OVERLAPPING DATA AND HEDGE FUNDS

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Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
December, 1999

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PREFACE

This dissertation consists of three separate essays. The reader is referred to the individual abstracts for a more complete description of the work contained in each essay. Essay I is entitled "The Overlapping Data Problem". Essay II and III are entitled "The Optimal Investment Strategy of a Hedge Fund" and "Performance Persistence of Hedge Funds" respectively. Essay I considers the overlapping data problem. A generalized least squares (GLS) estimator is derived and its properties are compared to the properties of commonly used estimators, like the Newey-West estimator. Also, combinations of the overlapping data problem with other econometric problems are addressed.

Essays II and III look at some issues related to hedge funds. Essay II develops a theoretical model regarding the optimal investment strategy of a hedge fund. The objective function in the model is maximization of manager's total fees. The model also allows for some concavity in the objective function that is introduced through an asymmetric withdrawals function. Essay III tests whether performance persistence exists in the hedge fund industry. Several procedures are employed to detect if performance persists among hedge funds. Essay III also uses some of the estimation methods developed and/or discussed in Essay I.

ACKNOWLEDGEMENTS

I would like to give my special appreciation to my wife, Donika, for her love, support, understanding, and encouragement at times of difficulty, throughout the program of study. Thank you Donika. I could not do it without you. Thank you to my daughters, Adina, and Angie for bringing new energy and motivation into my life. A special thank you to Adina for understanding when daddy had to go to school. I also would like to thank my family, Mother, Father, and my sisters Beti, and Nila, for their belief in me, their support, and their encouragement.

I wish to express my sincere appreciation to my major advisor, Dr. B. Wade Brorsen for his intelligent supervision, constructive guidance, inspiration and friendship. My sincere appreciation extends to my other committee members Dr. Daniel Tilley, Dr. Harry Mapp, and Dr. John Polonchek whose help and advise are also invaluable. I would like to thank the Department of Agricultural Economics for providing me the opportunity and financial support for conducting this research. Thanks to all of the members of the faculty and staff in the Department of Agricultural Economics at Oklahoma State University for their aid throughout my program. I want to thank especially Joice Grizzle and Cathy Grove for their help and support.

I also thank all other friends, and graduate students in the Department of Agricultural Economics for their help and assistance during the completion of my program.

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Essay I

The Overlapping Data Problem

The Overlapping Data Problem

Abstract

We consider the overlapping data problem. The conventional estimation approach with overlapping data is to use the Newey-West estimation procedure. When the standard assumptions hold generalized least squares is asymptotically efficient. Monte Carlo results show that the Newey-West procedure has considerably larger variances of parameter estimates and lower power than GLS. Hypothesis tests using the Newey-West procedure also have incorrect size even with sample sizes as large as one thousand. We also discuss possible estimation approaches when overlapping data occurs in conjunction with some other econometric problem. With lagged dependent variables or errors in the explanatory variables, GLS is no longer the preferred estimator.

Key words: autocorrelation, Monte Carlo, Newey-West, overlapping data

The Overlapping Data Problem

Introduction

Time series studies estimating multiple-period changes can use overlapping data in order to achieve greater efficiency (Gilbert). A common example is using annual returns when monthly data are available. A one-year change could be calculated from January to December, another from February to January, and so on. In this example the January to December and February to January changes would overlap for eleven months. The overlapping of observations creates a moving average (MA) error term and thus ordinary least squares (OLS) parameter estimates would be inefficient and hypothesis tests biased (Hansen and Hodrick). Past literature has recognized the presence of the moving average error term. Our paper provides a criticism of econometric practice.

One way of dealing with the overlapping observations problem is to use a reduced sample in which none of the observations overlap. For the example given above, the reduced sample will have only one observation per year. Thus, for a 30-year period of monthly data only 30 annual changes or observations will be used instead of 249 (the maximum number of overlapping observations that can be created for this period) annual observations. This procedure will eliminate the autocorrelation problem but it is obviously highly inefficient. A second way involves using average data. For our example this means using the average of the 12 overlapping observations that can be created for each year. This procedure results in the same degree of data reduction and apparently 'uses' all the information. In fact, not only is it inefficient, it also, as Gilbert shows, does not eliminate the moving average error term and can complicate estimation. A third way is to use the overlapping data and to account for the moving average error term in hypothesis testing. Several generalized method of moments (GMM) estimators have been constructed that can provide asymptotically valid hypothesis tests when using data with overlapping observations. These GMM estimators include Hansen and Hodrick (HH) (1982), Newey-West (NW) (1987), and Andrews and Monahan (AM) (1992). A fourth way is to use OLS estimation with overlapping data which yields biased hypothesis tests. We argue that all of these methods are inferior to other methods.

To illustrate the enormity of the problem the number of empirical articles involving the use of overlapping data in regression analysis in three journals during 1996 were counted. The journals were, *The Journal of Finance*, *The American Economic Review*, and *The Journal of Futures Markets*. The methods of estimation are classified as OLS with non-overlapping data (OLSNO), OLS with the Newey-West (1987) variance covariance estimator, OLS with any of the other GMM estimators, and just OLS. The numbers are presented in Table 1.

Table 1 shows the number of empirical articles involving the use of overlapping data as a total and as a percentage of the total number of the empirical articles in the journal for that year. Most of the empirical articles that use overlapping data involve asset returns or economic growth. A common feature of these articles is that returns or growth are measured over a period that is longer than the observation period. For example, data are observed monthly and the estimation is done annually. As a result, the estimation involves temporal aggregation. There are several possible reasons to use aggregated data. The most common reason given is measurement error in independent variables. For example, Jones and Kaul (p. 469), state that they select "use of quarterly data on all variables as a compromise between the measurement errors in monthly data ...". Another reason could be the lack of normality in the nonaggregated data. Also, when some data are missing, using overlapping data allows using all of the data. Finally, when many lags are included as explanatory variables, using aggregated data would appear to require estimating fewer lag parameters[1] and thus reduce the loss of degrees of freedom. Most authors provide no justification for using overlapping data, but there must be some advantage to using it or it would not be so widely used.

Table 1 also shows each of the estimation methods frequency of use. The OLSNO and Newey-West estimation methods are used most often. We defined OLSNO as estimation using non-overlapping observations. This means that the data exist to create overlapping observations but the researchers chose to work with non-overlapping observations. It might be more correct to say that OLSNO is used simply because it is not a practice to create overlapping data. The OLSNO method will yield unbiased and consistent parameter estimates and valid hypothesis tests. But it will be inefficient since it "throws away information."

The GLS estimation procedure derived in this paper could not be applied in every situation described by Table 1 where Newey-West or OLSNO estimation is used. An example would be the case when lagged values of the dependent variable or some other

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1 While fewer lags are used in practice, as we discuss later, the true autoregressive lag polynomial is typically unchanged when overlapping data are used.

endogenous variable are used as an explanatory variable. In this case, as Hansen and Hodrick argue, the GLS estimates will be inconsistent since an endogeneity problem is created when the dependent and explanatory variables are transformed. We suggest to use the unrestricted maximum likelihood estimation methods developed for time-series models when lagged dependent variables are used as explanatory variables and overlapping data are used. The number of cases where lagged values of the dependent variable are used as an explanatory variable is reported for two of the journals mentioned earlier. In *The Journal of Finance*, from a total of 26 articles reported in Table 1, only six include a lagged dependent variable as an explanatory variable (three with the Newey-West estimator and three with OLSNO). For the *American Economic Review* journal only one (with the Newey-West estimator) of 14 articles included a lagged dependent variable.

In this paper we will discuss the general overlapping data problem and argue that the Newey-West and OLSNO estimation are grossly inefficient ways of handling the overlapping data problem since the order of the MA process is known. This will be done by determining and comparing the small-sample properties of Newey-West, OLSNO, MLE, and GLS estimates. Unrestricted maximum likelihood estimation is included as an alternative to GLS to show what happens when the MA coefficients are estimated[3]. Also, the power and size of the hypothesis tests for the four methods of estimation will be compared. Monte Carlo simulation methods are used. Finally, we discuss ways of adapting the GLS

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3 The GLS estimator is the maximum likelihood estimator. The true MLE would have the parameters of the moving average process be known rather than estimated. Such a restricted MLE should be used with large sample sizes since it uses less storage than GLS.

estimation procedure to handle additional econometric problems such as lagged dependent variables, missing data or heteroskedasticity.

Theory

Estimation with multiple-period changes can use data with overlapping observations in order to ensure greater efficiency of estimates. Here, we consider only strictly exogenous explanatory variables. Other variations of the overlapping data problem are considered in Section VI.

To consider the overlapping data problem we start with the following regression equation:

$$y_t = \beta' x_t + u_t \tag{1}$$

where, y_t is the dependent variable, x_t is the vector of strictly exogenous independent variables, and u_t the error term. Equation (1) represents the basic data which are then used to form the overlapping observations. The error terms, u_t, in (1) have the following properties: $E[u_t] = 0$, $E[u_t^2] = \sigma_u^2$, and $Cov[u_t, u_s] = 0 \quad$ if $t \neq s$.

However, one might want to use aggregated data and instead of (1) estimate the following equation:

$$Y_t = \beta' X_t + e_t \tag{2}$$

where Y_t and X_t represent an aggregation of y_t and x_t respectively. To estimate (2) the overlapping observations are created by summing the original observations as follows:

$$Y_t = \sum_{j=t}^{t+k-1} y_j,\ X_t = \sum_{j=t}^{t+k-1} x_j,\ \text{and}\ e_t = \sum_{j=t}^{t+k-1} u_j \qquad (3)$$

where k is the number of periods for which the changes are estimated. If n is the original sample size, then $n - k + 1$ is the new sample size. These transformations of the dependent and independent variables induce a MA process in the error terms of (2).

From the assumption that the original error terms were uncorrelated with zero mean, it follows that:

$$E[e_t] = E[\sum_{j=0}^{k-1} u_{t-j}] = \sum_{j=0}^{k-1} E[u_{t-j}] = 0. \qquad (4)$$

Also, since the successive values of u_j are homoskedastic and uncorrelated, the unconditional variance of e_t is:

$$\mathrm{Var}[e_t] = \sigma_e^2 = E[e_t^2] = k\sigma_u^2. \qquad (5)$$

Based on the fact that two different error terms, e_t and e_{t+s}, have $k - s$ common original error terms, u, for any $k - s > 0$, the covariances between the error terms are:

$$\mathrm{cov}[e_t, e_{t+s}] = E[e_t e_{t+s}] = (k-s)\sigma_u^2 \quad \forall (k-s)>0. \qquad (6)$$

Dividing by $k\sigma_u^2$ gives the correlations:

$$\mathrm{corr}[e_t, e_{t+s}] = \frac{k-s}{k} \quad \forall (k-s)>0. \qquad (7)$$

Collecting terms we have:

$$\Omega = \begin{bmatrix} 1 & \frac{k-1}{k} & \cdots & \frac{k-s}{k} & \cdots & \frac{1}{k} & 0 & 0 \\ \frac{k-1}{k} & 1 & \frac{k-1}{k} & \cdots & \frac{k-s}{k} & \cdots & \frac{1}{k} & 0 \\ \cdots & \frac{k-1}{k} & 1 & \frac{k-1}{k} & \cdots & \frac{k-s}{k} & \cdots & \frac{1}{k} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \frac{1}{k} & \cdots & \frac{k-s}{k} & \cdots & \frac{k-1}{k} & 1 & \frac{k-1}{k} & \cdots \\ 0 & \frac{1}{k} & \cdots & \frac{k-s}{k} & \cdots & \frac{k-1}{k} & 1 & \frac{k-1}{k} \\ 0 & 0 & \frac{1}{k} & \cdots & \frac{k-s}{k} & \cdots & \frac{k-1}{k} & 1 \end{bmatrix} \qquad \textbf{(8)}$$

where, Ω is the correlation matrix. The correlation matrix, Ω, appears in Gilbert's paper without a derivation, but we have not found it elsewhere, although the presence of a moving average error term is commonly recognized.

With Ω derived analytically the generalized least squares (GLS) parameter estimates and their variance-covariance matrix can be obtained as follows:

$$\hat{\beta} = (\boldsymbol{X}'\Omega^{-1}\boldsymbol{X})^{-1}\boldsymbol{X}'\Omega^{-1}\boldsymbol{Y} \qquad \textbf{(9)}$$

and

$$\mathrm{Var}[\hat{\beta}] = \sigma_e^2(\boldsymbol{X}'\Omega^{-1}\boldsymbol{X})^{-1}. \qquad \textbf{(10)}$$

where $\boldsymbol{X} = (X_1', \ldots, X_{n-k+1}')$ and $\boldsymbol{Y} = (Y_1, \ldots, Y_{n-k+1})$. Under these assumptions, the GLS estimator will be best linear unbiased and asymptotically efficient. If errors are normally distributed, then GLS is efficient in small samples, standard hypothesis test procedures would be valid in small samples, and the GLS estimator would be the maximum likelihood estimator.

Alternative Estimation Methods

The next issue to be discussed is the OLSNO and Newey-West estimation methods and their inefficiency. We consider only Newey-West rather than the alternative GMM estimators. As Davidson and MacKinnon (p. 611) say "the Newey-West estimator is never greatly inferior to that of the alternatives." First a review of Newey-West's estimation method is presented. Parameter estimates are obtained by using OLS with overlapping data as follows:

$$\boldsymbol{b} = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{Y} \quad \textbf{(11)}$$

and the variance of b is:

$$\mathrm{Var}[\boldsymbol{b}] = \sigma_e^2(\boldsymbol{X}'\boldsymbol{X})^{-1}. \quad \textbf{(12)}$$

The OLS estimate b is unbiased and consistent but inefficient. While the OLS estimate of σ_e^2 is biased and inconsistent. To calculate Newey-West's autocorrelation consistent covariance matrix first the OLS residuals are obtained. Then the Newey-West's autocorrelation consistent estimator is calculated using the formula:

$$S = S_0 + \frac{1}{n-k+1}\sum_{i=1}^{k-1}\sum_{t=i+1}^{n-k+1} w_i e_t e_{t-i}(x_t x_{t-1}' + x_{t-1} x_t') \tag{13}$$

where,

$$S_0 = \frac{1}{n-k+1}\sum_{i=1}^{n-k+1} e_i^2 x_i x_i' \tag{14}$$

is the White heteroskedasticity consistent estimator, $w_i = 1 - i / k$, is a scalar weight, and $n - k + 1$ is the sample size. Then the autocorrelation consistent covariance matrix is estimated as:

$$V = (n-k+1)(X'X)^{-1}S(X'X). \tag{15}$$

The OLSNO method of estimation obtains parameter estimates using OLS with a reduced sample where the observations do not overlap. The OLS estimates of the variance are unbiased since with no overlap there is no autocorrelation. The OLSNO parameter estimates are less efficient than the GLS estimates because of the reduced number of observations used in estimation. For the example of one-year changes the number of observations in OLSNO estimation is 12 times less than the number of observations in GLS estimation.

The Newey-West estimator uses OLS with the overlapping data to obtain the parameter estimates which results in those parameter estimates being inefficient. In addition, the Newey-West estimator of the variance-covariance matrix is only consistent and thus the

GLS estimator will provide more accurate hypothesis tests in small samples. While it is known that GLS is the preferred estimator, the loss from using one of the inferior estimators in small samples is not known. We use a Monte Carlo study to provide information about the small-sample differences among the estimators.

Monte Carlo Study

A Monte Carlo study was conducted to determine the size and power of the hypothesis tests when using overlapping data and GLS, OLSNO, Newey-West, and unrestricted MLE, estimation methods. The Monte Carlo study also provides a measure of the efficiency lost from using OLSNO, Newey-West, and when the MA coefficients are estimated. The mean and the variance of the parameter estimates are calculated to measure bias and efficiency. Mean-squared error (MSE) is computed for each method of estimation. To determine the size of the hypothesis tests, the percentages of the rejections of the true null hypotheses are calculated. To determine the power of the hypothesis tests the percentage of the rejections of false null hypotheses are calculated.

Data and Procedure

Data are generated using Monte Carlo methods. A single independent variable x with an i.i.d. uniform distribution[4] (0,1) and error terms u with a standard normal distribution are

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When autocorrelation in x is large and the error term follows a first-order autoregressive process, Greene (1997, p.589) finds that the inefficiency of OLS relative to GLS increases when the x's are positively autocorrelated. Since many real-world datasets have explanatory variables that are positively autocorrelated, the inefficiency of OLS found here may be conservative.

generated. We also considered a N(0,1) for x but these results are not included in the paper since the conclusions did not change. The options RANUNI and RANNOR in SAS Version 6.11 are used. The dependent variable y is calculated based on the relation represented in equation (1). For simplicity β is assumed equal to one. The data set with overlapping observations of X and Y is created by summing the x's and y's as in (3).

The regression defined in (2) was estimated using the set of data containing X and Y. The number of replications is 2000. For each of the 2000 original samples, different vectors x and u are used. This is based on Edgerton's findings that using stochastic exogenous variables in Monte Carlo studies improves considerably the precision of the estimates of power and size of the hypothesis tests. Six sample sizes T are used, respectively, 30, 100, 200, 500, 1000, and 2000. Three levels of overlapping k-1 are used, respectively, 1, 11, and 29. The levels 1 and 29 are chosen to represent two extreme levels of overlapping of practical interest. The level 11 is chosen because it corresponds to using annual changes when monthly data are available.

The OLSNO, the Newey-West, and GLS estimates of β were obtained for each of the 2000 samples using PROC IML in SAS software version 6.12. The unrestricted MLE estimates of β were obtained using PROC ARIMA in SAS. The Ω matrix to be used in GLS estimation was derived in equation (8). The Newey-West estimation was validated by comparing it with the available programmed estimator in SHAZAM software Version 7.0 using the OLS ... /AUTCOV option. The power of the tests are calculated for the null hypothesis $\beta = 0$.

Results

The means of the parameter estimates and their standard deviations as well as the MSE values for the three overlapping levels 1, 11, and 29, for the OLSNO, Newey-West, and GLS are presented in Tables 2, 3, and 4. The true standard deviations for the GLS estimation are lower than those for the OLSNO and Newey-West estimation. This shows that the Newey-West's and OLSNO parameter estimates are less efficient than the GLS estimates. The inefficiency is greater as the degree of overlapping increases and as the sample size decreases. For a sample size of 100 and overlapping level 29, the sample variance of the GLS estimates is 0.119 while the sample variance of the Newey-West and OLSNO estimates is 2.544 and 7.969 respectively. Besides the more efficient parameter estimates, the difference between the estimated and actual standard deviations of the parameter estimates are almost negligible for the GLS estimation regardless of sample size or overlapping level. The estimated standard deviations for the OLSNO estimation show no biases as expected, but the estimated standard deviations do vary from actual standard deviations in small samples. The Newey-West estimation tends to underestimate the actual standard deviations even for overlapping level 1. The degree of underestimation increases with the increase of overlapping level and as sample size decreases. Sometimes the estimated standard deviation is only one-fourth of the true value. The Newey-West covariance estimates have previously been found to be biased downward in small samples (eg. Nelson and Kim; Goetzmann and Jorion). The parametric bootstrap suggested by Mark can lead to tests with correct size, but still uses the inefficient OLS estimator.

The inferiority of the Newey-West and OLSNO parameter estimates compared to the GLS estimates is also supported by the MSE values computed for the three methods of estimation. Thus, for the sample size 100 and the overlapping level 29, the MSE for the GLS, Newey-West, and OLSNO estimation is respectively 0.12, 2.55, and 8.02.

The means of the parameter estimates and their standard deviations as well as the MSE values for the three overlapping levels 1, 11, and 29, for the unrestricted MLE are presented in Table 5. The results are similar to the results presented for the GLS estimation. However, in small samples the actual standard deviations of the MLE estimates are larger than those of the GLS estimates. As the degree of overlapping increases the sample size, for which the standard deviations for both methods are similar, also increases (e.g. from 100 for overlapping 1 to 1000 for overlapping 29).

The Newey-West and OLSNO estimation methods also perform considerably poorer than the GLS estimation in hypothesis testing. The results of the hypothesis tests are presented in Table 6. The Newey-West estimator rejects true null hypotheses far too often. In one extreme case, it rejected a true null hypothesis 50.0% of the time instead of the expected 5%. In spite of greatly underestimating standard deviations the Newey-West estimator has considerably less power than GLS except with the smallest sample sizes considered. While the OLSNO estimation has the correct size, the power of the hypothesis tests is much less than the power of the tests with GLS.

The results of the hypothesis tests for the unrestricted MLE are presented in Table 7. While the power of the hypothesis tests is similar to the power for the GLS estimation, the size is generally larger than the size for the GLS estimation. Unrestricted MLE tends to reject the true null hypotheses more often than it should. However, this problem is reduced or eliminated as larger samples are used, i.e. 500, 1000, 2000 observations. Table 7 also presents the number of iterations for each run, as well as the number/percentage of iterations that converge. The number/percentage of iterations that converge decreases as the degree of overlap increases and sample size decreases. Given the convergence problems, as shown in Table 7, it can be concluded that, when MLE is chosen as the method of estimating (2), the MA coefficients should be restricted rather than estimated unless the sample size is quite large. On the other hand, the GLS estimator, depending on computer resources, tends to run into storage problems when the sample size is around 2500 observations with the 64 MB computer used here. MLE provides an alternative estimation method that does not create a storage problem.

Variations on the Overlapping Data Problem

In practice, overlapping data often occur at the same time as some other econometric problems. Since the solutions are not obvious, we now discuss how the properties and estimation methods would need to change with changes in the assumptions. Also, if the explanatory variables were strictly exogenous, no observations were missing, and the errors were distributed normally as assumed so far there would be no need to use overlapping data since the disaggregate model could be estimated. For some changes in assumptions we present solutions, but for others we can only make suggestions to be pursued in further research.

Lagged dependent variables.

The case of overlapping data and a lagged dependent variable (or some other variable that is not strictly exogenous) was a primary motivation for Hansen and Hodrick's estimator. In the usual case of autocorrelation and a lagged dependent variable, ordinary least squares estimators are inconsistent. Engle shows, for the case where the first lag of the dependent variable is used as an explanatory variable, that the use of OLS with aggregated data could lead to biases of either sign and almost any magnitude. It is a general belief that with nonoverlapping data, ordinary least squares parameter estimates are consistent even with a lagged dependent variable if the lag is greater than the level of overlap. However, as we will show, this is not the case. With a lagged dependent variable, autocorrelation exists beyond the level of overlap and thus OLS estimates are inconsistent. Generalized least squares estimates are also inconsistent, but consistent estimates can be obtained using the maximum likelihood methods developed for time-series models. Therefore, we suggest maximum likelihood estimation for models with a lagged dependent variable when overlapping data are used. When nonoverlapping data are used, estimates of the parameters of the disaggregated process can often no longer be recovered. With nonoverlapping data, MLE is still preferred even though the time-series process can be quite different than the original process. The models usually estimated with OLSNO or Newey-West are misspecified.

Marcellino (1996, 1999) discusses in detail the issues related to temporal aggregation of time-series models. Following his notation, (except that x and y are switched) let

$$g(L)y_t = f(L)x_t + s(L)u_t \qquad t = 1,2,\ldots,T \tag{16}$$

represent a general autoregressive disaggregated model where L is the lag operator, $g(L)$, $f(L)$, and $s(L)$ are polynomials of orders g, f, and s in the lag operator, x_t is strictly exogenous, and u_t is a white noise (WN) process, $u_t \sim WN(0, \sigma_u)$. The overlapping observations are obtained using the following relation:

$$(1 + L + ... + L^{k-1})g(L)y_t = (1 + L + ... + L^{k-1})f(L)x_t + (1 + L + ... + L^{k-1})s(L)u_t \quad \textbf{(17)}$$

or

$$G(L)Y_t = F(L)X_t + S(L)e_t \qquad t = k, k+1, ..., T \quad \textbf{(18)}$$

where k is the order of the summation, and Y_t and X_t are the overlapping observations. Our previous results in (9) and (10) can be derived as a special case of (18). In most instances, $G(L)$=$g(L)$. If $s(L)$=1, then $S(L)$ will provide the same covariance matrix as in (5) and (6). While GLS estimates would not be consistent, consistent estimates can be obtained with the maximum likelihood methods developed for time-series models. When $s(L)$=1 the MA coefficients would be known and asymptotically efficient estimates would require restricting the MA coefficients.

Marcellino refers to the process of creating overlapping data as the first step of the average sampling. The second step, that is often applied by past literature, is what Marcellino calls point-in-time sampling of order k to the overlapping data. In a point-in-time sampling process only the k^{th} Y_t and X_t observations of the process in (17) and (18), for our example, are retained:

$$G^*(B)Y_\tau = F^*(B)X_\tau + S^*(B)e_\tau \qquad \textbf{(19)}$$

where $Y_\tau = Y_{tk}$, and $B = L^\tau$. Our nonoverlapping observations are average sampling of the disaggregated process in (1). Marcellino derives the upper bounds of the autoregressive (AR), g, and moving average (MA), s, order for the aggregated process obtained by point-in-time or average sampling. In the case of overlapping observations, the usual practice in empirical work is to estimate the average sampling process in (19) rather than the process that involves overlapping data in (18). The assumption made is that lagged dependent values of order k or higher are uncorrelated with the error terms (i.e. $S*(L) = 1$). However, Marcellino (1996) shows that "there is an aggregated MA component even with an original pure AR process" (p. 13)[5]. Thus, if the autocorrelation in the error term in (18) is ignored in the estimation, as is usually done with OLSNO or Newey-West, parameters are estimated inconsistently. To illustrate and confirm the theoretical results, an example is now provided.

Consider the disaggregated model given below:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 x_t + u_t, \qquad u_t \sim N(0,1) \qquad \textbf{(20)}$$

where for simplicity $\alpha_0 = 0$ and $\alpha_2 = 1$. The value selected for α_1 is 0.5. For $k = 3$, the model usually estimated is:

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See also Brewer (1973), Wei (1981), and Weiss (1984).

$$Y_t = \beta_0 + \beta_1 Y_{t-3} + \beta_2 X_t + \epsilon_t \tag{21}$$

where $Y_t = y_t + y_{t-1} + y_{t-2}$, and $X_t = x_t + x_{t-1} + x_{t-2}$. As we will show, the error term in this model is an MA(1) and additional lags of X should be included. To get the overlapping observations apply (17) to (20) to get:

$$(1 + L + L^2)(1 - 0.5L)y_t = (1 + L + L^2)x_t + (1 + L + L^2)u_t \tag{22}$$

where $g(L) = (1 - 0.5L)$, $f(L) = 1$, and $s(L) = 1$, and therefore the model analogous to our previous model in (2) is

$$Y_t = 0.5Y_{t-1} + X_t + e_t. \tag{23}$$

The model in (23) also has the same variance-covariance matrix, described by (5) and (6), as our previous model in (2).

To obtain (21) we can start from (23), substitute for Y_{t-1} and then for Y_{t-2} to get:

$$Y_t = 0.5^3 Y_{t-3} + X_t + 0.5X_{t-1} + 0.5^2 X_{t-2} + \varepsilon_t. \tag{24}$$

The error term ε_t in (24) is a MA process of order four of the error term u_t in (20) with coefficients 1.5, 1.75, 0.75 and 0.25, $\varepsilon_t = u_t + 1.5u_{t-1} + 1.75u_{t-2} + 0.75u_{t-3} + 0.25u_{t-4}$. The MA process for ε_t can be derived simply by substituting for the original error term u_t or by following the procedure discussed by Marcellino (1996, 1999). Following Marcellino's procedure, the MA process, $N(L)$, for ε_t, can be derived using the following relation $N(L) = C(L) * S(L)$, where, for our example, $C(L) = (1 + 0.5L + 0.25L^2)$ and $S(L) = (1 + L + L^2)$.

If only the k^{th} Y_t and X_t observations are observed in practice (average sampling) then, X_{t-1}, and X_{t-2} are not observable. In this case, an analytical solution of (24) cannot be derived. To be consistent with our previous result, X is strictly exogenous and not autocorrelated. Based on the temporal aggregation literature (Brewer (1973), p.141, Weiss (1984), p. 272, and Marcellino (1996) p. 32), no analytical solution is possible unless x_t is generated by some autocorrelated process and the unobserved terms can be derived from the observed terms. However, based on the fact that the AR coefficient is the same whether point-in-time or average sampling is used, we know then that the AR coefficient is 0.125. The number of lags for the X and the order of the MA process cannot be derived analytically. Therefore, we used Box-Jenkins methods to identify which lags to include in the model. We estimated the following models:

$$Y_\tau = 0.5^3 Y_{\tau-3} + \beta_2 X_\tau + \beta_3 X_{\tau-3} + v_\tau \quad \textbf{(25)}$$

and

$$Y_\tau = 0.5^3 Y_{\tau-3} + X_t + 0.5 X_{t-1} + 0.5^2 X_{t-2} + \eta_\tau . \quad \textbf{(26)}$$

The model in (26) is sound theoretically in the sense that the unobserved lags for X are X_{t-1} and X_{t-2} and thus it makes sense to include them in the model. However, the model in (26) may not be feasible in practice. It uses nonoverlapping data for the Y, but it requires overlapping data on the X which may not always be available.

To confirm our analytic findings we estimated the models in (23), (24), (25), and (26) with MLE using PROC ARIMA in SAS software version 6.12 using a large Monte Carlo sample of 500,000 observations. The results are reported in Table 8. The empirical estimates of the AR and MA coefficients and the coefficients of the Xs for the models in (23) and (24) fully support our analytic findings. One potential problem with the model in (24) is the noise introduced in estimating X_{t-1}, and X_{t-2}. The variable X_{t-1} includes x_{t-1}, x_{t-2}, and x_{t-3}, and X_{t-2} includes x_{t-2}, x_{t-3}, and x_{t-4}, while only x_{t-1} and x_{t-2} are relevant. This errors-in-variables problem biases parameter estimates toward zero. The noise introduced and the associated bias would be greater as the degree of overlap increases.

We estimated (25) with MLE and nonoverlapping data, while (26) is estimated using both overlapping and nonoverlapping data. Both models result in an ARMA(1,1) process with the AR coefficient 0.118 for (25) and 0.123 for (26) which are close to the analytical value of 0.125. The MA coefficient is the same for both models, 0.163 which provides support to the choice of these models. Higher lags of X for the model in (25) were not significant.

We also estimated (25) with Newey-West and OLSNO. The lagged value of the X is not included in the estimation in order to be consistent with the models usually estimated in the empirical literature. These models are the same as the model presented in (21). The parameter estimates were identical for both methods. The parameter estimates are 0.278 for the coefficient on $Y_{\tau-3}$, and 1.415 for the coefficient on X_{τ}. The parameter estimate for $Y_{\tau-3}$ is biased upwards for two reasons. First, $Y_{\tau-3}$ is correlated with the missing explanatory variable $X_{\tau-3}$. Also, the coefficient of $Y_{\tau-3}$ is capturing part of the effect of the missing MA term. Thus, our empirical estimates confirm the inconsistency of Newey-West and OLSNO.

With overlapping data and a lagged dependent value as an explanatory variable the only consistent estimation method is maximum likelihood with (23). Unlike GLS, maximum likelihood provides consistent estimates when the explanatory variables are predetermined whether or not they are strictly exogenous. Also, the model in (23) has the familiar ARMA process, with the AR order the same as the AR order of the disaggregated model (in our case (20)) and MA order k-1.

Nonnormality

The GLS estimator does not assume normality, so estimates with GLS would remain best linear unbiased and asymptotically efficient. The hypothesis tests derived depend on normality. Hypothesis tests based on normality would still be valid asymptotically provided the assumptions of the central limit theorem hold. As the degree of overlapping increases, the residuals would approach normality, so nonnormality would be less of a concern. The Newey-West estimator is also only asymptotically valid. The GLS transformation of the residuals might also speed the rate of convergence toward normality since it is "averaging" across more observations than the OLS estimator used with Newey-West. However, the empirical results show that the faster rate of convergence for GLS is small.

We estimated (2) with two correlated x's and with the error term u following a t-distribution with four degrees of freedom. Results are reported in Table 9. The main difference with the previous results is the increased standard deviations for all methods of estimation. Proportionally, the increase in standard deviations is slightly larger for Newey-West and OLSNO. Thus, the Monte Carlo results support our hypothesis that the advantages of GLS would be even greater in the presence of nonnormality. This can also be seen from the hypothesis test results presented in Table 9. The power of the three methods of estimation is reduced with the biggest reduction occurring for the Newey-West and OLSNO. Finally, the increase of the standard deviations and the resulting reduction in power of hypothesis tests, is larger when the correlation between the two x's increases. This is true for the three methods of estimation.

Missing observations

Missing observations can be a reason to use overlapping data. It is not unusual in studies of economic growth to have key variables observed only every five or ten years at the start of the observation period, but every year in more recent years. Using overlapping data allows using all of the data.

When some observations are missing, one can derive the correlation matrix in (8) as if all observations were available and then delete the respective rows and columns for the missing overlapping observations. The Newey-West estimator assumes autocovariance stationarityand so available software packages that include the Newey-West estimator would not correctly handle missing observations. It should, however, be possible to modify the Newey-West estimator to handle missing observations.

Varying levels of overlap

It is not uncommon in studies of hedging to consider different hedging horizons which leads to varying levels of overlap (i.e. k is not constant). This introduces heteroskedasticity of known form in addition to the autocorrelation. In this case it is easier to work with the covariance matrix than the correlation matrix. The covariance matrix is σ_u^2 times a matrix that has the number of time periods (the value of k_t) used in computing that observation down the diagonal. The off diagonal terms would then be the number of time periods for which the two observations overlap. Allowing for the most general case of different overlap between every two consecutive observations, the unconditional variance of e_t (given in (5)) now is:

$$\mathrm{Var}[e_t] = \sigma_e^2 = E[e_t^2] = k_t \sigma_u^2. \tag{27}$$

Previously, two different error terms, e_t and e_{t+s}, had $k - s$ common original error terms, u, for any $k - s > 0$. Now, they may have less than $k - s$ common u's and there no longer is a monotonic decreasing pattern of the number of the common u's as e_t and e_{t+s} get further apart. We let k_{ts} represent the number of common u's (overlapping periods) between e_t and e_{t+s}. Therefore, the covariances between the error terms e_t and e_{t+s}, are:

$$\mathrm{cov}[e_t, e_{t+s}] = E[e_t e_{t+s}] = (k_{ts})\sigma_u^2 \tag{28}$$

The covariance matrix is then:

$$\Sigma = \sigma_u^2 \begin{bmatrix} k_1 & k_{12} & k_{13} & \dots & k_{1s} & 0 & 0 \\ k_{21} & k_2 & k_{23} & \dots & \dots & k_{2s} & 0 \\ \dots & k_{32} & k_3 & k_{34} & \dots & \dots & k_{3s} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & k_{ts} & \dots & k_{t(t-2)} & k_{t(t-1)} & k_t \end{bmatrix} \tag{29}$$

where, $k_{ts} = k_{st}$. The standard Newey-West procedure does not handle varying levels of overlap since it assumes autocovariance stationarity.

Additional source of autocorrelation

In practice there may be sources of autocorrelation in addition to that caused by the overlapping data problem. Mathematically, this would imply that u_t in (1) is autocorrelated. If the disaggregated process is an MA process, then the procedure developed in the lagged dependent variable section can be applied straight forward. If the error term in (1) follows an ARMA process then the same procedure can be applied with slight modification. Assume that u_t in (1) follows the process:

$$m(L)u_t = h(L)\xi_t \qquad \textbf{(30)}$$

where ξ_t is a white noise (WN) process, $\xi_t \sim WN(0, \sigma_\xi)$. Aggregation of (1) to obtain the overlapping observations

$$(1 + L + ... + L^{k-1})y_t = (1 + L + ... + L^{k-1})x_t + (1 + L + ... + L^{k-1})u_t \qquad \textbf{(31)}$$

introduces the same level k of aggregation to (30), which now becomes:

$$(1 + L + ... + L^{k-1})m(L)u_t = (1 + L + ... + L^{k-1})h(L)\xi_t \qquad \textbf{(32)}$$

or

$$M(L)e_t = H(L)E_t. \qquad \textbf{(33)}$$

Then, the procedures discussed in the lagged dependent variable case can be applied with respect to (30) to obtain the order and the values of the AR and MA coefficients in (33) to be used in estimating (2). In this case, any of the standard methods for estimating a regression with ARMA errors can be used.

Heteroskedasticity

If the residuals in the disaggregated data (u_t in (1)) are heteroskedastic, then estimation is more difficult. Define σ^2_{ut} as the time-varying variance of u_t and σ^2_{et} as the time-varying variance of e_t. Assume the u_t's are independent and thus $\sigma^2_{et} = \sum_{j=0}^{k-1} \sigma^2_{ut-j}$. For simplicity, assume that σ^2_{ut} depends only on x_t. If σ^2_{ut} is assumed to be a linear function of x_t ($\sigma^2_{ut} = \gamma' x_t$) then the function aggregates nicely so that $\sigma^2_{et} = \sum_{j=0}^{k-1} \gamma' x_{t-j} = \gamma' X_t$. But, if multiplicative heteroskedasticity is assumed ($\sigma^2_{ut} = \exp(\gamma' x_t)$) then $\sigma^2_{et} = \sum_{j=0}^{k-1} \exp(\gamma' x_{t-j})$ and there is no way to consistently estimate γ using only aggregate data (nonoverlapping data also have the same problem).

The covariance between e_t and e_{t+s} for any $k - s \geq 0$ would be

$$\mathrm{Cov}(e_t, e_{t+s}) = \sum_{j=s}^{k-1} \sigma^2_{u(t-j)}. \qquad \textbf{(34)}$$

Since the correlation matrix, Ω is known, as given by (8), the covariance matrix can be derived using the relation:

$$\Sigma = \Gamma' \Omega \Gamma \qquad \textbf{(35)}$$

where $\Gamma = DIAG\left[\gamma' X_1, \ \gamma' X_2, \ ..., \ \gamma' X_T\right]$ where the DIAG function creates a diagonal matrix from the vector argument. A feasible generalized least squares estimator can then be developed using (16). It might be reasonable to use (9) as the first stage in a FGLS estimation that corrected for heteroskedasticity.

Errors in variables

The most common reason authors give for using overlapping data is a problem with errors in the explanatory variables. Errors in the explanatory variables causes parameter estimates to be biased toward zero, even asymptotically. Using overlapping data reduces this problem, but the problem is only totally removed as the level of overlap, k, approaches infinity.

We added to the x in (1) a measurement error, ω, that is distributed normally with the same variance as the variance of x, $\omega \sim N\ (0,\ 1/12)$. We then conducted the Monte Carlo study with x not being autocorrelated and also with x being autocorrelated with a autoregressive coefficient of 0.8. In addition to estimating (2) with GLS, Newey-West, and OLSNO, we also estimated (1) using the disaggregate data. The results are reported in Table 10. The estimation was performed only for two sample sizes, respectively 100 and 1000 observations. In the case when x is not autocorrelated, there is no gain in using overlapping observations, in terms of reducing the measurement error. This is true for all methods of estimation.

In the case when x is autocorrelated, the largest reduction in measurement error occurs when Newey-West and OLSNO are used. Moreover, the bias is always larger for

GLS estimates compared to Newey-West and OLSNO estimates. The reduction in the measurement error because of using overlapping observations is confirmed by comparing the Newey-West and OLSNO estimates to the disaggregate estimates. The GLS transformation of the variables instead of further reducing the measurement error, compounds the error on the overlapping observations. This compounding effect almost totally offsets the error reduction effect of the aggregation process that creates the overlapping observations. This can be seen from the results of Table 10 where the GLS estimates are just barely less biased than the disaggregate estimates. Therefore, the GLS estimation is not an appropriate estimation method if the reason for using overlapping data is errors in the variables. Newey-West standard errors are still biased, so the preferred estimation method in the presence of large errors in the variables would be OLS with overlapping data and with standard errors calculated using Monte Carlo methods.

Imperfect overlap

Sometimes observations overlap, but they do not overlap in the perfect way assumed here and so the correlation matrix is no longer known. An example would be where the dependent variable represents six months returns on futures contracts. Assume that there are four different contracts in a year, the March, June, September, and December contracts. Then, the six-month returns for every two consecutive contracts would overlap while, the six-months returns between say March and September contracts would not overlap. Two six-month returns for, say the March contract, that overlap for three months would be perfectly correlated for these four months. The six-month returns for the March and June contracts would overlap for three months, but they would not be perfectly correlated during these three months, since the March and June contract are two different contracts. Let

$$Cov(u_{jt}, u_{st+m}) = \begin{cases} \sigma_{js} \text{ if } m = 0 \\ 0 \text{ otherwise} \end{cases} \quad \textbf{(36)}$$

be the covariance between the monthly returns m months (or days if disaggregated data are daily data) apart for the March and June contracts where u_{jt} and u_{st} are the error term from regression models with disaggregate data for the March and June contract. Then,

$$Var(u_{jt}) = Var(u_{st}) = \sigma_u^2, \quad Var(e_{jt}) = Var(e_{st}) = k\sigma_u^2 \quad \textbf{(37)}$$

and

$$Cov(e_{jt}, e_{st-m}) = k_{js}\sigma_{js} \quad \textbf{(38)}$$

where k_{js} is the number of overlapping months between the March and May contracts and $\sigma_{js} = \rho_i \sigma_u^2$ where ρ_i (i = 1, 2) is the correlation between the u's for two consecutive contracts with maturities three (ρ_1) and six (ρ_2) months apart. The covariance matrix for (2) in this case is:

$$
\Sigma = \sigma_u^2
\begin{bmatrix}
k & \frac{k-1}{k} & \frac{k-2}{k}\rho_1 & \frac{k-3}{k}\rho_1 & \frac{k-4}{k}\rho_2 & \frac{k-5}{k}\rho_2 & 0 & 0 & 0 & 0 & 0 & 0 \\
\frac{k-1}{k} & k & \frac{k-1}{k} & \frac{k-2}{k}\rho_1 & \frac{k-3}{k}\rho_1 & \frac{k-4}{k}\rho_2 & \frac{k-5}{k}\rho_2 & 0 & 0 & 0 & 0 & 0 \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\frac{k-3}{k}\rho_1 & \frac{k-2}{k}\rho_1 & \frac{k-1}{k} & k & \frac{k-1}{k} & \frac{k-2}{k}\rho_1 & \frac{k-3}{k}\rho_1 & \frac{k-4}{k}\rho_2 & \frac{k-5}{k}\rho_2 & 0 & 0 & 0 \\
\frac{k-4}{k}\rho_2 & \frac{k-3}{k}\rho_1 & \frac{k-2}{k}\rho_1 & \frac{k-1}{k} & k & \frac{k-1}{k} & \frac{k-2}{k}\rho_1 & \frac{k-3}{k}\rho_1 & \frac{k-4}{k}\rho_2 & \frac{k-5}{k}\rho_2 & 0 & 0 \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
0 & 0 & 0 & 0 & 0 & 0 & \frac{k-5}{k}\rho_2 & \frac{k-4}{k}\rho_2 & \frac{k-3}{k}\rho_1 & \frac{k-2}{k}\rho_1 & \frac{k-1}{k} & k
\end{bmatrix}
\qquad \textbf{(39)}
$$

Nonparametric methods

Sometimes authors want to use nonparametric methods that assume independence. In this case the only general solutions we can propose are to use nonoverlapping data, switch to a parametric method, or use Monte Carlo hypothesis testing procedures such as bootstrapping.

Cross-section time-series data

Sometimes the overlapping data are part of a cross-section time-series dataset. Studies of economic growth are an example of where such a dataset would be used. In this case Ω is still constructed in much the same way except it now becomes block diagonal. Cross-section time-series data will often be cross-sectionally heteroskedasticand so the same problems as discussed above under heteroskedasticity apply except that the covariance of the errors becomes block diagonal.

Next, assume that the disaggregate data have an error component so (1) becomes

$$y_{it} = \beta' x_{it} + u_t + \zeta_{it}$$

where $\mathrm{var}(u_t) = \sigma_u^2$, $\mathrm{var}(\zeta_{it}) = \sigma_\zeta^2$ and $\mathrm{cov}(u_t, \zeta_{it}) = 0$.

Then (2) becomes

$$Y_{it} = \beta' X_{it} + e_{it}$$

where $Y_{it} = \sum_{j=t}^{t+k-1} y_{ij}$, $X_{it} \sum_{j=t}^{t+k-1} x_{ij}$, and $e_{it} = \sum_{j=t}^{t+k-1} u_{ij}$

Now $\mathrm{var}(e_{it}) = (k+1)\sigma_u^2 + (k+1)^2 \sigma_\zeta^2$ and

$$\mathrm{cov}(e_{it}, e_{js}) = \begin{cases} 0 \quad \text{if} \quad t \neq s \\ (k-s)\sigma_u^2 + (k+1)^2 \sigma_\zeta^2 & \text{if } k-s \geq 0 \\ (k+1)^2 \sigma_\zeta^2 & \text{if } k-s < 0. \end{cases}$$

One possible estimator is an FGLS estimator which estimates the fixed effects model corrected for autocorrelation and then uses the estimated fixed effects to estimate the error components. The second is a maximum likelihood or restricted maximum likelihood estimator analogous to those discussed by Searle, Casella, and McCulloch. We leave the appropriateness of such estimators to be resolved by subsequent research. The Newey-West estimator can handle overlapping data and error components, but the covariance matrix needs to be estimated separately for each block.

Conclusions

We have explored using the GLS estimator when working with overlapping data. When explanatory variables are strictly exogenous the GLS estimator is superior to the commonly used estimators. The alternative estimators that were compared with the GLS estimator were, the Newey-West estimator and ordinary least squares with nonoverlapping data (OLSNO) and unrestricted MLE. Unrestricted MLE tends to reject the true null hypotheses more often than it should. However, this problem is reduced or eliminated as larger samples are used, i.e. 1000, 2000 observations. GLS estimator can exhaust computer memory limits when the sample size is large. MLE can be used instead since it requires less memory.

There is a gain in the efficiency of the parameter estimates when the GLS estimator is used instead of the other two estimators. The gain in efficiency increased with the level of overlapping. With overlapping of 29 time periods, the MSE of Newey-West was roughly 20 times larger than the MSE of GLS. The MSE of the OLSNO estimator was even larger.

The Newey-West estimator rejected true null hypotheses too often. This problem persisted even with sample sizes of 1,000. The power of the Newey-West hypotheses tests also was much slower to converge to one than the power of the GLS estimator. While hypothesis tests with the OLSNO estimator had the correct size, they had considerably lower power than either of the other two estimators.

We have also evaluated ways of obtaining parameter estimates when our original assumptions are relaxed. Several of these are especially important since they provide the motivation for using overlapping data in the first place. Others are important because they are commonly faced in empirical work. If the motivation for using overlapping data is missing observations or nonnormality then GLS is still the preferred estimator. When lagged dependent variables are used as explanatory variables, GLS is inconsistent, but the usual Newey-West and OLSNO estimators are misspecified and therefore also inconsistent. Consistent parameter estimates can be obtained with maximum likelihood. When the reason for using overlapping data is to reduce bias due to errors in the variables, GLS is nearly as biased as the disaggregate model. We suggest using OLS to estimate parameters and using Monte Carlo methods to calculate standard errors.

As we have shown, overlapping data is often used in finance and in studies of economic growth. The commonly used estimators are either inefficient or yield biased hypothesis tests. The appropriate estimator to use with overlapping data depends on the situation.

Table 1. Number of Articles Using Overlapping Data, 1996.

Journal	Number of articles					Total number of empirical articles in the journal	Percentage of articles with overlapping data
	OLSNO	N-W	Other[a]	OLS	Total		
J. Finance	16	8	8	-	26	55	47.3
Amer. Econ. Rev.	10	3	2	-	14	77	18.2
J. Fut. Mkts.	12	3	5	2	19	43	44.2

Note: The sum of the columns 2 through 5 may be larger than the total in column 6 since some articles use more than one method of estimation.

[a] These include HH and AM estimators.

Table 2. Parameter Estimates, Standard Deviations, and MSE for OLSNO, Newey-West, and GLS Estimation (Overlapping 1).

	GLS Estimation			Newey-West Estimation			Non-overlapping Estimation		
Sample Size	Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviations	MSE
30	0.981	0.639 [a] 0.663 [b]	0.440	0.971	0.631 [a] 0.808 [b]	0.654	0.970	0.893 [a] 0.930 [b]	0.865
100	1.005	0.348 [a] 0.345 [b]	0.119	0.996	0.374 [a] 0.423 [b]	0.179	0.997	0.490 [a] 0.497 [b]	0.247
200	0.993	0.246 [a] 0.244 [b]	0.060	0.993	0.269 [a] 0.303 [b]	0.092	0.989	0.346 [a] 0.345 [b]	0.119
500	1.001	0.155 [a] 0.154 [b]	0.024	1.003	0.172 [a] 0.189 [b]	0.036	1.001	0.219 [a] 0.218 [b]	0.048
1000	1.001	0.110 [a] 0.109 [b]	0.012	0.997	0.122 [a] 0.134 [b]	0.018	1.005	0.155 [a] 0.156 [b]	0.024
2000	1.002	0.077 [a] 0.082 [b]	0.007	0.998	0.086 [a] 0.098 [b]	0.010	1.002	0.110 [a] 0.116 [b]	0.014

Note: The sample sizes are the sizes for samples with overlapping observations.
[a] These are the estimated standard deviations of the parameter estimates.
[b] These are the actual standard deviations of the parameter estimates.

Note: The model estimated is $Y_t = \beta' X_t + e_t$ where Y_t and X_t represent some aggregation of the original disaggregated variables. For simplicity β is chosen equal to 1. The model is estimated using Monte Carlo methods involving 2000 replications. The errors for the original process are generated from a standard normal distribution and are homoskedastic and not autocorrelated. As a result of the aggregation, e_t follows an MA process with the degree of the process depending on the aggregation level applied to y and x.

Table 3. Parameter Estimates, Standard Deviations, and MSE for OLSNO, Newey-West, and GLS Estimation (Overlapping 11).

	GLS Estimation			Newey-West Estimation			Non-overlapping Estimation		
Sample Size	Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviations	MSE
30	1.001	0.647 [a] 0.647 [b]	0.418	1.032	0.665 [a] 1.878 [b]	3.527	1.220	2.940 [a] 4.601 [b]	21.216
100	0.998	0.348 [a] 0.359 [b]	0.129	1.003	0.651 [a] 1.047 [b]	1.096	1.008	1.256 [a] 1.308 [b]	1.711
200	0.994	0.245 [a] 0.236 [b]	0.056	0.989	0.527 [a] 0.698 [b]	0.487	0.993	0.871 [a] 0.895 [b]	0.802
500	1.005	0.155 [a] 0.155 [b]	0.024	1.005	0.363 [a] 0.455 [b]	0.207	1.026	0.540 [a] 0.542 [b]	0.294
1000	0.997	0.110 [a] 0.112 [b]	0.013	1.004	0.262 [a] 0.315 [b]	0.099	1.002	0.382 [a] 0.390 [b]	0.152
2000	0.995	0.078 [a] 0.077 [b]	0.006	0.999	0.189 [a] 0.223 [b]	0.050	0.999	0.270 [a] 0.272 [b]	0.074

Note: The sample sizes are the sizes for samples with overlapping observations.
[a] These are the estimated standard deviations of the parameter estimates.
[b] These are the actual standard deviations of the parameter estimates.

Table 4. Parameter Estimates, Standard Deviations, and MSE for OLSNO, Newey-West, and GLS Estimation (Overlapping 29).

	GLS Estimation			Newey-West Estimation			Non-overlapping Estimation		
Sample Size	Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviations	MSE
30	0.996	0.648 [a] 0.668 [b]	0.446	0.996	0.539 [a] 2.204 [b]	4.858	-- [c]	-- [c] -- [c]	-- [c]
100	1.005	0.349 [a] 0.345 [b]	0.119	1.077	0.711 [a] 1.595 [b]	2.551	1.233	2.228 [a] 2.823 [b]	8.023
200	0.996	0.245 [a] 0.248 [b]	0.062	1.016	0.694 [a] 1.216 [b]	1.478	0.988	1.467 [a] 1.571 [b]	2.469
500	1.005	0.155 [a] 0.158 [b]	0.025	1.029	0.523 [a] 0.726 [b]	0.528	1.025	0.867 [a] 0.893 [b]	0.798
1000	1.004	0.110 [a] 0.110 [b]	0.012	1.011	0.394 [a] 0.496 [b]	0.246	1.010	0.605 [a] 0.611 [b]	0.374
2000	1.002	0.077 [a] 0.078 [b]	0.006	1.002	0.290 [a] 0.343 [b]	0.118	1.004	0.427 [a] 0.425 [b]	0.181

Note: The sample sizes are the sizes for samples with overlapping observations.
[a] These are the estimated standard deviations of the parameter estimates.
[b] These are the actual standard deviations of the parameter estimates.
[c] These values cannot be estimated because of the very small number of observations.

Table 5. Parameter Estimates, Standard Deviations, and MSE for the Maximum Likelihood Estimates Assuming the MA Coefficients are Unknown for Three Levels of Overlapping (1, 11, and 29).

	Overlapping 1			Overlapping 11			Overlapping 29		
Sample Size	Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviations	MSE
30	0.975	0.622 [a] 0.624 [b]	0.391	1.019	0.541 [a] 0.833 [b]	0.694	- [c]	- [c] - [c]	- [c]
100	1.010	0.343 [a] 0.347 [b]	0.120	0.998	0.311 [a] 0.374 [b]	0.140	0.991	0.281 [a] 0.455 [b]	0.207
200	0.989	0.243 [a] 0.247 [b]	0.061	0.995	0.230 [a] 0.256 [b]	0.065	0.984	0.216 [a] 0.278 [b]	0.078
500	0.990	0.154 [a] 0.156 [b]	0.025	0.990	0.149 [a] 0.158 [b]	0.025	0.986	0.145 [a] 0.165 [b]	0.027
1000	0.991	0.112 [a] 0.109 [b]	0.013	0.991	0.107 [a] 0.112 [b]	0.013	0.990	0.105 [a] 0.112 [b]	0.013
2000	0.995	0.078 [a] 0.077 [b]	0.006	0.995	0.076 [a] 0.078 [b]	0.006	0.995	0.075 [a] 0.080 [b]	0.006

Note: The sample sizes are the sizes for samples with overlapping observations.
[a] These are the estimated standard deviations of the parameter estimates.
[b] These are the actual standard deviations of the parameter estimates.
[c] These values cannot be estimated because of the very small number of observations.

Table 6. Power and Size Values of the Hypothesis Tests for OLSNO, Newey-West, and GLS Estimation (Overlapping 1, 11, 29).

Degree of Overlapping	Sample Size	GLS Estimation		Newey-West Estimation		Non-overlapping Estimation	
		Power	Size	Power	Size	Power	Size
1	30	0.319	0.052	0.366	0.135	0.181	0.044
	100	1	0.043	0.500	0.090	0.500	0.052
	200	1	0.042	1	0.081	1	0.049
	500	1	0.053	1	0.078	1	0.052
	1000	1	0.049	1	0.075	1	0.056
	2000	1	0.058	1	0.089	1	0.072
11	30	0.315	0.044	0.500	0.492	0.045	0.044
	100	1	0.056	0.434	0.254	0.111	0.046
	200	1	0.039	0.486	0.169	0.194	0.045
	500	1	0.048	0.500	0.124	0.455	0.050
	1000	1	0.053	1	0.104	0.500	0.051
	2000	1	0.046	0.997	0.094	0.958	0.049
29	30	0.340	0.049	0.500	0.500	-- [a]	-- [a]
	100	1	0.044	0.500	0.417	0.070	0.056
	200	1	0.055	0.449	0.291	0.070	0.046
	500	1	0.061	0.500	0.176	0.203	0.044
	1000	1	0.050	0.500	0.132	0.364	0.055
	2000	1	0.059	0.885	0.113	0.646	0.051

Note: The sample sizes are the sizes for samples with overlapping observations.
[a] These values cannot be estimated because of the very small number of observations.

Table 7. Power and Size Values of the Hypothesis Tests for the Maximum Likelihood Estimates Assuming the MA Coefficients are Unknown for Three Levels of Overlap (1, 11, and 29).

Degree of Overlap	Sample Size	Total Number of Iterations	Iterations that Converge		Power [b]	Size [b]
			Number	Percentage		
1	30	1000	999	99.9	0.331	0.070
	100	1000	1000	100	0.827	0.047
	200	1000	1000	100	0.982	0.058
	500	1000	1000	100	1.000	0.060
	1000	1000	1000	100	1.000	0.062
	2000	1000	1000	100	1.000	0.051
11	30	1400	994	71.0	0.476	0.252
	100	1000	995	99.5	0.884	0.109
	200	1000	1000	100	0.980	0.085
	500	1000	998	99.8	0.998	0.075
	1000	1000	1000	100	1.000	0.069
	2000	1000	1000	100	1.000	0.056
29	30	-- [a]	-- [a]	-- [a]	-- [a]	-- [a]
	100	1600	970	60.6	0.814	0.254
	200	1200	1027	85.6	0.980	0.135
	500	1200	1082	90.2	1.000	0.081
	1000	1100	1066	96.9	1.000	0.078
	2000	1000	932	93.2	1.000	0.060

Note: The sample sizes are the sizes for samples with overlapping observations.

[a] These values cannot be estimated because of the very small number of observations.

[b] These are calculated based on the number of replications that converged.

Table 8. Parameter Estimates of Different Models for the Case of the Lagged Dependent Variable.

Equation Number	Method of Estimation	Data	Estimated Model
(23)	MLE	Overlapping	$Y_t = 0.0016 + 0.496\,Y_{t-1} + 1.0065 X_t + \epsilon_t + \epsilon_{t-1} + 0.99999\,\epsilon_{t-2}$
(24)	MLE	Overlapping	$Y_t = 0.078 + 0.108\,Y_{t-3} + 1.007 X_t + 0.493 X_{t-1} + 0.234 X_{t-2} + \epsilon_t + 1.471\,\epsilon_{t-1} + 1.69\,\epsilon_{t-2} + 0.69\,\epsilon_{t-3} + 0.219\,\epsilon_{t-4}$
(26)	MLE	Overlapping	$Y_\tau = 0.019 + 0.123\,Y_{\tau-3} + 1.002 X_{t-1} + 0.489 X_{t-2} + 0.251 X_{t-3} + \epsilon_\tau + 0.163\,\epsilon_{\tau-1}$
(25)	MLE	Nonoverlapping	$Y_\tau = 0.015 + 0.118\,Y_{\tau-3} + 1.413 X_\tau + 0.342 X_{\tau-3} + \varepsilon_\tau + 0.163\,\varepsilon_{\tau-3}$
(25)	Newey-West OLSNO	Nonoverlapping	$Y_\tau = 0.278\,Y_{\tau-3} + 1.415 X_\tau + \varepsilon_\tau$

Note: The models in Table 8 are estimated using a large Monte Carlo sample of 500,000 observations. The unrestricted maximum likelihood estimates are obtained using PROC ARIMA while the Newey-West and OLSNO estimates are obtained using PROC IML in SAS.

Table 9. Parameter Estimates, Standard Deviations, MSE, and Power and Size of Hypothesis Tests for OLSNO, Newey-West, and GLS Estimation with Two Xs and Nonnormal Errors(Overlapping 1, 11, and 29).

Degree of Overlap	Sample Size	GLS Estimation					Newey-West Estimation					Non-overlapping Estimation				
		Parameter Estimates	Standard Deviations	MSE	Power	Size	Parameter Estimates	Standard Deviations	MSE	Power	Size	Parameter Estimates	Standard Deviations	MSE	Power	Size
1	30	1.014	0.953 [a] 1.003 [b]	1.007	0.208	0.046	0.997	0.898 [a] 1.267 [b]	1.606	0.288	0.152	1.049	1.334 [a] 1.794 [b]	3.220	0.201	0.128
	100	0.969	0.498 [a] 0.510 [b]	0.261	0.494	0.053	0.969	0.526 [a] 0.621 [b]	0.386	0.460	0.095	0.999	0.700 [a] 0.875 [b]	0.766	0.342	0.111
	500	1.008	0.226 [a] 0.223 [b]	0.050	0.988	0.051	1.005	0.249 [a] 0.273 [b]	0.074	0.956	0.082	0.996	0.317 [a] 0.390 [b]	0.152	0.832	0.117
	1000	1.004	0.159 [a] 0.155 [b]	0.024	1	0.042	1.001	0.177 [a] 0.192 [b]	0.037	0.999	0.070	1.002	0.225 [a] 0.286 [b]	0.082	0.971	0.121
11	30	1.019	0.943 [a] 0.943 [b]	0.890	0.202	0.049	0.977	0.830 [a] 2.585 [b]	6.684	0.579	0.541	-- [c]	-- [c] -- [c]	-- [c]	-- [a]	-- [a]
	100	0.994	0.507 [a] 0.523 [b]	0.274	0.498	0.052	0.998	0.915 [a] 1.482 [b]	2.196	0.338	0.244	0.944	2.059 [a] 2.230 [b]	4.975	0.072	0.051
	500	1.008	0.226 [a] 0.225 [b]	0.051	0.993	0.049	1.010	0.524 [a] 0.663 [b]	0.439	0.517	0.138	1.035	0.810 [a] 0.828 [b]	0.687	0.236	0.056
	1000	1.003	0.159 [a] 0.159 [b]	0.025	1	0.042	1.022	0.378 [a] 0.457 [b]	0.209	0.734	0.107	1.016	0.557 [a] 0.568 [b]	0.323	0.432	0.057
29	30	1.014	0.935 [a] 0.995 [b]	0.990	0.193	0.056	1.014	0.654 [a] 2.614 [b]	6.833	0.629	0.611	-- [c]	-- [c] -- [c]	-- [c]	-- [a]	-- [a]
	100	1.009	0.507 [a] 0.543 [b]	0.294	0.513	0.046	0.995	0.911 [a] 2.328 [b]	5.420	0.505	0.455	0.982	4.919 [a] 9.052 [b]	81.94	0.063	0.059
	500	1.010	0.226 [a] 0.225 [b]	0.051	0.989	0.050	0.958	0.759 [a] 1.041 [b]	1.085	0.335	0.177	0.950	1.350 [a] 1.385 [b]	1.920	0.103	0.052
	1000	1.000	0.160 [a] 0.162 [b]	0.026	1	0.058	1.008	0.570 [a] 0.739 [b]	0.547	0.464	0.143	1.023	0.898 [a] 0.904 [b]	0.818	0.200	0.056

Note: The sample sizes are the sizes for samples with overlapping observations.

[a] These are the estimated standard deviations of the parameter estimates.

[b] These are the actual standard deviations of the parameter estimates.

[c] These values cannot be estimated because of the very small number of observations.

Table 10. Parameter Estimates, Standard Deviations, and MSE, for GLS, Newey-West, OLSNO, and the Disaggregate Estimation with Measurement Errors in X (Overlapping 1, 11, and 29).

Correlat. of X	Sample Size	Degree of Overlap	GLS Estimation			Newey-West Estimation			Non-overlapping Estimation			Disaggregate Estimation		
			Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviations	MSE	Parameter Estimates	Standard Deviatio ns	MSE
0	100	1	0.494	0.252 [a] 0.252 [b]	0.320	0.493	0.269 [a] 0.311 [b]	0.354	0.494	0.360 [a] 0.361 [b]	0.389	0.494	0.250 [a] 0.250 [b]	0.318
		11	0.509	0.252 [a] 0.263 [b]	0.310	0.512	0.479 [a] 0.739 [b]	0.784	0.503	0.952 [a] 1.028 [b]	1.303	0.510	0.239 [a] 0.251 [b]	0.303
		29	0.495	0.253 [a] 0.254 [b]	0.320	0.480	0.501 [a] 1.185 [b]	1.675	0.390	1.789 [a] 2.310 [b]	5.709	0.497	0.222 [a] 0.223 [b]	0.303
	1000	1	0.499	0.079 [a] 0.077 [b]	0.257	0.502	0.088 [a] 0.095 [b]	0.257	0.501	0.112 [a] 0.111 [b]	0.261	0.499	0.079 [a] 0.077 [b]	0.257
		11	0.502	0.079 [a] 0.080 [b]	0.255	0.499	0.189 [a] 0.227 [b]	0.303	0.497	0.277 [a] 0.281 [b]	0.332	0.501	0.079 [a] 0.080 [b]	0.255
		29	0.499	0.079 [a] 0.078 [b]	0.257	0.517	0.285 [a] 0.364 [b]	0.366	0.509	0.441 [a] 0.445 [b]	0.440	0.499	0.078 [a] 0.077 [b]	0.257
0.8 [c]	100	1	0.718	0.191 [a] 0.199 [b]	0.119	0.816	0.174 [a] 0.214 [b]	0.080	0.816	0.218 [a] 0.223 [b]	0.084	0.716	0.190 [a] 0.198 [b]	0.120
		11	0.731	0.187 [a] 0.196 [b]	0.111	0.931	0.187 [a] 0.302 [b]	0.096	0.934	0.337 [a] 0.351 [b]	0.127	0.721	0.181 [a] 0.187 [b]	0.113
		29	0.730	0.186 [a] 0.194 [b]	0.110	0.963	0.174 [a] 0.429 [b]	0.186	0.966	0.536 [a] 0.701 [b]	0.493	0.720	0.166 [a] 0.174 [b]	0.109
	1000	1	0.735	0.058 [a] 0.060 [b]	0.074	0.833	0.055 [a] 0.065 [b]	0.032	0.832	0.066 [a] 0.067 [b]	0.033	0.734	0.058 [a] 0.060 [b]	0.074
		11	0.733	0.058 [a] 0.062 [b]	0.075	0.940	0.071 [a] 0.086 [b]	0.011	0.941	0.096 [a] 0.097 [b]	0.013	0.732	0.058 [a] 0.062 [b]	0.075
		29	0.736	0.058 [a] 0.061 [b]	0.073	0.954	0.091 [a] 0.116 [b]	0.016	0.950	0.135 [a] 0.138 [b]	0.021	0.735	0.057 [a] 0.060 [b]	0.074

Note: The sample sizes are the sizes for samples with overlapping observations.

[a] These are the estimated standard deviations of the parameter estimates.

[b] These are the actual standard deviations of the parameter estimates.

[c] The x is generated as follows: $x_t = x_{0t} + \omega_t$, where $x_{0t} \sim uniform\ (0, 1)$ and $\omega_t \sim N\ (0, 1/12)$.

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Essay II

The Optimal Investment Strategy of a Hedge Fund

The Optimal Investment Strategy of a Hedge Fund

Abstract

This paper presents a model of a hedge fund manager's decision problem.. The objective is to maximize the net present value of the manager's fees. The model assumes fees are paid discretely and that the manager is paid both of fixed fee and an incentive fee. The inclusion of withdrawals in the model introduces nonlinearity in the objective function. This nonlinearity in the objective function and the inclusion of fixed fees may explain why poor performers do not increase the variance of their portfolio to infinity as previous work suggest.

Key words: hedge funds, optimal investment strategy, fixed fee, incentive fee.

The Optimal Investment Strategy of a Hedge Fund

Introduction

The potential conflict of interest between investment advisors and their clients concerns economists, policy makers, and investors, among others. Of particular interest is the way in which compensation arrangements between the two parties affect the conflict (Cohen and Starks). The fiduciary relationship between portfolio managers and the investors is often viewed as a principal-agent relationship. An agency relationship exists when one party, the agent, is engaged by another party, the principal, to perform some specified service on behalf of the principal (Starks). The methodology from the agency literature in economics and finance has been used to study the impact of various compensation arrangements on the conflict of interest between these two groups in a world where only mean (return) and variance (risk) matter.

Starks (1987), using agency theory, investigates the effect of two types of performance incentive fees: symmetric performance incentive fees and "bonus" performance incentive fees. In the case of the symmetric performance fee schedule, the manager receives a percentage of the market value of the assets plus a bonus or a penalty, depending on whether the portfolio return was higher or lower than the return on some market index. In the case of the "bonus" performance fee schedule, the manager receives a percentage of the market value of the assets plus a bonus if the portfolio's return exceeds the return on the index (benchmark). No penalty is assessed when the return is below the benchmark return. Starks finds that when the manager's only decision is to select the portfolio's risk level, the symmetric performance fee schedule will provide the appropriate incentives for selecting the investor's desired risk level. On the other hand, if the manager will also decide the level of resources, then the agency problem will not be eliminated by the symmetric performance fee schedule. In this case, the manager's optimal level of resources will be less than the investor's optimal level of resources. However, under the bonus performance fee schedule the manager will choose an even lower level of resources and a higher than optimal level of risk.

Cohen and Starks employing a principal-agent model and the assumptions of the Capital Asset Pricing Model (CAPM) show that for certain utility functions, estimation risk leads the manager to choose a lower beta portfolio than otherwise. By making more strict assumptions about preferences, they show that the manager will provide more effort but also a riskier portfolio than the investor prefers. They also show that the investor will prefer a manager who is more risk preferring than the investor.

Golec provides empirical tests of the investor-investment advisor relationship. His model, also based on agency theory, differs from Starks' model and other models in two aspects. In Golec's model, the input of the agent is clearly specified as investment information rather than general effort. In addition, the investment information (the input) affects not only the expected return of the portfolio, it also affects the variance of returns. Golec examines the relation between the fixed fees and incentive fees with the fund size (dollar amount of investment), fund's beta with respect to a market index, the agent's information ratio (defined as the tradeoff between expected return and variance of returns), and the nonrandom return associated with the information available to the agent. Golec finds that the incentive fee should be negatively related to the fund size and positively related to the beta, the agent's information ratio, and the nonrandom return. Golec also finds that contrary to the prediction the fixed fee and the incentive fee are not negatively related.

Several papers (Grinblattand Titman; Carpenter; Goetzmann, Ingersoll, and Ross) have also looked at the effect of asymmetric contracts upon the manager's incentives to invest effort and take risks. An asymmetric contract contains a "high water mark" provision that requires the manager to make up past deficits before earning the incentive portion of the fee (Brown, Goetzmann, and Park). All of these studies show analytically that the value of the manager's contract increases with portfolio variance due to the call-like feature of the "high water mark" contract. In their study of the fund manager's investment problem, Grinblatt and Titman assume that the manager can hedge the fee in his personal portfolio. Thus the objective of the manager is to maximize the market value of the fee. However, as Carpenter shows, this objective leads to the manager opting to increase the fund volatility to infinity. Carpenter in her study "assumes that the manager cannot hedge the fee in his private account because shorting securities that he purchases on his client's behalf is a breach of fiduciary duty" (Carpenter, p.1). Then the manager's objective in Carpenter's model becomes the maximization of the expected utility of the incentive fee. Carpenter derives the optimal investment policy for the one-period and multi period-cases. Carpenter shows that a manager with constant relative and absolute risk averse utility functions, rather than maximizing portfolio risk, dynamically adjusts volatility in response to changes in the asset value over time. As assets grow large and the manager accumulates profits, he begins gambling with his own money and therefore prefers to lower asset volatility. On the other hand, when asset value approaches zero, the manager increases portfolio volatility up to infinity. Goetzmann, Ingersoll and Ross find that the value of the incentive fee for the asymmetric contracts depends on the volatility of the assets as well as on the investor withdrawal policy. The value of the incentive fee is high when the asset volatility is high and when the probability of investors withdrawing too soon is high. The fixed fee provides the greatest value to the manager when asset volatility is low and when investors are expected to remain for a long term.

However, Brown, Goetzmann, and Park show that hedge fund managers and commodity trading advisors (CTA) behavior is different from what theory predicts. They find that managers that performed well significantly reduced their variance. Based on theory predictions, the poor performers are expected to increase volatility to meet their high water mark. They find that this is not the case for the hedge fund/CTA managers. Brown, Goetzmann, and Park argue that the reason why hedge fund/CTA managers do not behave as the theory says they should is the great implicit costs to taking risks that might lead to termination.

Richter and Brorsen develop a model that accounts for a knockout feature (fund termination) to analyze its influence on the incentive fee and manager's performance. Using the continuous-time approach they derive the distributions for the life of the fund and the maximum value reached by the managed capital during the life of the fund. The continuous-time model developed by Richter and Brorsen incorporates a knockout feature, an innovation compared to previous models, but considers neither investor's nor manager's withdrawals. Goetzmann, Ingersoll, and Ross incorporate withdrawals in their differential equation approach but they also assume away riskless arbitrage. The assumption of no-riskless arbitrage is not realistic for hedge funds. In addition, managers are usually paid the incentive fee at the end of a certain period, a quarter or year and not continuously as in the models of Richter and Brorsen and Goetzmann, Ingersoll, and Ross.

The purpose of this research is to determine the optimal investment strategy for an individual hedge fund. The optimal investment strategy will be determined by maximizing manager's fees. In her multi-period model Carpenter assumes that the strike price of the incentive fee is reset each year at the current fund level. Instead, in this paper, the benchmark will be some market index and its value will change from year to year. We will also add to the multi period model developed by Carpenter the possibility to account for investor's and manager's withdrawals. An additional feature in the model will be the cumulative net loss, *NL*. According to the disclosure document of Steven C. Hutson, Inc., the cumulative net loss, if any, carried over from previous periods is subtracted from the returns before the incentive fee is calculated.

The Model

The manager controls a fund with the size X_t at time t. At the end of each year, $t = 1, 2, ..., T$, the manager receives the fixed fee, $\alpha_0 X_t$, plus the incentive fee IF_t,

$$IF_t = \max\ [\alpha_1[(R_{t+1} - R_{0t})X_t - NL_t],\ 0] \qquad \textbf{(45)}$$

where α_1 is a constant that may vary for each fund, R_{t+1} is one plus the fund rate of return for the period t+1 which is calculated after the fixed fee has been subtracted and is expressed as a function of the fund size, $R_{t+1} = f(x_t)$ with $f^{`}(x_t) < 0$, R_{0t} is one plus the benchmark rate of return, such as the riskless rate, S&P500, or zero, and NL_t is the net loss for the period t expressed as follows:

$$NL_t = \max[(NL_{t-1} - R_t X_{t-1}),\ 0](1 - W_t/X_t) \qquad \textbf{(46)}$$

where W_t accounts for investor and manager withdrawals as well as the new money and will also be expressed as an asymmetric function of past returns and variability:

$$W_t = g(R_{t-i}, \sigma_{R,(t-i)}), \quad i = 1, 2, 3; \quad \frac{\partial W_t}{\partial R_{t-i}} < 0; \quad \frac{\partial W_t}{\partial \sigma_{R,(t-1)}} > 0 \qquad \textbf{(47)}$$

where σ_R is the variability of the returns. The X_{t+1} is calculated using the relation:

$$X_{t+1} = R_{t+1} X_t - W_{t+1} - IF_t \qquad \textbf{(48)}$$

Thus, at the end of the year the manager's total fee equals:

$$V_t = \alpha_0 X_t + \max[\alpha_1((R_{t+1} - R_{0t})X_t - NL_t),\ 0]. \qquad \textbf{(49)}$$

In this paper incentive fees are assumed to be paid in discrete-time, similar to the model developed by Carpenter. The manager's utility function, U, is assumed to be a Von-Neumann Morgenstern utility function that satisfies the conditions of being strictly increasing, strictly concave, and at least twice continuously differentiable. The manager operates in a complete, no-arbitrage, continuous-time financial market that consists of a riskless asset with interest rate r, and n risky assets. As in Carpenter, the risky asset prices,

P_i, are assumed to be governed by a standard n-dimensional Brownian motion, Z, as presented by the equations:

$$\frac{dP_{i,t}}{P_{i,t}} = (r_t + \mu_{i,t})dt + \sigma_{i,t} dZ_{i,t} \quad \textbf{(50)}$$

where the interest rate r_t, the excess appreciation rates $\mu_{i,t}$, and the volatilities $\sigma_{i,t}$, are bounded and progressively measurable with respect to I_t, the information available at time t. In addition,

$$\mu_{i,t+1} = f(\pi_{i,t}); \qquad f' < 0 \quad \textbf{(51)}$$

where π denotes the manager's investment strategy which is a function of fund size and net losses as given by:

$$\pi_s = \gamma_1(s, X_s, NL_{tru(s)})X_s \quad \textbf{(52)}$$

where s represents continuous time and $tru(s)$ represent the truncated s so that it equals the latest discrete point in time. The use of $tru(s)$ is necessary since net loss is measured annually. The relation in (52) will be approximated as linear, but the parameters will also be a function of time, fund size, and net loss. The instantaneous change in the parameters in a continuous time framework allows for the change in π_t during this continuous time framework.

The investment strategy for the manager is an n-dimensional process π_t, whose i-th component, $\pi_{i,t}$, is the value of the holdings of risky asset i in the portfolio at time t. An admissible strategy must be progressively measurable with respect to I_t, must prevent fund value from falling below zero, and must have finite variance. Under such a strategy, portfolio value evolves according to:

$$dX_t = (r_t X_t + \pi'_t \mu_t)dt + \pi'_t \Sigma_t dW_t \quad \textbf{(53)}$$

where Σ_t is the variance-covariance matrix of the variances of the n risky assets.

The manager chooses an investment strategy to maximize his expected discounted utility of total fee. Then the value function for his problem at any year $t = 0, 1, ..., T$-1 is:

$$F_t(x) = \max_{(\pi_s,\ t \le s \le T)} \sum_{j=0}^{T-t-1} \beta^j E[U(\alpha_0 X_{t+j} + \max[\alpha_1((R_{t+j+1} - R_{0(t+j)})X_{t+j} - NL_{t+j}),\ 0] | I_t)] \quad \textbf{(54)}$$

subject to:

$$dX_s = (r_s X_s + \pi'_s \mu_s)ds + \pi'_s \Sigma_s dW_s \quad \textbf{(55)}$$

$$NL_t = \max[-[(R_t - R_{0(t-1)})X_{t-1} - NL_{t-1}],\ 0](1 - W_t/X_t) \quad \textbf{(56)}$$

$$X_{t+1} = R_{t+1}X_t - W_{t+1} - IF_t; \quad X_t = x \quad \textbf{(57)}$$

$$\iota'\gamma_1 \le 1 \quad \textbf{(58)}$$

$$X_t - W_t \le X_{\max} \quad \textbf{(59)}$$

$$X_{t+j} \geq 0 \quad \forall j = 1, 2, ..., T-t \tag{60}$$

where β is the discount rate, R_{t+j} is the annual rate of return as defined earlier, I_t is the information available at time *t*, and ι is a vector of ones. The subscript *t* represents discrete points in time while the subscript *s* represent the continuous time for the process governing the value of the portfolio, *X*. The constraint in (58) means that borrowing at the risk free rate *r* is not allowed. The constraint in (59) says that when the fund size reaches a specified maximum level X_{max}, the fund will be closed to new money.

Dynamic Programming

The maximization problem represented in (54) through (60) can be modeled as a dynamic programming (DP) problem. The parts of the DP model will be defined as follows. The objective function, F_m consists in maximizing the expected utility of the present value of V_m over the planning horizon:

$$F_m(X_m, NL_m) = \max_{\pi_m} EU[V_m(X_m, NL_m, \pi_m) + \beta F_{m+1}(k(X_m, NL_m, \pi_m))] \tag{61}$$

with

$$F_{M+1}(X_{M+1}, NL_{M+1}) = 0. \tag{62}$$

The planning horizon, *M* is the number of stages in the decision problem. Taylor and Duffy argue that five to ten discrete stages ($m = 0, \ldots, M$) are usually adequate to provide a reasonable approximation to the solution to a continuous variable problem. The state variables will be the levels of the fund size, X_m, and the net losses, NL_m for each stage. The decision variable, the variable which the fund managers can control, will be the proportion of the funds under management that will be invested, π_m. The restriction on π_m will be such that the amount of finds invested in risky assets does not exceed the amount of funds available to the manager. The state transition equation that shows the relationship between current decisions and states, and states in the next stage, is given by

$$X_{m+1} = k(X_m, NL_m, \pi_m); \quad X_0 = x \tag{63}$$

where x is the initial fund size. The fund size is assumed to be lognormally distributed. The net loss is not a stochastic variable. The net loss is a deterministic variable once the value of the fund size is determined. The return function that gives the returns at each stage as a function of state and decision variables is given by $V_m(X_m, NL_m, \pi_m)$. The optimal decision rule that shows the relation between the optimal value of the decision variable and the state variables is represented by:

$$\pi_m = h(X_m). \tag{64}$$

Conclusions

This paper addresses the issue of an optimal investment strategy for a hedge fund. The objective function is maximizing the manager's discounted utility of total fees. The model assumes the manager is paid both the fixed fee and an incentive fee and that the fees are paid discretely. To be able to determine the manager's decision process information on fund size and carryover losses is needed. Also, the return function with respect to fund size and the withdrawals function with respect to past returns and volatility will need to be estimated. In addition, the withdrawals function should allow for an asymmetric effect of returns. Negative returns may cause investors to take their money out of the fund, while positive returns do not necessarily mean more money is flowing into the fund. This asymmetry introduces nonlinearity in the objective function that could explain why the poor performers do not increase the variance of the portfolio to infinity as previous theoretical work suggests.

Regarding the estimation of the withdrawals function it is important to separate funds that accept new money from funds that do not. The sign of the first derivatives of the withdrawals function with respect to returns will be ambiguous if one cannot separate funds that take new money. If possible to separate, then only the funds that accept new money should be used in the estimation. In this case, the sign of the first derivatives will be negative. The sign of derivatives could also be positive if fund size is at the maximum level. Regarding the returns function, it is important to take into account the fact that the returns/size relation could be different for every fund.

The choice variables in the maximization problem are the maximum fund size and the trading strategy, that is, how and where will the money be invested? The choice of risk level will depend on the fixed vs. incentive fee levels. Fixed fee encourages surviving, while incentive fee encourages a more risk taking behavior. The carryover net losses also affect the risk choice. If a net loss has already occurred the manager may increase risk to make up this loss. The choice of risk level can be incorporated through the manager's utility function.

As a final conclusion the discrete approach looks promising. However, further research is needed to address this issue. Solving the maximization problem represented in (54) through (60) via dynamic programming, or through comparative dynamics would provide more insight regarding the hedge fund managers behavior.

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Essay III

Performance Persistence of Hedge Funds

Performance Persistence of Hedge Funds

Abstract

This paper tests whether performance persistence exists in the hedge fund industry in the sense that some funds have consistently higher returns than others. Several procedures are used to determine if performance persists. The results show that performance persists in hedge funds with some funds showing the greatest persistence across all the procedures. The results also indicate a strong negative relation between hedge fund capitalization and returns. The results are consistent with the hypothesis that hedge fund managers exploit market inefficiencies.

Key words: hedge funds, performance persistence, style analysis, overlapping data.

Performance Persistence of Hedge Funds

Introduction

Hedge funds are similar to mutual funds except they have considerably fewer restrictions on their trading. Most U.S. hedge funds are organized as a limited partnership, or a limited liability company (Brown, Goetzmann, and Ibbotson (BGI)) established to invest in public securities where the general partners make a substantial personal investment. Caldwell (p. 1) argues that hedge funds are "broadly perceived by the investing public to be imprudent investments." Better understanding of how to evaluate hedge fund returns is needed in providing a better product to investors and in successfully marketing the better product. A common definition of hedge funds does not exist. Hedge funds are mostly defined by their freedom from the regulatory controls based on the Investment Company Act of 1940. They are designed to exploit market inefficiencies. A hedge fund can take both long and short positions, use leverage and derivatives, invest in concentrated portfolios, and move quickly between different markets. Hedge funds can also take large risks on speculative strategies like short sales, swaps and arbitrage.

There are several classifications for hedge funds. In our data, hedge funds are classified based on their strategy. Some of these strategies are: global, regional, market neutral, short sales, long only, event driven, and macro (Table 1). A broader classification of the hedge fund strategies by Agarwal and Naik groups them into two categories, non-directional and directional. Non-directional strategies have low correlation with the market, while directional strategies have high correlation with the market. Also, hedge funds are classified into two major types, U.S. (or onshore) and offshore. Offshore funds are limited liability corporations or partnerships established in tax neutral jurisdictions that allow investors an opportunity to invest outside their own country and minimize their tax liabilities (Liang, p.1). BGI argue that the most interesting feature of hedge funds is that they are perceived mostly as pure "bets" on managerial skill. While the mutual fund strategies are considered as investment styles with relative return targets, the hedge fund strategies are considered as investment styles with absolute return targets (Fung and Hsieh). In other words, the mutual fund performance is evaluated relative to certain benchmarks while hedge funds are not judged by their ability to track a passive benchmark. In addition, compensation in mutual funds is generally based on the fund size independent of performance. On the other hand, compensation in hedge funds is largely based on performance. Fung and Hsieh (1997) using Sharpe's style analysis show the distinction between mutual and hedge fund investment strategies. Fung and Hsieh argue that manager's returns have three key determinants: 1) the asset categories the manager invests in, 2) strategy or direction component (short/long), and 3) the use of leverage. Mutual fund managers usually employ only the first component in their strategies. Hedge fund managers, on the other hand, employ dynamic, leveraged strategies that also involve the second and third component of the return.

As a result of their absolute return target nature, the compensation of hedge fund managers is based largely on performance. Hedge fund managers receive a fixed fee, usually 1 to 2 % of net assets, and an incentive fee. Some hedge funds pay the incentive fee only after some hurdle rate is met. The hurdle rate, depending on the fund, may be fixed, ranging from zero to 10%, or set equal to the return on some stock index. In addition, most hedge funds have a "high watermark" provision so that incentive fees are only paid when the annual realized profit is above the previous maximum share value of the fund (Brown, Goetzmann, and Park).

In contrast to mutual funds, hedge funds are not required to register with the SEC and disclose their asset holdings (Liang). As of June 1997, the SEC allows hedge funds to have up to 499 limited partners without any registration and disclosure requirements. However, 65% of investors must be accredited investors with a net worth of at least $1 million, or steady annual incomes of $200,000 or more. There is also a minimum investment requirement of typically $250,000. In addition, first time investors cannot withdraw their money for a specified time period (a lockup period feature).

The limited reporting required of hedge funds makes it difficult to estimate the size of the industry. Pacelle (1997) notes that hedge funds currently have $200-300 billion under management and are growing rapidly. Agarwal and Naik (1999) report an estimated number of about 4000 onshore and offshore hedge funds with more than $400 billion of invested capital compared to about 6,000 mutual funds with $2 trillion in assets. However, Fung and Hsieh note that "on a leveraged basis the positions taken by a large hedge fund often exceed those of the largest mutual fund" (p. 281). Due to the difficulty of obtaining data about hedge funds, there is limited academic research in this area.

Fung and Hsieh's (1997) extension of Sharpe's (1992) style regressions includes dynamic strategies as additional regressors and can be used in performance attribution and style analysis of both mutual and hedge fund managers. Following Fung and Hsieh researchers studying hedge funds have used a multi-factor model to perform the style regression analysis. Examples include Liang (1998) and Agarwal and Naik (1999). BGI (1997) examine the performance of hedge funds and whether returns are predictable from past returns. They use annual data and a sample containing only offshore hedge funds. BGI find positive risk-adjusted performance for offshore funds but no performance persistence, or managerial skill. Thus they attribute offshore hedge fund performance to the style effects. Moreover, they conclude that "Funds-of-Funds" (funds that invest in winning hedge funds) perform more poorly than the average return for their sample. If there is some performance persistence, managers of "Funds-of-Funds" have apparently not learned how to exploit it. Ackerman, McEnally, and Ravenscraft (1997) conclude that hedge funds outperform mutual funds. Liang (1998) finds that on a risk-adjusted basis, most hedge funds earn positive abnormal returns. Liang also concludes that compared with mutual funds as a whole, hedge funds offer a better risk-return trade-off. In general, hedge funds provide a more efficient investment opportunity set for investors compared to mutual funds. Agarwal and Naik (1999) add that a portfolio that combines alternative and passive investment strategies provides a significantly better risk-return trade-off than passive-only investment strategy. Agarwal and Naik also find that hedge funds outperform the benchmark consisting of a combination of the various asset classes by 6% to 15% per year. In addition they find some performance persistence for various hedge fund strategies. However, they conclude that this persistence is mostly driven by losers continuing to be losers rather than winners being winners. Park and Staum using the nonparametric procedure of Spearman rank correlation present evidence for performance persistence among Commodity Trading Advisors (CTAs) and hedge funds.

This paper addresses the issue of performance persistence of hedge funds in the sense that some funds have consistently higher returns than others and the source of returns for hedge funds. In addition, the impact of size on performance will be studied. Only two previous papers address primarily the performance persistence of hedge funds BGI, and Park and Staum. The evidence from these two papers is mixed, one does not find performance persistence while the other does. However, Park and Staum use only one nonparametric method to study performance persistence while BGI use several methods. Agarwal and Naik also provide evidence of performance persistence for some hedge fund strategies. Three alternative methods will be used to test for performance persistence. To determine if performance persists, one of the usual procedures employed is to regress current returns on past returns. In addition, we regress Sharpe's ratio against a lagged Sharpe's ratio. The Sharpe ratio will be used as a dependent variable because studies involving commodity funds find greater performance persistence using a Sharpe ratio rather than returns (Brorsen). We improve on previous research by using overlapping data (with annual observations) to increase the number of our observations and so increase the efficiency of our parameter estimates and the power of our tests. In addition, this procedure will be performed by estimating separate regressions for each style of trading.

Secondly, the style analysis similar to the Sharpe's (1992) and Fung and Hsieh (1997) style regressions will be considered. The null hypothesis to be tested is whether once adjusted for changes in overall returns do funds all have the same mean returns? The rationale behind this is that if all funds have the same mean returns then no performance persistence exists. Finally, an out-of-sample test using the Spearman rank correlation test will be used. The ranking and the testing will be performed based on four measures, the mean returns, the Sharpe's ratio, the ratio of the mean returns to the standard deviation of returns, and the ratio of the intercepts from the style regressions to the standard deviation of returns.

To identify the source of returns for hedge funds a measure of the size of funds will also be considered as an additional explanatory variable in the regressions in the first and second procedure, both in their estimation for the whole sample and in the subsamples for each style. One hypothesis concerning the source of returns for hedge funds is the existence of inefficiencies in pricing of assets in the debt, equity, currency and commodities markets. If size of fund matters, it offers support for the hypotheses that inefficiency exploitation is the source of returns for hedge funds.

Performance Persistence

Performance persistence usually means identifying winners and losers within a particular industry. Moreover, it means identifying winners that follow winners or losers that follow losers. From a practical point of view the interest is to determine if some funds have consistently higher returns than others. The importance of finding performance persistence rests on the fact that it would enable investors to beat the market average. The winners and losers within an industry are determined by evaluating them based on a given benchmark or an index for the industry. For the mutual fund industry the most commonly used benchmark is the S&P500 index. However, the S&P500 index could not be used as a benchmark for the hedge fund industry given the diversity of hedge fund strategies and their exposure to different security markets. One possibility in the case of the hedge fund industry is to create an index for the industry. Creating such an index is difficult due to the lack of data available to truly represent the whole hedge fund industry and a single index cannot represent the diverse strategies that hedge funds use. The other possibility is to use a multi-factor model with the factors representing the asset classes where hedge funds invest, equities, bonds, currencies, commodities, and cash.

Hedge fund managers employ dynamic and leveraged strategies that are also perceived as strategies with absolute return targets. These are the features, as Park and Staum argue, that have given the hedge fund industry a reputation for manager skill. But, why do hedge funds exist? One hypothesis regarding the source of returns for hedge funds is existence of market inefficiencies in the sense of mispriced securities. Hedge fund managers seek out and exploit these market inefficiencies. If one accepts the above hypothesis, then the existence of performance persistence would imply market inefficiency. Hedge fund managers dynamically change their strategies by constantly seeking out new market inefficiencies to exploit and therefore, it is difficult to evaluate the above question. However, evidence of an inverse relation between a hedge fund returns and its market capitalization would imply that hedge fund managers exploit market inefficiencies. The argument for this is that these market inefficiencies cannot be scaled up, thus putting more money to exploit the inefficiency should cause the returns to decrease. Another issue related to performance persistence is the fees charged by the hedge fund managers. If the compensation of hedge fund managers is largely based on performance then the return to unique skills could be captured by a manager in the form of higher fees. However, this pattern of managers with unique skills charging higher fees is difficult to observe for the hedge fund industry given the short life of the industry. Most existing hedge funds were established in the 90's. Also, the small number of funds before the 90's makes it difficult to accurately estimate performance persistence and observe a relation between performance persistence and manager fees.

As Gruber (p. 793) notes "The surprising thing about persistence is not that it exists, but rather how strong it appears to be." Several measures can be used to quantify performance persistence. One of the widely used measures is Jensen's alpha, the intercept in the Capital Asset Pricing Model (CAPM). In the case of hedge funds that extensively use leverage in their investment strategies the leverage invariant measures of performance persistence are more appropriate. Such measures include the Sharpe's ratio and the appraisal ratio, defined as the ratio of alpha to the standard deviation.

Data

Data about hedge funds were provided by LaPorte Asset Allocation. There are two datasets about hedge funds. One data set contains monthly data about fund returns (arithmetic) and size, or the total capitalization. There are 1209 hedge funds included in the data set. The second data set provides information regarding the characteristics of the hedge funds. These characteristics include whether a fund is a hedge fund or Fund-of Funds, whether it is a U.S. (or onshore), or offshore fund, the date the fund started, location and the name of the manager, as well as the style of the fund. The style of the fund is basically determined by the markets and/or securities where the fund invests. There are seven styles in the data set: 1) Global, 2) Sector, 3) Market Neutral, 4) Global Macro, 5) Short Sales, 6) Event Driven, and 7) Long Only. The two types of Fund-of-Funds (FOF), U.S. and offshore FOF (or FOF NonU.S.), are also considered as separate styles in the paper. In addition, the datasets include information about incentive, and management fees.

Table 2 reports the annual summary statistics about the hedge fund data. The number of funds increased from just 2 in 1977 to 1209 in 1998. Also, the total capitalization increased from $195 million in 1977 to $ 110,560 million in 1998. There is a slight decrease in the capitalization from 1997 (the maximum for the sample) to 1998. Table 2 also shows that the average management fee decreased over time while the average incentive fee has grown. One problem with the data set is that no fund drops out of the sample. This would of course introduce survival bias in the empirical analysis. However, for the problem of performance persistence that will be investigated in this paper this bias should have a minimum or no effect at all on the results. As Park and Staum report this bias would weaken the evidence for the hypothesis that losers repeat. It does however bias the average returns across all funds reported. Thus, caution is needed when comparing the results for hedge funds versus results from other industries.

Table 3 reports the mean, standard deviation, and the Sharpe ratio for both S&P500 and the equal-weighted portfolio of the hedge funds for each year. The annually reported means for both the S&P500 and hedge funds portfolio are averages of monthly means for each year. The standard deviation for the equal-weighted portfolio for each year is calculated as an average of the individual fund's annual standard deviations. This is done to eliminate the cross-sectional variation in the estimates of the standard deviation and thus allows for a comparison with the S&P500 standard deviation. The average mean for the equal-weighted portfolio is 1.39% which is higher than the mean 0.87% of the S&P500. Also the mean standard deviation for the equal-weighted portfolio is slightly smaller than the standard deviation for the S&P500. The numbers respectively are 0.034 and 0.039. This can also be seen by the values of the Sharpe ratios. The mean Sharpe ratio (calculated as an average of the annual Sharpe Ratios) for the equal-weighted portfolio is 0.357 while the mean Sharpe ratio for the S&P500 is 0.16. In term of the Sharpe ratio, the equal-weighted portfolio beats the S&P500 in all the years before 1995 with the exception of 1989. Remember that the hedge fund data set does not include defunct funds. Thus, the returns for the equal-weighted portfolio of hedge funds are likely overestimated.

Table 4 reports number of funds for each style. The largest number of funds, 430 fall into the style Global. The styles Market Neutral and Event-Driven are also represented by a large number of funds, respectively 232 and 123. In addition, there are a large number of Funds-of-Funds, with a total of 267. From these 127 are U.S. FOF and 140 are offshore FOF. The smallest number of funds, 14 and 18 are for the styles Short Sales and Long Only respectively. The Long Only funds appear only in the last seven years starting in 1992.

Table 5 reports capitalization of funds for each style. The largest capitalizations are for the styles Global, Global Macro, and Market Neutral with million U.S.$ respectively 29,685, 25,324, and 20,263. The U.S. FOF have a small capitalization given the relatively large number of such styles. The styles Short Sales and Long Only besides having the smallest number of funds also have the smallest capitalizations respectively million U.S.$ 676 and 400.

The data for the asset classes to be used in the style analysis regressions were obtained as follows. Several Morgan Stanley Capital International (MSCI) Equity indices, MSCI World index, MSCI USA index, and MSCI Emerging Markets index were provided by Morgan Stanley Dean Witter. The Federal Reserve Bank Trade-Weighted Dollar Index, the bond indices, and the risk-free rate data were collected from the Saint Louis Federal Reserve Economic Database. The S&P500 data were obtained from the daily master file of the Center for Research of Security Prices (CRSP).

Procedures

Three alternative methods are used to test for performance persistence. First, returns are regressed against lagged returns:

$$\sum_{t=j}^{j+k-1} r_{it} = \alpha_i + \beta_i \sum_{t=j}^{j+k-1} r_{i(t-12)} + \sum_{t=j}^{j+k-1} \epsilon_{it} \tag{65}$$

$$i = 1,\ldots,n; \quad t = 1,\ldots,T; \quad j = 1,\ldots,T-k+1; \quad \epsilon_{it} \sim N(0,\sigma^2_{i\epsilon})$$

where, r_{it} is excess return of fund i in month t, $k = 12$ so that we have the jth annual return. We use overlapping data (with annual observations) to increase the number of our observations and to increase the efficiency of our parameter estimates and the power of our tests. Two consecutive annual overlapping observations will, in this case, overlap for eleven months. For example, one annual observation will be from January to December and the other observation from February to January, thus overlapping for eleven months. The generating process for the returns is assumed to be:

$$r_{it} = a_i + e_{it} \qquad e_{it} \sim N(0,\sigma^2_{ie}) \tag{66}$$

where a_i is the mean return of fund i. Substituting (66) into (65) we get:

$$12a_i + \sum_{t=j}^{j+k-1} e_{it} = \alpha_i + 12a_i\,\beta_i + \beta_i \sum_{t=j}^{j+k-1} e_{i(t-12)} + \sum_{t=j}^{j+k-1} \epsilon_{it}. \tag{67}$$

By taking the expectations of both sides in (67) it can be seen that $\alpha_i = 0$ and $\beta_i = 1$. If, however, we assume no performance persistence, ie. ($\alpha_i = \alpha \;\; \forall\, i$), the empirical estimate of β from (1) should be zero. Any positive estimate of β would imply performance persistence. We estimate (65) using maximum likelihood estimation (MLE) methods developed for time-series models. As Harri and Brorsen show, MLE is the only method of estimation that provides consistent estimates in the case of a lagged dependent explanatory variable and overlapping observations. The model in (65) is estimated using PROC ARIMA in SAS software version 6.12. The potential problem with MLE estimation is the missing observations. Missing observations occur because of creating the lagged values and also because fund returns between two consecutive funds need to be separated from each other. Therefore, we also estimate (65) by simple OLS. In addition, we estimate (65) using disaggregate monthly data. The regression in (65) is also estimated by regressing the Sharpe's ratio against a lagged Sharpe's ratio:

$$\sum_{t=j}^{j+k-1} (r_{it} - rf_t) / \delta_{ij} = \alpha_i + \beta_i \sum_{t=j}^{j+k-1} (r_{i(t-12)} - rf_{t-12}) / \delta_{i(j-1)} + \sum_{t=j}^{j+k-1} \epsilon_{it} \quad (68)$$
$$i = 1,\ldots,n; \quad t = 1,\ldots,T; \quad j = 1,\ldots,T-k+1; \quad \epsilon_{it} \sim N(0,\sigma^2_{\epsilon i})$$

where, δ_{ij} is the standard deviation of fund i for the jth annual observation and rf is the interest rate on three-month constant maturity Treasury Bills. The Sharpe ratio is used as a dependent variable because studies involving commodity funds find greater performance persistence using a Sharpe ratio rather than returns. In addition, the regressions in (65) and (68) are estimated separately for each style of trading.

Secondly, the style analysis similar to Sharpe's (1992) and Fung and Hsieh (1997) style regressions is considered. Style here is determined based on the strategy followed by a particular hedge fund. The regression to be estimated is:

$$r_{it} = \alpha_i + \sum_{k=1}^{K} \beta_k F_{kt} + \epsilon_{it}; \quad i = 1,\ldots,n; \quad t = 1,\ldots,T; \quad \epsilon_{it} \sim N(0,\sigma^2_{\epsilon i}) \quad (69)$$

where, r_{it} is the return of fund i in month t, β_k is the factor loading, and F_{kt} is the return on the k^{th} asset class factor in month t. Eight asset classes are used. These are three equity classes: S&P500, Morgan Stanley Capital International (MSCI) world equities excluding U.S. equities (Wexus), and MSCI emerging markets equities (Em); two bond indices: a government bond index (Govbd) and a corporate bond index (Corpbd); the 1-month eurodollar deposit for cash (Edmth); the price of gold for commodities (Gold); and the Federal Reserve's Trade Weighted Dollar Index for currencies (Trdwgtd). The regression in (69) allows for different intercepts for each fund within a particular style. The null hypothesis to be tested is whether once adjusted for changes in overall returns do funds all have the same mean returns? The rationale behind this is that if all funds have the same mean returns then no performance persistence exists. The style regressions in (69) are estimated using the PROC MIXED procedure of the SAS software version 6.12. The BY option is used to run separate regressions for each style. The CLASS statement is used to identify a fixed effects model that allows for different intercepts across funds for a particular style. The REPEATED/GROUP statement is used to correct for heteroskedasticity.

Finally, an out-of-sample test using the Spearman rank correlation test is used. Four measures are used to rank the funds. These are 1) the mean returns; 2) the Sharpe's ratio; 3) the ratio of the mean returns to the standard deviation of returns; and 4) the α-s from the regression in (5). The test is performed over a one-year selection period and a three-year performance period. For example, one test is performed starting with 1977 as the selection period and 1978-1980 as the performance period. The next test is conducted with 1978 as the selection period and 1979-1981 as the performance period. Then, the correlation estimates from each period are averaged. The arithmetic average and the weighted average with the number of observations for each period used as weights are calculated. Monte Carlo hypothesis tests are performed on the two averaged correlation estimates. To perform the Monte Carlo hypothesis tests 1000 thousand samples of the same sizes as the size of the actual data are generated under the null hypothesis of no performance persistence. The RANNOR command in SAS is used to generate the data from a standard normal N(0, 1) distribution. Then, the two averaged correlation estimates are obtained for all 1000 samples and compared to the actual averaged correlation estimates obtained from our original data. A p-value is calculated based on the number of the correlation estimates from the generated samples that are larger than the actual estimates. Also, a five-percent critical value is obtained by selecting the 50^{th} observation from the sample of 1000 estimates from the generated samples after they are first ranked on a descending order. This procedure is performed using all funds and for each style separately.

A measure of the size of funds, the logarithm of the market capitalization, is also considered as an additional explanatory variable in the regressions in (65), (68), and (69), both in their estimation for the whole sample and for each style. One hypothesis concerning the source of returns for hedge funds is the existence of inefficiencies in pricing of assets in the debt, equity, currency and commodities markets. If size of fund matters, it offers support for the hypotheses that inefficiency exploitation is the source of returns for hedge funds. This is based on the hypothesis that hedge fund managers exploit market inefficiencies in the form of mis-priced securities. Since the size of these inefficiencies is fixed, putting more money to exploit a particular inefficiency would cause the returns to decrease.

Results

Table 6 presents the results from the regressions of returns versus lagged returns and the Sharpe's ratios versus lagged Sharpe's ratios for the MLE and OLS estimations. The *t*-statistics are given in parentheses. In general, the results from the Sharpe's ratios regressions are stronger in support of performance persistence then the results from the returns regressions, consistent with previous research. However, the Sharpe's ratio does not separate persistence due to the mean from persistence due to the variance of returns. The MLE estimates for the lagged returns and most of the MLE estimates for the lagged Sharpe's ratios are negative. This could be due to negative autocorrelation present in fund returns for the short-term horizon of one year. Again caution is needed in describing the MLE results because of the uncertain effect of missing observations in the estimation. Based on the results from the disaggregate model presented in Table 7, there is evidence of very short-term performance persistence for almost all styles except Short Sales. For most of the styles performance persists for three to four months with the biggest effect observed in the first month. Most of the lagged values beyond lag twelve have negative and very small coefficients. This could also explain the negative coefficient obtained with the MLE estimation.

Table 8 reports the results for the style analysis using the multi factor regression in (69). The results are reported for all styles and for each style separately. The last three rows of Table 8 report the F-value, the degrees of freedom, and the p-value for the null hypothesis that the intercepts for all funds within a style are equal. The rejection of this hypothesis implies that performance persistence exists. The hypothesis is rejected for five styles, the Global, Market Neutral, Global Macro, FOF-U.S., and FOF offshore styles. The hypothesis of no performance persistence is also rejected when the estimation is performed with all styles.

Table 9 reports summary results for the Spearman rank correlation tests. The table reports the Spearman correlations for all the funds and for each style separately. Also, the Spearman correlations are estimated using four different measures, the mean returns, the

Sharpe's ratio, the mean returns divided by the standard deviation of returns, and each fund's intercept from the style regressions. The correlation estimates reported in Table 9 are averages, a simple average and a weighted average, across the different estimation periods. The entries for each cell in Table 9 are the average (simple or weighted) correlation estimate, the p-value, and the five-percent critical value. The number of periods varies for each style. The Spearman correlations for each period are reported in the Appendix. The correlations in Table 9 are all positive with the exception of the correlation for the Long Only style when the intercepts from the style regression are used to rank the funds. Moreover, with few exceptions, most of the coefficients are below the five-percent critical value where the null hypothesis of no performance persistence would be rejected. This evidence provides little support for the hypothesis that performance persistence does exist in the hedge fund industry. The strongest evidence for performance persistence comes when the intercepts from the style regressions are used to rank the funds. Styles that show the most performance persistence, are Market Neutral, Global Macro, Short Sales, Long Only, and the two types of FOFs. None of the correlations for the Global style is significant. The average correlations in Table 9 should be interpreted carefully. They weight equally the correlations from the earlier periods when the number of funds is small and the correlations are usually small and not accurately estimated. Most of the correlation for the early periods are not significant supporting the view that it is difficult to detect performance persistence given the short life of the hedge fund industry. In addition, there is an obvious decrease of the correlation for the last period, 1994-1997, regardless of the measure used to rank the funds. Also, some correlations are not significant. Thus, the small correlations from the earlier and the last periods may bias downward the average correlation reported in Table 9.

Table 10 presents results for the size /returns relation. The logarithm of the market capitalization for each fund is added as an additional explanatory variable in the regressions (65), (68), and (69). The parameter estimates and the *t*-statistics (in parentheses) for the logarithm of the market capitalization are presented in Table 10. The results for the other variables are not reported in Table 10 since they are very similar to results reported in Tables 6, 7, and 8. The results regarding the role of size in returns are mixed across different regressions. Three out of four methods of estimation provide evidence in support of the size/returns relation. The exception is the disaggregate estimation where most of the coefficients for the size variable are not significant. For the other methods of estimation the size variable is significant for almost all styles. However, the coefficients for the style analysis estimation are almost all negative while the coefficients for the OLS and MLE estimation are mostly positive. The results of Table 10 should be interpreted with caution because, as Ackermann et. al. that also use an earlier version of the same data note, the time series on size is not complete (for a number of funds size is reported only annually).

Conclusions

This paper finds evidence of performance persistence in the hedge fund industry. The data used in this study cover a longer period than most of the previous research on hedge funds. In addition, several procedures are used to determine if performance persistence exists. We use overlapping observations to add power to our estimation and obtain more efficient estimates. All three procedures, the regression of mean returns and Sharpe's ratios against their lagged values, the style regressions, and the Spearman rank correlation test, provide evidence that performance persists in the hedge fund industry. This is consistent with the findings of Park and Staum, and Agarwal and Naik that performance persistence exists in the hedge fund industry. The performance persistence is greater for some of the fund styles. The ones that show the greatest persistence are Global Macro, Market Neutral, and the two FOF styles. They are consistently picked as such by the three different procedures. The Event Driven, Sector, Global, and Long Only styles also show some performance persistence. The Short Sales styles is not selected by any of the procedures as persistent. Agarwal and Naik also find that some hedge fund styles exhibit greater performance persistence than others.

The results for the size/return relation are mixed. The style analysis finds a strong negative relation between the size and returns and thus supports the hypothesis that hedge fund mangers exploit market inefficiencies. The results from the mean returns and Sharpe's ratio regressions are not so supportive to this hypothesis with most of the funds showing no relation at all between size and returns.

Table 1. Definitions of Hedge Fund Styles.

Style	Definition
Global	Manager pays attention to economic change around the world (except the United States).
Sector (Regional)	Manager focuses on specific regions of the world, e.g. Latin America, Asia, Europe.
Market Neutral	Half long/half short. Manager attempts to lock-out or neutralize market risk.
Global Macro	Opportunistic trading manager that profits from changes in global economies, typically based on major interest rate shifts.
Short Sales	Manager takes a position that stock prices will go down. Used as a hedge for long-only portfolios.
Long Only	Manager takes a position that stock prices will go up. Used as a hedge for short-only portfolios.
Event Driven	Manager focuses on securities of companies in reorganization and bankruptcy, ranging from senior secured debt to the common stock of the company.
Fund of Funds	Capital is allocated among a number of hedge funds, providing investors with access to managers they might not be able to discover or evaluate on their own.

Source: Ackermann et. al. (p. 843).

Table 2. Annual Summary Statistics for All Hedge Funds.

Year	Number of Funds[a]	Total Capitalization in million U.S. Dollars[a]	Mean Return (arithmet. (%))[b]	Standard Deviation [b]	Maximum Return [b]	Minimum Return [b]	Average Annual Mngt. Fee (%)	Average Annual Incentive Fee (%)
1977	2	195.2	0.38	0.528	1.50	-0.22	1.9	2
1978	2	196.9	1.55	3.58	6.49	-11.90	1.75	5
1979	2	199.2	2.58	4.08	10.35	-7.35	1.75	5
1980	4	206.828	2.30	5.03	11.91	-13.06	1.73	6.15
1981	4	212.6	0.60	4.71	11.82	-13.90	1.83	10
1982	5	300.14	2.10	3.55	12.61	-6.66	1.53	12.78
1983	9	394.602	1.52	2.43	6.55	-7.96	1.27	12.18
1984	17	532.07	1.31	6.95	75.90	-27.38	1.09	12.51
1985	25	937.187	2.67	3.59	19.09	-9.37	1.08	12.20
1986	36	1,344.9	1.63	5.48	36.78	-36.82	0.97	14.07
1987	50	1,662.63	1.21	9.08	86.15	-42.84	1.06	14.86
1988	67	6,699.46	1.57	3.67	20.85	-12.21	1.06	15.34
1989	98	7,265.24	1.40	3.91	53.36	-18.12	1.07	16.15
1990	140	8,640.58	0.61	4.84	34.68	-20.78	1.09	16.11
1991	190	12,981.46	2.02	5.41	81.11	-27.41	1.07	16.25
1992	270	18,706.04	1.31	4.15	38.57	-34.39	1.09	16.58
1993	371	34,093.27	1.95	4.15	42.39	-35.09	1.12	16.89
1994	547	55,577.47	0.09	4.04	53.16	-25.80	1.14	17.08
1995	699	59,347.57	1.58	4.65	184.17	-27.27	1.17	17.24
1996	941	84,079.72	1.76	4.85	65.24	-37.02	1.19	17.58
1997	1166	120,722.49	1.66	5.61	115.66	-58.26	1.21	17.87
1998 [c]	1209	110,560.10	-0.53	7.66	92.16	-99.99	1.22	18.05

Source: Hedge fund data were provided by LaPorte Asset Allocation.

Note: [a] These are calculated at the end of the year.

[b] These are calculated using monthly data.

[c] For 1998 the calculations are for the months January through August.

Table 3. Mean Returns, Standard Deviations, and Sharpe Ratios for S&P500 and the Equally Weighted Portfolio of Hedge Funds.

Year	S&P500			Hedge Funds		
	Mean	Std. Dev	Sharpe Ratio	Mean	Std. Dev	Sharpe Ratio
1977	-1.018%	0.027	-0.376	0.377%	0.003	1.204
1978	0.088%	0.048	0.018	1.478%	0.029	0.508
1979	0.967%	0.039	0.249	2.472%	0.030	0.824
1980	1.911%	0.052	0.364	2.157%	0.042	0.516
1981	-0.853%	0.037	-0.230	0.488%	0.041	0.120
1982	1.147%	0.053	0.042	2.020%	0.032	0.342
1983	1.328%	0.028	0.206	1.476%	0.018	0.400
1984	0.116%	0.039	-0.179	1.113%	0.033	0.089
1985	1.948%	0.034	0.385	2.580%	0.028	0.701
1986	1.137%	0.051	0.122	1.460%	0.045	0.210
1987	0.167%	0.094	-0.035	0.772%	0.075	0.037
1988	0.974%	0.029	0.137	1.496%	0.027	0.344
1989	2.008%	0.035	0.372	1.318%	0.027	0.228
1990	-0.565%	0.053	-0.229	0.495%	0.039	-0.038
1991	1.946%	0.044	0.332	1.870%	0.036	0.384
1992	0.364%	0.021	0.031	1.216%	0.032	0.292
1993	0.568%	0.017	0.184	1.850%	0.032	0.504
1994	-0.129%	0.031	-0.160	0.010%	0.031	-0.114
1995	2.446%	0.015	1.359	1.472%	0.030	0.333
1996	1.538%	0.031	0.360	1.632%	0.034	0.356
1997	2.251%	0.046	0.399	1.498%	0.041	0.261
1998				-1.276%	0.073	-0.231
Average	0.873%	0.039	0.160	1.393%	0.034	0.357

Table 4. Number of Hedge Funds for Each Style and Year.

Year	Globa l	Sector	Market Neutral	Global Macro	Short Sales	Event Driven	Long Only	FOF-U.S.	FOF NonU.S.	Total
1977	1					1				2
1978	1					1				2
1979	1					1				2
1980	1					1		1	1	4
1981	1					1		1	1	4
1982	1		1			1		1	1	5
1983	3		2			2		1	1	9
1984	9		2	1		2		2	1	17
1985	11		4	2		5		2	1	25
1986	15		5	6		6		2	2	36
1987	18		10	8	2	5		5	2	50
1988	22		14	8	4	6		8	5	67
1989	30	1	17	10	4	16		12	8	98
1990	52	1	19	11	6	18		19	14	140
1991	71	3	24	14	7	22		27	22	190
1992	98	6	44	19	8	26	4	34	31	270
1993	128	8	65	28	9	39	5	47	42	371
1994	194	14	92	32	11	55	7	75	67	547
1995	243	22	125	41	12	76	8	85	87	699
1996	337	34	168	52	12	104	13	105	116	941
1997	415	55	219	63	13	122	18	124	137	1166
1998	430	57	232	68	14	123	18	127	140	1209

Table 5. Market Capitalization of Hedge Funds for Each Style and Year (million $U.S.).

Year	Global	Sector	Market Neutral	Global Macro	Short Sales	Event Driven	Long Only	FOF-U.S.	FOF NonU.S.	Total
1977	193.2					2				195.2
1978	193.2					3.7				196.9
1979	193.2					6				199.2
1980	193.2					12		1.628	0	206.828
1981	193.2					19.4		0	0	212.6
1982	193.2		13.545			27.7		0	65.695	300.14
1983	193.2		20.385			84.3		0	96.717	394.602
1984	290.471		22.509	0		112.2		0.9	105.99	532.07
1985	516.633		16.501	36		183.626		3.6	180.827	937.187
1986	684.696		63.629	65		297.126		13.5	220.948	1344.899
1987	751.576		159.349	62.813	30.182	298.225		48.316	312.166	1662.627
1988	2253.17		199.514	3238.08	28.4	470.896		121.438	387.965	6699.463
1989	1564.22	1.242	769.289	3312.45	155.1	677.060		268.639	517.238	7265.238
1990	1636.02	5.933	619.89	4481.02	186.617	769.404		462.628	479.064	8640.576
1991	2689.53	20.057	876.015	6679.26	239.176	956.93		578.138	942.356	12981.46
1992	4512.64	57.504	1591.17	8678.33	228.891	1237.97	16.49	808.946	1574.09	18706.03
1993	7387.72	97.097	3273.03	14676.92	250.328	2276.49	27.1	1356.54	4748.04	34093.27
1994	13176.85	157.99	4622.12	25089.67	420.780	3735.03	46.188	2091.11	6237.74	55577.48
1995	16268.18	422.475	5899.92	22314.75	451.376	4535.13	84.097	2405.34	6966.31	59347.58
1996	22519.90	1144.20	10922.96	29510.68	489.951	6540.15	180.977	3470.40	9300.50	84079.72
1997	34880.66	2273.71	21067.14	32232.60	536.39	10371.64	404.802	5129.34	13826.20	120722.5
1998	29685.09	1724.62	20263.98	25324.54	676.98	11674.72	400.85	5727.47	15081.85	110560.1

Table 6. Results for the Regressions of Mean Returns and Sharpe Ratio on Their Lagged Values for the MLE and OLS Estimations (t-statistics are given in parentheses).

Style	Number of Observations	OLS Estimation						Maximum Likelihood Estimation [a]			
		Sharpe Ratio Regressions			Return Regressions			Sharpe Ratio Regressions		Return Regressions	
		Intercept	Lagged Sh. Ratio	R^2	Intercept	Lagged Returns	R^2	Intercept	Lagged Sh. Ratio	Intercept	Lagged Returns
All	27561	0.146	0.636	0.68	15.597	0.0315	0.001	0.102	0.271	18.435	-0.283
		(6.68)	(240.2)		(104.9)	(5.35)		(1.95)	(65.73)	(73.87)	(-58.24)
Global	9792	0.1033	0.591	0.62	18.91	-0.036	0.001	0.152	0.04	19.99	-0.288
		(14.8)	(127.1)		(61.0)	(-3.5)		(8.62)	(7.48)	(35.5)	(-32.9)
Sector	688	0.333	0.175	0.034	24.88	0.053	0.003	0.43	-0.25	31.08	-0.378
		(15.7)	(4.9)		(19.5)	(1.38)		(17.7)	(-8.32)	(13.95)	(-10.2)
Market Neutral	4529	0.347	0.495	0.24	10.86	0.175	0.035	0.508	0.109	14.27	-0.14
		(25.9)	(37.4)		(41.2)	(12.8)		(34.98)	(10.31)	(35.5)	(-11.7)
Global Macro	1708	0.192	0.01	0.0001	17.25	-0.002	0.0001	0.282	-0.169	22.1	-0.274
		(19.7)	(0.48)		(27.0)	(-0.09)		(18.4)	(-9.86)	(20.1)	(-14.7)
Short Sales	422	-0.008	0.007	0.0001	3.97	-0.069	0.004	0.03	-0.184	7.24	-0.348
		(-0.58)	(0.16)		(3.90)	(-1.34)		(1.26)	(-5.94)	(4.65)	(-12.2)
Event Driven	3399	0.195	0.638	0.68	17.7	0.006	0.0002	-0.813	0.258	22.26	-0.337
		(1.12)	(84.8)		(46.4)	(0.39)		(-1.7)	(25.8)	(28.7)	(-23.7)
Long Only	246	0.462	-0.178	0.033	38.0	-0.335	0.11	0.409	-0.276	32.86	-0.409
		(12.6)	(-2.88)		(16.6)	(-5.46)		(14.5)	(-8.01)	(11.99)	(-9.95)
FOF-U.S.	3559	0.405	0.277	0.08	12.83	0.02	0.0004	0.329	-0.046	15.31	-0.32
		(31.1)	(17.5)		(49.1)	(1.18)		(6.85)	(-4.04)	(37.7)	(-21.2)
FOF Offshore	3210	0.324	0.04	0.002	14.36	-0.059	0.003	0.32	-0.149	15.44	-0.333
		(32.8)	(2.55)		(39.6)	(-3.18)		(25.95)	(-11.7)	(24.4)	(-18.9)

Note: [a] The data generating process for the returns is given in (2). In the estimation we use overlapping observations created as shown in (3).

Table 7. Results for the Regressions of Mean Returns on Their Lagged Values for the Disaggregate Estimation (t-statistics are given in parentheses).

Style	All	Global	Sector	Market Neutral	Global Macro	Short Sales	Event Driven	Long Only	FOF-U.S.	FOF Offshore
Obs.	31945	11341	730	5374	2330	753	3551	306	3912	3648
Intercept	0.768 (52.8)	0.798 (10.3)	1.731 (6.5)	0.666 (33.1)	0.803 (8.03)	0.522 (2.67)	0.996 (14.4)	2.261 (2.8)	0.832 (22.4)	0.75 (15.7)
Lag 1	0.077 (17.3)	0.087 (8.8)	0.101 (2.9)	0.068 (7.8)	0.042 (2.4)	0.047 (1.3)	0.120 (8.5)	0.103 (1.6)	0.059 (5.2)	0.075 (5.4)
Lag 2	0.029 (6.6)	0.043 (4.3)	0.024 (0.7)	0.026 (3.1)	0.008 (0.5)	-0.09 (-2.5)	0.04 (2.9)	0.045 (0.7)	0.014 (1.3)	0.038 (2.8)
Lag 3	0.016 (3.9)	0.048 (4.8).	-0.005 (-0.1)	0.03 (3.8)	-0.002 (-0.1)	-0.025 (-0.7)	-0.029 (-2.1)	0.02 (0.3)	0.008 (0.8)	0.009 (0.7)
Lag 4	-0.014 (-3.3)	-0.024 (-2.34)	0.032 (0.95)	-0.009 (-1.1)	-0.004 (-0.3)	-0.053 (-1.5)	-0.009 (-0.7)	-0.084 (-1.2)	-0.006 (-0.6)	-0.026 (-2.1)
Lag 5	-0.012 (-3.0)	-0.039 (-3.9)	-0.075 (-2.2)	0.012 (1.5)	0.027 (1.6)	-0.077 (-2.1)	-0.018 (-1.3)	-0.012 (-0.2)	-0.025 (-2.4)	-0.006 (-0.5)
Lag 6	-0.018 (-4.4)	-0.039 (-3.8)	-0.046 (-1.3)	-0.001 (-0.1)	-0.009 (-0.5)	-0.077 (-2.1)	-0.007 (-0.5)	-0.077 (-1.1)	-0.013 (-1.3)	-0.031 (-2.6)
Lag 7	0.035 (8.9)	0.10 (9.8)	-0.028 (-0.8)	0.025 (3.6)	0.020 (1.2)	0.092 (2.5)	0.003 (0.2)	0.006 (0.1)	0.039 (3.9)	0.039 (3.4)
Lag 8	0.025 (6.6)	0.051 (4.9)	0.014 (0.4)	0.018 (2.6)	0.041 (2.5)	-0.015 (-0.4)	0.009 (0.7)	0.071 (1.01)	0.004 (0.4)	0.054 (4.8)
Lag 9	0.025 (6.7)	0.05 (5.1)	0.07 (2.2)	0.007 (1.1)	0.035 (2.1)	0.103 (2.8)	0.028 (2.2)	0.232 (3.3)	0.032 (3.3)	0.031 (2.8)
Lag 10	0.007 (1.7)	0.024 (2.3)	-0.028 (-0.8)	0.012 (1.7)	0.028 (1.7)	0.016 (0.4)	-0.025 (-1.99)	-0.041 (-0.6)	-0.015 (-1.7)	0.021 (1.95)
Lag 11	-0.033 (-9.1)	-0.077 (-7.4)	-0.155 (-4.6)	-0.004 (-0.6)	-0.012 (-0.8)	-0.086 (-2.4)	-0.016 (-1.3)	-0.308 (-4.2)	-0.037 (-4.1)	-0.052 (-4.9)
Lag 12	0.001 (0.4)	-0.02 (-1.9)	-0.035 (-1.1)	0.016 (2.6)	-0.023 (-1.4)	0.024 (0.7)	0.012 (1.0)	-0.118 (-1.5)	-0.001 (-0.1)	-0.037 (-3.5)
Lag 13	-0.008 (-2.3)	-0.026 (-2.5)	0.029 (0.87)	-0.006 (-0.98)	-0.024 (-1.5)	-0.115 (-3.1)	-0.019 (-1.6)	-0.044 (-0.6)	-0.007 (-0.8)	-0.025 (-2.4)
Lag 14	-0.003 (-0.9)	0.015 (1.5)	-0.081 (-2.4)	-0.005 (-0.86)	0.003 (0.2)	0.054 (1.5)	-0.022 (-1.9)	-0.132 (-1.6)	-0.01 (-1.2)	-0.002 (-0.2)
Lag 15	-0.004 (-1.2)	-0.041 (-3.9)	-0.042 (-1.3)	0.005 (0.89)	0.022 (1.4)	-0.103 (-2.8)	-0.017 (-1.4)	-0.104 (-1.3)	-0.017 (-2.1)	-0.002 (-0.2)
Lag 16	-0.003 (-1.0)	-0.078 (-7.5)	-0.008 (-0.3)	0.004 (0.67)	-0.016 (-0.9)	-0.04 (-1.1)	0.013 (1.1)	0.052 (0.6)	0.008 (1.0)	-0.011 (-1.2)
Lag 17	0.008 (2.4)	0.053 (5.0)	0.066 (1.98)	0.002 (0.4)	0.019 (1.2)	0.048 (1.3)	-0.008 (-0.8)	0.069 (0.8)	0.006 (0.8)	-0.009 (-0.9)

Table 7. (Continued) Results for the Regressions of Mean Returns on Their Lagged Values for the Disaggregate Estimation (t-statistics are given in parentheses).

Style	All	Global	Sector	Market Neutral	Global Macro	Short Sales	Event Driven	Long Only	FOF-U.S.	FOF Offshore
Num. of Obs.	31945	11341	730	5374	2330	753	3551	306	3912	3648
Lag 18	0.007 (2.3)	-0.004 (-0.4)	0.047 (1.4)	0.001 (0.1)	0.063 (3.8)	0.008 (0.2)	0.013 (1.2)	0.008 (0.1)	0.006 (0.8)	0.007 (0.7)
Lag 19	-0.019 (-6.2)	-0.031 (-2.9)	-0.044 (-1.4)	-0.019 (-3.8)	-0.027 (-1.6)	-0.019 (-0.5)	-0.032 (-2.8)	-0.135 (-1.5)	-0.018 (-2.4)	-0.01 (-1.1)
Lag 20	0.007 (2.3)	0.010 (0.9)	-0.068 (-2.1)	-0.0001 (-0.01)	0.039 (2.3)	0.036 (0.98)	0.002 (0.2)	0.17 (1.9)	0.013 (1.7)	0.017 (1.92)
Lag 21	0.007 (2.2)	0.010 (0.9)	-0.021 (-0.6)	0.012 (2.4)	0.006 (0.3)	-0.019 (-0.5)	-0.0002 (-0.2)	-0.015 (-0.2)	-0.001 (-0.1)	-0.001 (-0.1)
Lag 22	0.005 (1.6)	0.008 (0.7)	-0.031 (-1.2)	-0.003 (-62)	0.021 (1.2)	0.105 (2.8)	0.008 (0.8)	0.144 (1.6)	0.001 (0.1)	0.011 (1.3)
Lag 23	-0.001 (-0.2)	-0.031 (-2.9)	-0.027 (-1.2)	-0.003 (-0.59)	0.042 (2.5)	0.01 (0.3)	0.007 (0.7)	0.037 (0.4)	-0.003 (-0.5)	0.017 (2.0)
Lag 24	0.007 (2.3)	0.009 (0.8)	0.003 (0.14)	0.0003 (0.07)	0.024 (1.4)	0.052 (1.4)	0.031 (2.98)	-0.056 (-0.6)	0.003 (0.4)	0.001 (0.1)

Note: The results for the Global style are not corrected for heteroskedasticity since otherwise the estimation did not converge.

Table 8. Results for the Style Regressions of Hedge Fund Returns on Eight Asset Classes (*t*-statistics are given in parentheses).

Variable	All	Global	Sector	Market Neutral	Global Macro	Short Sales	Event Driven	Long Only	FOF-U.S.	FOF NonU.S.
Intercept	-10.40 (-9.47)	-16.25 (-7.74)	-20.67 (-1.59)	-3.378 (-2.12)	-3.99 (-1.06)	9.75 (0.96)	-9.13 (-3.65)	74.06 (2.6)	-6.99 (-4.48)	-8.53 (-3.04)
S&P500	0.011 (21.44)	0.014 (12.75)	0.021 (4.81)	0.006 (7.79)	0.011 (5.93)	-0.005 (-1.0)	0.009 (6.35)	0.023 (2.98)	0.008 (10.04)	0.013 (11.23)
Wexus	-0.005 (-20.33)	-0.006 (-11.59)	-0.005 (-2.74)	-0.003 (-7.61)	-0.006 (-6.51)	0.0008 (0.34)	-0.005 (-6.45)	-0.005 (-1.65)	-0.004 (-9.85)	-0.006 (-10.38)
Em	0.014 (28.94)	0.02 (19.74)	0.037 (9.38)	0.006 (7.77)	0.01 (5.32)	-0.018 (-3.25)	0.011 (8.03)	0.073 (8.83)	0.010 (13.73)	0.014 (12.55)
Gold	0.028 (21.92)	0.037 (14.36)	0.018 (1.21)	0.013 (7.07)	0.028 (6.39)	0.006 (0.41)	0.025 (7.31)	-0.057 (-1.88)	0.018 (9.10)	0.027 (8.21)
Trdwgtd	-0.006 (-1.25)	-0.019 (-1.83)	-0.287 (-4.69)	-0.007 (-0.88)	0.015 (0.83)	0.188 (3.68)	0.0008 (0.06)	-0.892 (-6.52)	0.008 (0.99)	-0.019 (-1.55)
Edmth	0.057 (1.7)	-0.049 (-0.69)	-0.946 (-3.26)	0.045 (0.92)	0.389 (3.15)	0.205 (0.73)	0.033 (0.35)	-3.582 (-5.32)	0.099 (2.0)	0.066 (0.86)
Govbd	-0.916 (-5.29)	-0.957 (-2.7)	-13.131 (-4.07)	-0.417 (-1.5)	-2.068 (-3.16)	11.525 (4.09)	-1.015 (-2.32)	-15.908 (-2.48)	-0.80 (-3.15)	-0.720 (-1.57)
Corpbd	1.09 (5.79)	1.47 (3.82)	16.132 4.35	0.449 (1.48)	1.302 (1.79)	-13.498 (-4.16)	1.043 (2.28)	16.773 (2.3)	0.769 (2.80)	0.735 (1.42)
F-value [a]	1.61	1.63	1.01	2.08	2.03	1.24	1.01	0.97	1.41	1.90
Df	1208	429	56	231	67	13	122	17	126	139
P-value	0.0001	0.0001	0.4546	0.0001	0.0001	0.2432	0.4384	0.4956	0.0018	0.0001

Note: [a] The null hypothesis being tested is the hypothesis of no performance persistence.

Table 9. Average Spearman Rank Correlations (5% critical value in parentheses).

Measure	All	Global	Sector	Market Neutral	Global Macro	Short Sales	Event Driven	Long Only	FOF-U.S.	FOF NonU.S.
Mean	0.38 (0.569)	0.33 (0.533)	0.59 [a] (0.582)	0.39 (0.5599)	0.42 (0.60)	0.20 (0.616)	0.35 (0.552)	0.17 (0.677)	0.24 (0.538)	0.30 (0.545)
Sh. Ratio	0.45 (0.623)	0.36 (0.538)	0.59 (0.65)	0.49 (0.607)	0.45 (0.67)	0.21 (0.639)	0.49 (0.636)	0.44 (0.75)	0.20 (0.603)	0.28 (0.62)
Mean/Std	0.57 (0.651)	0.31 (0.475)	0.58 (0.588)	0.70 [a] (0.573)	0.44 (0.615)	0.53 (0.61)	0.60 [a] (0.562)	0.31 (0.65)	0.20 (0.549)	0.33 (0.553)
Alpha	0.19 (0.211)	0.11 (0.113)	-0.34 (0.123)	0.27 [a] (0.156)	0.16 [a] (0.1559)	0.59 [a] (0.151)	0.31 (0.393)	0.65 [a] (0.126)	0.38 [a] (0.16)	0.33 [a] (0.15)

Note: [a] Denotes that the correlation coefficient is significant at the 5% level of significance.

Table 10. Results for the Regressions of Returns on the Lagged Value of the Logarithm of Market Capitalization (*t*-statistics are given in parentheses).

Regression	OLS Estimation		MLE Estimation		Disaggregate Estimation	Style Analysis
	Mean Returns	Sharpe Ratio	Mean Returns	Sharpe Ratio		
All	1.11 (17.5)	0.02 (1.79)	3.23 (32.2)	0.05 (8.11)	0.07 (3.86)	-0.34 (-9.87)
Global	1.62 (11.9)	0.007 (1.7)	6.98 (32.2)	0.11 (12.85)	-0.02 (-0.1)	-0.43 (-5.76)
Sector	-0.82 (-1.17)	-0.06 (-4.57)	6.44 (5.49)	0.05 (3.39)	-0.33 (-1.8)	-0.51 (-2.0)
Market Neutral	-0.03 (-0.3)	0.07 (10.4)	1.04 (5.97)	0.07 (8.02)	-0.06 (-5.7)	-0.13 (-2.75)
Global Macro	2.45 (12.5)	0.05 (13.7)	3.92 (12.7)	0.06 (13.6)	0.2 (4.4)	-0.52 (-3.57)
Short Sales	4.49 (8.34)	0.05 (5.99)	6.15 (9.07)	0.09 (6.89)	0.33 (1.88)	1.21 (2.01)
Event Driven	0.05 (0.3)	0.11 (1.18)	0.76 (3.4)	-0.01 (-0.81)	-0.03 (-1.74)	-0.29 (-3.69)
Long Only	-3.56 (-3.67)	-0.08 (-4.36)	1.2 (1.06)	0.02 (0.97)	-0.37 (-1.16)	-0.24 (-0.42)
FOF-U.S.	1.32 (1.07)	0.09 (11.1)	2.67 (12.6)	0.13 (16.2)	-0.02 (-0.6)	-0.49 (-7.52)
FOF NonU.S.	0.87 (5.31)	0.02 (3.72)	2.8 (9.24)	0.03 (5.44)	0.001 (0.02)	-0.51 (-5.26)

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Appendix

Table 11. Spearman Rank Correlations of Mean Returns.

Period	All	Global	Sector	Market Neutral	Global Macro	Short Sales	Event Driven	Long Only	FOF-U.S.	FOF NonU.S.
'83 - '86	0.13	-0.76 [a]		-0.30			0.25		-0.17	0.56 [a]
'84 - '87	-0.19 [a]	0.37 [a]		-0.16			0.21		-0.39 [a]	0.42 [a]
'85 - '88	0.12 [a]	0.67 [a]		0.07	-0.31		0.10		0.16	-0.003
'86 - '89	0.50 [a]	0.55 [a]		0.64 [a]	0.76 [a]		0.18 [a]		0.60 [a]	0.20
'87 - '90	0.57 [a]	0.67 [a]		0.86 [a]	0.38 [a]		0.59 [a]		-0.08	0.50 [a]
'88 - '91	0.49 [a]	0.37 [a]		0.52 [a]	0.47 [a]	0.50 [a]	0.30 [a]		0.14	0.53
'89 - '92	0.45 [a]	0.34 [a]		0.59 [a]	0.69 [a]	-0.03	0.42 [a]		0.44 [a]	0.02
'90 - '93	0.46 [a]	0.41 [a]	0.83 [a]	0.62 [a]	0.74 [a]	-0.23 [a]	0.38 [a]		0.42 [a]	-0.10
'91 - '94	0.44 [a]	0.46 [a]	0.72 [a]	0.45 [a]	0.46 [a]	0.45 [a]	0.73 [a]		0.55 [a]	0.63 [a]
'92 - '95	0.64 [a]	0.44 [a]	0.71 [a]	0.51 [a]	0.55 [a]	0.10	0.59 [a]		0.63 [a]	0.68 [a]
'93 - '96	0.57 [a]	0.33 [a]	0.49 [a]	0.57 [a]	0.39 [a]	0.65 [a]	0.33 [a]	0.33 [a]	0.50 [a]	0.42 [a]
'94 - '97	0.43 [a]	0.10 [a]	0.20 [a]	0.36 [a]	0.02 [a]	-0.05	0.09 [a]	0.02	0.08 [a]	0.06 [a]

Note: [a] denotes the correlation coefficient is significant at the 5% level of significance.

Table 12. Spearman Rank Correlations of Sharpe Ratios.

Period	All	Global	Sector	Market Neutral	Global Macro	Short Sales	Event Driven	Long Only	FOF-U.S.	FOF NonU.S.
'84 - '87	0.79 [a]	0.42 [a]		-0.87 [a]			0.86 [a]			
'85 - '88	0.35 [a]	0.09		0.87 [a]			0.44 [a]		0.02	
'86 - '89	0.16 [a]	0.02		0.87 [a]	0.44 [a]		-0.02		0.37	0.02
'87 - '90	0.30 [a]	0.56 [a]		0.91 [a]	0.27 [a]		0.58 [a]		-0.61 [a]	-0.19
'88 - '91	0.49 [a]	0.36 [a]		0.50 [a]	0.35 [a]	-0.58 [a]	0.14		-0.07	0.59 [a]
'89 - '92	0.36 [a]	0.61 [a]		0.76 [a]	0.82 [a]	0.44 [a]	0.61 [a]		0.59 [a]	-0.10
'90 - '93	0.62 [a]	0.51 [a]		0.73 [a]	0.48 [a]	0.12	0.33 [a]		0.41 [a]	0.58 [a]
'91 - '94	0.49 [a]	0.52 [a]	0.77 [a]	0.26 [a]	0.71 [a]	0.24	0.57 [a]		0.36 [a]	0.69 [a]
'92 - '95	0.57 [a]	0.51 [a]	0.58 [a]	0.27 [a]	0.68 [a]	0.45 [a]	0.59 [a]		0.33 [a]	0.47 [a]
'93 - '96	0.51 [a]	0.22 [a]	0.54 [a]	0.54 [a]	0.15 [a]	0.72 [a]	0.52 [a]	0.38 [a]	0.25 [a]	0.27 [a]
'94 - '97	0.30 [a]	0.17 [a]	0.46 [a]	0.52 [a]	0.11	0.12	0.64 [a]	0.51 [a]	0.12 [a]	0.17 [a]

Note: [a] denotes the correlation coefficient is significant at the 5% level of significance.

Table 13. Spearman Rank Correlations of Mean Returns/Standard Deviation Ratios.

Period	All	Global	Sector	Market Neutral	Global Macro	Short Sales	Event Driven	Long Only	FOF-U.S.	FOF NonU.S.
'83 - '86	0.72[a]	-0.82[a]		0.77[a]			0.71[a]		-0.38[a]	0.57[a]
'84 - '87	0.79[a]	0.33[a]		0.79[a]			0.74[a]		-0.28	0.20
'85 - '88	0.53[a]	0.11		0.70[a]	-0.07		0.66[a]		-0.06	-0.21
'86 - '89	0.28[a]	0.27[a]		0.66[a]	0.71[a]		0.69[a]		0.59[a]	0.40[a]
'87 - '90	0.47[a]	0.65[a]		0.83[a]	0.28[a]		0.44[a]		0.01	0.35[a]
'88 - '91	0.53[a]	0.29[a]		0.73[a]	0.55[a]	0.80[a]	0.48[a]		0.38[a]	0.21
'89 - '92	0.49[a]	0.50[a]		0.76[a]	0.76[a]	0.36[a]	0.52[a]		0.28[a]	0.09
'90 - '93	0.62[a]	0.58[a]	0.83[a]	0.79[a]	0.63[a]	0.70[a]	0.61[a]		0.55[a]	0.56[a]
'91 - '94	0.64[a]	0.62[a]	0.78[a]	0.69[a]	0.66[a]	0.53[a]	0.70[a]		0.48[a]	0.77[a]
'92 - '95	0.69[a]	0.51[a]	0.47[a]	0.56[a]	0.66[a]	0.34[a]	0.53[a]		0.40[a]	0.59[a]
'93 - '96	0.62[a]	0.37[a]	0.51[a]	0.66[a]	0.18[a]	0.73[a]	0.53[a]	0.40[a]	0.27[a]	0.25[a]
'94 - '97	0.47[a]	0.25[a]	0.34[a]	0.50[a]	0.06	0.23[a]	0.60[a]	0.22[a]	0.14[a]	0.12[a]

Note: [a] denotes the correlation coefficient is significant at the 5% level of significance.

Table 14. Spearman Rank Correlations of Style Regression Intercepts.

Period	All	Global	Sector	Market Neutral	Global Macro	Short Sales	Event Driven	Long Only	FOF-U.S.	FOF NonU.S.
'85 - '88	0.03	0.76 [a]								
'86 - '89	-0.05	-0.08		0.50	-0.5		1 [a]			
'87 - '90	0.3	0.04		0.80	0.7		0.2			
'88 - '91	0.51 [a]	0.33		-0.17	0.036		0. 8		1 [a]	
'89 - '92	0.18	0.29		-0.005	0.75	1 [a]	0.3		0.36	0.4
'90 - '93	0.38 [a]	0.008		0.27	0.25	1 [a]	0.58 [a]		0.37	0.74 [a]
'91 - '94	0.26 [a]	0.014		0.19	0.15	0.2	0.39		0.90 [a]	0.52
'92 - '95	-0.06	-0.34		-0.12	-0.24	0.66	-0.17		0.084	0.23
'93 - '96	0.09	-0.22 [a]	0.30	0.44 [a]	0.27	0.29	-0.14	0.5	0.16	0.17
'94 - '97	0.27 [a]	0.29 [a]	-0.32	0.52 [a]	0.0005	0.41	-0.19	0.8	-0.22	-0.10

Note: [a] denotes the correlation coefficient is significant at the 5% level of significance.

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