Common Volatility in MBS Returns: A Factor GARCH Approach

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The literature on pricing mortgage-backed securities is essentially an adaptation of the literature on fixed-income instruments with embedded options (e.g., Dunn and McConnell [1981], Brennan and Schwartz [1985] and Breeden [1991]). Specifically, the value of an MBS consists of the value of a non-callable self-amortizing loan minus the value of the prepayment option. Valuation of the first component requires explicit modeling of interest rate yield curves, while valuation of the second component requires an explicit modeling of prepayment behavior.

While this approach is useful and still widely practiced, it leaves no room for investigating the impact of risk on MBS returns. And the cornerstone of modern finance is the premise that returns on risky assets are governed by risk considerations. Normally, such risk is induced by a set of factors common to all risky assets.

The notion that a set of common factors drive asset returns is not new. It forms the basis of the arbitrage pricing theory (APT) advanced by Ross [1976] in which the vector of asset risk premiums is related to a set of factor risk premiums. Early interpretation and testing of the APT was based on the assumption that the first and second moments of asset returns were time-invariant, and empirical investigation focused primarily on cross-sectional variations in asset risk premiums. Recent evidence, however, decisively rejects first- and second-moment stationarity of asset returns. See, for example, Bollerslev, Chou, and Kroner [1992] for stocks and bonds, and Koutmos, Kroner, and Pericli [1998] and Koutmos and Pericli [1999] for MBS returns.

Despite the growing importance of MBS in the marketplace, there has not so far been any systematic theoretical or empirical work dealing with the properties of volatility of MBS over time or the extent to which changes in the level of volatility imply changes in returns and risk premiums. The pricing of MBS has been based on traditional models that assume risk is constant over time. The evidence from the fixed-income and the equities markets, however, suggests that such an assumption is unduly restrictive as well as possibly erroneous.

This article offers a systematic study of volatility and risk-return trade-off for MBS returns. The analysis contributes to the literature in two ways. First, by modeling volatility and the presence of a common factor, it provides important insights regarding the proper risk management and the pricing of derivative assets for which MBS are the underlying assets. Second, the modeling of a conditional risk-return trade-off offers new ways of thinking about the risk premium in this important class of financial assets.

The econometric model is based on the factor GARCH model suggested by Engle, Ng, and Rothschild [1990] and Ng, Engle, and Rothschild [1992]. It offers a convenient

EXHIBIT 1
Correlation Matrix of Returns

	Coupon 6.5%	Coupon 7.0%	Coupon 7.5%	Coupon 8.0%	Coupon 8.5%	Coupon 9.0%
Coupon 6.5%	1.0000					
Coupon 7.0%	0.9964	1.0000				
Coupon 7.5%	0.9821	0.9938	1.0000			
Coupon 8.0%	0.9575	0.9765	0.9936	1.0000		
Coupon 8.5%	0.9321	0.9554	0.9796	0.9946	1.0000	
Coupon 9.0%	0.8964	0.9179	0.9413	0.9587	0.9711	1.0000
T-note 10-year rate	0.8990	0.8399	0.8529	0.8167	0.7813	0.7442

Sample period 4/1/1993–12/11/1998—1,453 daily observations.

framework for the study of the volatility dynamics of MBS returns as well as the possibility of a time-varying risk premium linked to a common risk factor.

I. ECONOMETRIC MODEL

The econometric model assumes that changes in MBS returns are governed by a single dynamic factor and possibly several static factors. Specifically, the return generating process is expressed as follows:

$$r_{i,t} - r_{i,t-1} = \mu_{i,t} + \beta_{i,m} f_{m,t} + \Sigma_j \beta_{i,j} f_{j,t} + \gamma_i r_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

for i = 1, ..., N and j = 1, ..., K, where $r_{i,t}$ is the return of MBS i; $\mu_{i,t}$ is the time-varying risk premium; $\beta_{i,m}$ is the dynamic factor loading; $f_{m,t}$ is the dynamic factor; and $\beta_{i,j}$ and $f_{j,t}$ are static factor loadings and static factors, respectively. The term $\gamma_i r_{i,t-1}$ is designed to test for mean reversion in returns. The parameter γ measures the speed of mean reversion. Specifically, the more negative γ is, the faster $r_{i,t}$ reverts to its mean level (see Brenner, Harjes, and Kroner [1996]). Finally, $\varepsilon_{i,t}$ is the error term or, innovation with zero mean and possibly time-varying variance.

Using the arbitrage arguments of Ross [1976], the dynamic risk premium for i can be written as:

$$\mu_{i,t} = \beta_{i,m} \mu_{m,t} + \mu_{i,s} \text{ for } i = 1, \ldots, N \quad (2)$$

where $\mu_{m,t}$ is the time-varying risk premium associated with the dynamic factor, and $\mu_{i,s}$ is the static risk premium associated with the static factors. The conditional variance of the returns $r_{i,t}$ consists of three components: the dynamic common to all MBS given by $\beta^2_{i,m}\sigma^2_{m,t}$; the static factor component, $\Sigma_j \beta^2_{i,j} \sigma^2(f_{j,t})$, which differs across MBS due to different factor loadings; and the idiosyncratic component $\sigma^2(\varepsilon_{i,t})$, or:

$$\sigma^2_{i,t} = \beta^2_{i,m}\sigma^2_{m,t} + \Sigma_j \beta^2_{i,j} \sigma^2(f_{j,t}) + \sigma^2(\varepsilon_{i,t}) \quad (3)$$

where $\sigma^2_{m,t}$ is the conditional variance of the dynamic factor common to all MBS, and $\sigma^2(f_{j,t})$ is the variance of the j-th static factor assumed to be constant. The idiosyncratic component in most related studies is also assumed to have constant variance. For greater flexibility, we allow the variance of this component to follow a GARCH(1,1) process given by

$$\sigma^2(\varepsilon_{i,t}) = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t} + \alpha_{i,2}\sigma^2(\varepsilon_{i,t-1}) \quad (4)$$

Thus, in addition to the common dynamic factor and the set of static factors, the conditional variance of the excess returns of MBS i is influenced by its own past values and past innovations.

Completion of the dynamic factor model requires

EXHIBIT 2
Preliminary Statistics on Levels

Variable	Mean	Variance	Autocorrelation	Q(5)	ADF	PP
Coupon 6.5%	7.3874*	0.6109	0.9950*	7,060*	-1.6348	-1.7811
Coupon 7.0%	7.4770*	0.7425	0.9951*	7,065*	-1.6744	-1.8091
Coupon 7.5%	7.4240*	0.8438	0.9950*	7,064*	-1.7349	-1.8559
Coupon 8.0%	7.1058*	1.0476	0.9948*	7,054*	-1.7935	-1.9046
Coupon 8.5%	7.1437*	0.5008	0.9940*	7,022*	-1.8385	-1.9815
Coupon 9.0%	6.9492*	0.3672	0.9950*	7,059*	-1.7659	-1.9725

Q(5) is the Ljung-Box statistic testing that all autocorrelations up to lag 5 are jointly zero. It follows χ with degrees of freedom equal to the number of lags. ADF and PP are augmented Dickey-Fuller and Phillips-Perron statistics testing for a unit root (5% critical value = –3.41).
*Statistically significant at 5% level at least.

specification of the conditional variance and the functional form of the time-varying premium. Following Ng, Engle, and Rothschild [1992], the conditional variance of the common factor is assumed to follow a GARCH(1,1) process given by

$$\sigma^2_{m,t} = \alpha_{m,0} + \alpha_{m,1}\varepsilon^2_{m,t-1} + \alpha_{m,2}\sigma^2_{m,t-1} \tag{5}$$

where $\varepsilon_{m,t} = r_{m,t} - \mu_{m,t}$ is the common factor innovation; $r_{m,t}$ and $\mu_{m,t}$ are the common factor return and the common factor premium, respectively; and $\sigma^2_{m,t}$ is the time-varying volatility following a GARCH(1,1) process.[1] The common factor used here is the first principal component of the returns of the various coupon MBS under analysis.[2] The dynamics of the return follow a mean-reverting process of the form:

$$r_{m,t} - r_{m,t-1} = \mu_{m,t} + \gamma_m r_{m,t-1} + \varepsilon_{m,t} \tag{6}$$

with mean reversion parameter γ_m.

The final step is to specify the risk premium associated with the dynamic common factor. The approach followed here is the one based on the ARCH-M model suggested by Engle, Lilien, and Robins [1987]. This is given by

$$\mu_{m,t} = \theta_0 + \theta_1\sigma^2_{m,t} \tag{7}$$

where $\theta_1 \geq 0$.

Equation (7) implies that investors perceive a higher risk when the volatility $\sigma^2_{m,t}$ of the common factor rises, thus requiring a higher risk premium. Idiosyncratic risks as well as risks due to static factors do not require a time-varying risk premium, or, equivalently, they are not dynamically priced.

The model is estimated using a two-step procedure along the lines of Ng, Engle, and Rothschild [1992]. In the first step, Equations (5), (6), and (7) are used to obtain maximum-likelihood estimates of the time-varying volatility of the dynamic factor and the dynamic risk premium. In the second step, these two series are used as predetermined variables in conjunction with Equations (2), (3), and (4) to obtain maximum-likelihood estimates of the time-varying risk premiums and the time-varying volatilities of individual MBS returns.

The vector of parameters describing the conditional means and the conditional variances can be obtained via maximum-likelihood estimation (MLE). Assuming the errors follow conditional normal density, the sample likelihood to be maximized can be expressed as

$$L(\Theta) = \Sigma^T_{t=1}\log f(\mu_t, \sigma^2_t) \tag{8}$$

where Θ is the parameter vector; μ_t and σ^2_t are the conditional mean and the conditional variance, respectively;

EXHIBIT 3
Preliminary Statistics on First Differences

Variable	Mean	Variance	Autocor-relation	Q(5)	ADF	PP
Coupon 6.5%	-0.0003	0.0051	0.0628	29.8185*	-18.7682*	-35.6633*
Coupon 7.0%	-0.0001	0.0061	0.0629	30.3300*	-18.6176*	-35.6641*
Coupon 7.5%	0.0001	0.0072	0.0601	30.3359*	-18.7227*	-35.7916*
Coupon 8.0%	0.0004	0.0094	0.0569	35.2616*	-18.9825*	-35.9230*
Coupon 8.5%	0.0002	0.0052	0.0497	43.3473*	-19.5489*	-36.2343*
Coupon 9.0%	0.0002	0.0034	0.0478	48.8949*	-19.8046*	-36.2846*

*Statistically significant at 5% level at least.

and $f(\cdot)$ is the conditional normal density.

Most studies dealing with financial time series find that the normality assumption is violated even after accounting for time-varying variances (see, for example, Bollerslev, Chou, and Kroner [1992]). The quasi-maximum-likelihood (QML) estimates will be consistent and asymptotically normally distributed, but the standard errors are downward-biased. Bollerslev and Wooldridge [1992] provide a method of computing standard errors that is robust to departures from normality. We use the Bollerslev-Wooldridge QML method along with the Berndt et al. [1974] numerical optimization algorithm to obtain parameter estimates.

II. DATA AND EMPIRICAL FINDINGS

The data used in this study include daily annualized rates on the 30-year fixed-rate GOLD securities issued by the Federal Home Loan Mortgage Corporation (FHLMC) with coupons 6.5%, 7.0%, 7.5%, 8.0%, 8.5%, and 9.0%.[3] The series have been compiled by the FHLMC; the sample period extends from March 1, 1993, through December 11, 1998, for a total of 1,453 daily observations. The first principal component of the six series is used as the common factor in the estimation of the factor GARCH model.

Exhibit 1 reports pairwise correlations of the six MBS returns as well as their correlations with the 10-year T-note rate. The pairwise correlations are very high, ranging from 0.896 to 0.996. Interestingly, although not unexpectedly, there is an inverse relationship between the correlation with the 10-year T-note rate and the coupon size. The 10-year T-note rate is very important for the 30-year fixed-rate MBS market because, typically, the duration of a 30-year fixed-rate mortgage is very close to that of the 10-year T-note. The estimated correlations of the MBS returns with the 10-year T-note provide indirect evidence of such a relationship. They also are very high, ranging from 0.744 to 0.899.[4]

Exhibit 2 reports several preliminary statistics on the returns of the various coupon MBS. The mean returns are very close to each other; the highest is 7.48% (for the 7% coupon), and the lowest is 6.95% (for the 9% coupon). The sample variance increases up to the 8% coupon, and then drops substantially. The first-order autocorrelations are indistinguishable from unity for the returns of all six MBS. This provides strong indication that the rates themselves may have a unit root in their univariate representations.[5]

The presence of a unit root is investigated by means of the augmented Dickey-Fuller [1981] (ADF) and the Phillips-Perron [1988] (PP) statistics. The ADF statistic is based on the regression:

$$\Delta r_{i,t} = a_0 + a_1 t + a_2 r_{i,t-1} + \Sigma_{s=1}^{\kappa} c_s \Delta r_{i,t-s} + u_{i,t} \tag{9}$$

where Δ is the first-difference operator, $r_{i,t}$ the annualized return, t a time trend, and a_0, a_1, a_2, and c_s fixed parameters. The null hypothesis is H_0: $a_2 = 0$, and the alternative is H_1: $a_2 < 0$. The PP test is based on the regression

$$r_{i,t} = b_0 + b_1 (t - T/2) + b_2 r_{i,t-1} + v_{i,t} \tag{10}$$

EXHIBIT 4
Maximum-Likelihood Estimates of Factor-GARCH Model

Variable	Time-Varying Premium Equations (1), (2) and (7)	Time-Varying Variance Equations (3), (4), and (5)
Common Factor	$\mu_{m,t} = 0.0119 + 1.0654\sigma^2_{m,t}$ (3.119)* (1.974)* γ = -0.0133 (-3.392)*	$\sigma^2_{m,t} = 0.54\text{x}10^{-5} + 0.0647\varepsilon^2_{m,t-1} + 0.9377\sigma^2_{m,t-1}$ (2.386)* (10.140)* (162.877)*
Coupon 6.5%	$\mu_{i,t} = 0.0858 + 0.8729\mu_{m,t}$ (2.787)* (1.978)* γ = -0.0116 (-2.914)*	$\sigma^2_{i,t} = 0.8729\sigma^2_{m,t} + \sigma^2(\varepsilon_{i,t})$ $\sigma^2(\varepsilon_{i,t}) = 0.22\text{x}10^{-5} + 0.0561\varepsilon^2_{i,t-1} + 0.9413\sigma^2(\varepsilon_{i,t-1})$ (3.023)* (9.711)* (160.681)*
Coupon 7.0%	$\mu_{i,t} = 0.0945 + 0.9780\mu_{m,t}$ (3.080)* (2.020)* γ = -0.0126 (-3.225)*	$\sigma^2_{i,t} = 0.9780\sigma^2_{m,t} + \sigma^2(\varepsilon_{i,t})$ $\sigma^2(\varepsilon_{i,t}) = 0.12\text{x}10^{-5} + 0.0540\varepsilon^2_{i,t-1} + 0.9458\sigma^2(\varepsilon_{i,t-1})$ (2.675)* (10.499)* (191.371)*
Coupon 7.5%	$\mu_{i,t} = 0.09663 + 0.9160\mu_{m,t}$ (3.277)* (2.078)* γ = -0.0129 (-3.431)*	$\sigma^2_{i,t} = 0.9160\sigma^2_{m,t} + \sigma^2(\varepsilon_{i,t})$ $\sigma^2(\varepsilon_{i,t}) = 0.50\text{x}10^{-5} + 0.0583\varepsilon^2_{i,t-1} + 0.9434\sigma^2(\varepsilon_{i,t-1})$ (2.201)* (10.119)* (179.670)*
Coupon 8.0%	$\mu_{i,t} = 0.0763 + 0.6519\mu_{m,t}$ (3.002)* (2.397)* γ = -0.0108 (-3.172)*	$\sigma^2_{i,t} = 0.6519\sigma^2_{m,t} + \sigma^2(\varepsilon_{i,t})$ $\sigma^2(\varepsilon_{i,t}) = 0.39\text{x}10^{-5} + 0.0672\varepsilon^2_{i,t-1} + 0.9359\sigma^2(\varepsilon_{i,t-1})$ (0.917) (9.658)* (148.751)
Coupon 8.5%	$\mu_{i,t} = 0.0697 + 0.4846\mu_{m,t}$ (3.554)* (2.272)* γ = -0.0096 (-3.682)*	$\sigma^2_{i,t} = 0.4846\sigma^2_{m,t} + \sigma^2(\varepsilon_{i,t})$ $\sigma^2(\varepsilon_{i,t}) = 0.10\text{x}10^{-5} + 0.0679\varepsilon^2_{i,t-1} + 0.6658\sigma^2(\varepsilon_{i,t-1})$ (7.730)* (7.589)* (18.882)*
Coupon 9.0%	$\mu_{i,t} = 0.0751 + 0.3347\mu_{m,t}$ (3.121)* (1.448) γ = -0.0107 (-3.126)*	$\sigma^2_{i,t} = 0.3347\sigma^2_{m,t} + \sigma^2(\varepsilon_{i,t})$ $\sigma^2(\varepsilon_{i,t}) = 0.18\text{x}10^{-5} + 0.0489\varepsilon^2_{i,t-1} + 0.9512\sigma^2(\varepsilon_{i,t-1})$ (1.928) (9.504)* (198.170)*

Numbers in parentheses are Bollerslev-Wooldridge robust t-statistics.
*Statistically significant at 5% level at least.

The null hypothesis is H_0: $b_2 = 1$ versus H_1: $b_2 < 1$, where T is the sample size. In either model, acceptance of the null hypothesis would imply that returns are non-stationary, or, equivalently, that there is a unit root in their univariate representation. It is interesting to see that both the ADF and the PP statistic fail to reject the hypothesis that the returns of all six MBS are non-stationary; that is, they have a unit root. Consequently, first-differencing is necessary to induce stationarity.

Preliminary statistics for the differenced returns are reported in Exhibit 3. The first-order autocorrelations are now much lower and statistically insignificant. There is some evidence of higher-order autocorrelation as evidenced by the significant Ljung-Box statistics calculated for five lags. The ADF and PP statistics confirm that the differenced returns are stationary.

Maximum-likelihood estimates of the factor GARCH model are reported in Exhibit 4. The first-step estimation produces parameter estimates for the conditional mean and the conditional variance of the common factor. The estimated parameters for the common factor are all positive, as expected, and statistically significant. The estimated function for the time-varying risk premium ($\mu_{m,t} = 0.0119 + 1.0654\sigma^2_{m,t}$) shows that the premium consists of a constant and a time-varying part. The latter rises proportionately with the conditional variance, the factor of proportionality being close to unity.

It can be said, in other words, that a 1 percentage point increase in the conditional variance will be accompanied by a 1 percentage point increase in the risk premium. The estimated conditional variance function ($\sigma^2_{m,t} = 0.54 \times 10^{-5} + 0.0647\varepsilon^2_{m,t-1} + 0.9377\varepsilon^2_{m,t-2}$) implies that variance at time t is a function of the squared error term at t – 1 and the value of the variance at t – 1. The past variance bears a much higher weight (0.9377) than the past squared residual (0.0647). This suggests a great deal of persistence in the conditional variance.

In the second step of the estimation, the estimated risk premium for the common factor is used as a predetermined variable for estimation of the individual MBS risk premiums. The estimated factor loadings are positive and statistically significant, with the exception of the 9% MBS. This in turn suggests that individual risk premiums rise in response to an increasing variance emanating from the common risk factor. This is the basic premise behind the arbitrage pricing theory. The only difference is that in the context of the factor GARCH model, risk premiums are time-varying, and so is the level of risk.

The extent of the factor loadings ranges from 1.06 to 0.33. Interestingly, they are inversely related to the size of the coupon, suggesting that high-coupon MBS have less sensitivity to the common risk factor.

The conditional variance of MBS depends on the conditional variance of the common factor as well as the variance of the idiosyncratic component. The latter follows a GARCH(1,1) process in all instances. The presence of GARCH effects in the idiosyncratic variance implies that second-moment dynamics cannot be explained by the common factor alone.

On reflection, this should not be surprising. Requiring that $\sigma^2(\varepsilon_{i,t})$ is constant is equivalent to requiring that all individual MBS have the same time-varying variance attributable to the common factor, except for a constant and a scale factor. This is too stringent a requirement. What is important, from our point of view, is that the risk premiums of all individual MBS are functions of the common factor premium alone and not the idiosyncratic risk.

A final important feature of MBS returns is the tendency to revert to its long-term mean. The mean reversion parameter γ is negative and statistically significant for both the individual MBS returns and the common factor. This is an important finding, given that studies dealing with interest rates find no significant tendency for mean reversion, even though from an economic perspective mean reversion makes sense.[6] When rates are high, economic activity slows, thereby putting pressure on rates to fall. The opposite holds true when rates are low.

III. CONCLUSION

We have investigated whether there is a common factor governing the volatility of mortgage-backed securities and the possibility that this factor is dynamically priced—that is, linked to a time-varying risk premium. Using a factor GARCH model, it has been shown that a single common factor can successfully describe the time-varying volatility and the time-varying risk premium of MBS. Interestingly, all MBS returns exhibit significant mean reversion.

These findings are important for risk management as well as pricing of MBS.

ENDNOTES

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[1]For details on the properties of GARCH(1,1) processes see Bollerslev [1996].

[2]Similar results are obtained when an equally weighted portfolio of MBS returns is used as the common dynamic factor.

[3]For more information on GOLD MBS, see Fabozzi [1996, p. 235].

[4]Koutmos and Pericli [2000] compare the effectiveness of the ten-year, five-year, and two-year futures on Treasuries in hedging the price risk of MBS. They find that the ten-year future provides the most efficient hedging.

[5]Such processes are said to be integrated of order one.

[6]Chan et al. [1992], for example, find no significant mean reversion for U.S. short-term rates while Koutmos [2000] reports similar findings for several international short-term rates.

REFERENCES

Berndt, E.K., B.H. Hall, R.E. Hall, and J. Hausman. "Estimation and Inference in Nonlinear Structural Models." *Annals of Economic and Social Measurement,* 3 (1974), pp. 653-665.

Bollerslev, Tim. "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics,* 31 (1996), pp. 307-327.

Bollerslev, Tim, Ray Y. Chou, and Kenneth F. Kroner. "ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence." *Journal of Econometrics,* 52 (1992), pp. 5-59.

Bollerslev, Tim, and J.M. Wooldridge. "Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances." *Econometric Reviews,* 11 (1992), pp. 143-172.

Breeden, Douglas T. "Risk-Return and Hedging of Fixed-Rate Mortgages." *Journal of Fixed Income,* September 1991, pp. 85-107.

Brennan, M.J., and E.S. Schwartz. "Determinants of GNMA Mortgage Prices." *Real Estate Economics, AREUEA,* 13 (1985), pp. 209-228.

Brenner, R.J., R.H. Harjes, and K. Kroner. "Another Look at Models of the Short-Term Interest Rate." *Journal of Financial and Quantitative Analysis,* 31 (1996), pp. 85-107.

Chan, K.C., G.A. Karolyi, F.A. Longstaff, and A.B. Sanders. "An Empirical Comparison of Alternative Models of the Short-Term Interest Rate." *Journal of Finance,* 47 (1992), pp. 1209-1227.

Dickey, D.A., and W.A. Fuller. "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root." *Econometrica,* July 1981, pp. 1057-1072.

Dunn, K.B., and J. McConnell. "A Comparison of Alternative Models for Pricing GNMA Mortgage-Backed Securities." *Journal of Finance,* 36 (1981), pp. 471-484.

Engle, Robert F., David M. Lilien, and Russel P. Robins. "Estimating Time-Varying Risk Premia in the Term Structure: The ARCH-M Model." *Econometrica*, 55 (1987), pp. 391-407.

Engle, Robert F., Victor K. Ng, and Michael Rothschild. "Asset Pricing with a Factor ARCH Covariance Structure: Empirical Estimates for Treasury Bills." *Journal of Econometrics,* 45 (1990), pp. 213-237.

Fabozzi, Frank J. *Bond Markets, Analysis and Strategies,* 3rd ed. Englewood Cliffs, NJ: Prentice-Hall, 1996.

Koutmos, G. "Modeling Short-Term Interest Rate Volatility: Information Shocks Versus Interest Rate Levels." *The Journal of Fixed Income,* 9 (2000), pp. 19-26.

Koutmos, G., K. Kroner, and A. Pericli. "Dynamic Cross Hedging with Mortgage-Backed Securities." *The Journal of Fixed Income,* 8 (1998), pp. 37-51.

Koutmos, G., and A. Pericli. "Hedging GNMA Mortgage-Backed Securities with T-Note Futures: Dynamic Versus Static Hedging." *Real Estate Economics AREUEA,* 27 (1999), pp. 335-363.

——. "Hedging Price Risk in MBS: Are Multiple Instruments Better than One?" *The Journal of Portfolio Management,* Winter 2000, pp. 63-70.

Ng, Victor K., Robert F. Engle, and Michael Rothschild. "A Multi-Dynamic Factor Model for Stock Returns." *Journal of Econometrics,* 52 (1992), pp. 245-266.

Phillips, P.C.B., and P. Perron. "Testing for a Unit Root in Time Series Regression." *Biometrika*, 75 (1988), pp. 335-346.

Ross, Stephen A. "The Arbitrage Theory of Capital Asset Pricing." *Journal of Economic Theory,* 13 (1976), pp. 341-360.