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ABSTRACT

The Euler equations derived from a broad range of intertemporal asset pricing models, together with the first two unconditional moments of asset returns, imply a lower bound on the volatility of the intertemporal marginal rate of substitution. We develop and implement statistical tests of these lower bound restrictions. We conclude that the availability of relatively short time series of consumption data undermines the ability of tests that use the restrictions implied by the volatility bound to discriminate among different utility functions.

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Testing Volatility Restrictions on Intertemporal Marginal Rates of Substitution Implied by Euler Equations and Asset Returns

Recent empirical research on asset pricing has examined the restrictions on the volatility of a representative consumer's intertemporal marginal rate of substitution (IMRS) implied by asset return data. The pioneering work of Hansen and Jagannathan (1991) shows that the Euler equations derived from a broad range of intertemporal asset pricing models, together with the first two unconditional moments of asset returns, imply a lower bound on the volatility of the IMRS. For an IMRS with a given mean, they derive and compute the minimum standard deviation it must possess. The goal of their work is to restrict the parameter space for a given class of preferences that can be used to understand the dynamics of asset pricing. The purpose of this paper is to develop and implement a statistical procedure for judging whether a particular model of preferences meets Hansen and Jagannathan's lower volatility bound.

The computation of the lower volatility bound has recently developed into a widely used diagnostic tool for assessing the usefulness of a number of classes of preference orderings. For example, Burnside (1990), Epstein and Zin (1991), Hansen and Jagannathan (1991), Heaton (1991a), and Ferson and Harvey (1992) all compare the lower volatility bound, computed from stock and bond returns data, with estimates of the mean and standard deviation of the IMRS implied by various utility functions, computed using data on aggregate U.S. consumption. Snow (1991) examines higher order moments, Bakaert and Hodrick (1992) apply the volatility bound analysis to the study of international equity returns data, while Backus, Gregory and Telmer (1991) use these methods in an attempt to understand foreign currency returns.¹

Thus far, researchers have employed this analysis by comparing point estimates of the volatility bound with point estimates of the mean and standard deviation of the IMRS implied by a specific utility function. While the comparison of point estimates may be useful for some purposes, there will be occasions where the investigator will

¹The recent paper by Cochrane and Hansen (1992) provides a survey of work on this topic.

want to employ formal tests of the restrictions that are implied. This paper develops and uses such a test.

Our approach is to formulate a procedure that accounts for the two sources of uncertainty that arise in the comparison of the mean and standard deviation of the IMRS implied by a particular model of preferences with the bound that is computed from asset returns data. First, because the volatility bound itself is estimated from the data, it is random. Second, the computation of the mean and standard deviation of the IMRS using a specific utility function relies on estimates of the moments of the consumption process, and so it too is random. As a consequence, a formal statistical evaluation of the restrictions imposed by the implied lower volatility bound requires a test of whether the difference between two random variables is zero.

We apply our test to four extensively studied data sets, and three popular preference specifications. We study both annual and monthly data on consumption, equity returns, and short term Treasury debt, as well as data that combines monthly U.S. consumption data with monthly Treasury bill term structure data and with monthly U.S. dollar returns on five major foreign currencies. The utility functions we consider are a one-lag model of consumption durability, a one-lag habit persistence model, and the conventional time-separable constant relative risk aversion model (CRRA).

An important issue that we address concerns the relative size of the two sources of sampling variation that are present in our test statistic. We find that the uncertainty induced by random returns in the estimation of the lower volatility bound, for a given mean of the IMRS, is small relative to the uncertainty in the calculation of the mean and standard deviation of the IMRS based on a model of preferences. Put differently, most of the variation in the comparison of the two random variables in our test is the result of uncertainty induced by estimation the mean of the IMRS. This is the result of uncertainty contained in the consumption data, which appears to be relatively high. Our conclusion is that the availability of relatively short time series of consumption data — less than 100 years of annual data, and approximately 30 years of monthly data — seriously undermines the ability of tests that use the restrictions implied by the volatility bound to discriminate among different utility functions. For example,

using the monthly U.S. data set, the point estimates of the standard deviation of the IMRS implied by time-separable CRRA utility appear to lie a considerable distance from the implied volatility bound. But, setting the annualized time discount factor to 0.99, and a coefficient of relative risk aversion of 0.2, we find that the implied volatility restrictions cannot be rejected based on a two standard error rule.

The remainder of this paper is divided into four sections. In Section I we begin with a review of Hansen and Jagannathan's method for computing the volatility bound from data on asset returns. This is followed by a description of the utility functions we examine, along with a discussion of the stochastic model for consumption. We then show how to compute the IMRS implied by the class of preferences we consider, and derive the statistic used to test whether a model meets the restrictions implied by the volatility bound.² Section II reports results of the applications we study. Section III discusses how to impose the restriction that the mean of the IMRS is nonnegative and reformulates the testing methodology appropriately. Using this modified procedure, we examine the implication for one of our applications — the annual data on consumption, equity returns and Treasury debt. While the nonnegativity restriction tightens the point estimates of the volatility bound, raising the minimum standard deviation of the IMRS for a given mean, the standard errors grow so much that the test imposing nonnegativity is no more informative than the one without it. Finally, Section IV provides concluding remarks.

I. A Testing Framework

The purpose of this section is to derive a test to evaluate whether a particular model of preferences is consistent with the restrictions implied by Hansen and Jagannathan's volatility bound. We begin with a review of the method used to compute the bound from data on asset returns.

In Section I.B we describe the specific utility functions that we examine. These

²Burnside (1991) has independently devised a set of tests that are similar to the ones discussed in Section I.

include simple forms of preferences that allow for either consumption durability or habit persistence, as well as the conventional time-separable, constant relative risk aversion case. In order to derive the mean and standard deviation of the IMRS implied by each model of preferences, we require knowledge of the consumption process. Section I.C describes the stochastic model for consumption that we employ. To this end, we assume that the consumption growth rate follows a random walk in annual data, and a first-order autoregression in monthly data. Section I.D then presents the derivation of the mean and standard deviation of the IMRS for the examples we consider.

Finally, Section I.E describes the statistical testing procedure we employ to determine the class of preferences that meet the Hansen and Jagannathan restrictions. Since both the bound itself and the implied volatility of the IMRS for a given utility function depend on data, the comparison of the model to the bound is a test of whether the difference between two random variables equals zero. We exploit this reasoning, together with standard asymptotic distribution theory, in the derivation of the test.

Throughout this section we ignore one important implication of asset pricing theory — that the expected value of the IMRS must always be nonnegative. Hansen and Jagannathan argue that use of this information can substantially change the location of the volatility bound, and so it can further restrict the set of models that meet the restrictions implied by the bound. We defer discussion of this nonnegativity constraint until Section III, where we present a testing framework in which it is incorporated.

I.A The Hansen-Jagannathan Volatility Bound

We begin with a brief description of the derivation of the lower volatility bound on the IMRS first suggested by Hansen and Jagannathan (1991).³ The starting point

³In addition to the exposition in Hansen and Jagannathan, and the one presented below, there are numerous ways to describe the derivation of the volatility bound. See, for example, Cochrane and Hansen (1992) for another alternative.

is the set of Euler equations implied by intertemporal asset pricing problems. We write these as

$$q_{t-1} = E_{t-1}(v_t x_t) (1)$$

where $E_{t-1}(\cdot)$ is the conditional expectation given information at t-1, q_{t-1} is an (nx1) vector of asset prices at date t-1, x_t is the corresponding vector of date t asset payoffs, and v_t is the intertemporal marginal rate of substitution, which is the discounted ratio of marginal utilities at t and t-1. In returns form, q_{t-1} may be a vector of known constants and x_t a vector of gross returns. For example, q_{t-1} might be a vector of ones, so that each asset is defined to command a unit price in return for a stochastic 'payoff' equal to its gross return.

To continue, take unconditional expectations of both sides of equation (1), and use the law of iterated expectations, to obtain

$$\mu_q = E(v_t x_t) , \qquad (2)$$

where μ_q is defined as the unconditional expectation of q_{t-1} , $E(q_{t-1})$. Next, define $\mu_v = E(v_t)$, $\sigma_v^2 = E(v_t - \mu_v)^2$, $\mu_x = E(x_t)$ and $\Sigma_x = E(x_t - \mu_x)(x_t - \mu_x)'$, and then project $(v_t - \mu_v)$, the deviation of the IMRS from its mean, onto $(x_t - \mu_x)$, the deviation of the asset payoffs from their means, to obtain a set of coefficients β_v , such that

$$(v_t - \mu_v) = (x_t - \mu_x)'\beta_v + u_t , \qquad (3)$$

where u_t is the projection error. Using the definitions of the unconditional means and variances, we can write

$$\beta_{v} = \Sigma_{x}^{-1} [E(x_{t} - \mu_{x})(v_{t} - \mu_{v})]$$

$$= \Sigma_{x}^{-1} [E(x_{t}v_{t}) - \mu_{x}\mu_{v}]$$

$$= \Sigma_{x}^{-1} [\mu_{q} - \mu_{x}\mu_{v}], \qquad (4)$$

where the last equality in (4) makes use of the Euler equation (2). Now, using (3) and (4), together with the fact that the projection error u_t is orthogonal to x_t , we

can derive the variance of the IMRS. We write this as

$$\sigma_v^2 = (\mu_q - \mu_v \mu_x)' \Sigma_x^{-1} (\mu_q - \mu_v \mu_x) + E(u_t^2) . \tag{5}$$

Since $E(u_t^2)$ is nonnegative, it follows that

$$\sigma_v \ge \sigma_x \equiv [(\mu_q - \mu_v \mu_x)' \Sigma_x^{-1} (\mu_q - \mu_v \mu_x)]^{\frac{1}{2}}$$
 (6)

The right-hand-side of (6) is the lower volatility bound derived by Hansen and Jagannathan (1991) and we label it σ_x . Provided that μ_q is not a zero-valued vector, the bound is a parabola in (μ_v, σ_v) -space. As Hansen and Jagannathan note, the derivation of this volatility bound may be viewed as the dual to the mean-standard deviation efficient frontier analysis in the theory of finance, except that there is no guarantee that the returns used to generate the IMRS volatility bound are on the efficient frontier.

The current practice in examining the implications embodied in the lower bound is as follows. First a point estimate of the bound is computed using point estimates of μ_x and Σ_x from data on asset returns. Next, point estimates of μ_v and σ_v are computed using a particular utility function and consumption data. The investigator then asks which values (if any) of the preference parameters for the utility function result in (μ_v, σ_v) pairs that lie inside the parabola.

As we note in the introduction, this procedure may be useful for addressing certain questions. The question we ask is whether the mean and standard deviation of the IMRS of the model is 'close' to the parabola in a statistical sense. The purpose of the remainder of this section is to describe a method for answering this question.

I.B Preferences

The main use of the volatility bound is to provide a set of restrictions that allow us to restrict the parameter space for a given class of utility function. We begin by studying the utility functions examined by Hansen and Jagannathan (1991). They assume that the period utility function displays constant relative risk aversion defined over consumption services derived at t, S_t . Expected utility is the discounted expected sum of period utilities, and is written as

$$U_{t} = E_{t} \sum_{k=0}^{\infty} \beta^{k} \frac{S_{t+k}^{1-\gamma} - 1}{(1-\gamma)} , \qquad (7)$$

where β is the discount factor and consumption services are generated by a simple one-lag model in consumption expenditure, C_t , such that

$$S_t = C_t + \delta C_{t-1} . (8)$$

This utility function includes three cases of interest. When $\delta = 0$, (7) is the familiar time-separable constant relative risk aversion formulation. For $\delta > 0$, (7) implies that consumption purchases contain a durable component of the type studied by Dunn and Singleton (1986) and Eichenbaum, Hansen and Singleton (1988). Finally, negative values of δ imply the kind of habit persistence Constantinides (1990) has found useful in explaining the equity premium puzzle.⁴

Using (7) and (8), we can write the IMRS between t and t+1 as

IMRS_{t,t+1} =
$$\frac{\beta[S_{t+1}^{-\gamma} + \beta \delta E_{t+1}(S_{t+2}^{-\gamma})]}{S_t^{-\gamma} + \beta \delta E_t(S_{t+1}^{-\gamma})} . \tag{9}$$

We will use (9), together with consumption data, to compute the mean and standard deviation of the IMRS, given values of the preference parameters (β, γ, δ) . For the familiar CRRA case in which $\delta = 0$, $\mathrm{IMRS}_{t,t+1} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}$, and so the mean and standard deviation, μ_v and σ_v , can be estimated nonparametrically from consumption data. For nonzero values of δ we must evaluate the conditional expectations in (9) parametrically. This requires that we specify the stochastic process governing consumption growth.

⁴We note that Heaton (1991) examines a model that combines aspects of both durability and habit persistence, while Ferson and Constantinides (1991) provide empirical evidence for this specification of the utility function.

I.C A Stochastic Process for Consumption Growth

Our goal is to examine data at both annual and monthly frequencies. As such, we must select a model for both annual and monthly consumption growth. It is useful to begin with a brief description of the consumption data we study. The annual real consumption series we use is for per capita nondurables plus services. From 1889 to 1928, this series is the data used in Grossman and Shiller (1981), and was provided by Robert Shiller. Beginning in 1929, and continuing through 1987 we use the NIPA series for real personal consumption expenditure on nondurables and services. Monthly data is the seasonally adjusted series on real consumption of nondurables and services from April 1964 to December 1988 obtained from CITIBASE.

In order to choose a stochastic model, we first estimate a fourth-order autoregression for the annual data, and a twelfth-order autoregression for the monthly data.⁵ The top panel of Table I reports ordinary least squares estimates of these simple autoregressions. The results clearly suggest that the annual data is well approximated by a random walk, and so this is the model that we use. For the monthly data, the coefficient on the first lag of consumption growth is -0.2704 with a t-statistic of 5.1, and a Wald test fails to reject that the second through twelfth coefficients are zero simultaneously. The p-value of this joint test is 0.121. We take these results to suggest that monthly consumption growth can be accurately modeled as an AR(1). The final estimates are reported in the bottom panel of Table I.⁶

⁵We find that the results are robust to changes in the process for consumption. See footnote 14

⁶We realize that the AR(1) for monthly data does not aggregate to a random walk at an annual frequency. The inconsistency could easily be explained by the fact that the data is time averaged. As He and Modest (1991) point out, the most common method for dealing with this is to assume a process for spot consumption, and derive the statistical implications for time-aggregated consumption. Heaton (1991a) examines this problem at length, and shows that use of data averaged over long periods of time reduces the impact of time-aggregation bias. For other discussions of the problems induced by time-aggregation see Grossman, Melino and Shiller (1987) and Breeden, Gibbons and Litzenberger (1989).

Table I: Estimated Consumption Processes
Annual and Monthly Real U.S. Consumption Growth Rates

	I. Autoregressions										
11	nnual Data 1		Monthly Data 1964:4-1988:12								
Four	th-order auto	oregression	Twel	fth-order aut	oregression						
	Coefficient	Standard Error		Coefficient	Standard Error						
Constant	0.0185	0.0054	Constant	0.0011	0.0004						
Lag 1	-0.0972	0.1398	Lag 1	-0.2989*	0.0470						
Lag 2	0.1651	0.1343	Lag 2	0.0329	0.0521						
Lag 3	-0.0670	0.0904	Lag 3	0.1130	0.0544						
Lag 4	-0.0567	0.1085	Lag 4	-0.0254	0.0596						
			Lag 5	0.0185	0.0549						
			Lag 6	0.0117	0.0497						
			Lag 7	0.0452	0.0517						
			Lag 8	0.0801	0.0462						
			Lag 9	0.0304	0.0531						
			Lag 10	0.1134*	0.0543						
			Lag 11	0.1463*	0.0492						
			Lag 12	0.0119	0.0504						

II. Final Estimates										
	ll .	Data 1890-1987	Monthly Data 1964:04-1988							
	1	idom Walk	First-order autoregression							
Parameter	Estimate Standard Error		Estimate	Standard Error						
μ_c	0.0172	0.0029	0.0016	0.0002						
σ_c^2	0.0012	0.0003	1.9e-5	1.5e-6						
ρ			-0.2839	0.0511						

Notes: Standard errors are robust to conditional heteroskedasticity. Asterisks indicate significance at the 5 percent level. The final parameter estimates and their standard errors taken from generalized method of moments estimates of the parameter vector θ and its covariance matrix, Σ_{θ} .

I.D The Mean and Standard Deviation of the IMRS

Using the stochastic model for consumption growth, we can now compute the mean and standard deviation of the IMRS implied by the preferences described in Section I.B. We consider both the case in which the sampling interval for the data and the holding period interval over which returns are computed are the same, and the one in which they are not. For the case of monthly data, this means that we are examining monthly data on both one and three month holding period returns, using a stochastic model of consumption that is assumed to be monthly.

We begin with the simpler case in which the holding period interval and the sampling interval coincide. First, write the consumption growth process as

$$m_t = \mu_c(1 - \rho) + \rho m_{t-1} + \epsilon_t , \qquad (10)$$

where m_t is the consumption growth rate, defined as $ln\left(\frac{C_t}{C_{t-1}}\right)$, and ϵ_t is an i.i.d. normal random variable with mean zero and variance σ_c^2 . Using (10), the IMRS, (9), can be rewritten as

$$IMRS_{t,t+1} = \mathcal{K}(m_t, m_{t+1}) = \frac{\beta e^{-\gamma m_t} \left[(e^{m_{t+1}} + \delta)^{-\gamma} + \beta \delta e^{-\gamma m_{t+1}} E_{t+1} (e^{m_{t+2}} + \delta)^{-\gamma} \right]}{(e^{m_t} + \delta)^{-\gamma} + \beta \delta e^{-\gamma m_t} E_t (e^{m_{t+1}} + \delta)^{-\gamma}}$$
(11)

where

$$\begin{split} E_t(e^{m_{t+1}}+\delta)^{-\gamma} &= \int_{\underline{\epsilon}}^{\infty} \left[e^{(\mu_c(1-\rho)+\rho m_t+\epsilon)} + \delta \right]^{-\gamma} \Phi_c(\epsilon) d\epsilon \ , \\ \underline{\epsilon} &= \left\{ \begin{array}{ll} -\infty & \text{if } \delta \geq 0 \\ \ln(-\delta) - \mu_c(1-\rho) - \rho m_t & \text{if } \delta < 0 \end{array} \right. \end{split}$$

and $\Phi_c(\epsilon)$ is the normal p.d.f. with mean zero and variance σ_c^2 .

The consumption process in (10) implies that ϵ can take on very small values. When δ is negative, and ϵ is sufficiently small, then (11) would require that we calculate the value of a negative number raised to the power $-\gamma$. This problem leads us to put a lower bound on the value of ϵ when we integrate the expression used to compute the IMRS. This lower bound is labeled $\underline{\epsilon}$. The definition of the $E_t(e^{mt+1}+\delta)^{-\gamma}$ in (11) is not entirely consistent with the stochastic process for consumption being correct, since (11) permits ϵ to take on large negative values with nonzero probability. In practice, this is not a serious problem as $\epsilon < \underline{\epsilon}$ is extremely unlikely for all of the cases we consider. The quadrature rule we use to compute a discrete approximation to the normal density never strays

It follows from (10) that the unconditional distribution of (m_t, m_{t+1}) is bivariate normal

$$\left[\begin{array}{c} m_t \\ m_{t+1} \end{array}\right] \sim N \left[\left(\begin{array}{c} \mu_c \\ \mu_c \end{array}\right), \frac{\sigma_c^2}{1-\rho^2} \left(\begin{array}{c} 1 & \rho \\ \rho & 1 \end{array}\right) \right] \ .$$

We denote this distribution $\Phi(m_t, m_{t+1})$. Now, using (11), we compute the mean and standard deviation of the IMRS as⁸

$$\mu_{v} = \int_{m}^{\infty} \int_{m}^{\infty} \mathcal{K}(m, m') \Phi(m, m') dm dm'$$
 (12)

and

$$\sigma_v^2 = \int_m^\infty \int_m^\infty [\mathcal{K}(m, m') - \mu_v]^2 \Phi(m, m') dm dm' , \qquad (13)$$

where

$$\underline{m} = \begin{cases} -\infty & \text{if } \delta \ge 0\\ \ln(-\delta) & \text{if } \delta < 0 \end{cases}.$$

When the holding period interval is k periods, for a data sampling interval of one period, then the relevant IMRS is the one from period t to period t + k. Using the consumption process (10), we can write this as

IMRS_{t,i+k} =
$$\Lambda(m_t, m_{t+k}, \sum_{i=0}^{k-1} m_{t+i})$$
 (14)
= $\beta^k e^{-\gamma \sum_{i=0}^{k-1} m_{t+i}} \frac{[(e^{m_{t+k}} + \delta)^{-\gamma} + \beta \delta e^{-\gamma m_{t+k}} E_{t+k} (e^{m_{t+k+1}} + \delta)^{-\gamma}]}{[(e^{m_t} + \delta)^{-\gamma} + \beta \delta e^{-\gamma m_t} E_t (e^{m_{t+1}} + \delta)^{-\gamma}]}$.

The consumption process implies that $\{m_t, m_{t+k}, \sum_{i=0}^{k-1} m_{t+i}\}$ is multivariate normal, given by

$$\left[\begin{array}{c} m_t \\ m_{t+k} \\ \sum_{i=0}^{k-1} m_{t+i} \end{array} \right] \sim N \left[\left(\begin{array}{c} \mu_c \\ \mu_c \\ k\mu_c \end{array} \right), \frac{\sigma_c^2}{1-\rho^2} \left(\begin{array}{ccc} 1 & \rho^k & \sum_{i=0}^{k-1} \rho^i \\ \rho^k & 1 & \sum_{i=1}^k \rho^i \\ \sum_{i=1}^{k-1} \rho^i & \sum_{i=1}^k \rho^i & k+2 \sum_{i=1}^{k-1} (k-i) \rho^i \end{array} \right) \right],$$

into the portion of the density where $\epsilon < \underline{\epsilon}$. This implies that our quadrature rule will yield the same results regardless of whether we impose a lower bound on ϵ .

⁸The use of \underline{m} in equations (12) and (13) is for reasons exactly analogous to the ones that required $\underline{\epsilon}$ in equation (11). See footnote 7.

which we label Γ .

The analogs to (12) and (13) follow as

$$\mu_{\nu k} = \int_{-\infty}^{\infty} \int_{m}^{\infty} \int_{m}^{\infty} \Gamma(m, m', m'') \Lambda(m, m', m'') dm dm' dm''$$
 (15)

and

$$\sigma_{\nu k}^2 = \int_{-\infty}^{\infty} \int_{\underline{m}}^{\infty} \int_{\underline{m}}^{\infty} [\Gamma(m, m', m'') - \mu_{\nu k}]^2 \Lambda(m, m', m'') dm dm' dm''$$
 (16)

with \underline{m} defined as it is in the simple case above.

In the applications, all of these integrals are evaluated using a 13-point Gauss-Hermite quadrature rule.

I.E Testing the Restrictions of the Volatility Bound

We now examine whether the model implied value for the standard deviation of the IMRS is consistent with the bound derived from the asset returns data. This involves asking whether the model values estimated using consumption data, $\hat{\sigma}_v$, is near the bound implied by the asset returns data, using equation (6).

In order to conduct such a comparison, begin by defining ψ as the vector of parameters associated with the stochastic process governing consumption growth. For the AR(1) model of Section I.C, $\psi = (\mu_c, \sigma_c, \rho)$. Next, define ϕ as the vector of parameters that characterize the utility function, (β, γ, δ) . Finally, recall that μ_q is the mean vector of the asset prices, and μ_x and Σ_x are the mean vector and covariance matrix of asset payoffs.

We now stack all of the parameters that must be estimated from the data into the vector θ , such that

$$\theta = \begin{pmatrix} \mu_q \\ \mu_x \\ \text{vec}(\Sigma_x) \\ \psi \end{pmatrix}$$

where $\text{vec}(\Sigma_x)$ is the vector obtained by stacking all of the unique elements of the

symmetric matrix Σ_x . Now let θ_o be the true value of θ , and $\hat{\theta}$ be a consistent estimator of θ_o such that $\sqrt{T}(\hat{\theta}-\theta_o) \stackrel{D}{\to} N(0,\Sigma_{\theta})$. We presume that we have available a consistent estimator of both θ_o and Σ_{θ} . In the applications, we compute $\hat{\theta}$ and $\hat{\Sigma}_{\theta}$ by generalized method of moments, in which $\hat{\Sigma}_{\theta}$ is the Newey and West (1987) covariance matrix estimator with 11 lags.

Using this notation, we can make explicit the fact that the moments of the IMRS and the volatility bound both depend on the sample. The estimated mean and standard deviation of the model values of the IMRS are $\hat{\mu}_{\nu} = \mu_{\nu}(\phi; \hat{\psi})$ and $\hat{\sigma}_{\nu} = \sigma_{\nu}(\phi; \hat{\psi})$, while the estimated volatility bound is

$$\hat{\sigma}_x = \sigma_x(\phi; \hat{\theta}) = [(\hat{\mu}_g - \mu_v(\phi; \hat{\psi})\hat{\mu}_x)'\hat{\Sigma}_x^{-1}(\hat{\mu}_g - \mu_v(\phi; \hat{\psi})\hat{\mu}_x)]^{\frac{1}{2}}.$$
 (17)

The comparison of the estimated volatility bound, $\sigma_x(\phi; \hat{\theta})$, and the estimated model implied standard deviation of the IMRS, $\sigma_v(\phi; \hat{\psi})$, can be carried out by examining the difference

$$\Delta(\phi; \hat{\theta}) = \sigma_x(\phi; \hat{\theta}) - \sigma_v(\phi; \hat{\psi}) . \tag{18}$$

In order to evaluate whether this difference is large, we require an estimate of the variance of $\Delta(\phi; \hat{\theta})$. This is constructed from the distribution of $\hat{\theta}$.

To proceed, take a mean-value expansion of Δ about θ_o . It follows that

$$\sqrt{T}(\Delta(\phi; \hat{\theta}) - \Delta(\phi; \theta_o)) \stackrel{D}{\rightarrow} N(0, \sigma_{\Delta}^2)$$
,

where

$$\sigma_{\Delta}^2 = \left. \left(\frac{\partial \Delta}{\partial \theta'} \right) \right|_{\theta_o} \Sigma_{\theta} \left. \left(\frac{\partial \Delta}{\partial \theta} \right) \right|_{\theta_o} \ .$$

⁹For all of our applications, μ_q is simply a vector of known constants, and so it can be omitted from the specification of θ .

¹⁰The vector θ is estimated using the first two moments of asset returns, the first two moments of consumption growth and the first order autocovariance of consumption growth.

¹¹The results do not appear sensitive to the number of lags used to compute the robust covariance matrix. For example, there is little change when only three lags are used.

This can be consistently estimated by

$$\hat{\sigma}_{\Delta}^{2} = \left(\frac{\partial \Delta}{\partial \theta'}\right) \Big|_{\hat{\theta}} \hat{\Sigma}_{\theta} \left(\frac{\partial \Delta}{\partial \theta}\right) \Big|_{\hat{\theta}} . \tag{19}$$

A test of whether a particular model meets the volatility restriction can now be constructed by testing the null hypothesis, $H_o: \Delta(\phi;\theta_o) \leq 0$. We advance this test procedure as a tool for constructing the regions of the preference parameter space that are not rejected by the volatility bound at various levels of significance. In particular, we compute the ratio $\Delta(\phi;\hat{\theta})/\hat{\sigma}_{\Delta}$ and look for values of ϕ that make it small. Since this ratio is asymptotically normal, we can construct the regions of the preference parameter space that are not rejected by the volatility bound at various levels of statistical significance. Given that H_o is an inequality, these tests are one-sided, and so appropriate critical values are -1.65 for tests at the five-percent level, and -2.33 for tests at the one-percent level. Implementation of this test is the task of Section II.

II. Applications

In this section we test the volatility bound restrictions using four well-known data sets on asset returns. We examine both annual and monthly data on equity returns and short term Treasury debt in the U.S., monthly returns on a portfolio constructed from the U.S. Treasury Bills term structure, and monthly U.S. dollar returns on five major foreign currencies. For each data set, we study the three forms of preferences described in Section I.B: (1) time-separable CRRA, (2) one-lag durability, (3) one-lag habit persistence. In all cases, we report representative values of the preference parameters.¹²

¹²All of the results were computed using FORTRAN programs, and checked with programs written in GAUSS. As a further check on the integrity of our results, both numerical and analytical derivatives were used in most of our computations.

2.A Annual U.S. Equity and Short Term Bond Returns: 1890-1987

The first returns data set we examine is the one used in Cecchetti, Lam and Mark (1991) to study the equity premium puzzle. The exact sources of the data are described in the Appendix to that paper. Briefly, the data set combines the annual consumption data described in Section I.C with annual returns on two assets: the Standard and Poors' index supplied by Campbell and Shiller (1987) and one year U.S. Treasury note yields, or their equivalent. Real returns are computed by deflating nominal values using the CPI.

The results of the testing procedure are in Table II. For the purposes of these example, we have set the discount factor equal to 0.99 and 1.02.¹³ The top panel of the table reports the results for the case of time-separable utility ($\delta = 0$), the middle panel includes results for the durability model with $\delta = +0.5$, and the bottom panel presents results for the habit persistence model with $\delta = -0.5$. Each row contains estimates for a particular value of the curvature parameter γ . For each discount factor, we report the model implied values of the mean and standard deviation of the IMRS, $\mu_{\nu}(\phi; \hat{\psi})$ and $\sigma_{\nu}(\phi; \hat{\psi})$, the volatility bound evaluated at $\mu_{\nu}(\phi; \hat{\psi})$, $\sigma_{x}(\phi; \hat{\theta})$, and the t-ratio associated with the comparison of model with the bound, $\Delta(\phi; \hat{\theta})/\hat{\sigma}_{\Delta}$.

The main results are as follows.¹⁴ For the case of time-separable utility and $\beta = 0.99$, the difference between the model and volatility bound is less than 1.65 standard deviations when γ is 10 or higher. With a discount factor of 1.02, then

¹³Following the theoretical arguments in Kocherlakota (1990), and the empirical evidence in our earlier paper [Cecchetti, Lam and Mark (1991)] we include values of β that exceed one.

¹⁴The results reported below are all robust to changes in the specification of the consumption process. Using the annual data, we have examined two additional cases: (1) consumption growth follows a simple AR(1) identical to the one used for monthly data, and (2) consumption growth is governed by the simple Markov switching model described and estimated in Cecchetti, Lam and Mark (1991). Using an AR(1), we obtain nearly identical results to the ones reported in Table 2. For the Markov Switching model, there is no material change in the results either. However, we do find that there is a smaller difference between the time-separable and the one-lag durability cases than is suggested by the results obtained using a random walk. For example, if $\beta = 0.99$ and utility is time-separable, the lowest γ not rejected by a t-test at the 5 percent level is 12 for the random walk case, 14 for the case when consumption growth is an AR(1), and 13 for the Markov Switching model. If $\delta = 0.5$, and so preferences exhibit durability, the equivalent values of γ are 22, 23 and 17, respectively.

Table II: Tests of the Volatility Bound Restriction (Annual Data on Equity Returns, 1890-1987)

	I. Time-separable utility: $\delta = 0$								
		$\beta =$	0.99	$\beta = 1.02$					
$ \gamma $	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_{m{x}}$		$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_{\boldsymbol{x}}$	t-ratio	
$\frac{\gamma}{0}$	0.990	0.000	0.320	-3.633	1.020	0.000	0.711	-3.073	
1	0.973	0.033	0.411	-2.201	1.003	0.034	0.437	-2.563	
2	0.958	0.066	0.644	-2.442	0.987	0.068		-2.537	
4	0.931	0.131	1.123	-2.615	0.959	0.135	0.620	-1.420	
10	0.881	0.339	2.063	-1.881	0.908	0.349		-1.343	
15	0.874	0.556	2.201	-1.103	0.900			-0.753	
20	0.900	0.850	1.698	-0.375	0.928	0.876		-0.137	
25	0.967	1.269	0.502	0.276	0.996	1.308		0.803	
30	1.084	1.883	1.889	-0.002	1.116	1.940	2.516	-0.139	
	II.			able utili	ty: $\delta =$				
		,	0.99				1.02		
γ	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio	
0	0.990	0.000		-3.633	1.020	0.000		-3.073	
1	0.973	0.027	0.413	-2.260	1.002	0.028		-2.607	
2	0.957	0.052	0.657	-2.595	0.986	0.054	0.315	-2.562	
4	0.928	0.102	1.182	-2.951	0.956	0.105	0.674	-1.717	
10	0.861	0.238	2.457	-2.684	0.887	0.246		-2.136	
15	0.825	0.351	3.146	-2.264	0.850	0.362		-1.881	
20	0.805	0.474	3.526	-1.805	0.830			-1.509	
25	0.800	0.620	3.610	-1.335	0.825	0.641		-1.098	
30	0.812	0.808	3.391	-0.876	0.837	0.836	2.901	-0.687	
I	II. Tim			utility: 8	$\delta = -0.5$			ence)	
			0.99				1.02		
γ	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_x$		$\hat{\mu}_{v}$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio	
0	0.990	0.000	0.320	-3.633	1.020	0.000			
1	0.979	0.115	0.347	-1.440	1.009	0.121			
2	0.982	0.231	0.330	-0.514	1.013	0.244		-1.225	
3	0.997	0.357	0.372	-0.068	1.030	0.377	0.894	-1.032	
4	1.028	0.504	0.848	-0.472	1.064	0.535	1.524	-1.167	
5	1.077	0.692	1.767	-0.864	1.119	0.744	2.575	-1.329	
6	1.154	0.983	3.244	-1.095	1.209	1.105	4.295	-1.397	

Tests use data for consumption, returns on the S&P index, and one-year T-bills (or the equivalent), 1890-1987. For chosen values of the subjective discount factor (β) , curvature parameter, (γ) , and lagged-consumption parameter (δ) , we estimate the mean $(\hat{\mu}_{\nu})$ and standard deviation $(\hat{\sigma}_{\nu})$ of the IMRS, and the lower volatility bound $(\hat{\sigma}_{x})$. Test statistic (t-ratio) is constructed under the null hypothesis $(\sigma_{v} = \sigma_{x})$.

values of γ below 4 are consistent with the bound. We contrast this with results that are based solely on the point estimates. Using these data, obtaining point estimates of (μ_v, σ_v) that lie within the volatility bound requires values of γ above 25.

The middle panel of Table II displays results for the one-lag durability model in which $\delta = +0.5$. Again, we report calculations based on γ from 0 to 30, with $\beta = (0.99, 1.02)$. As is well known, for given values of β and γ , this model of preferences produces uniformly less variability in the IMRS than the time-separable model. But even so, the one-lag durability model cannot be rejected at the five-percent level for $\gamma \geq 20$ when $\beta = 0.99$, and for $\gamma \geq 4$ when $\beta = 1.02$.

Results from the third case we consider, one-lag habit persistence with $\delta=-0.5$, are reported in the bottom panel of Table II. Here we allow for γ ranging from zero to six. As one would expect, habit persistence yields substantially more variation in the IMRS for any given value of γ . Consequently, no γ 's from one to six is rejected using the 1.65 standard error rule when $\beta=0.99$. In addition, with $\beta=1.02$, γ from two to six are not rejected at the five-percent level.¹⁵

Our results are driven by the fact that the point estimate of the mean of the IMRS for a particular model of preferences, $\hat{\mu}_v(\phi;\hat{\psi})$, is very imprecise. To show this, Table III reports a decomposition of the uncertainty in the comparison of σ_v with σ_x for the time-separable case. We think of this uncertainty as arising from three basic sources. Given the expected value of the IMRS, μ_v , there is uncertainty in both the location of the bound, σ_x , and in the mean of the standard deviation implied by the model, σ_v . In addition, there is uncertainty induced by the fact that

$$q_t' = \{1, 1, r_{1,t-1}, r_{2,t-1}, r_{1,t-1}, r_{2,t-1}, n_{t-1}, n_{t-1}\}$$

and

$$x_i' = \{r_{1,t}, r_{2,t}, r_{1,t}r_{1,t-1}, r_{1,t}r_{2,t-1}, r_{2,t}r_{1,t-1}, r_{2,t}r_{2,t-1}, r_{1,t}n_{t-1}, r_{2,t}n_{t-1}\} \ .$$

¹⁵For all of these cases, as well as those in Section II.B, we have examined the impact of expanding the number of assets from two to eight by multiplying each of the original asset prices by the lagged gross return of the assets and the lagged consumption growth rate. Writing the problem in returns form, denoting the gross return on debt as $r_{1,t}$, the gross return on equity as $r_{2,t}$ and n_t as the consumption growth rate we consider

The effect of creating these additional assets is to raise the point estimate of volatility bound, but when the standard errors are considered, it does not substantively alter the results.

¹⁶We thank Robert Stambaugh for pointing this out.

Table III: Comparison of Sources of Uncertainty

μ_v :	fixed	fixed	fixed	random	random	random	random
Returns:	random	n.a.	random	fixed	n.a.	fixed	random
γ	$s.e.(\hat{\sigma}_x)$	$s.e.(\hat{\sigma}_v)$	s.e. $(\hat{\Delta})$	$s.e.(\hat{\sigma}_x)$	s.e. $(\hat{\sigma}_v)$	s.e. $(\hat{\Delta})$	$\mathrm{s.e.}(\hat{\Delta})$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
O O	0.088	0.000	0.088	0.000	0.000	0.000	0.088
1	0.151	0.089	0.204	0.037	0.087	0.050	0.172
4	0.184	0.101	0.260	0.226	0.087	0.139	0.380
8	0.257	0.129	0.352	0.505	0.089	0.416	0.724
10	0.286	0.147	0.392	0.670	0.091	0.579	0.917
15	0.305	0.209	0.456	1.190	0.098	1.092	1.492
20	0.240	0.303	0.489	1.911	0.107	1.805	2.265
25	0.160	0.444	0.565	2.346	0.119	2.227	2.774
30	0.432	0.663	0.738	4.472	0.135	4.608	4.010

Standard errors for estimated lower volatility bound $(\hat{\sigma}_x)$, IMRS standard deviation $(\hat{\sigma}_v)$, and the difference $(\hat{\Delta} = \hat{\sigma}_v - \hat{\sigma}_x)$, under alternative assumptions regarding the sources of uncertainty. The utility function is time-separable; γ is the coefficient of relative risk aversion and β =0.99 is the subjective discount factor. Annual data for consumption, returns on the S&P index, and one-year T-Bills (or the equivalent), 1890-1987.

mean IMRS for the model, μ_v , must be estimated.

For each value of γ , Table 3 reports a decomposition of the uncertainty in the estimate of $\Delta = (\sigma_v - \sigma_x)$ into its components. The standard error of the estimate of the Hansen-Jagannathan bound for fixed μ_v , $\hat{\sigma}_x$, is in column (2).¹⁷ Columns (3) and (4) report standard errors for $\hat{\sigma}_v$ and $\hat{\Delta}$, again for fixed μ_v . The next three columns of the Table, labelled (5), (6) and (7), report the uncertainty in $\hat{\sigma}_x$, $\hat{\sigma}_v$ and $\hat{\Delta}$, that arises solely due to randomness in $\hat{\mu}_v$. The final column of the table is our estimate of the 'total' standard error in $\hat{\Delta}$, $\hat{\sigma}_{\Delta}$, computed using the technique described in Section I.E.¹⁸

The results in the table show clearly that the main source of uncertainty is the fact that μ_v must be estimated. For example, when γ equals 15, then the estimate of σ_Δ , including all sources of uncertainty, is 1.49, of which approximately two-thirds can be attributed to the uncertainty arises from the estimation of the mean of the IMRS. The source of the uncertainty in the estimate of μ_v can be linked to the consumption data, since error in estimating the moments of consumption growth lead directly to variance in the estimate of the mean IMRS from the model. Consequently, we conclude that the large standard errors associated with the comparison of the volatility bound with the IMRS moments implied by the models of preferences can be traced to the relatively high uncertainty contained in the consumption data.

II.B Monthly U.S. Equity and Short Term Bond Returns: 1964-1988

We now examine a monthly U.S. data set that combines the consumption data described in Section I.C with the return to the CRSP valued-weighted index of NYSE stocks and the one month holding period return to three-month Treasury Bills.¹⁹

¹⁷Hansen and Jagannathan (1988), an earlier version of the 1991 paper, studies this source of uncertainty.

¹⁸We note that all of these quantities can be computed by setting various elements in equation (19) to zero. The presence of nonzero covariances implies that entries in the Table need not add up to other elements in the same row.

¹⁹It is common to use the one-month Treasury Bill for this exercise. But, as discussed in Section II.C below, we feel that the one-month data have problems that do not arise at longer maturities.

The two return series are from the 'Fama file' available from CRSP. Real returns are constructed using the implicit price deflator for consumption of nondurables and services. The complete data set extends from April 1964 to December 1988.

Any attempt to meet the restrictions of the volatility bound using monthly data is hampered by the relative smoothness of consumption growth during this time period. As Hansen and Jagannathan (1991) show, this lack of variation in consumption growth prevents the point estimates of the mean and standard deviation of the IMRS implied by the time-separable ($\delta = 0$) and the one-lag durability ($\delta = +0.5$) models from satisfying the bound unless γ is extremely large. But once sampling variability is taken into account, this is no longer the case. In fact, we are able to find cases in which γ is less than thirty that are not rejected by our test.

Table IV reports the results for the three preference specifications using monthly data on stock and bond returns. Again, the top panel reports findings for the $\delta=0$ case, while the middle and bottom panels depict the results for $\delta=+0.5$ and $\delta=-0.5$, respectively. The results are striking, in that all three preference specifications imply that, for $\beta=0.99$ at an annual rate, there are values of γ between zero and one that are not rejected at the five-percent level — i.e. the t-ratio is below 1.65 in absolute value. In addition, for the habit persistence case, there are intermediate values of γ between five and ten that are consistent with the bound. For $\beta=1.02$, the story is slightly different, with values $\gamma=2$ not being rejected in the time-separable and durability cases, and γ between 2 and 9 not being rejected when there is habit persistence.

These results contrast sharply with those that are obtained when sampling variability is ignored. For example, Hansen and Jagannathan (1991) note that γ must exceed 100 in the CRRA case, and suggest that the monthly data provides a more stringent set of restrictions than the annual data do.

II.C Monthly U.S. Treasury Bills Term Structure: 1964-1988

In choosing the next data set for study, we follow Hansen and Jagannathan and examine the term structure of U.S. Treasury Bill data. Specifically we consider a portfolio of three, six and nine months bills, and use monthly observations on three

Table IV: Tests of the Volatility Bound Restrictions (Monthly Data on Equity Returns, April 1964-December 1988)

	I. Time-separable utility: $\delta = 0$								
-			= 0.99	umiy:		= 1.02			
η	$\hat{\mu}_{m{v}}$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio	$\hat{\mu}_v$			t-ratio	
0	$\frac{\mu v}{0.999}$	0.000	$\frac{0_x}{0.214}$	-1.604	$\frac{\mu_v}{1.002}$	$\frac{\hat{\sigma}_v}{0.000}$	$\frac{\hat{\sigma}_x}{0.981}$		
1	0.998	0.004	0.306	-1.731	1.002			-7.157	
2	0.996	0.004	0.802	-3.109	0.998	0.004	0.475	-3.414	
4	0.993	0.009	1.780	-3.109	0.995	0.009 0.017	$0.065 \\ 1.012$	-0.491	
10	0.984	0.017	4.557	-4.376	0.986	0.017	$\frac{1.012}{3.796}$	-2.571	
15	0.977	0.043	6.694	-4.377	0.979	0.043 0.064	5.938	-3.843	
20	0.971	0.085	8.671	-4.323	0.973	0.085	7.920	-4.021	
25	0.965	0.106	10.490		0.973	0.106	9.746	-4.051	
30	0.959	0.100	12.160	-4.153	0.962	0.100	11.420	-4.023	
100				able utili			11.420	-3.964	
			0.99	able utili	v : v = 0		= 1.02		
γ	$\hat{\mu}_v$	$\hat{\sigma}_{v}$		t-ratio	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio	
0	0.999	0.000	$\frac{0.214}{0.214}$	-1.604	$\frac{\mu_v}{1.002}$	0.000	0.981	-7.157	
1	0.998	0.003	0.214	-1.749	1.002	0.00	0.981	-7.137	
2	0.996	0.006	0.87	-3.151	0.998	0.00	0.08	-0.493	
4	0.993	0.012	1.83	-4.057	0.995	0.00	1.05	-2.658	
10	0.983	0.031	4.69	-4.523	0.986	0.03	3.98	-4.002	
15	0.976	0.046	7.00	-4.581	0.978	0.04	6.25	-4.236	
20	0.969	0.061	9.20	-4.585	0.971	0.04	8.40	-4.325	
25	0.962	0.076	11.30	-4.568	0.964	0.07	10.60	-4.358	
30	0.955	0.090	13.40	-4.541	0.958	0.09	12.60	-4.364	
	III. Ti			utility:		(habit	persisten	ce)	
		$\beta =$	0.99			$\beta =$	1.02		
γ	$\hat{\mu}_{m{v}}$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio	
0	0.999	0.000	0.214	-1.604	1.002	0.000	0.981	-7.157	
1	0.998	0.022	0.24	-1.247	1.000	0.02	0.59	-3.864	
2	0.997	0.044	0.51	-1.933	0.999	0.04	0.21	-1.220	
3	0.996	0.066	0.62	-1.794	0.999	0.06	0.17	-0.333	
4	0.997	0.088	0.65	-1.317	0.999	0.08	0.16	-0.235	
5	0.997	0.111	0.49	-0.694	1.000	0.11	0.31	-0.496	
6	0.998	0.133	0.11	-0.031	1.001	0.13	0.69	-0.920	
7	1.000	0.155	0.32	-0.250	1.002	0.15	1.10	-1.396	
8	1.002	0.178	0.98	-0.894	1.004	0.17	1.76	-1.865	
9	1.004	0.202	1.71	-1.478	1.007	0.20	2.58	-2.298	
10	1.007	0.225	2.63	-1.991	1.010	0.22	3.40	-2.683	
15	1.030	0.353	9.88	-3.593	1.033	0.35	10.70	-3.898	
20	1.070	0.513	22.10	-4.117	1.073	0.51	23.10	-4.259	
25	1.134	0.771	42.10	-3.819	1.138	0.78	43.40	-3.867	

Tests use data for consumption, returns on the value-weighted NYSE index, and three month T-bills, April 1964- December 1988. See Table II for details.

month holding period returns constructed from the average of the bid and ask prices. Real returns are computed using the deflator the nondurable plus service component of consumption. Again, the data is from the 'Fama file' supplied by CRSP. In contrast with Hansen and Jagannathan, we choose not to include the twelve month Treasury bill, since the data set contains a large number of missing observations — i.e. months in which there was no twelve month bill outstanding.²⁰ Also, following common practice, we exclude the one-month Treasury Bill.²¹

Since we are using monthly observations on three month holding period returns to compute the bounds, we must compute the model implied values of the mean and standard deviation of the IMRS that mimics this timing. In the notation of Section I, this means that we must calculate $IMRS_{t,t+3}$, which is just equation (14) with k=3. The model implied values of the moments of the IMRS follow immediately from equations (15) and (16) of Section I.D, again setting k=3.

We begin by noting that the bound we compute using three, six and nine month data is substantially below the one in Hansen and Jagannathan's Figure 6, which uses three, six, nine and twelve month data. For example, we find that a μ_{ν} of 0.996 implies a σ_x of only 0.178 (see Table V, $\delta = -0.5$, $\beta = 1.02$ $\gamma = 2$), while adding the twelve month Treasury bill data (without adjusting for missing observations) results in a value in excess of 0.5.

Table V reports the results of using monthly consumption data, together with the three, six and nine month data on Treasury Bills, to test the models of interest.

²⁰We note that the data file itself codes these missing observations as having returns of zero—reporting prices at par. This seems to be the reason for the results Hansen and Jagannathan report in their Figure 6, which appear to pose a substantial challenge to asset pricing models, particularly when the nonnegativity constraint is imposed. But when the twelve month data are deleted, the bound falls to nearly the level of the one computed using the so-called 'equity premium' data set used in Section II.C.

²¹Recent work by Luttmer (1991), and Cochrane and Hansen (1992) examines data on one, three, six and nine month bills, and finds that the addition of the one month bill substantially raises the bound. But the one-month bill market is extremely thin, with most trading occurring outside the standard dealer/broker system and transactions costs being substantial — see, for example Stigum (1990, pg. 667ff). As a result, quoted bid/ask spreads are very large, and there is the potential for reported prices to be inaccurate. The methods of both Luttmer and He and Modest, which treat market frictions explicitly and so do not impose the law of one price, are less sensitive to the problems posed by the one-month data.

Table V: Tests of the Volatility Bound Restrictions (Monthly Data on 3, 6 and 9 Month Treasury Bills, April 1964-December 1988)

I. Time-separable utility: $\delta = 0$								
		β =	0.99					
γ	$\hat{\mu}_v$	$\hat{\sigma}_{\pmb{v}}$	$\hat{\sigma}_x$	t-ratio	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio
0	0.997	0.000	0.253	-1.907	1.005	0.000	1.211	-7.510
1	0.993	0.006	0.513	-2.299	1.000	0.006	0.552	-3.280
2	0.988	0.012	1.157	-3.302	0.995	0.012	0.223	-1.066
4	0.978	0.024	2.445	-3.958	0.985	0.025	1.456	-2.711
10	0.951	0.060	6.132	-4.303	0.958	0.060	5.167	-3.831
15	0.930	0.088	8.993	-4.336	0.937	0.088	8.048	-4.019
20	0.910	0.115	11.669	-4.323	0.917	0.116	10.744	-4.081
25	0.892	0.142	14.168	-4.289	0.898	0.143	13.262	-4.092
30	0.874	0.169	16.498	-4.244	0.881	0.170	15.610	-4.075
	II			able utilit	$y: \delta = 0$			
		•	- 0.99				= 1.02	
γ	$\hat{\mu}_{v}$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio_	$\hat{\mu}_{v}$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio
0	0.997	0.000	0.253	-1.907	1.005	0.000	1.211	-7.510
1	0.993	0.006	0.504	-2.177	1.000	0.006	0.562	-3.213
2	0.988	0.013	1.137	-3.130	0.995	0.013	0.211	-1.016
4	0.978	0.025	2.405	-3.752	0.986	0.025	1.415	-2.523
10	0.952	0.060	6.028	-4.064	0.959	0.061	5.062	-3.595
15	0.931	0.089	8.835	-4.083	0.938	0.089	7.890	-3.768
20	0.912	0.116	11.457	-4.058	0.918	0.117	10.531	-3.818
25	0.894	0.143	13.903	-4.016	0.900	0.144	12.995	-3.819
30	0.877	0.168	16.181	-3.963	0.883	0.170	15.290	-3.795
	III. Ti	ne-nons	eparable	utility: 6	$\hat{s} = -0.5$		persister	ice)
		$\beta =$	- 0.99				= 1.02	
γ	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio
0	0.997	0.000	0.253	-1.907	1.005	0.000	1.211	-7.510
1	0.993	0.018	0.486	-1.951	1.000	0.018	0.581	-3.014
2	0.988	0.036	1.060	-2.719	0.996	0.036	0.178	-0.913
3	0.984	0.054	1.600	-3.010	0.992	0.054	0.615	-1.318
4	0.981	0.071	2.098	-3.119	0.988	0.072	1.107	-1.826
5	0.977	0.089	2.552	-3.148	0.985	0.090	1.561	-2.098
6	0.974	0.106	2.961	-3.133	0.982	0.107	1.971	-2.242
7	0.972	0.124	3.327	-3.091	0.979	0.125	2.338	-2.310
8	0.969	0.141	3.649	-3.031	0.977	0.142	2.660	-2.331
9	0.967	0.158	3.927	-2.956	0.974	0.160	2.939	-2.318
10	0.965	0.176	4.162	-2.871	0.973	0.178	3.174	-2.280
15	0.962	0.266	4.674	-2.308	0.969	0.268	3.678	-1.850
20	0.966	0.364	4.021	-1.541	0.974	0.367	3.004	-1.139
25	0.981	0.479	2.016	-0.546	0.989	0.484	0.963	-0.174

Tests of the volatility bound restrictions using monthly data for consumption, three, six, and nine month T-bills, April 1964-December 1988. See Table II for details.

Once again, the three panels of the Table refer to the time separable ($\delta=0$), one-lag durability ($\delta=+0.5$), and one-lag habit persistence ($\delta=-0.5$) cases, with β equal to 0.99 and 1.02. When the discount factor is set to 0.99 at an annual rate, all of the models reported are rejected at the five-percent level, since there are no t-ratios with absolute value less than 1.65. But in all cases, values of γ between zero and two are not rejected at the one-percent level, as the t-ratios are less than 2.33 in absolute value.

When the discount rate is 1.02 at an annual rate, then, for each of the preference specifications, there is a set of values for γ that is not rejected using the 1.65 standard deviation rule. For time separable utility and one-lag durability, values of γ near two are consistent with the bound, while for the one-lag habit persistence model values of γ between one and five are consistent with the volatility bound at the five-percent level.

These results suggest that, while the Treasury Bill data set does present some obstacles for asset pricing models, it is nowhere near as large a problem as originally suggested by Hansen and Jagannathan. Consistent with both Luttmer (1991) and Cochrane and Hansen (1992), we find that the restrictions imposed by the monthly Treasury Bill term structure are roughly equivalent to those imposed by the monthly data on equity and bonds reported in Section II.B.

II.D Monthly Foreign Currency Returns: 1973 to 1988

The final application we examine uses monthly U.S. dollar speculative returns on five major currencies, together with the monthly consumption data described above. We study spot and one-month forward U.S. dollar prices of the Canadian dollar, the deutchmark, the French franc, the pound, and the yen. These data are the Friday closing quotations reported in the Harris Bank Foreign Exchange Weekly Review. The sample is drawn from those Friday quotations that fell nearest to the end of the calendar month. Again, we calculate real magnitudes using the implicit deflator for consumption of nondurables plus services.

In order to construct the asset portfolios, we begin by defining s_{it} to be the dollar

spot price of foreign currency i, and f_{it} to be the one-month dollar forward price of a unit of this currency determined at date t. In determining an investment strategy at date t, an investor will want to go long in the forward foreign currency contract if $(f_{it} - s_{it+1})$ is expected to be positive, and short if $(f_{it} - s_{it+1})$ is expected to be negative.

Let I_{it} be an indicator function such that

$$I_{it} = \begin{cases} 1 & \text{if } E_t(f_{it} - s_{it+1}) > 0 \\ -1 & \text{if } E_t(f_{it} - s_{it+1}) < 0 \end{cases}.$$

The Euler equations implied by this investment strategy can be expressed as

$$0 = E_t \left(v_{t+1} I_{it} \frac{f_{it} - s_{it+1}}{s_{it}} \frac{P_t}{P_{t+1}} \right) , (i = 1, 2, ..., n) ,$$
 (20)

where P_t is the aggregate U.S. price level.

In notation corresponding to that of Section I, we have $q_t = 0$ and the *i*th element of the gross return vector x_t equals

$$x_{it+1} = I_{it} \frac{f_{it} - s_{it+1}}{s_{it}} \frac{P_t}{P_{t+1}} \ .$$

Since μ_q is a zero-valued vector, the implied lower volatility bound is now a ray from the origin given by

$$\sigma_x = \mu_v [\mu_x' \Sigma_x^{-1} \mu_x]^{\frac{1}{2}} .$$
(21)

Backus, Gregory and Telmer (1991) investigate the lower volatility bound (21) using univariate data on the five currencies we examine. They evaluate the indicator function by projecting the currency speculative return, $\left(\frac{f_{it}-s_{it+1}}{s_{it}}\right)$, on the forward premium, $\left(\frac{f_{it}-s_{it}}{s_{it}}\right)$ and using the fitted values as the estimates of the conditional expectation of the return. The indicator I_{it} is then assigned a value of +1 when this fitted value is positive, and -1 when the fitted value is negative.²²

²²The projection strategy is defensible on the grounds that the forward premium has proved to be a robust predictor of future currency returns during the modern period of floating exchange rates.

When preferences are given by the one-lag habit persistence model, with a γ of 10, Backus, Gregory and Telmer find that the point estimate of the volatility of the IMRS, $\hat{\sigma}_v$ is less than one-third of the volatility implied by the foreign currency returns data and the Euler equations. From this, they conclude that these preferences are not capable of explaining the dynamics of foreign currency returns.

Using the Backus, Gregory and Telmer method for evaluating the indicator function, we examine the portfolio constructed from the five currencies. Again we examine all three preference specifications, $\delta = (0, +0.5, -0.5)$, and two values for the discount factor, $\beta = (0.99, 1.02)$. The results are reported in Table VI. For these data, the volatility bound is substantially higher than it is when we use domestic U.S. stock and bond data. At a mean IMRS value of one, $\mu_{\nu} = 1$, the implied lower volatility bound has risen from 0.322 for the monthly stock returns data discussed in Section II.B, to 0.402.

It is obvious from the top two panels of Table VI that both the model with timeseparable utility, and the one with one-lag durability, imply much too little variation in the IMRS relative to that implied by the data. For all of the parameter values we consider, both of these cases are easily rejected by our testing procedure as the t-ratio always exceeds 3.8 in absolute value.

The bottom panel of Table VI reports the results for the one-lag habit persistence model using the data on the five foreign currency returns. Here, values of γ of 15 and higher cannot be rejected at the five-percent level.

It is with substantial caution that we conclude that the restrictions imposed by foreign currencies returns pose quite a challenge to asset pricing models. The source of our prudence is the observation that frictions are often an important problem in these markets. As both Luttmer (1991) and He and Modest (1991) suggest, transactions costs, short sale constraints and restrictions on borrowing against future labor income can have a very important impact on the height and shape of the volatility bound. It is very possible that once the size of the bid/ask spread is taken into account, then

See Hodrick (1987) for a survey of theoretical developments and empirical evidence concerning the behavior of foreign currency returns.

Table VI: Tests of the Volatility Bound Restrictions (Monthly Data on Forward Foreign Exchange, March 1973-December 1988)

	I. Time-separable utility: $\delta = 0$								
			= 0.99	$\beta = 1.02$					
γ	$\hat{\mu}_v$	$\hat{\sigma}_{v}$	$\hat{\sigma}_x$	t-ratio	$\hat{\mu}_v$	$\hat{\sigma}_{m{v}}$	$\hat{\sigma}_{x}$	t-ratio	
0	0.999	0.000	0.402	-5.749	1.002	0.000	0.403	-5.749	
1	0.998	0.004	0.401	-5.685	1.000	0.004	0.402	-5.685	
2	0.996	0.009	0.401	-5.621	0.999	0.009	0.402	-5.621	
4	0.994	0.017	0.400	-5.491	0.996	0.017	0.401	-5.492	
10	0.986	0.043	0.397	-5.106	0.989	0.043	0.398	-5.105	
15	0.981	0.064	0.394	-4.785	0.983		0.395	-4.785	
20	0.976	0.085	0.392	-4.464	0.978	0.085	0.393	-4.464	
25	0.971	0.106	0.391	-4.143	0.974	0.106	0.391	-4.143	
30	0.967	0.126	0.389	-3.823	0.969	0.127	0.390	-3.823	
L	II.			able utili	ty: $\delta =$				
ı			= 0.99		ĺ		1.02		
γ	$\hat{\mu}_{v}$	$\hat{\sigma}_{v}$	$\hat{\sigma}_x$	t-ratio	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio	
0	0.999	0.000	0.402	-5.749	1.002	0.000	0.403	-5.749	
1	0.998	0.003	0.401	-5.705	1.000	0.003		-5.705	
2	0.996	0.006	0.401	-5.661	0.999	0.006	0.402	-5.661	
4	0.994	0.012	0.400	-5.572	0.996	0.012	0.401	-5.572	
10	0.986	0.030	0.396	-5.306	0.988	0.030	0.397	-5.306	
15	0.980	0.044	0.394	-5.084	0.982	0.044		-5.084	
20	0.974	0.059	0.392	-4.863	0.976	0.059	0.393	-4.863	
25	0.968	0.073	0.389	-4.642	0.971	0.073	0.390	-4.642	
30	0.963	0.087	0.387	-4.421	0.965	0.087	0.388	-4.421	
-	111. 11m			utility: δ	= -0.5		persiste	nce)	
	•		0.99				1.02		
$\frac{\gamma}{0}$	$\hat{\mu}_{v}$	$\hat{\sigma}_{v}$	$\hat{\sigma}_x$	t-ratio	$\hat{\mu}_v$	$\hat{\sigma}_v$	$\hat{\sigma}_x$	t-ratio	
0	0.999	0.000	0.402	-5.749	1.002	0.000	0.403	-5.749	
1	0.998	0.021	0.401	-5.430	1.001	0.021	0.402	-5.429	
2	0.997	0.042	0.401	-5.109	1.000	0.042	0.402	-5.107	
3	0.997	0.063	0.401	-4.787	1.000	0.064	0.402	-4.785	
4	0.997	0.084	0.401	-4.465	1.000	0.085	0.402	-4.461	
5	0.998	0.106	0.401	-4.142	1.000	0.106	0.402	-4.138	
6	0.999	0.127	0.402	-3.819	1.001	0.128	0.403	-3.814	
7	1.000	0.148	0.402	-3.496	1.003	0.149	0.403	-3.490	
8	1.002	0.170	0.403	-3.173	1.005	0.171	0.404	-3.166	
9	1.005	0.192	0.404	-2.850	1.007	0.193	0.405	-2.843	
10	1.008	0.215	0.405	-2.528	1.010	0.216	0.406	-2.519	
15	1.030	0.336	0.414	-0.934	1.033	0.338	0.415	-0.922	
20	1.067	0.485	0.429	0.544	1.070	0.488	0.430	0.558	
25	1.125	0.709	0.452	1.548	1.129	0.714	0.454	1.518	

Tests of the volatility bound restrictions using monthly data for consumption, and speculative returns on forward foreign exchange on the Canadian dollar, deutchmark, French franc, pound, and yen, March 1973-December 1988. See Table II for details.

the bound will no longer be as significant as it appears from the results reported in Table VI.

III. Nonnegativity of the Mean IMRS

In this section we show how to generalize the framework described in Section I to incorporate an important implication of asset pricing theory. As Hansen and Jagannathan discuss, the mean IMRS must be nonnegative or the model will imply that assets with a zero probability of a negative payoff will command negative prices. This means that it is of interest to reformulate the test of Section I taking into account this information.

In what follows, we describe two methods for constructing test statistics that allow us to measure whether a model is close to the bound when the nonnegativity restriction is taken into account. The first method we propose does not require distributional assumptions about returns, and so it is nonparametric. The second method is parametric, and is based on the assumption that the unconditional distribution of returns is normal. Following the discussion of the methods we use for computing test statistics, Section III.C reports results for the annual data studied in Section II.A.

III.A The Nonparametric Method

We begin by describing Hansen and Jagannathan's (1988) method for computing point estimates of the volatility bound that impose the nonnegativity restriction. Expressing the problem in returns form, which means that asset prices are all one, the bound they derive is

$$\sigma_x = [\lambda^{-1} - \mu_v]^{\frac{1}{2}} \,, \tag{22}$$

where μ_v is the mean of the IMRS, λ is defined by

$$\lambda = \min_{w,a} E \max[0, w + a'x]^2$$
s.t. $w\mu_v + a'\ell = 1$, (23)

x is an n-dimensional vector of returns, ℓ is a n-dimensional vector of ones, w is a scalar parameter, and a is an n-dimensional vector of parameters. In the absence of the 'max' expression, (23) collapses to the simple case of Section I.A.

Hansen and Jagannathan propose estimating σ_x using the sample analog of λ ,

$$\hat{\lambda} = \min_{w,a} \sum_{t=1}^{T} \max[0, w + a'x_t]^2$$
s.t. $w\mu_v + a'\ell = 1$, (24)

Then an estimate of the volatility bound is

$$\hat{\sigma}_x = [\hat{\lambda}^{-1} - \mu_v]^{\frac{1}{2}} \ . \tag{25}$$

Following the method in Section I.E, we can construct the standard error for the difference between the volatility bound and the model implied value of the standard deviation of the IMRS: $\Delta = \sigma_x - \sigma_v$. As is apparent from (24), $\hat{\lambda}$ depends on the sequence $\{x_t\}$, rather than the sample moments of returns, $\hat{\mu}_x$ and $vec(\hat{\Sigma}_x)$. This means that we cannot express Δ directly as a function of the estimated moments of consumption and returns, as is done in (18). Nevertheless, we can use the same procedure if we redefine the vector of parameters θ as

$$\theta_n = \begin{bmatrix} \lambda \\ \psi \end{bmatrix} , \tag{26}$$

where λ is defined by (23) and ψ is the parameter vector associated with the consumption growth process, (μ_c, σ_c, ρ) .

With this redefinition, we can compute the analog of (19),

$$\hat{\sigma}_{\Delta}^{2} = \left. \left(\frac{\partial \Delta}{\partial \theta_{n}'} \right) \right|_{\hat{\theta}_{n}} \hat{\Sigma}_{\theta_{n}} \left. \left(\frac{\partial \Delta}{\partial \theta_{n}} \right) \right|_{\hat{\theta}_{n}} . \tag{27}$$

Evaluation of (27) requires an estimate of Σ_{θ_n} , which depends on the covariance of $\hat{\lambda}$ and $\hat{\psi}$, rather than the covariance of the samples moments of returns and $\hat{\psi}$.

We can compute an estimate, $\hat{\Sigma}_{\theta_n}$ by stacking the moment conditions implied by the minimization problem that defines $\hat{\lambda}$, (24), together with the moment conditions used to estimate ψ and applying GMM.

III.B The Parametric Method

An alternative, and simpler, method for incorporating the nonnegativity restriction, begins by assuming that returns are jointly normally distributed. If the vector of returns x is multivariate normal, then (w + a'x) is univariate normal with mean $(wu_v + a'u_x)$ and variance $a'\Sigma_x a$. It follows that λ is (23) can be written as a function of μ_v , μ_x and Σ_x ,

$$\lambda = g(\mu_v, \mu_x, \Sigma_x)$$

$$= \min_{w,a} \int_0^\infty y^2 f(y) dy ,$$
s.t. $w\mu_v + a'\ell = 1 ,$ (28)

where y = w + a'x and f(y) is the normal density associated with y. An estimate of λ can now be computed as

$$\tilde{\lambda} = g(\hat{\mu}_v, \hat{\mu}_x, \hat{\Sigma}_x) \tag{29}$$

Using (22) we can estimate σ_x as

$$\tilde{\sigma}_x = [\tilde{\lambda}^{-1} - \hat{\mu}_v]^{\frac{1}{2}} \ . \tag{30}$$

It is straightforward to obtain an estimate of the standard error of Δ when it is computed from $\tilde{\sigma}_x$. To see this, note that in this case, Δ can be written in a form equivalent to (18). Specifically, (29) and (30) imply that $\tilde{\sigma}_x$ is a function of $\hat{\mu}_x$, $\hat{\mu}_v$ and $\hat{\Sigma}_x$. Since $\hat{\mu}_x$, $\hat{\Sigma}_x$, and the estimated parameters needed to compute $\hat{\mu}_v$ are all elements of $\hat{\theta}$, we can express the distance between the model implied value of the standard deviation of the IMRS and the volatility bound, when the nonnegativity

restriction is considered, as

$$\tilde{\Delta} = \tilde{\sigma}_x(\phi; \hat{\theta}) - \sigma_v(\phi; \hat{\psi}) . \tag{31}$$

Since $\tilde{\sigma}_x$ depends on g, $\sigma_{\tilde{\Delta}}$, the analog to (19), will depend on the derivatives of g. Furthermore, g is the solution to the optimization problem (28), and so its derivatives must be evaluated numerically.

III.C Results with Nonnegativity

The results of including the nonnegativity restriction are presented in Table VII. Here we report estimates of the mean and standard deviation of the IMRS, the volatility bound, and the t-ratio for Δ , using the annual data of Section II.A, time-separable utility and a discount factor of 0.99. The top panel of the table reports results using the nonparametric method, while the bottom panel contains results from using the parametric method. For comparison, the table reports values of the bound and the t-ratio both with and without the nonnegativity restriction.

As Hansen and Jagannathan observed, the incorporation of the nonnegativity restriction does sharpen the point estimates of the bounds. The effect of the restriction is particularly pronounced when μ_v is small. For example, when μ_v is 0.881, σ_x equals 2.063 when nonnegativity is ignored. But with nonnegativity, σ_x rises to 4.749 when computed using the nonparametric method, and to 5.059 using the parametric method.²³

This sharpening of the bound necessarily increases the estimate of Δ , the distance between the estimates of σ_v and σ_x . But, as the Table shows, the estimated standard error of Δ with nonnegativity increases by so much that the t-ratios are now closer to zero, than they were without the restriction for all but the lowest values of γ we study.

This result is the opposite of that implied by Hansen and Jagannathan. By

²³The two estimates of σ_x differ because the true returns distribution is fat tailed and negatively skewed, relative to the normal. This implies that the two methods of computation will yield different point estimates of σ_x .

Table VII: Tests of the Volatility Bound Restrictions, With Nonnegativity (Annual Data on Equity Returns, 1890–1987)

(Timular Bases on Equity Tecourist, 1999-1997)									
		<u> </u>		t Nonnegativity					
γ	$\hat{\mu}_v$	$\hat{\sigma}_{m{v}}$	$\hat{\sigma}_x$	t-ratio	$\hat{\sigma}_x$	t-ratio			
A. Nonparametric method									
0	0.990	0.000	0.320	-3.633	0.320	-3.633			
1	0.973	0.033	0.411	-2.201	0.411	-2.203			
2	0.958	0.066	0.644	-2.441	0.675	-1.975			
4	0.931	0.131	1.123	-2.615	1.500	-1.753			
10	0.881	0.339	2.063	-1.880	4.749	-0.967			
15	0.874	0.556	2.201	-1.103	5.613	-0.473			
20	0.900	0.850	1.698	-0.375	3.033	-0.279			
25	0.967	1.269	0.502	0.277	0.505	0.261			
30	1.084	1.883	1.889	-0.002	2.107	-0.041			
			A. Pa	rametric method					
0	0.990	0.000	0.320	-3.588	0.320	-3.590			
1	0.973	0.033	0.411	-2.256	0.411	-2.231			
2	0.958	0.066	0.644	-2.524	0.654	-2.332			
4	0.931	0.131	1.123	-2.674	1.296	-1.976			
10	0.881	0.339	2.063	-1.901	5.059	-0.626			
15	0.874	0.556	2.201	-1.112	6.344	-0.439			
20	0.900	0.850	1.698	-0.377	2.770	-0.271			
25	0.967	1.269	0.502	0.277	0.505	0.271			
30	1.084	1.883	1.889	-0.002	2.849	-0.076			

Tests of the volatility bound restrictions that incorporate nonnegativity of the mean IMRS, using annual data for consumption, returns on the S&P index, and one-year T-bills (or the equivalent), 1890-1987. See Table II for details.

focusing on the implication for the point estimates, they suggest that inclusion of the nonnegativity restriction will further limit the class of models that can meet the constraints implied by the volatility bounds. Our finding is that imposing this restriction actually makes the volatility bound *less* informative.

The added uncertainty driving our results comes from the truncation in the computation of λ . This is evident from the 'max' in (23) and from the form of the integral in (28). The intuition for both cases is straightforward. In the nonparametric case, as μ_v decreases from the point at which σ_x is minimized (the bottom of the parabola) the truncation caused by the 'max' function implies that more and more information is thrown out in the calculation of $\hat{\lambda}$. As less data is used to compute the bound, the precision of the bound deteriorates.

The parametric case is very similar. Note from (28) that calculation of the bound requires computation of the expectation of a squared truncated normal random variable. As μ_v decreases from the point at which σ_x is at its minimum, a larger portion of the distribution is truncated. This implies that the variation in the moments of the returns now cause large percentage changes in λ , and so any uncertainty in the sample moments of returns is translated into large uncertainty in the bound.

Finally, we note that the usefulness of the volatility bound when nonnegativity is imposed is likely to improve with sample size. As the sample size increases, the standard error of Δ will shrink and statistical tests will be increasingly dominated by the comparison of point estimates of the bounds, which are sharpened by the nonnegativity restriction. But, the sample sizes we have here — roughly 100 years of annual data — are not large enough for the nonnegativity restriction to be useful.

IV. Conclusion

This paper has developed and implemented a procedure for testing the restrictions implied by Hansen and Jagannathan's (1991) lower volatility bound for the intertemporal marginal rate of substitution. Our approach allows us to evaluate whether the standard deviation of the IMRS implied by a particular model of preferences is con-

sistent with the bound derived from asset return data. The result is a statistical test that can be used to formally reject some models.

Previous investigators have concluded that the restrictions implied by the bound allow rejection of many commonly used utility functions for reasonable parameter values. But their methods involve comparison of the point estimates of the bound with the IMRS volatility derived using different utility functions. In contrast to these results, we find that by taking explicit account of the sampling variability, in a number of cases the restrictions implied by the bound do not allow rejection of models with reasonable parameter values. In particular, using annual data on equity and bond returns in the U.S. over the last century, we find that the constant relative risk aversion utility is consistent with the bound when the discount factor is 0.99 and a CRRA coefficient of 6 or higher. From this we conclude that the failure of some models is not nearly as extreme as the point estimates would suggest.

We go on to examine three additional data sets, and discover that we can always find a set of preferences that are not rejected by the restrictions implied by the volatility bounds. This is true of (1) monthly data on stock prices and Treasury debt, where we find that time separable utility with a discount factor of 0.99 and a CRRA coefficient below one is consistent with the data; (2) monthly Treasury Bill term structure data, where we find that time separable utility with a discount factor of 1.02 and a CRRA coefficient of two is consistent with the data; and (3) data on returns to five foreign currencies, where we find that preference exhibiting habit persistence with a discount factor of 0.99 and curvature parameter of fifteen is consistent with the data.

We also examine the importance of explicitly considering the fact that the mean of the IMRS must be nonnegative. While the incorporation of the information in this restriction does sharpen the volatility bounds, as Hansen and Jagannathan originally found, our results suggest that the uncertainty associated with the location of the bound grows so rapidly as to make it less informative than tests that ignore the restriction.

Our conclusion is that the tests based on the volatility bound contain roughly

the same statistical information as tests of Euler equations based on unconditional moments. That is to say, these tests seldom either allow us to reject a particular model, or help us to discriminate among alternative models.

REFERENCES

- Backus, David K., Allan W. Gregory and Chris I. Telmer, 1991, Accounting for forward rates in markets for foreign currency, mimeo., Stern School of Business, New York University.
- Bakaert, Geert and Robert J. Hodrick, 1992, Characterizing predictable components in excess returns on equity and in foreign exchange markets, *Journal of Finance*, 47, 467-510.
- Breeden, Douglas T., Michael R. Gibbons and Robert H. Litzenberger, 1989, Empirical tests of the consumption-oriented CAPM, Journal of Finance, 44, 231-262.
- Burnside, A. Craig, 1990, The comovement of asset returns with time non-separable preferences, mimeo., Department of Economics Queens University.
- _____, 1991, Hansen-Jagannathan bounds as classical tests of asset pricing models, mimeo., Department of Economics, Queens University.
- Campbell, John Y. and Robert J. Shiller, 1987, Cointegration and tests of the present value model, *Journal of Political Economy*, 95, 1062-1088.
- Cecchetti, Stephen G., Pok-sang Lam and Nelson C. Mark, 1991, The equity premium and the risk-free rate: Matching the moments, NBER Working Paper No. 3752.
- Cochrane, John H., and Lars Peter Hansen, 1992, Asset pricing lessons for macroe-conomics, in O.J. Blanchard and S. Fischer, eds.: NBER Macroeconomics Annual volume 7, (Cambridge, Mass.: M.I.T. Press).
- Constantinides, George M., 1990, Habit formation: A resolution of the equity premium puzzle, Journal of Political Economy, 98, 519-543.
- Dunn, Kenneth and Kenneth J. Singleton, 1986, Modeling the term structure of interest rates under nonseparable utility and durability of goods, *Journal of Financial Economics*, 41, 333-355.
- Eichenbaum, Martin S., Lars Peter Hansen and Kenneth J. Singleton, 1988, A time series analysis of representative agent models of consumption and leisure choice under uncertainty, Quarterly Journal of Economics, 103, 51-78.
- Epstein, Larry G. and Stanley E. Zin, 1991, The independence axiom and asset returns,' mimeo., G.S.I.A., Carnegie-Mellon University.
- Ferson, Wayne E. and George M. Constantinides, 1991, Habit persistence and durability in aggregate consumption: empirical tests, Journal of Financial Economics, 29, 199-240.
- Ferson, Wayne E. and Campbell R. Harvey, 1992, Seasonality and consumption-based asset pricing, Journal of Finance, 47, 511-552.

- Grossman, Sanford J. and Robert J. Shiller, 1981, The determinants of the variability of stock market prices, *American Economic Review*, 71, 222-227.
- ———, Angelo Melino and Robert J. Shiller, 1987, 'Estimating the continuous-time consumption-based asset pricing model, *Journal of Business and Economic Statistics*, 5, 315–328.
- He, Hua and David M. Modest, 1991, Market frictions and consumption-based asset pricing, mimeo., Haas School of Business, University of California at Berkeley.
- Heaton, John, 1991a, An empirical investigation of asset pricing with temporally dependent preference specifications, mimeo., Department of Economics, M.I.T..
- Heaton, John, 1991b, The Interaction Between Time-Nonseparable Preferences and Time Aggregation, Sloan School, M.I.T. Working Paper No. 3376-92-EFA.
- Hansen, Lars P. and Ravi Jagannathan, 1991, Implications of security market data for models of dynamic economies, *Journal of Political Economy*, 91, 225-262.
- and ______, 1988, Restrictions on Intertemporal Marginal Rates of Substitution Implied by Asset Returns, mimeo., Department of Economics, University of Chicago.
- Hodrick, Robert J., 1987, The Empirical Evidence on the Efficiency of Forward and Futures Foreign Exchange Markets (New York: Harwood Academic Publishers).
- Kocherlakota, Narayana R., 1990a, A note on the "discount" factor in growth economies, Journal of Monetary Economics, 25, 43-48.
- ———, 1990b, On tests of representative consumer asset pricing models, *Journal of Monetary Economics*, 26, 285–304.
- Luttmer, Erzo G.J., 1991, Asset pricing in economies with frictions, mimeo., Department of Economics, University of Chicago.
- Newey, Whitney K. and Kenneth D. West, 1987, A simple, positive definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica*, 55, 703-708.
- Snow, Karl N., 1991, Diagnosing asset pricing models using the distribution of asset returns, *Journal of Finance*, 46, 955-984.
- Stigum, Marcia L., The Money Market, 3rd edition (New York: Richard Irwin Inc.).