (1995)).

Evidence of the predictability of excess returns has been interpreted to indicate the existence of a time-varying term premium. To explicitly model the behavior of the (unobserved) term premium using the time series of (observable) excess returns as in equation (3), Engle et al. (1987) assume that term premia are given by:

$$TP_t^k = \beta + \delta h_t \tag{4}$$

where h_t is the standard deviation of the holding return forecast error, ν_t, which represents the risk of holding the $k-$period bond. This formulation assumes that the term premium has a less than proportional relation to the variance of the holding return, h_t^2, consistent with a two-asset model in which the supply of the risky asset is fixed. Substituting (4) into (3) and specifying an autoregressive process for h_t^2, the model, termed the autoregressive conditional heteroskedasticity in mean (ARCH-M) model, is formulated as:

$$
\begin{aligned}
XR_t^k &= \beta + \delta h_t + \nu_t, \quad \nu_t \sim N(0, h_t^2) && (5)\\
h_t^2 &= c + \sum_{i=1}^{q} q_i \nu_{t-i}^2 && (6)
\end{aligned}
$$

Engle et al. (1987) find that the ARCH-M model with $q = 4$ is a good representation of quarterly excess returns on six-month Treasury bills[3].

Since our study employs a number of excess return series which vary by maturity and sampling frequency, we consider a more general version of the model in (5)-(6), a GARCH-M, which allows for autoregressive terms and exogenous variables in the mean and variance equations. In addition, the model is estimated using a generalized error distribution (GED) when we find evidence that the errors are non-normal. The general model is formulated as:

$$
\begin{aligned}
XR_t^k &= a_0 + \sum_{i=1}^{Arlag} a_i XR_{t-i}^k + \sum_{i=1}^{exog} b_i X_{it} + m h_t + \nu_t, \quad \nu_t \sim (0, h_t^2) && (7)\\
h_t^2 &= c + \sum_{i=1}^{q} q_i \nu_{t-i}^2 + \sum_{i=1}^{p} p_i h_{t-i} + \sum_{i=1}^{vexog} d_i Z_{it} && (8)
\end{aligned}
$$

Where $Arlag$ is the number of autoregressive lags in the mean equation and $exog$ and $vexog$ are the number of exogenous variables, X_{it} and Z_{it}, entering the mean and the variance equations, respectively. An exogenous variable which is likely to be significant in the mean of XR_t^k is the spread between the long term yield and the one-period yield, $S_t^k = R_t^k - R_t^1$. To illustrate this it is helpful to rewrite equation (2) as:

$$
TP_t^k = E_t H_t^{(k,1)} - R_t^1 \qquad (9)
$$

After substituting for $H_t^{(k,1)}$ from (1), adding and subtracting R_t^k, and rearranging we get:

[3] Engle et al.'s (1987) final model uses $\log h_t$ in the mean equation and applies declining weights on the lags in the variance equation.

$$TP_t^k = (R_t^k - R_t^1) + (k-1)(R_t^k - E_t R_{t+1}^{k-1}) \tag{10}$$

Equation (10) shows that the term premium can be decomposed into two components: the spread between the long and the short term yields and a multiple of the expected change in the long term yield. Therefore, the spread is likely to be an important predictor of the term premium and may contain information about the term premium which is not captured in the conditional variance term (the in-mean term), h_t. Since h_t is the standard deviation of the forecast error of the holding period return which is the same as the forecast error of the future long-term yield, $E_t R_{t+1}^{k-1}$, the in-mean term in equation (7) reflects the second term in (10), while the spread reflects the first term[4].

In the empirical results below, we include the spread as a regressor in equation (7) and test whether the results are consistent with the relationship described in (10). We also consider the inclusion of the spread as an explanatory variable in the conditional variance equation. The spread could affect the term premium indirectly through the variance equation if the spread is correlated with uncertainty about the long term yield. For example, the spread may increase when uncertainty (or risk) about the long-term yield increases if investors require a higher yield on the long-term bond to compensate for the increased uncertainty.

Our approach to selecting a final specification of the model in (7)-(8) for each of the excess returns series is as follows. We begin by estimating the ARCH(4)-M model which has been previously used in the literature for each series and conducting a number of diagnostic tests on the model's residuals. We test for serial correlation in the standardized residuals and squared residuals for up to 24 lags, and conduct F-tests for the presence of remaining ARCH effects up to 24 lags. Ensuring that the squared residuals are properly modeled is particularly important since the in-mean term cannot be consistently estimated if the conditional variance is misspecified. We also test for normality and for the presence of sign bias in the standardized residuals. We use the GARCH(1,1)-M model in cases where we detect the presence of high order ARCH in the residuals and we include lagged excess returns in the mean equation in cases where we found serial correlation in the residuals. Where we reject normality, we employ the generalized error distribution, detailed in Appendix

[4]Engle et al. (1987) suggest that the spread can predict excess returns since it represents information about the riskiness of the long term bond, which is modeled using the in-mean term h_t. To test this proposition, they compare the coefficients on the spread from an equation regressing the excess return on a constant and the spread to that from the ARCH-M model. They find that the spread remains significant but at a lower level of significance and that its coefficient is drastically reduced. Thus, they conclude that the spread's explanatory power is merely a reflection of the information captured by h_t.

C, to obtain estimates of the model parameters[5]. Therefore, we choose the final specification for which the residuals and squared residuals are free from any serial correlation, remaining ARCH effects and sign bias. After selecting the best univariate model for each excess returns series, we reestimate the models by adding the spread as an explanatory variable in the mean equation and checking the estimated residuals as previously described. In the empirical results presented in Section 4, the final specification for each series includes the spread as an explanatory variable.

3 Description of the data

We use two different data sets derived from U.S. Treasury securities' quotations in our analysis. The first dataset, used to construct excess returns for 1-, 2-, 3-, 4-, and 5-year securities, makes use of the Fama-Bliss Discount Bonds file and the CRSP Riskfree Rates file from CRSP's monthly dataset. The Fama-Bliss file contains monthly price and yield quotations on zero-coupon securities for one- to five-year tenors generated from fully taxable, non-callable, non-flower Treasury securities. Details of its construction are given in the *1997 CRSP Monthly US Government Bond File Guide* (p.22). The Riskfree Rates file contains nominal one- and three-month risk free rates, constructed from Treasury bill quotations. Yields are expressed as continuously compounded 365-day rates. Approximate holding period returns are calculated from these quotations, as described in Appendix A.

The second dataset, used to construct excess returns for several tenors, makes use of the CRSP daily dataset's Fixed Term Indices files, combined with individual securities' quotations from the daily CRSP file and a measure of the daily Fed Funds rate from the Federal Reserve Board. The Fixed Term Indices files contain price, yield and duration quotations for 1-, 2-, 5-, 7-, 10-, 20- and 30-year terms, constructed by CRSP from individual Treasury securities' quotations as described in the *1997 CRSP US Government Bond File Guide* (pp.23-25). The identification of the underlying individual security allows us to calculate an approximate holding period return for five-day (one-week), one-month and three-month holding periods, as described in Appendix B. These measures, available at a daily frequency, provide us with a much richer set of holding period returns in two senses. First, they gauge the return from holding medium and long-term Treasuries, whereas most research has been based on returns from Treasury bills, of no more than one year tenor. Second, they are available at a daily frequency, facilitating the study of a sizable sample of weekly excess returns,

[5] An alternative to using a non-normal distribution would be to employ the quasi-maximum likelihood estimation (QMLE) method developed by Bollerslev and Wooldridge (1992). The authors provide computable formulas for asymptotic standard errors that are valid when a normal log-likelihood function is maximized, even when the assumption of normality is violated.

whereas much of the literature utilizes monthly series.[6] Although computations with these data must take into account the nature of the quotations (measures of yield on coupon securities, rather than the more analytically tractable zero-coupon instruments) these two advantages outweigh the difficulties.

Descriptive statistics for the excess returns series calculated for this study are given in Table 1. Panels A, B, and C present the descriptive statistics for quarterly, monthly, and five-day excess returns, respectively. Series denoted 'Z' are derived from the zero-coupon quotations, while series labeled 'C' are constructed from the Fixed Term Indices quotations on coupon securities. Differences in methodology of excess returns' computation seem to be most apparent for the quarterly holding period returns at the one-year tenor, in which the zero-based series have a considerably higher mean and lower variance than the coupon-based series. For the other two overlapping tenors (two-year and five-year) there is much closer agreement between the series. The discrepancy between means persists for the monthly excess returns, where the zero-based measures have a much higher mean for each of the three overlapping tenors, but similar variances. The variances of excess returns increase with tenor in almost every instance for both zero-based and coupon-based excess returns. Returns are generally positively skewed, with greater skewness at shorter tenors. Excess kurtosis is present in almost all series, and is most pronounced for shorter tenors for most of the series. A significant degree of autocorrelation is apparent in all but the quarterly series calculated from zero-coupon securities.

Since estimation of models for excess returns depends on the stationarity of the series (finite unconditional second moments), we perform Augmented Dickey-Fuller and Phillips-Perron unit root tests on each of the excess returns series[7]. The null hypothesis of nonstationary behavior is decisively rejected for all series.

4 Empirical Results

We have estimated ARCH and GARCH models of excess returns, as described in the previous section, for several maturities and data frequencies, making use of two distinct datasets. In this section, we present and interpret our findings from this set of estimates. Several common features emerge. First, it appears that low-order ARCH and GARCH models adequately describe the

[6] This data set also allows us to construct excess returns for a one-day holding period. Our preliminary analysis indicates that the time series characteristics of these daily data are considerably different from their weekly, monthly and quarterly counterparts. Estimation of these models requires the use of highly nonlinear and computationally intensive methods. Given that such analysis shifts the focus of the paper away from its purpose, we chose to defer analysis of the daily data to future research.

[7] The unit root test results are available from the authors upon request.

stochastic properties of excess returns series. Second, the term spread is significant in the conditional mean equation for excess returns, for all maturities and data frequencies, in both datasets. Third, an ARCH-in-mean term is an important component of some models of excess returns, over and above the role of the term spread, but fails to be universally significant. Fourth, the error processes in these models are generally non-normal; a generalized error distribution with 'fat tails' is a more appropriate representation of their kurtosis.[8] We turn now to a detailed investigation of these findings.

4.1 Results for the Zero-Coupon Dataset

The zero-coupon dataset, described in Section 3, contains monthly quotations on one- to five-year zero coupon securities constructed from Treasury quotations. We have selected the one-, two-, and five-year tenors for our modeling, all of which overlap with the available tenors from the Fixed Term Indices dataset. We fit models to these three tenors for two holding periods: monthly and quarterly. A summary of the specifications used appears as Table 2.

Table 2. Excess Returns Model Specifications for the Zero-Coupon Dataset

	Holding Period	
Tenor	*Quarterly*	*Monthly*
1 year	ARCH(2)-M	AR1-GARCH(1,1)-M, GED
2 year	ARCH(2)-M	AR1-ARCH(4)-M, GED
5 year	ARCH(2)-M, GED	AR1-ARCH(4)-M, GED

In this summary, all models include an in-mean term (-M) which is the conditional standard error of excess returns. Models including 'GED' are fit with a generalized error distribution, and include an additional estimated parameter (the v tail-thickness parameter). The quarterly series' conditional mean equations contain only a constant, term spread, and in-mean term; the monthly series also include a lagged value of the conditional mean. The empirical results from these models are presented in Table 3.

As indicated above, the term spread is universally significant in these models, with a positive estimated coefficient increasing in tenor. The spread coefficients are of similar magnitude across quarterly and monthly holding periods. The in-mean term is significant in the one- and two-year models for quarterly holding periods, and for the two-year model at the monthly frequency. When these models are estimated without the term spread, the in-mean term is always significant; thus, there seems to be some substitutability between including the term spread or the volatility term in

[8] A description of the generalized error distribution and its properties is presented in Appendix C.

the conditional mean equation.

We may also compare the term spread coefficients with their corresponding estimates from OLS-based models of excess returns[9]. Modeling the excess returns series' conditional heteroskedasticity always diminishes the magnitude of the coefficient on the term spread, but it remains significantly positive in all cases. In contrast, Engle et al. (1987) and Brunner and Simon (1996) found that when conditional heteroskedasticity was accounted for with an ARCH structure, the term spread became much less significant. Our findings suggest that the term spread has played an important role in the excess returns process, even in the presence of conditional heteroskedasticity and an explicit ARCH-in-mean term. Since excess returns may be decomposed into two components, the term spread and a multiple of the change in yield on the longer-term bond over the holding period, our findings suggest that both components have been responsible for fluctuations in excess returns over our sample period. In contrast, a study focusing on recent term structure behavior might attribute a much larger role to yield volatility (as do Brunner and Simon (1996) when studying the 1982-1993 period)[10].

In applying the GED as an alternative to normality for the error process, the tail thickness parameter for all monthly holding periods may be distinguished from 2.0, the value corresponding to normally distributed errors, and signals excess kurtosis. All models' errors are free of residual ARCH, and Ljung-Box tests for autocorrelation in their squares are insignificant.

Thus, for the zero-coupon dataset, it appears that an appropriate model of excess returns may be constructed with the (G)ARCH-M methodology. The term spread plays a qualitatively similar role in each of the resulting models, irrespective of choice of tenor or the distinction between monthly and quarterly holding periods. They appear to capture the dynamics of excess returns over this period, including the sharp spike in volatility in the 1979-1982 period, as Figure 1 (for the quarterly volatility series) and Figure 2 (for the monthly volatility series) indicates.

4.2 Results for the Coupon Dataset

The coupon dataset, described in Section 3, contains quotations on several tenors of Treasury securities generated from the CRSP Fixed Term Indices. The data are originally available at the daily frequency. For this analysis, we have examined weekly, monthly and quarterly holding periods

[9]Appendix Tables A.1 and A.2 present the results of estimating each of the excess returns models with OLS, allowing for AR(1) errors.

[10]Note that we should interpret the comparison between our results and other studies with caution. Since we use a different specification for the mean equation for excess returns, changes in the coefficients for the yield spread may occur due to a change in the amount of small sample bias. We thank an anonymous reviewer for bringing this point to our attention.

for four tenors: the one-, two-, and five-year tenors considered above, and the 30-year tenor. A summary of the specifications chosen for these models appears as Table 4.

Table 4. Excess Returns Model Specifications for the Coupon Dataset

	Holding Period		
Tenor	*Quarterly*	*Monthly*	*Weekly*
1 year	ARCH(4)-M, GED	AR1-GARCH(1,1)-M, GED	AR4-GARCH(1,1)-M, GED
2 year	ARCH(4)-M, GED	AR1-GARCH(1,1)-M, GED	AR4-GARCH(1,1)-M, GED
5 year	ARCH(4)-M, GED	AR1-ARCH(4)-M, GED	AR4-GARCH(1,1)-M, GED
30 year	ARCH(4)-M, GED	ARCH(4)-M, GED	AR4-GARCH(1,1)-M, GED

Abbreviations used in this summary are those used in Table 2 above. The empirical results from these models are presented in Tables 5, 6, and 7 for quarterly, monthly and weekly holding periods, respectively. The term spread is universally significant at better than the 5% level in these specifications. In contrast to the zero-coupon estimates, the magnitude of the term spread coefficients is not always reduced by taking account of conditional heteroskedasticity. For the quarterly holding period, the (G)ARCH coefficients on the term spread are uniformly larger than their OLS counterparts. In the monthly and weekly holding periods, all but the 30-year monthly returns have smaller coefficients on the term spread when conditional heteroskedasticity is taken into account.[11]

All models contain in-mean terms, so that the effects of the term spread are estimated controlling for the possible confounding of volatility and term spreads' impact on excess returns. The in-mean term is not significant in the quarterly estimates, and only appears as an important determinant of one-year excess returns for the monthly holding period. For the weekly estimates, the in-mean term is significant for one- and two-year tenors, and marginally significant for the five-year tenor. The GED tail-thickness parameter may be distinguished from 2.0 (denoting normality) for each of the estimated models, indicating a considerable degree of excess kurtosis for many of the series. With the exception of the weekly two-year returns series, all models' errors are free of residual ARCH, with insignificant autocorrelation in their squares.

The models of excess returns fitted from coupon bonds' quotations appear to be largely similar in their qualitative characteristics. The term spread plays an important role in explaining excess returns' behavior, even when conditional heteroskedasticity and in-mean terms are included.

[11] We also fit models including the term spread as a potential component of the conditional variance equation, as suggested by Engle et al. (1987, p.403). The term spread was significant in only one of the many models estimated. It does not appear that the level of the term spread has any explanatory power over and above past values of the conditional variance.

Although the results for a weekly holding period are more volatile than those for longer holding periods, there are qualitative similarities among the results for all three holding periods for each tenor studied. The models appear to capture the dynamics of excess returns over this period, and their conditional heteroskedasticity component accounts for the sizable changes in bond markets' volatility experienced in the 1979-1982 monetary control episode (see Figures 3, 4, and 5a-5b for the estimated volatility series for quarterly, monthly and weekly holding periods, respectively).

4.3 Summary of Findings

In summary, the model of excess returns presented here, incorporating the term spread, conditional heteroskedasticity, and a more flexible error distribution, appears to be quite robust to variations in tenor, holding period, and the form of the underlying data. This robust behavior holds up over a lengthy sample period encompassing structural changes in the behavior of the Federal Reserve as a dominant force in the Treasury markets, with concomitant fluctuations in the volatility of interest rates and returns from holding fixed-income securities. Alternative sampling intervals and holding periods, ranging from a five-day to a 90-day period, do not appear to have a qualitative impact on these findings. To put it another way, one should not draw different conclusions about the importance of the current slope of the yield curve to the performance of fixed-income portfolios whether one studies 5-, 30-, or 90-day holding period returns. These qualitative findings appear to hold for both short-term (one- and two-year) tenors as well as much longer-term instruments such as the 30-year long bond.

These results also highlight the importance of modeling the conditional heteroskedasticity of excess returns series as an essential component of any characterization of their stochastic properties. Although this message is not new, it plays an important role in the robustness of our findings over holding periods and tenors. However, inclusion of an in-mean term in the conditional mean equation, taken by Engle et al. (1987) as a clear indication of the interaction of risk and return, is not consistently supported by our findings. In-mean terms play an important role in some of our estimated models, but one cannot generalize over tenor, holding period, or dataset on their relation to the model.

5 Suggestions for Further Research

In this study, we have evaluated the robustness of the relationship between the term spread and excess returns on holding Treasury securities of short, medium and long tenors. Our findings that the term spread is an important contributor to the explanatory power of ARCH-based models of excess returns appear to generalize across holding periods, from one week to a calendar quarter, suggesting that systematic sampling in this range does not have a qualitative impact on an appropriate specification. These conclusions also suggest that the form of the underlying data, whether the more tractable zero-coupon quotations or returns derived from coupon securities' quotations, is not responsible for the main features of the models presented.

Our further work with these data will focus on extending these results by making use of the Fixed Term Indices-based data at their original daily frequency, and in exploring a variety of advanced GARCH specifications to investigate the importance of asymmetries and non-normal behavior in their error processes. Use of the daily data will also permit us to conduct subsample analysis with more sizable samples than have been commonly analyzed in the empirical literature. Our preliminary findings from weekly through quarterly holding periods should be strengthened by the consideration of daily holding periods.

Appendices

A Excess Returns series from zero-coupon quotations

The monthly excess returns series make use of the Fama-Bliss price quotations on 1- to 5-year zero-coupon securities for 1964:3 through 1996:12. Since only these five tenors are available, one-month (three-month) holding period returns cannot be constructed directly from these data, since that would require, for example, the price of 11-month (9-month) zero-coupon securities. To construct estimates of holding period returns for one-month and three-month holding periods, the approximation defined by Campbell (1995, p.132) in terms of yields is expressed in terms of zero-coupon bond prices. He assumes that the yield on the security does not change over the holding period in order that its price at the end of the holding period may be inferred (cf. Campbell, fn.7). Define p_{mt} as the logarithm of the bond price for a \$1 par bond with m periods to maturity. Then the one-year log holding period return for an $m-$period bond is $r_{m,t+1} = p_{m-1,t+1} - p_{mt}$.[12] Since the price and continuously compounded (log) yield, y_{mt}, are linked by the relation $p_{mt} = -my_{mt}$, the log holding period return may be expressed in terms of yields as $y_{mt} - (m-1)(y_{m-1,t+1} - y_{mt})$. In the absence of measures of a performance of an $(m-1)$ period security, we apply the approximation $y_{m-1,t+1} \approx y_{m,t+1}$. In price terms, this implies that $r_{m,t+1} = \left[\left(\frac{m-1}{m}\right) p_{m,t+1} - p_{mt}\right]$, which makes it possible to calculate the (log) holding period return from available data. For instance, the one-month log holding period return on a one-year security will be $\frac{11}{12}$ of next month's (log) price of the zero-coupon security minus this month's (log) price of that security. For a three month holding period, we calculate $r_{m,t+3} = \left[\left(\frac{m-3}{m}\right) p_{m,t+3} - p_{mt}\right]$, where again m is measured in months. Excess returns are computed from these series (expressed in per cent per annum by $h_{m,t+1} = 1200 r_{m,t+1}$ and $h_{m,t+3} = 400 r_{m,t+3}$) by subtracting the CRSP Riskfree Rates for one- and three-month tenors, respectively. The average of bid and ask yields provided in the Riskfree Rates file are used.

B Excess Returns series from Fixed Term Indices quotations

We generate excess returns series from the CRSP Fixed Term Indices quotations from 14 June 1961 through 30 September 1996, for a total of 8,804 business days. Each quotation is identified with the specific Treasury security from which it is derived in the Fixed Term Index file; that identifier is used on the Daily Government Bond file to recover the yield of that specific security

[12] In Campbell (1995, p.132), this formula incorrectly refers to $p_{m-1,t-1}$ and $y_{m-1,t-1}$ rather than their counterparts dated $(t+1)$.

at the end of the holding period, be it one day, five days, one month, or three months hence. Although the holding period return for that specific security could be computed exactly for that interval, we want to remove the 'coupon effect' from the calculation. We do so by employing the approximation developed by Shiller (1990, p. 640), originally presented in Shiller et al. (1983), and widely employed in the term structure literature. He expresses the 'holding period rate' or return from t to t' on a bond maturing at time T, $t \leq t' \leq T$, as

$$h_t\left(t, t', T\right) = \frac{D(T-t)r(t,T) - \left[D(T-t) - D(t'-t)\right] r(t',T)}{D(t'-t)}$$

where $h_t\left(t, t', T\right)$ is the holding period return, $r(t,T)$ is the yield on a security held from t to T, $r(t',T)$ is the yield on a security held from t' to T, $D\left(T-t\right)$ is the Macaulay duration of the security, and $D\left(t'-t\right)$ is the duration of a hypothetical security held from t to t', which is approximated as $D\left(m\right) = \frac{1-e^{-r(t,T)}}{r(t,T)}$ (Shiller, 1990, Table 13.1, p.640). Our application of Shiller's approximation requires three pieces of information: the yield to maturity of the security underlying the index on the quotation date, $r\left(t,T\right)$, the yield to maturity of that security at the end of the holding period, $r\left(t',T\right)$, and Macaulay's duration for the security as of the quotation date, $D(T-t)$. From these elements, we calculate daily holding period returns series for each tenor. The daily Fed Funds rate from the Federal Reserve Board's H.15 databank is used to generate excess returns series.[13]

C The Generalized Error Distribution

In estimating an ARCH or GARCH model, an assumption must be made regarding the distribution of the conditional mean equation's error process. We consider three alternatives in estimating the models reported in this study: normally distributed errors, Student $t-$distributed errors, and errors following a Generalized Error Distribution (henceforth GED). This distribution, first used in an ARCH modeling context by Nelson (1991), is also known as the exponential power distribution (Box and Tiao, 1973). As Nelson points out, the GED includes the normal as a special case, with alternatives exhibiting greater or lesser degrees of kurtosis than the normal. This makes the GED particularly attractive, as it allows for both positive and negative excess kurtosis in the error process (as opposed to the Student t) with a single 'tail-thickness' parameter. The density of a normalized (zero mean, unit variance) GED random variate is given by (Nelson, 1991, p.352):

$$f\left(z\right) = \frac{\upsilon \exp\left[-\frac{1}{2}\left|z/\lambda\right|^{\upsilon}\right]}{\lambda 2^{\left(1+\frac{1}{\upsilon}\right)}\Gamma\left(1/\upsilon\right)},\ -\infty < z < \infty,\ 0 < \upsilon \leq \infty$$

[13]Ideally, term Federal funds rates for one week, one month, or one quarter would be used to calculate excess returns for those holding periods, but these data are not publicly available.

where $\Gamma(\cdot)$ is the gamma function and

$$\lambda = \left[2^{(-2/\upsilon)} \frac{\Gamma(1/\upsilon)}{\Gamma(3/\upsilon)} \right]^{1/2}$$

The tail-thickness parameter υ takes on the value 2 for a standard normal distribution, with values less than 2 denoting thicker tails than the normal, and vice versa. In the limit, as $\upsilon \rightarrow \infty$, the GED converges on a uniform distribution. Nelson finds this distribution particularly useful in the context of his Exponential GARCH (E-GARCH) model, but it may be used to advantage in any ARCH modeling context. The GED has recently been applied to the modeling of excess returns from Treasuries by Brunner and Simon (1996).

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Table 1: Descriptive Statistics for Excess Return Series

(A) Quarterly Excess Returns

SERIES	Type	NOBS	AVE.	VAR	SKEW	KURT	MIN	MAX	Q-STAT (20 LAGS)	SIGNIF LEVEL
1964:3 - 1996:4										
1 Year	Z	130	0.45	12.78	1.03	7.36	-12.15	19.48	16.42	0.69
2 Year	Z	130	0.59	52.77	0.80	4.57	-23.32	35.27	17.72	0.61
3 Year	Z	130	0.67	105.66	0.45	2.42	-30.83	41.40	14.39	0.81
4 Year	Z	130	0.72	168.90	0.34	1.34	-35.43	43.68	19.59	0.48
5 Year	Z	130	0.72	231.77	0.27	1.42	-45.25	50.70	14.93	0.78
1961 - 1996										
1 Year	C	135	0.25	17.48	2.09	18.13	-14.18	29.40	28.72	0.09
2 Year	C	135	0.41	51.81	1.17	10.42	-24.51	43.66	29.76	0.07
5 Year	C	135	0.79	190.54	0.53	4.64	-42.53	68.22	24.71	0.21
7 Year	C	135	0.81	263.48	0.47	3.13	-45.22	72.01	19.89	0.46
10 Year	C	135	-0.20	392.94	0.25	1.78	-56.86	67.66	25.38	0.19
20 Year	C	135	-0.56	615.74	0.06	2.05	-83.25	92.43	30.86	0.06
30 Year	C	135	-1.43	682.19	-0.19	1.82	-87.46	85.63	24.97	0.20

(B) Monthly Excess Returns

SERIES	TYPE	NOBS	AVE.	VAR	SKEW	KURT	MIN	MAX	Q-STAT (20 LAGS)	SIGNIF LEVEL
1964:3 - 1996:4										
1 Year	Z	393	0.81	43.35	0.94	10.39	-30.17	49.39	69.45	0.00
2 Year	Z	393	0.96	138.56	0.64	7.70	-53.02	78.72	54.10	0.00
3 Year	Z	393	1.05	271.61	0.05	5.44	-87.05	97.52	36.60	0.01
4 Year	Z	393	1.11	458.82	0.13	3.67	-94.19	103.32	39.71	0.01
5 Year	Z	393	1.10	615.22	0.25	3.49	-95.69	125.44	32.08	0.04
1961 - 1996										
1 Year	C	400	0.14	49.84	1.55	18.65	-31.56	64.02	109.73	0.00
2 Year	C	400	0.27	152.39	1.16	14.30	-62.32	103.15	87.61	0.00
5 Year	C	400	0.56	469.92	0.57	6.68	-92.58	148.67	59.80	0.00
7 Year	C	400	0.65	675.03	0.13	4.29	-111.53	141.72	66.25	0.00
10 Year	C	400	-0.31	926.43	0.06	2.38	-122.61	135.96	34.82	0.02
20 Year	C	400	0.25	1526.93	0.25	2.73	-130.85	196.83	41.77	0.00
30 Year	C	400	-0.73	1611.32	0.18	2.24	-141.89	189.59	47.81	0.00

(C) Five-Day Excess Returns

SERIES	Type	NOBS	AVE.	VAR	SKEW	KURT	MIN	MAX	Q-STAT (20 LAGS)	SIGNIF LEVEL
1961 - 1996										
1 Year	C	1760	0.32	276.67	1.00	16.50	-114.28	183.50	204.16	0.00
2 Year	C	1760	0.56	953.01	0.67	16.28	-281.21	279.61	137.88	0.00
5 Year	C	1760	0.99	3441.53	0.53	9.63	-468.85	448.28	62.82	0.00
7 Year	C	1760	0.41	4915.44	0.62	9.80	-543.34	546.41	45.24	0.00
10 Year	C	1760	-0.57	7982.80	0.69	14.57	-795.62	790.86	35.44	0.02
20 Year	C	1760	-1.02	12563.79	0.54	6.41	-668.42	870.71	31.30	0.05
30 Year	C	1760	-1.85	14080.76	0.35	7.98	-898.51	981.33	26.08	0.16

Table 3
Parameter Estimates for Zero Coupon models with Spread[a]

Quarterly: 1965:1-1996:4

$$Model: \quad XR_t^k = a_0 + a_1 XR_{t-1}^k + bSpread_t + mh_t + \varepsilon_t, \quad \varepsilon_t \sim (0, h_t^2), \quad k = 1, 2, 5 \quad year$$

$$h_t^2 = c + \sum_{i=1}^{4} q_i \varepsilon_{t-i}^2 + p_1 h_{t-1}^2$$

	1 year		***2 year***		***5 year***	
	ARCH(2)-M		ARCH(2)-M		ARCH(2)-M/GED	
		p-val		*p-val*		*p-val*
a_0	-2.253	0.000	-5.038	0.001	-4.538	0.590
b	**1.578**	**0.008**	**1.582**	**0.023**	**2.998**	**0.003**
c	2.857	0.006	13.096	0.003	155.668	0.000
q_1	0.327	0.008	0.381	0.004	0.352	0.122
q_2	0.509	0.004	0.385	0.029	0.000	0.999
$\mathbf{h_t}$	**0.801**	**0.000**	**0.866**	**0.000**	**0.161**	**0.787**
ν_t					1.771	0.000
					(0.306)	
Skew	0.211		0.167		0.502	
Kurtosis	3.451		2.892		4.331	
LB(24)	17.800	0.813	14.990	0.921	22.324	0.559
LBsq(24)	14.606	0.932	15.213	0.914	17.862	0.809
F-test for Arch(24)	0.507	0.968	0.445	0.985	0.599	0.921
JB	1.988	0.370	0.639	0.726	14.145	0.000
LogLik	-307.905		-400.843		-497.500	

[a] *Standard errors are in parentheses.*

Table 3 (cont.)
Parameter Estimates for Zero Coupon models with Spread[a]

Monthly: 1964:8-1996:12

$$Model: \quad XR_t^k = a_0 + a_1 XR_{t-1}^k + bSpread_t + mh_t + \varepsilon_t, \quad \varepsilon_t \sim (0, h_t^2), \quad k = 1, 2, 5 year$$

$$h_t^2 = c + \sum_{i=1}^{4} q_i \varepsilon_{t-i}^2 + p_1 h_{t-1}^2$$

	1 year		2 year		5 year	
	AR1-GARCH(1,1)-M/GED		AR1-ARCH(4)-M/GED		AR1-ARCH(4)-M/GED	
		p-val		*p-val*		*p-val*
a_0	-0.984	0.137	-5.593	0.000	-8.019	0.040
a_1	0.181	0.000	0.154	0.003	0.080	0.123
b	**1.336**	**0.000**	**1.647**	**0.001**	**2.704**	**0.001**
c	0.930	0.180	41.637	0.000	233.446	0.000
q_1	0.188	0.000	0.137	0.075	0.172	0.086
q_2			0.220	0.006	0.148	0.074
q_3			0.137	0.058	0.234	0.053
q_4			0.168	0.050	0.106	0.198
p_1	0.801	0.000				
h	**0.123**	**0.361**	**0.480**	**0.003**	**0.238**	**0.201**
ν_t	1.307		1.375		1.286	
	(0.148)		(0.159)		(0.125)	
Skew	-0.131		-0.170		-0.269	
Kurtosis	4.359		4.004		4.624	
LB(24)	19.596	0.666	15.793	0.863	22.122	0.512
LBsq(24)	21.133	0.572	24.872	0.357	24.252	0.389
F-test for Arch(24)	0.815	0.717	0.859	0.658	0.817	0.715
JB	30.424	0.000	18.172	0.000	47.339	0.000
LogLik	-1153.791		-1427.294		-1749.364	

Table 5

Parameter Estimates for coupon models with Spread[a]

Quarterly: 1961-1996

$$Model: \quad XR_t^k = a_0 + bSpread_t + mh_t + \varepsilon_t, \qquad \varepsilon_t \sim (0, h_t^2), \quad k = 1,2,5,30 \quad year$$

$$h_t^2 = c + \sum_{i=1}^{4} q_i \varepsilon_{t-i}^2$$

	1 year		***2 year***		***5 year***		***30 year***	
	ARCH(4)-M/GED		ARCH(3)-M/GED		ARCH(4)-M/GED		ARCH(4)-M/GED	
		p-val		*p-val*		*p-val*		*p-val*
a_0	0.102	0.544	-0.149	0.879	-1.506	0.516	0.070	0.987
b	**0.935**	**0.000**	**0.750**	**0.000**	**1.072**	**0.036**	**2.632**	**0.000**
c	0.206	0.302	10.345	0.011	37.492	0.040	187.217	0.031
q_1	0.413	0.089	0.324	0.107	0.300	0.068	0.203	0.169
q_2	0.410	0.173	0.490	0.101	0.529	0.056	0.684	0.037
q_3	0.307	0.270	0.174	0.398	0.215	0.313	0.008	0.952
q_4	0.659	0.041			-0.037	0.789	0.122	0.392
$\mathbf{h_t}$	**0.090**	**0.272**	**0.035**	**0.852**	**0.120**	**0.557**	**-0.094**	**0.662**
v_t	0.996		1.166		1.322		1.098	
	(0.216)		(0.210)		(0.237)		(0.204)	
Skew	0.027		0.088		-0.418		-0.620	
Kurtosis	4.524		4.590		4.816		4.618	
LB(24)	22.357	0.577	15.478	0.906	13.383	0.959	25.064	0.402
LBsq(24)	18.296	0.788	36.014	0.055	17.867	0.809	20.690	0.656
F-test for Arch(24)	0.646	0.887	0.806	0.719	0.539	0.955	0.780	0.749
JB	12.694	0.001	14.078	0.000	21.816	0.000	22.684	0.000
LogLik	-301.887		-412.024		-509.812		-594.722	

[a] *Standard errors are in parentheses.*

Table 6

Parameter Estimates for coupon models with Spread[a]

Monthly: 1961-1996

$$Model: \quad XR_t^k = a_0 + a_1 XR_{t-1}^k + bSpread_t + mh_t + \varepsilon_t, \quad \varepsilon_t \sim (0, h_t^2), \quad k = 1,2,5,30 \quad year$$

$$h_t^2 = c + \sum_{i=1}^{4} q_i \varepsilon_{t-i}^2 + p_1 h_{t-1}^2$$

	1 year		***2 year***		***5 year***		***30 year***	
	AR1-GARCH(1,1)-M/GED		AR1-GARCH(1,1)-M/GED		AR1-ARCH(4)-M/GED		ARCH(4)-M/GED	
		p-val		*p-val*		*p-val*		*p-val*
a_0	-0.396	0.064	-0.808	0.241	-1.651	0.195	-6.742	0.170
a_1	0.106	0.018	0.094	0.063	0.097	0.026		
b	**0.788**	**0.000**	**0.717**	**0.000**	**1.157**	**0.001**	**2.579**	0.000
c	0.156	0.302	1.367	0.183	58.782	0.001	525.214	**0.000**
q_1	0.282	0.000	0.225	0.000	0.274	0.027	0.134	0.082
q_2					0.258	0.046	0.047	0.378
q_3					0.413	0.010	0.547	0.165
q_4					0.322	0.031	0.082	0.280
p_1	0.780	0.000	0.802	0.000				
$\mathbf{h_t}$	**0.122**	**0.079**	**0.095**	0.302	**0.076**	**0.340**	**0.143**	**0.311**
v_t	1.059		1.182		1.037		1.325	
	(0.118)		(0.120)		(0.095)		(0.122)	
Skew	-0.135		-0.342		-0.559		-0.414	
Kurtosis	4.246		4.903		6.608		5.518	
LB(24)	18.797	0.712	15.561	0.873	20.523	0.610	24.166	0.452
LBsq(24)	16.065	0.852	17.785	0.769	17.643	0.776	18.062	0.799
F-test for Arch(24)	0.642	0.903	0.775	0.769	0.877	0.634	0.724	0.826
JB	0.642	0.000	67.803	0.000	234.838	0.000	115.944	0.000
LogLik	-1136.383		-1435.383		-1697.855		-1981.427	

[a] *Standard errors are in parentheses.*

Table 7

Parameter Estimates for coupon models with Spread[a]

Weekly: 1961-1996

$$Model: \quad XR_t^k = a_0 + \sum_{i=1}^{4} a_i XR_{t-i}^k + bSpread_t + mh_t + \varepsilon_t, \quad \varepsilon_t \sim (0, h_t^2), \quad k = 1,2,5,30 \quad year$$

$$h_t^2 = c + q_1 \varepsilon_{t-1}^2 + p_1 h_{t-1}^2$$

	1 year		***2 year***		***5 year***		***30 year***	
	AR4-GARCH(1,1)-M/GED		AR4-GARCH(1,1)-M/GED		AR4-GARCH(1,1)-M/GED		AR4-GARCH(1,1)-M/GED	
		p-val		*p-val*		*p-val*		*p-val*
a_0	-0.648	0.038	-1.338	0.047	-1.665	0.081	-3.274	0.123
a_1	0.139	0.000	0.094	0.000	0.074	0.002	0.073	0.002
a_2	0.032	0.125	0.063	0.004	0.085	0.000	0.034	0.149
a_3	0.054	0.008	0.048	0.027	0.001	0.976	0.014	0.541
a_4	0.047	0.020	-0.002	0.942	-0.027	0.267	-0.014	0.537
b	**0.804**	**0.000**	**0.570**	**0.023**	**1.114**	**0.029**	**2.658**	**0.002**
C	1.191	0.001	1.366	0.132	2.588	0.213	15.047	0.109
q_1	0.154	0.000	0.096	0.000	0.153	0.000	0.145	0.000
p_1	0.865	0.000	0.913	0.000	0.870	0.000	0.877	0.000
$\mathbf{h_t}$	**0.129**	**0.000**	**0.099**	**0.012**	**0.058**	**0.073**	**0.011**	**0.742**
v_t	1.019		1.156		1.314		1.240	
	(0.000)		(0.042)		(0.049)		(0.035)	
Skew	-2.441		0.036		0.023		0.620	
Kurtosis	42.850		7.801		6.073		10.478	
LB(24)	15.608	0.741	17.471	0.622	21.000	0.397	23.624	0.259
LBsq(24)	1.605	1.000	34.634	0.022	26.261	0.157	13.415	0.858
F-test for Arch(24)	0.074	1.000	1.390	0.098	1.092	0.344	0.545	0.964
JB	117869.000	0.000	1685.825	0.000	690.547	0.000	4201.834	0.000
LogLik	-6688.231		-7862.873		-9089.360		-10414.678	

[a] *Standard errors are in parentheses.*

Figure 1. Estimated Volatility for Quarterly Holding Period

Zero-Coupon dataset

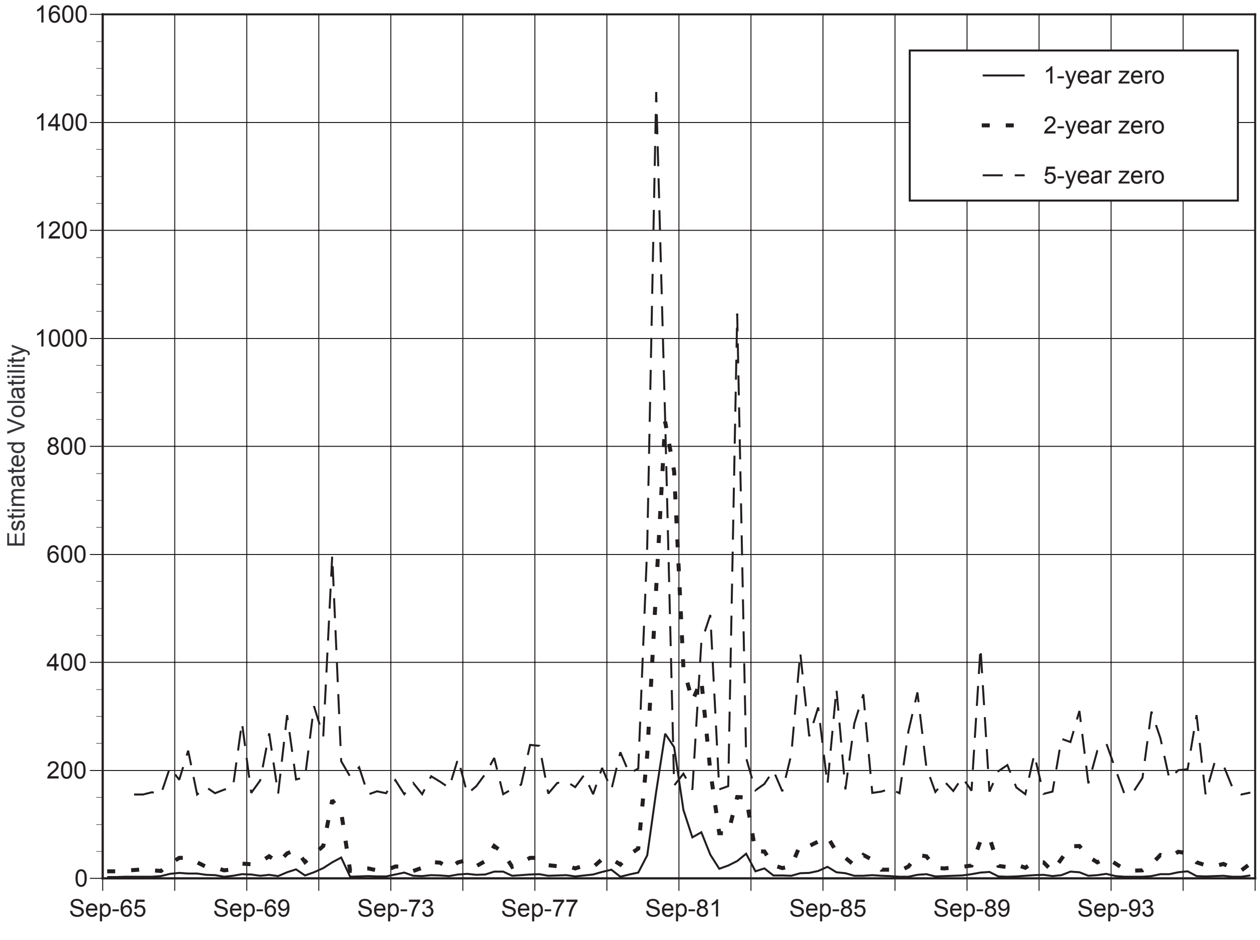

Figure 2. Estimated Volatility for Monthly Holding Period

Zero-Coupon dataset

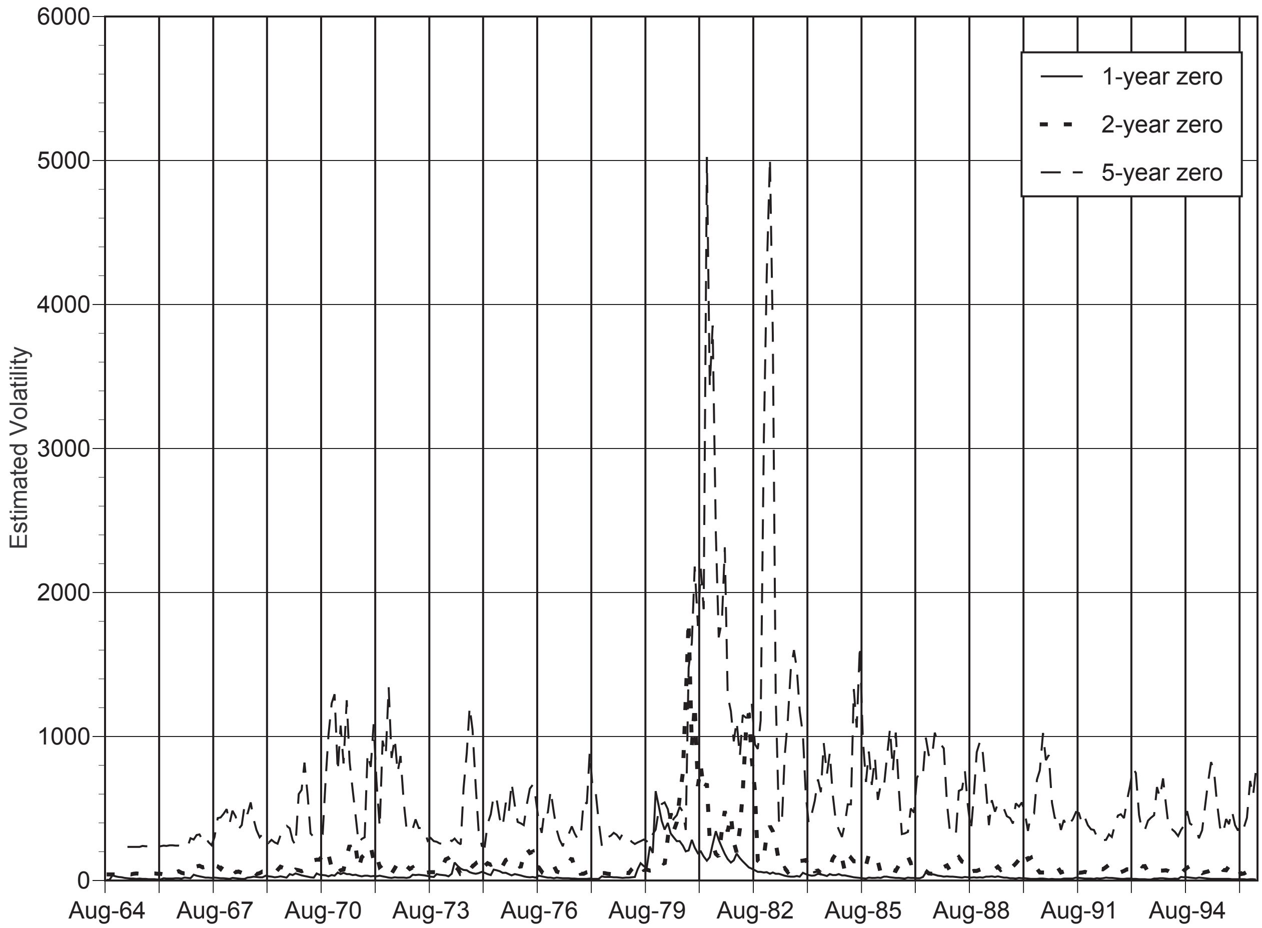

Figure 3. Estimated Volatility for Quarterly Holding Period

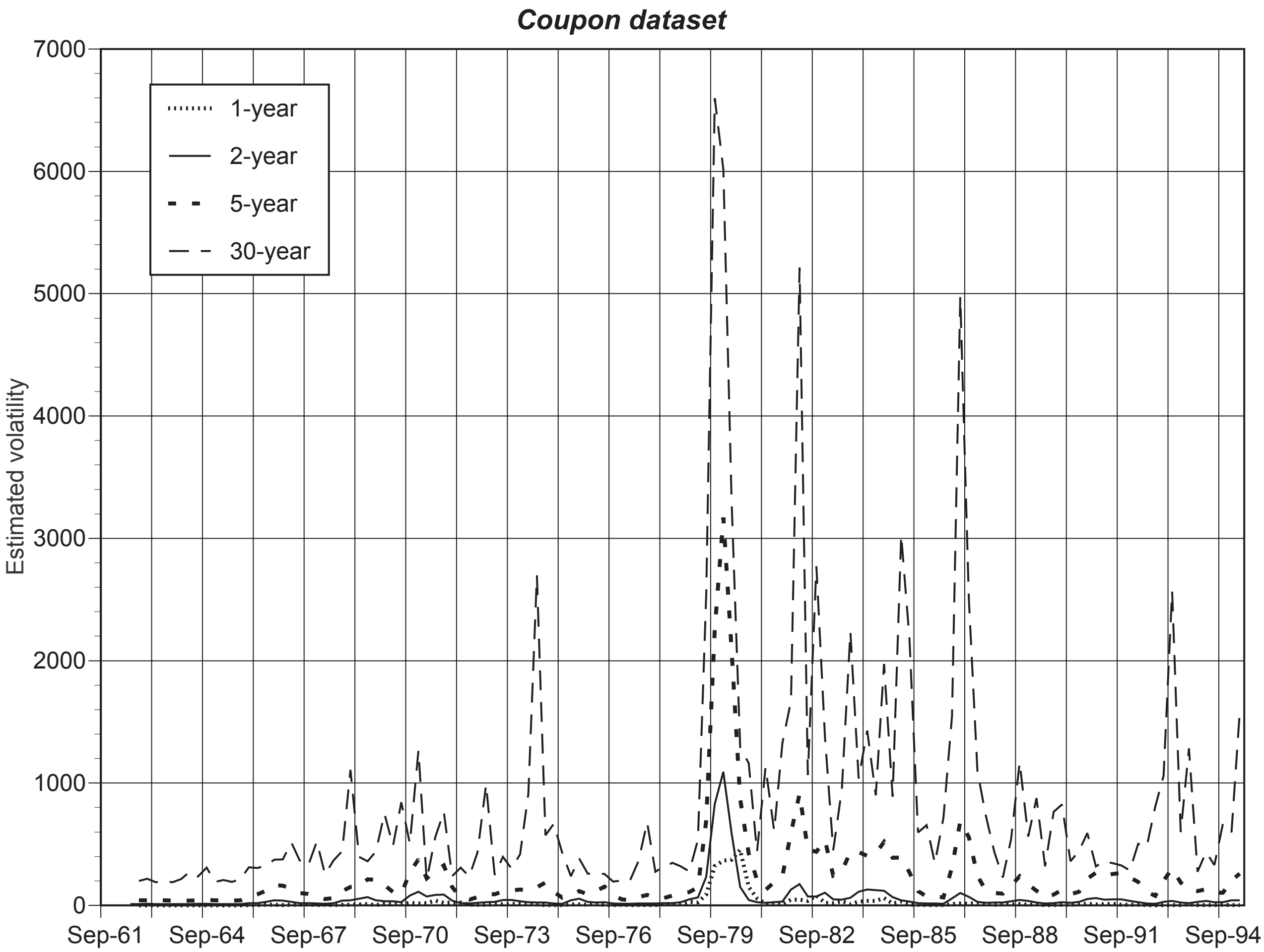

Figure 4. Estimated Volatility for Monthly Holding Period

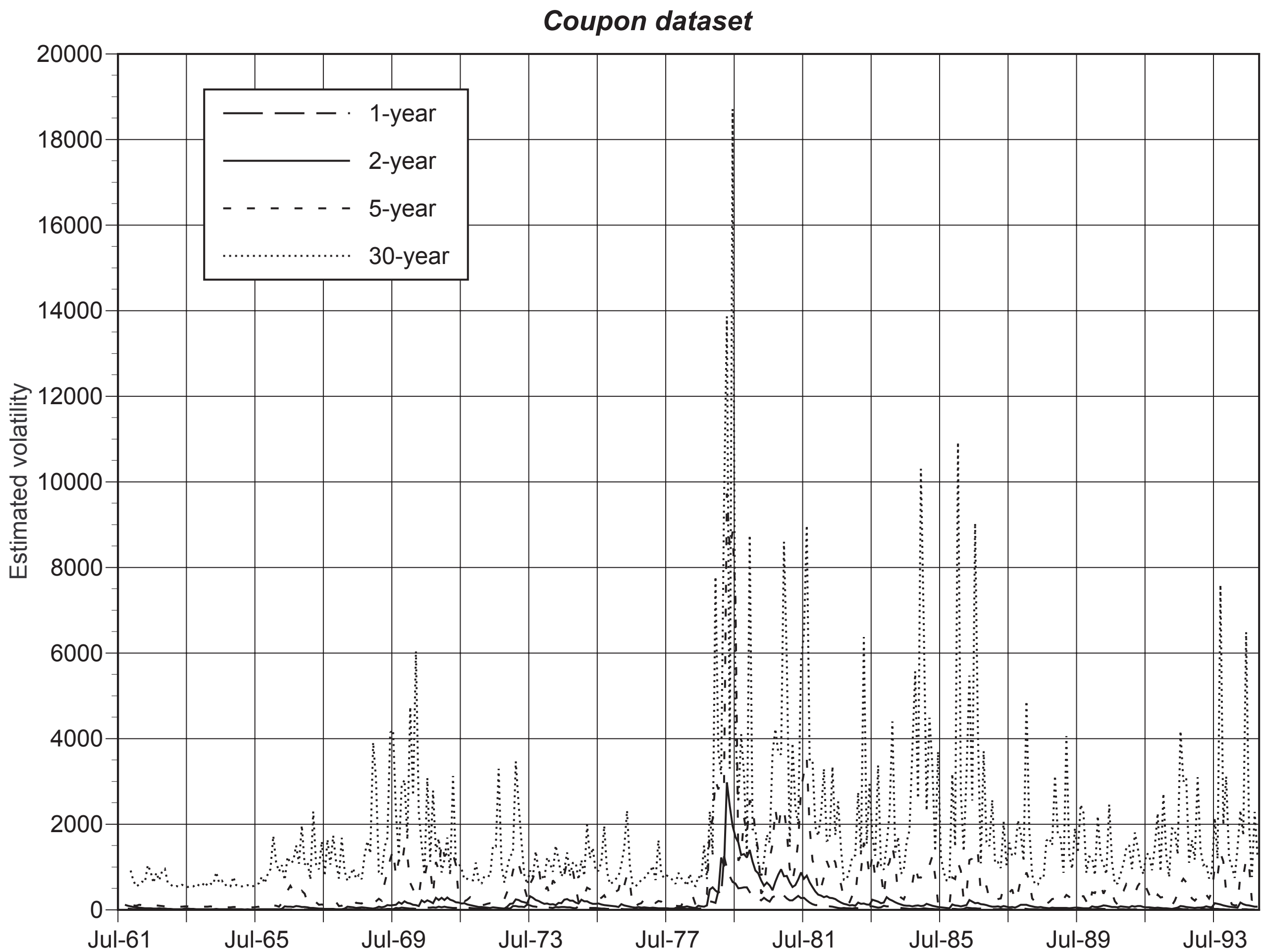

Figure 5a. Estimated Volatility for Weekly Holding Period

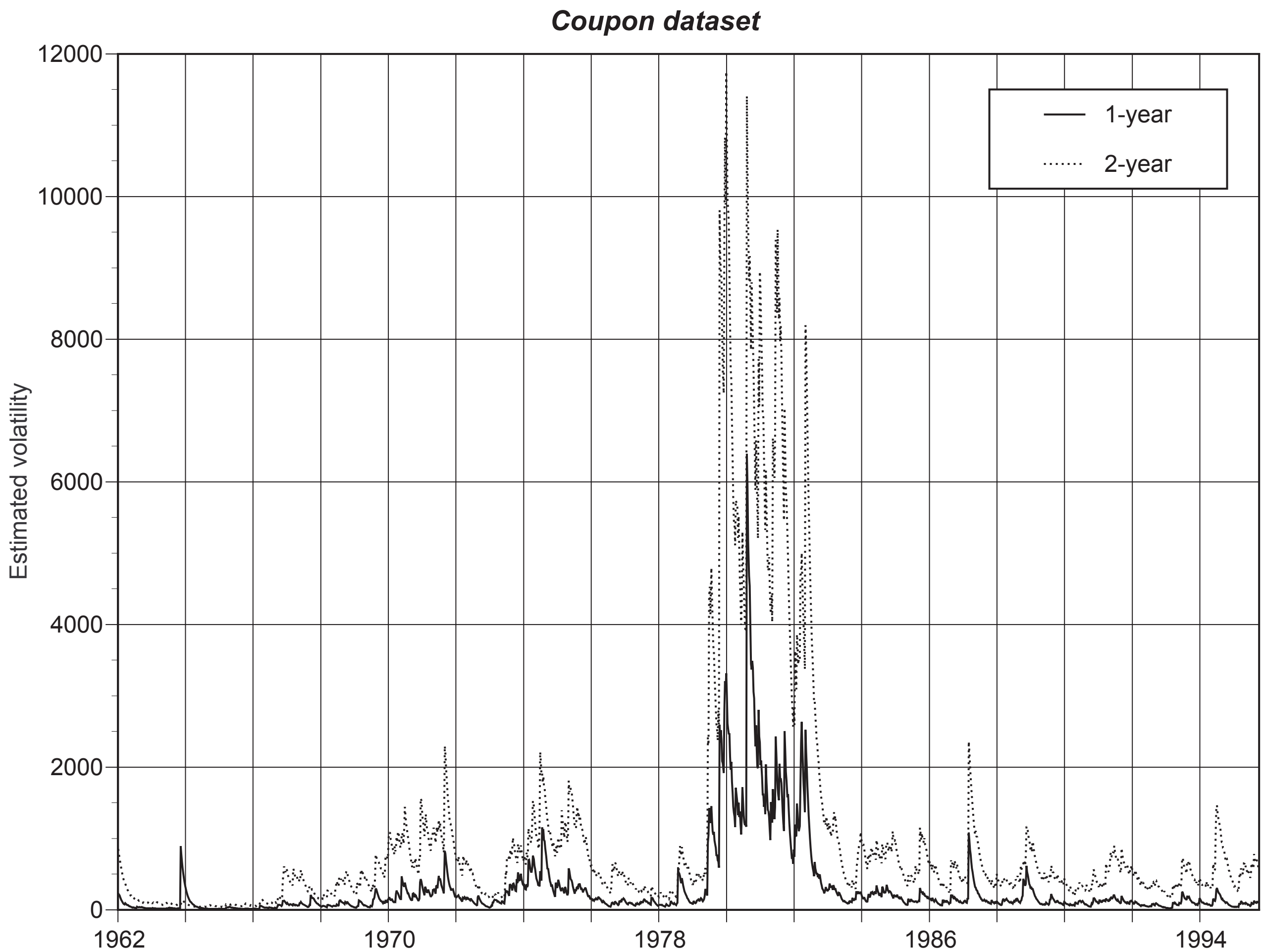

Figure 5b. Estimated Volatility for Weekly Holding Period

Coupon dataset

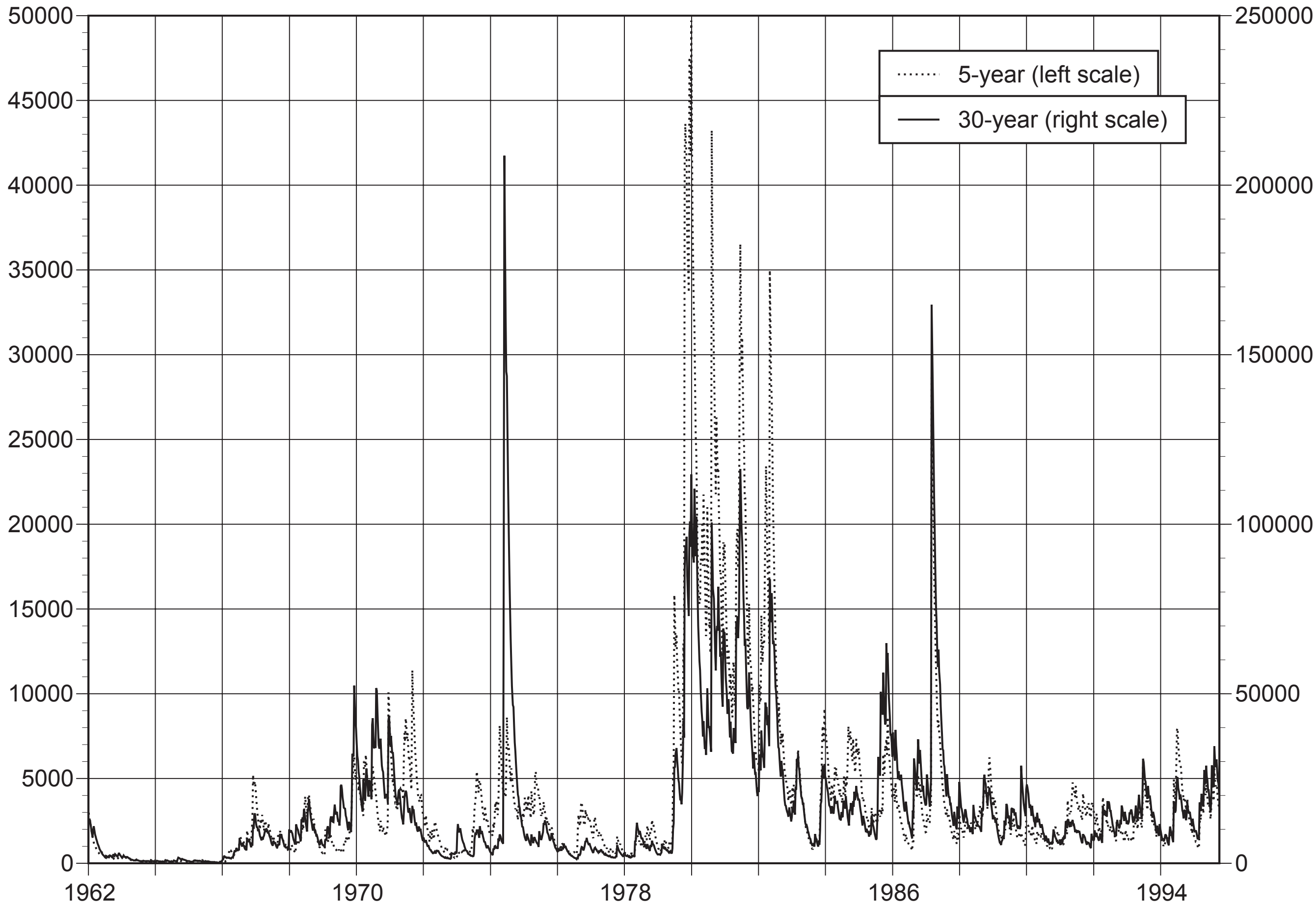

Table A.1

Parameter Estimates for zero coupon models with spread[a]

$$\textit{Model:} \quad ER_t = \alpha + \beta (R_t - r_t) + u_t$$

$$u_t = \rho u_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2)$$

(A) Quarterly: 64:3 - 96:3

Dependent Variable	1 Year	2 Year	5 Year
α	-0.475	-1.035	-2.630
	(0.351)	(0.688)	(1.487)
β	2.034**	2.428**	3.283**
	(0.571)	(0.704)	(0.971)
ρ	-0.257**	-0.223*	-0.170
	(0.086)	(0.087)	(0.088)
S.E.E.	3.374	6.967	14.753
QSTAT[b]	20.051	20.136	20.048
	(0.455)	(0.449)	(0.455)
QSTATSQ[b]	28.178	33.422	39.221
	(0.105)	(0.030)	(0.006)
D. W.	2.054	2.046	2.027
CENTERED R^2	0.130	0.102	0.083

(B) Monthly: 64:4 - 96:11

Dependent Variable	1 Year	2 Year	5 Year
α	-0.594	-1.446	-3.289
	(0.591)	(1.049)	(1.993)
β	1.641**	2.257**	3.107**
	(0.538)	(0.740)	(1.047)
ρ	0.124*	0.165**	0.074
	(0.051)	(0.050)	(0.051)
S.E.E.	6.477	11.497	24.517
QSTAT[b]	78.145	51.232	31.789
	(0.000)	(0.000)	(0.046)
QSTATSQ[b]	144.059	144.384	139.995
	(0.000)	(0.000)	(0.000)
D. W.	1.969	1.953	1.983
CENTERED R^2	0.039	0.053	0.030

[a] *Standard errors are in parentheses.*

[b] *P-values are in parentheses.*

* *Significant at the 5 percent level.*

** *Significant at the 1 percent level.*

Table A.2

Parameter Estimates for coupon models with spread[a]

1961-1996

Model:

$$ER_t = \alpha + \beta(R_t - r_t) + u_t$$

$$u_t = \rho u_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0,\sigma^2)$$

(A) Weekly

Dependent Variable	1 Year	2 Year	5 Year	30 Year
α	0.510	0.580	0.402	-3.021
	(0.511)	(0.859)	(1.544)	(2.846)
β	0.989**	1.124**	1.924**	3.354*
	(0.226)	(0.403)	(0.745)	(2.566)
ρ	0.221**	0.129**	0.066**	-0.025
	(0.024)	(0.024)	(0.024)	(1.307)
S.E.E.	16.365	30.859		
QSTAT[b]	73.219	97.614	49.269	22.553
	(0.000)	(0.000)	(0.000)	(0.311)
QSTATSQ[b]	554.060	601.827	665.387	296.241
	(0.000)	(0.000)	(0.000)	(0.000)
D. W.	2.041	2.029	2.014	1.998
CENTERED R^2	0.057	0.020	0.008	0.005

(B) Monthly

Dependent Variable	1 Year	2 Year	5 Year	30 Year
α	0.453	0.381	0.144	-1.345
	(0.394)	(0.671)	(1.218)	(2.194)
β	1.056**	1.143**	1.613**	1.912
	(0.175)	(0.317)	(0.585)	(0.998)
ρ	0.137**	0.093	0.111*	0.075
	(0.053)	(0.052)	(0.051)	(0.051)
S.E.E.	6.721	12.160	21.448	39.990
QSTAT[b]	104.764	82.962	51.540	44.569
	(0.000)	(0.000)	(0.000)	(0.001)
QSTATSQ[b]	118.405	121.550	99.057	123.429
	(0.000)	(0.000)	(0.000)	(0.000)
D. W.	1.966	1.974	1.967	1.982
CENTERED R^2	0.100	0.037	0.028	0.014

[a] *Standard errors are in parentheses.*
[b] *P-values are in parentheses.*
* *Significant at the 5 percent level.*
** *Significant at the 1 percent level.*

Table A.2 (cont.)

Parameter Estimates for coupon models with spread[a]

1961-1996

Model: $ER_t = \alpha + \beta(R_t - r_t) + u_t$

$u_t = \rho u_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0,\sigma^2)$

(C) Quarterly

Dependent Variable	1 Year	2 Year	5 Year	30 Year
α	0.416	0.389	0.430	-2.316
	(0.242)	(0.459)	(0.946)	(1.888)
β	0.856**	0.743**	0.970*	1.874*
	(0.118)	(0.232)	(0.473)	(0.870)
ρ	-0.249**	-0.265**	-0.236**	-0.189*
	(0.088)	(0.087)	(0.087)	(0.087)
S.E.E.	3.487	6.716	13.293	25.456
QSTAT[b]	18.055	13.841	15.629	23.393
	(0.584)	(0.838)	(0.739)	(0.270)
QSTATSQ[b]	35.550	40.773	37.467	29.292
	(0.017)	(0.004)	(0.010)	(0.082)
D. W.	2.038	2.005	1.976	1.952
CENTERED R^2	0.320	0.149	0.093	0.071

[a] *Standard errors are in parentheses.*
[b] *P-values are in parentheses.*
* *Significant at the 5 percent level.*
** *Significant at the 1 percent level.*