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Abstract

We apply nonparametric kernel methods to estimate the conditional mean of weekly gold rates of return in order to examine whether the market overlooks usable nonlinear structure. Linear and ARCH-M models are fitted as parametric benchmarks. The BDS statistic of Brock, Dechert and Scheinkman (1987) is used to test for nonlinear dependence. We find evidence of nonlinearities in the residuals of the linear and ARCH-M models. However, kernel estimation of the conditional mean based on only four lags filters out all detectable nonlinear structure. Nevertheless, the kernel estimator has no forecasting ability whatsoever in 84 one-step-ahead out-of-sample forecasts. We conclude that the structure that the BDS is capturing in the parametric benchmark models pertains to higher moments and it does not help provide better forecasts of the conditional mean once captured. Hence, the Weak Market Efficiency Hypothesis is upheld.

Introduction

The purpose of this paper is to estimate a nonlinear time series model for the weekly rates of return on gold and to use this model to test the martingale version of the market efficiency hypothesis. The approach we take to modeling the structure of gold rates of return is to estimate the time varying conditional mean by nonparametric kernel methods. This method of statistical estimation is straightforward to apply and very successfully captures nonlinearities that are present in the time series of gold rates of return.

The hypothesis of market efficiency suggests that asset prices are determined by the interaction of rational agents. In addition one usually also requires that publicly available information cannot be used to construct profitable trading rules. In other words market efficiency has come to be associated with the notion that information acquisition by individuals is a futile activity. Underlying the above notion of efficiency, the martingale model allows for a particular equilibrium that specifies precisely how information is reflected in prices. The above model was formalized by Samuelson (1965) under certain assumptions about the behaviour of agents including constant and common time preferences, common probabilities and risk neutrality and has been incorporated into textbooks such as Brealy and Myers (1984). LeRoy (1989) provides an excellent survey of the martingale hypothesis, its relation to the more restrictive random walk model, and its empirical success (or lack of it).

Evidence from studies on variance bounds, see LeRoy (1989) for references, and from such studies as Fama and French (1988) have suggested that rates of return have zero autocorrelations over short and long time intervals but negative ones over intermediate ones. This finding agrees with Sims (1984) who argues that the martingale model is consistent with "instantaneously unpredictable" processes, a property satisfied by many stochastic processes.

Contrary evidence to the above findings are to be found in two recent sources of the literature. Lo and MacKinlay (1988) found that weekly and monthly stock returns had positive autocorrelations contradicting the assertion of zero autocorrelations suggested above. Additional evidence on this has been provided by studies that use tools from nonlinear dynamics to test for nonlinear dependence in the series, such as Scheinkman and LeBaron (1989), Frank and Stengos (1989) and Hsieh (1989). These findings raise the possibility that systematic and usable nonlinear structure in the rates of return has yet to be accounted for. Brock (1987) discusses from a theoretical point of view some of the issues associated with the presence of nonlinearities in finance. White (1988) has pointed to bounded rationality as an explanation as to why such potentially useful information has remained uncovered. He employs neural networks to investigate the nonlinear structure of IBM daily stock return.

The above mentioned studies employ tests that look for dependence of the entire conditional distribution of the process. However, it is only dependence in the first moment that violates the martingale hypothesis. Dependence in the higher conditional moments would violate the more restrictive random walk hypothesis. There is a tremendous amount of evidence that suggests that higher conditional moments are correlated. For example, time-varying volatility has been captured by the ARCH and GARCH models of Engle (1982) and Bollerslev (1986). McCurdy and Morgan (1987) used the GARCH model to investigate the time series of several exchange rates and found support for the martingale hypothesis. The ARCH-M model is a further generalization that has been explored by Domowitz and Hakkio (1985) and Engle, Lilien and Robin (1987). In this formulation, the mean of the series is a function of the time-varying conditional variance, which provides a changing measure of risk. When the market is particularly volatile, the additional risk is built into the expected return. The disturbances in the ARCH-M model also should be serially independent, since under the null, any time dependence in the original rates of return is captured in the time-varying risk premium.

In this paper we will use the testing methodology of nonlinear dynamics mentioned above but we will try to isolate the effect of nonlinear dependence in the first moment and hence test the martingale hypothesis from this angle.

We define a martigale in the following way. Let p_t be a suitably transformed asset price to account for cumulated dividends discounted back to the present. Then p_t can be shown to follow a martingale

$$(1) \qquad E(p_t | I_{t-1}) = p_{t-1}$$

where I_{t-1} is the information set available at time t-1. Similarly if rates of return r_t are defined as the sum of dividend yield plus capital gain minus one, then r_t is known as a martingale difference

$$(2) \qquad E(r_t | I_{t-1}) = 0.$$

The formal relationship between the martingale and the efficient markets hypothesis has been explored by Lucas (1978) and Brock (1982). Sims (1984) has also provided an explanation of the empirical success of the martingale hypothesis, such as documented by Fama (1970).

We will use nonparametric kernel methods to estimate the conditional mean function of a nonlinear time series process. Robinson (1983) has discussed nonparametric kernel methods in this context. Since no assumptions are made about the form of the joint density function, this approach is extremely flexible. To test for the presence of nonlinearities in gold rates of return we employ a recently developed nonparametric test by Brock, Dechert and Scheinkman (1987), hereafter referred to as the BDS test. The paper is organized in the following way. The next section briefly presents the manner in which we implement nonparametric kernel estimation for the purpose of estimating the conditional mean of gold rates of return. Then we briefly discuss the BDS test which we use to test for the presence of nonlinear structure in the residuals. In the following section we report the empirical results of the study and we analyze the findings. Finally we conclude with a brief summary and some comments on the issues that are raised in the empirical section.

Nonparametric Kernel Estimation

Silverman (1986) presents a general introduction to nonparametric density estimation while Ullah (1988) focuses on nonparametric estimation of econometric functionals. The conditional mean of a random variable x, given a vector of conditioning variables w, can be written as $E(x|w) = M(w)$. In parametric estimation M(w) is typically assumed to be linear in w but in the nonparametric approach M(w) remains a general functional form. The conditional mean of x can be expressed as

$$(3) \qquad E(x|w) = M(w) = \int x \frac{f(x,w)}{f_1(w)}\,dx$$

where $f_1(w)$ is the marginal density of w. In the nonparametric framework, forecasts of x conditional on w are calculated directly by constructing an empirical counterpart to (3).

The approach can be illustrated by considering the problem of estimating a univariate density function f(z) using the random sample $z_{1,\ldots,}z_n$, see for example Silverman (1986). Let $\hat{F}(z)$ be the empirical cumulative distribution function defined as the proportion of the sample values that are less than or equal to z. An estimate of the density function f(z) can be obtained from

$$\hat{f}(z) = \frac{\hat{F}(z + h/2) - \hat{F}(z - h/2)}{h}$$

for small values of h, or

$$(4) \qquad \hat{f}(z) = (hn)^{-1} \sum_{t=1}^{n} I\left(\frac{z - z_t}{h}\right)$$

where
$$I(.) = 1 \text{ if } -\frac{1}{2} < \frac{z - z_t}{h} < \frac{1}{2}$$
$$= 0 \text{ otherwise.}$$

The estimate $\hat{f}(z)$ described by (4) has the significant deficiency that it is not smooth. Spikes and potholes are likely to characterize $\hat{f}(z)$, especially where the data are sparse. The family of kernel estimators, introduced by Rosenblatt (1956), attempts to correct this problem:

$$(5) \qquad \hat{f}(z) = (nh)^{-1}\sum K\left(\frac{z - z_t}{h}\right)$$

where the kernel function K satisfies certain conditions, including:

$$(6) \qquad K(z^*) \geq 0, \int K(z^*)dz^* = 1, \text{ for } z^* = (z - z_t)/h.$$

Certain kernels, such as the normal density function used in this paper also satisfy $\int z^* K(z^*)dz^* = 0$. Since it is possible to choose the function K so that it is continuous, the resulting kernel estimator of the density function will also be continuous. In the present paper, the kernel is chosen to be the standard multivariate normal density function, which assigns a positive weight to every observation in the sample when estimating the point f(z). The largest weights are attached to the observations closest to the point z. Unlike the histogram estimator (4), the kernel estimator (5) uses the information on each side of a spike or a pothole to flatten spikes and fill in potholes. Clearly, the choice of kernel and the "window width" h determine the degree of smoothness imposed on $\hat{f}(z)$. If the kernel function is very flat all data points in the sample receive similar weights in the estimation of f(z) and this imposes a high degree of smoothing. Similarly, if the window width h is large, the estimation of f(z) draws in distant data points and this also has a smoothing effect.

Consider now the time series process $\{x_t\}$ and in particular the problem of estimating the mean of x_t conditional on $(x_{t-1},\ldots,x_{t-p})$. Robinson (1983) has discussed the nonparametric estimation of the joint density of the time series data generating process (DGP) of (x_t,y_t) and of the conditional mean of x_t, given $(x_{t-1},\ldots,x_{t-p},y_t,\ldots,y_{t-p})$. Central limit theorems are established and the author obtains results for the rate at which consistency is achieved.

Let f(z) be the multivariate DGP of the p+1 dimensional random vector z, which we write as $z = (x_t, w_t)$, where $w_t = (x_{t-1}, \ldots, x_{t-p})$. The kernel estimator of the joint density is

$$\hat{f}(x_1, w) = n^{-1}h^{-(p+1)} \sum_{t=1}^{n} K\left(\frac{x - x_t}{h}, \frac{w - w_t}{h} \right)$$

Similarly, the estimator for the marginal distribution of w is

$$\hat{f}(w) = n^{-1}h^{-p} \sum_{t=1}^{n} K_2 \left(\frac{w - w_t}{h} \right)$$

where $K_2(w^*) = \int K(x^*, w^*)dx^*$. Again the asterisk denotes the transformation $x^* = (x - x_t)/h$, where x_t is considered fixed. Similar transformations apply to the elements of w. Given equation (3) above that defines the conditional expectation of x given w, and some algebraic manipulations one can derive the nonparametric estimator of the regression function to be

$$\hat{E}(x|w) = \sum_{t=1}^{n} x_t r_t \tag{7}$$

where

$$r_t = K_2 \left(\frac{w - w_t}{h} \right) / \sum_{t=1}^{n} K_2 \left(\frac{w - w_t}{h} \right)$$

Expression (7) can be evaluated at any value of w to yield the nonparametric estimator of the regression function. Clearly, out-of-sample forecasts conditional on a set of known w values, can be calculated using (7), see for example Moschini, Prescott and Stengos (1988).

In applications, the investigator must choose the window width h as well as the kernel function. The choice of the window width is important since bias is an increasing function of h while variance is a decreasing function of h. Although we are dealing with a regression estimation problem, we have followed the suggestion of Silverman (1986, p.86) who shows that when the density function to be estimated is the p-dimensional normal density function, the mean square error optimal value of h is proportional to $n^{-1/(4+p)}$. The proportionality factor depends on the kernel, but in the case of the normal kernel the factor is close to unity. Accordingly, we set the window width h_i in the following way:

$$h_i = s_i n^{-1/(4+p)}, \text{ for } i=1,\ldots,p.$$

In the above formula s_i denotes the standard deviation of w_i.

Testing for Nonlinearities

The BDS statistic is designed to test the null hypothesis that a time series is i.i.d. against a variety of alternative nonlinear hypotheses. Below we will discuss briefly its structure and the intuition behind it.

Let $\{x_t : t=1,2,\ldots,T\}$ be a sequence of observations that are i.i.d. From this series, construct the m-dimensional vector, or "m-history"

$$x_t^m = \{x_t, x_{t+1}, \ldots, x_{t+m-1}\}.$$

Using these m-histories we can compute the following quantity, known as the correlation integral:

$$C_m(\varepsilon) = \lim_{T \to \infty} \frac{2}{T_m(T_m - 1)} \sum_{t<s} I_\varepsilon(x_t^m, x_s^m)$$

where $T_m = (T - m + 1)$ and $I_\varepsilon(x,z)$ is an indicator function that equals unity if $|x - z| < \varepsilon$. Here $|.|$ is the supnorm. The correlation integral measures the proportion of the m-dimensional points that are "close" to each other, where "close" is defined in terms of the supnorm criterion. Given a sample of size T, the following sample correlation dimension statistic can be computed

$$C_m(\varepsilon,T) = \frac{2}{T_m(T_m - 1)} \sum_{t<s} I_\varepsilon(x_t^m, x_s^m)$$

Brock, Dechert and Scheinkman (1987) show that if $\{x_t\}$ is i.i.d. with a non degenerate density f(.) then, for fixed m and ε,

$$C_m(\varepsilon,T) \longrightarrow [C_1(\varepsilon)]^m \text{ with probability 1, as } T \longrightarrow \infty.$$

Furthermore,

$$\sqrt{T}(C_m(\varepsilon,T)) - C_1(\varepsilon,T)^m) \longrightarrow N(0,V_m(\varepsilon)).$$

The authors derived the expression for the variance term, which allows the following asymptotically normally distributed test statistic (the BDS statistic) to be calculated

(9) $$W_m(\varepsilon,T) = \sqrt{T}(C_m(\varepsilon,T) - C_1(\varepsilon,T)^m)/\sqrt{V_m(\varepsilon)}.$$

We can get some insight into this test statistic by noting that $C_m(\varepsilon,T)$ is an estimate of the probability that the distance between any two m-histories x_t^m and x_s^m is less than ε. Thus,

$$C_m(\varepsilon,T) \longrightarrow \text{Prob } \{|x_{t+i}^m - x_{s+i}^m| < \varepsilon, \text{ for all } i = 0,1,2,\ldots,m\}.$$

where x_{t+i}^m and x_{s+i}^m are the ith entries of x_t^m and x_s^m respectively. Recall that distance is measured using the supnorm and for the vectors to be closer than ε, the absolute difference between all corresponding elements must be less than ε. If the x_t's are independent, then for $t \neq s$, the probability of this joint event equals the product of the individual probabilities, i.e.

$$C_m(\varepsilon,T) \longrightarrow \prod_{i=0}^{m-1} \text{Prob } \{|x_{t+i} - x_{s+i}| < \varepsilon\}.$$

Furthermore, if the x_t's are also identically distributed, then all m probabilities under the product sign are identical and

$$C_m(\varepsilon,T) \longrightarrow C_1(\varepsilon)^m.$$

Thus under the null hypothesis that the series $\{x_t\}$ is i.i.d. the term $C_m(\varepsilon,T) - C_1(\varepsilon,T)^m$, which appears in the numerator of the BDS statistic converges to zero with probability one.

It is clear from the form of the BDS statistic (9) that in practice numerical values must be assigned to the two parameters ε and m. For a given value m, ε should not be too small, otherwise that sample correlation integral will capture too few points. Similarly, ε should not be chosen too large. Since there is no unique choice for these two parameters users report a number of statistics. although these statistics are not independent, a battery of significant BDS statistics does provide strong evidence against the null hypothesis.

Monte carlo simulations by Brock, Dechert and Scheinkman (1987) provide evidence that the BDS statistic has good power against a variety of nonlinear alternatives. More recently, extensive simulations by Hsieh and LeBaron (1989) indicate that the BDS statistic has good size and power characteristics even in moderately sized samples. Moreover, the statistic has good power against a wide variety of nonlinear alternatives, including tent map chaotic processes and stochastic processes such as autoregressive, threshold autoregressive, nonlinear moving average and ARCH.

Empirical Results

The data that we use come from the the I.P. Sharp daily commodities data base called Comdaily series EAUD. The series starts at the beginning of 1975 and runs through June 1986. We use the closing price in London, England in US dollars per fine ounce. From the daily series we constructed weekly rates of return computed as Wednesday to Wednesday changes in the logarithm of the price. We use a weekly series in order to avoid weekend effects that are present in daily data. We tested for stationarity of the rates of return series, since the kernel techniques that we will use require stationary data. We report the Augmented Dickey Fuller test statistic for the levels and the first difference series . The null hypothesis that logarithm of gold prices series is integrated of order one for one (I(1)) cannot be rejected, since the ADF test statistic is -0.3225. However, the null that the first difference series is also I(1) is rejected strongly at the one percent level of significance with an ADF statistic of -9.0351. The critical values for the ADF test statistic can be found in Fuller (1976 p.373). Hence, we conclude that the first difference series (e.g. the rates of return series) is I(0).

In Table 1 we report the results from three alternative regressions on the rates of return series. The linear time series model finds no structure, the coefficients are insignificant and the fit is poor. Also as it can be seen from Table 2, where we report a number of BDS statistics for the residuals of the various models, there is considerable evidence of nonlinear structure in the residuals of the linear specification.

The second column of Table 1 reports the results of an ARCH-M model, see Engle et al (1987). We have not attempted to search exhaustively over a variety of ARCH-M model specifications. Rather, the reported model is used simply as a benchmark for the kernel estimation procedure (both approaches include the same number of lagged values of gold rates of return). The conditional mean of the ARCH-M model also includes the term q_t, which is a linear function of past conditional variances; in this application we include six lagged terms in q_t. Generally, the slope coefficients are insignificant but the coefficient on q_t has a t-statistic in excess of 3.0. In the ARCH-M literature this is typically given the interpretation of a risk premium. Thus, rates of return on gold are highest when returns are more volatile. However, this particular ARCH-M model does account for only a small proportion of the variation of gold rates of return and as the second column of Table 2 shows, the standardized ARCH-M residuals seem not to be i.i.d. according to the BDS statistics.[1]

The third column of Table 1 shows the results of the nonparametric kernel procedure. Some experimentation with the number of lagged terms revealed that with four lags, the residuals show no trace of nonlinear structure (see the last column of Table 2 for the BDS statistics). Moreover, the four lagged terms do account for a substantial share of the total variation in gold rates of return.

In order to compare the three modeling approaches, we have calculated the partial derivatives of the estimated density function at the sample mean. An alternative procedure is to calculate the partial derivatives at each point and then compute the mean of these partial derivatives. However, Ullah (1988) argues that the partial derivative at the mean is often more robust than the mean of the partial derivatives. Interestingly, in the present study

[1]Note that simulations with ARCH type residuals suggest that the finite sample approximation of the BDS statistic has fatter tails than the standard normal. Hence one should view rejections of the null hypothesis with caution when one applies the BDS to standardized ARCH type residuals.

the partial derivatives of the regression function calculated at the sample mean are not significantly different from zero, despite the model's ability to fit the data well. It seems that the derivatives themselves vary considerably as the values of the conditioning variables change. Consequently, neighboring data do not help to estimate the derivatives at a given point. This instability is a warning that, despite the good fit within the sample period, the model may not predict the conditional mean well out-of-sample.

To examine the predictive abilities of the three models, we calculated 84 out-of-sample one-period-ahead forecasts and then regressed the actual value against the forecast. If the model were to generate unbiased forecasts then the coefficient estimate of the forecast variable should not be significantly different from one. Also the presence of any forecasting ability should be reflected in a reasonable measure of fit in this regression. The results are presented in Table 3. None of the three models is able to forecast gold rates of return to any extent whatsoever. In order to examine the ability of the kernel method to forecast we have undertaken an extensive analysis of a number of actual as well as generated series and evaluated the kernel forecasts vis-a-vis forecasts from certain linear models, see Prescott and Stengos (1989). We have found that the kernel forecasts were superior in general to the linear ones in terms of MSE. Additional results on the forecasting properties of the kernel estimator is presented in Moschini, Prescott and Stengos (1988). Hence, the lack of forecastability in the present context is not due to any limitations in the kernel procedure. Rather, we believe that the empirical results imply that there was no forecastable structure in the conditional mean of the gold rates of return series. Therefore, the structure that the BDS statistics are capturing in the residuals of the linear specification cannot be taken as evidence against the martingale hypothesis. The empirical results suggest that the time dependence does not pertain to the conditional mean of the series but presumably to higher conditional moments.

Summary and Conclusions

We have applied nonparametric kernel methods to estimate a nonlinear time series model of the weakly rates of return on gold. Linear and ARCH-M models were fitted to establish parametric benchmarks. The BDS statistic of Brock, Dechert and Scheinkman (1987) was used to test for i.i.d. residuals against the alternative of nonlinear dependence. The BDS statistic found evidence of nonlinearities in the residuals of the linear and ARCH-M models, but the estimated conditional mean fitted by the kernel approach apparently absorbed all of the nonlinearity. Of particular interest is the fact that neither the ARCH-M model nor the kernel estimator had any forecasting ability whatsoever in 84 one-step-ahead out-of-sample forecasts. We conclude that this is strong evidence for the martingale version of the market efficiency hypothesis, in the sense that the forecasts of the conditional mean from a very flexible nonlinear model are orthogonal to actual rates of return. The nonlinearity that is present seems to originate from dependent higher conditional moments. This is evident from the fact when fitting a kernel regression of the conditional mean none of the partial derivatives of the regression function are significant.

These conclusions are reinforced by similar results obtained by White (1988) who used neural networks to investigate IBM daily stock returns. He found that a simple network can account for the extremely rich dynamic behavior of daily stock returns, yet the estimated structure had no forecasting ability. Similar results are obtained more recently by Diebold and Nasan (1990), who apply a nonparametric nearest neighbor method to forecast spot exchange rates. A valuable lesson that is implied from our analysis and the papers mentioned above is that it is important to use out-of-sample forecasting for validating nonlinear time series models.

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Table 1

Different Specifications of the Conditional Mean of the Gold Rates of Return

Dependent Variable : r_t, the weekly rate of return.

Explanatory Variable	Linear Model		ARCH-M model		Kernel Estimator	
	Coeff.	St. Error	Coeff.	St. Error	Coeff.	St. Error
Constant	0.002	0.002	-0.003	0.002		
r_{t-1}	0.050	0.042	0.033	0.041	0.160	0.094
r_{t-2}	0.054	0.041	0.029	0.042	-0.046	0.094
r_{t-3}	0.087	0.041	0.080	0.041	0.052	0.086
r_{t-4}	-0.034	0.042	-0.021	0.041	0.005	0.099
q_t			0.207	0.058		
R^2	0.015		0.036			
TSS, SSR	0.714,0.704		0.714,0.689		0.714,0.273.	

Table 2

BDS Statistics for Independence of residuals*

Neighboring Parameter, $\varepsilon = 1$.

Embedding Dimension m	Raw Series	Linear Model	ARCH-M model	Kernel model
10	12.49	11.47	3.13	0.23
15	19.62	18.05	3.28	0.61
20	40.34	37.50	4.44	0.90
	Neighboring Parameter, $\varepsilon = 1.5$.			
10	8.84	8.37	1.92	1.39
15	11.07	10.35	2.65	1.48
20	15.01	13.68	3.85	1.10

*The neighbouring parameter is measured in satndard deviations of the relevant series. We report absolute values of the BDS statistics. The critical value is 1.96 at the five percent level.

Table 3

Gold Rates of Return : One Period-Ahead- Forecasts

Model : $r_t = \alpha r_t^f$ + forecast error.

	Linear Model	ARCH-M model	Kernel Estimator
Coefficient	-1.153	-2.351	0.153
Standard Error	1.133	1.735	0.357
Std. Dev(r_t)	0.025	0.025	0.025
SER	0.024	0.024	0.024
TSS	0.047	0.047	0.047
SSR	0.047	0.047	0.047

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