A Comparison of Alternative Covariance Matrices for Models with Over-Lapping Observations

Jeremy Smith
Department of Economics
University of Warwick
Coventry

and

Sanjay Yadav
Financial Options Research Centre,
Warwick Business School, The University of Warwick

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Financial Options Research Centre
Warwick Business School
University of Warwick
Coventry
CV4 7AL
Phone: (01203) 524118

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Abstract

This paper investigates the relative performance of alternative covariance matrices for models with over-lapping observations commonly used in the finance literature. The alternative covariance matrices used are those of Hansen (1982), Newey and West (1987) (Bartlett and Quadratic Sprectral (QS) weights) and Andrews and Monahan (1992) (QS weights). All matrices produce standard errors which are too small, yielding empirical size probabilities above their corresponding theoretical values, even in large samples. Empirical examples, such as testing efficiency in the foreign exchange market and mean reversion in stock prices, show that the choice of covariance matrix can affect the outcome of a hypothesis test. (JEL C15 and C22)

Abbreviated Title: Alternative covariance matrices

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The use of quantitative expectations data in macro economics increased through the 1980s as part of the interest in investigating the efficiency of markets. This was especially true in the foreign exchange market where papers by Frankel and Froot (1987), Goodhart (1988) and Froot and Frankel (1989), led the way. These papers considered equations of the form,

$$s_{t,t+k} - s_t = \alpha + \beta\,(f_t^k - s_t) + \varepsilon_t^k \qquad (1)$$

where, s_t is the logarithm of the exchange rate in period t, $s_{t,t+k}$ is the logarithm of the expectation formed in period t of the exchange rate in period t+k, f_t^k is the logarithm of the forward rate of the exchange rate at time t for period t+k and ε_t^k is the error term. Under the null hypothesis of an efficient market, $\alpha = 0$ and $\beta = 1$.

For many studies using equations of the form of (1), data are sampled more finely than the horizon length of the expectations, for example Froot and Frankel (1989) using weekly data considered expectations for up to 3 months ahead. The effect of over-lapping observations is that the error term in equation (1), ε_t^k, is serially correlated, following a moving average process, and conventionally programmed OLS standard errors are incorrect. Consequently, reported standard errors are invariably corrected for the presence of serial correlation, using a Generalised Method of Moments (GMM) estimator.

The first of the GMM estimators that was used in this framework was that suggested by Hansen (1982). The covariance matrix for the vector of parameters in equation (1), $\delta' = (\alpha, \beta)$, is calculated as

$$V(\hat{\delta}) = (X'X)^{-1}\hat{S}_T(X'X)^{-1},$$

where, $\hat{S}_T = \hat{\Omega}_0 + \sum_{j=1}^{m} [\hat{\Omega}_j + \hat{\Omega}'_j]$, $\hat{\Omega}_j = \sum_{t=j+1}^{T} e_t x_t' x_{t-j} e_{t-j}$, x_t is the vector of explanatory variables and e_t the residuals. This GMM method is used in Hansen and Hodrick (1980), and they note (p.836) this procedure has greater power than an alternative solution, which involves constructing new series y_t^*, x_t^* made up of non-overlapping observations of the original series y_t, x_t and undertaking the analysis using standard OLS on this subsets of observations. Gruen and Smith (1994) use both the Hansen (1982) method to correct the standard errors and non-overlapping data to estimate equations of the form of equation (1).

Hansen's (1982) method does not ensure that the covariance matrix is positive definite. Newey and West (1987) proposed an alternative method for obtaining serially correlated heteroscedasticity consistent standard errors, with a positive definite covariance matrix. This new procedure modified the Hansen (1982) GMM estimator by weighting the sample autocovariance function, such that the weights decline as j increased. For the Bartlett weighting method, $\hat{S}_T = \hat{\Omega}_0 + \sum_{j=1}^{m} \omega(j,m)\,[\hat{\Omega}_j + \hat{\Omega}'_j]$, where $\omega(j,m) = 1 - [j/(m+1)]$. Alternatively, for the Quadratic Spectral (QS) weights, $\hat{S}_T = \hat{\Omega}_0 + \sum_{j=1}^{n-1} \omega(j)\,[\hat{\Omega}_j + \hat{\Omega}'_j]$, where $\omega(j) = \frac{25}{12\pi^2 u^2}\left(\frac{\sin(6\pi u/5)}{6\pi u/5} - \cos(6\pi u/5)\right)$, and $u = j/(m+1)$.[1] The Newey-West method with Bartlett weights has been used by Frankel and Froot (1987), however, there are few examples of an application of Newey-West with QS weights.

Finally, Andrews and Monahan (1991) extended the class of GMM estimators, by first prewhitening the series and then using the Newey-West covariance matrix with QS weights on the prewhitened series. The prewhitening entails fitting a Vector AutoRegressive model of order b (VAR(b)) to the series $z_t = x_t e_t$. In their study Andrews and Monahan (1991) use a VAR(1) model to approximate both autoregressive (AR) and moving average (MA) processes.

For these alternative covariance matrices the choice of the bandwidth parameter, m, is important for obtaining good standard error estimates. Hansen and Hodrick (1980) use a bandwidth parameter, m = order of the moving average process. Frankel and Froot (1987) consider two values of m, m = order of the moving average process and m = twice the order of the moving average process.[2] Recently, Andrews (1991) developed a method for choosing the optimal bandwidth parameter, $\hat{Z}_T$, according to the type of weighting scheme used. For Bartlett weights, $\omega(j) = 1 - (j/\hat{Z}_T)$, $\hat{Z}_T = 1.1447(\hat{\alpha}(1)T)^{1/3}$, where

$$\hat{\alpha}(1) = \frac{\sum_{a=1}^{p} w_a \frac{4\hat{\rho}_a^2 \hat{\sigma}_a^4}{(1-\hat{\rho}_a)^6 (1+\hat{\rho}_a)^2}}{\sum_{a=1}^{p} w_a \frac{\hat{\sigma}_a^4}{1-\hat{\rho}_a)^4}}$$ and $w_a = \begin{bmatrix} 0, & a=1 \\ 1, & a \neq 1 \end{bmatrix}$, $\{(\hat{\rho}_a, \hat{\sigma}_a^2), a=1,.., p\}$ are the parameter estimate and innovation variance of an AR(1) model fitted to each of the series formed as the product of the p explanatory variables, x_{at}, and the residuals, e_t. For the QS weights the parameter u is calculated as $u = j/\hat{Z}_T$ where $\hat{Z}_T = 1.3221(\hat{\alpha}(2)T)^{1/5}$, and

$$\hat{\alpha}(2) = \frac{\sum_{p=1}^{p} w_a \frac{4\hat{\rho}_a^2 \hat{\sigma}_a^4}{(1-\hat{\rho}_a)^8}}{\sum_{a=1}^{p} w_a \frac{\hat{\sigma}_a^4}{(1-\hat{\rho}_a)^4}}.$$

This paper investigates the performance of these alternative methods for calculating the standard errors in models when the data are over-lapping.

I. Method

A variety of experiments are considered allowing for different orders of MA errors, from an MA(0) to an MA(12) (which corresponds to having weekly data and forecast horizons varying from weekly to 3 monthly), different sample sizes (T = 50, 75, 100, 200), and altering the process generating the explanatory variable, x_t. The basic model is:

where, $\alpha = 0$, $\beta = 1$ and $\sigma^2 = 1$. The explanatory variable, x_t, is assumed to be generated by

$$y_t = \alpha + \beta x_t + u_t, \quad u_t = \sum_{j=1}^{n} \varepsilon_{t-j}, \quad n = 0, \ldots, 12, \quad \varepsilon_t \sim N(0, \sigma^2) \tag{2}$$

an AR(1) process, that is, $x_t = \mu + \phi x_{t-1} + \eta_t, \; \eta_t \sim N(0, \sigma_\eta^2)$ and $E(\varepsilon_t, \eta_t) = 0$. In terms of equation (1), x_t represents the forward discount rate and y_t the expected appreciation (depreciation) in the spot exchange rate. If the exchange rate is in equilibrium, then one might anticipate the forward rate for k periods ahead, f_t^k, deviating from the spot rate, s_t, by a random error, that is, $\phi = 0, \; x_t = \mu + \eta_t$. However, if the exchange rate is believed to be over- or under-valued then the forward discount will be highly serially correlated until the actual exchange rate adjusts towards its equilibrium rate, $\phi > 0$. Gruen and Smith (1994) present evidence for Australia over a considerable period in the 1980s to suggest that the Austrlian dollar ($A) may have been suffering a type of 'peso' problem, with the forward rate at a continual discount and highly serially correlated. In fact, over the period from 1985 to 1988 the correlogram for the forward discount is well represented by an AR(1) model with $\phi = 0.88$. Consequently, we use a range of values for ϕ, $\phi \subset (0.0, 0.1, 0{,}2, .., 0.9)$.

An alternative interpretation of equation (2) is as the model used by Fama and French (1988) to investigate the issue of mean reversion in stock prices. Defining R_t as the one-period return on the stock market index, the Fama and French (1988) model can be written as

$$\sum_{i=1}^{k} R_{t+i} = \alpha + \beta \sum_{i=1}^{k} R_{t-i+1} + u_t \tag{3}$$

In terms of equation (2) this implies that y_t is the sum of stock returns over the next k periods and x_t is the sum of stock returns over the previous k periods. Under the null hypothesis of a random walk, $\alpha = 0$ and $\beta = 0$.

In estimating this model Fama and French (1988) used the method of White (1980) and Hansen (1982) to correct for heteroscedasticity and serial correlation. Using a model to explain realised volatility in stock returns, Lamoureux and Lastrapes (1993) used the Newey-West (with Bartlett weights) covariance matrix estimator to address the problem of over-lapping observations.

II Results from Simulation

A variety of alternative covariance matrix estimation methods are considered: standard OLS (OLS), OLS with non-overlapping observations (N-O), Newey-West with Bartlett weights and m = order of MA process (NWB), Newey-West with Quadratic Spectral weights and m = order of MA process (NWQ), Newey-West with Bartlett weights and m chosen using Andrews (1991) procedure (NWAB), Newey-West with Quadratic Spectral weights and $\hat{z}_T$ chosen using Andrews (1991) procedure (NWAQ), the Andrews and Monahan (1992) method with QS weights and $\hat{z}_T$ chosen using Andrews (1991) procedure (A-M), and the Hansen (1982) method (HAN). The results are based on 5000 replications.

Table 1 reports the empirical size probabilities for a number of these alternative estimation methods when the errors follow an MA(3) process for alternate values of ϕ and T.[3] For this reported model and all other models considered the OLS estimation method yields size probabilities closer to their theoretical value compared with the GMM methods, irrespective of the MA process and the sample size, for ϕ close to zero. For all of the GMM estimation methods the empirical size probabilities are too large, although as the sample size increases so the empirical size slowly approaches the theoretical size. For larger values of ϕ, OLS performs markedly worse than the alternative estimators, although all estimators over-reject the true null hypothesis in finite samples.

For the GMM procedures the choice of the bandwidth parameter is important. Two alternatives are compared here, the first sets the bandwidth parameter, according to the order of the MA process (m = 3), the second sets the bandwidth parameter using the results of Andrews (1991). Comparing columns 5 (NWB) and 6 (NWAB) it is clear that for larger values of ϕ and T, the Andrews method yields superior size results using Bartlett weights, for T = 200 and $\phi = 0.8$, NWB = 12.7 and NWAB = 11.2. For QS weights, there is no unambiguous outcome, with a bandwidth parameter of m = 3 yielding similar size probabilities to those obtained from the Andrews procedure.

Increasing the bandwidth to equal twice the order of the MA process as suggested by Frankel and Froot (1987) yields less satisfactory results for HAN and NWQ. For NWB for large T and increasing values of ϕ, choosing m equal to twice the order of the MA process does, on the whole, produce size probabilities which are slightly closer to their theoretical level. An explanation for why choosing m equal to twice the order of the MA process in the NWB might produce better standard errors is provided in Figure 1. This figure plots the distribution of the bandwidth parameter, $\hat{z}_T$, obtained by the Andrews (1991) procedure as a function of ϕ for T = 100. As ϕ increases so the distribution of the bandwidth parameter, $\hat{z}_T$, shifts to the right. For $\phi = 0.1, 0.2$ the mode of the distribution is around 1 whereas, for $\phi = 0.9$ the mode is around 7 or 8. Therefore, for larger values of ϕ the optimal choice for the bandwidth parameter can be much larger than the order of the MA process.

Comparing the weighting schemes in the Newey-West estimation method, it appears that QS is superior to Bartlett, and this superiority increases with T and ϕ. Of the alternative GMM procedures, not surprisingly, we find that as T increases so the flat weighting scheme of HAN tends towards the theoretical 5% size value at a quicker rate than the Newey-West matrices with either the Bartlett or QS weights (regardless of how the bandwidth parameter is chosen). For larger values of ϕ, even at small sample sizes HAN produces size probabilities closer to their theoretical values, and its relative performance improves as T increases. Somewhat more surprising is the strong performance of the A-M procedure for nearly all sample sizes and all values of ϕ, even when compared with HAN.[4]

As ϕ increases the empirical size probabilities increase for all the alternative standard error estimates, so that for $\phi = 0.9$ and T = 200, NWB = 13.3, NWAB = 11.8, HAN = 8.3, and A-M = 8.1.[5] However, these size probabilities are too large, and are larger than the corresponding size values obtained from the use of non-overlapping observations, reported in column 4. In general across all values of ϕ and all sample sizes the calculated standard errors are too small, a fact which could possibly account for the frequent rejection of the market efficiency hypothesis in the foreign exchange market, see, for example, Goodhart (1988) and Gruen and Smith (1994). However, Fama and French (1988) use T = 720 and the results obtained here suggest that the size bias of the HAN procedure will only be small even for large values of ϕ.

III Empirical Results

Table 2 reports the results from estimating equation (1) for a number of the alternative covariance matrices considered in this paper, using data from Gruen and Smith (1994). The data are weekly and for a four week forward discount horizon, over the period March 1985 to September 1987 for the \$A relative to the US dollar (\$US) (T=128). In addition, results from estimating equation (3) are reported (using four period over-lapping observations) for both monthly stock returns on the UK FTA All Share index from January

1978 to December 1992 (T=180) and annual returns on the US S&P 500 index from 1879 to 1986 (T=108).

While Table 2 reports coefficient estimates and t-ratios for both α and β, attention will focus on the slope coefficient. The t-ratios on β differ markedly according to both the covariance matrix used and the choice of the bandwidth parameter, m (or, in the case of Andrews, $\hat{S}_T$). The methods of Hansen with (m=6), and Newey-West with QS weights and the bandwidth parameter chosen according to Andrews yield similar sized t-ratios on β; and these are generally smaller than those obtained from Newey-West with Bartlett weights (irrespective of the bandwidth) and Newey-West with QS weights and bandwidth chosen according to the order of the MA process. The Andrews and Monahan (1992) procedure yields the smallest t-ratios, although these are still, in general, larger than those obtained from the non-overlapping regressions.

For the exchange rate example, the null hypothesis of $\beta = 1$ is rejected at the 5% significance level for all covariance matrix calculations, with the exception of A-M and the non-overlapping regressions. For the U.K. stock return data, the null hypothesis of $\beta = 0$ is rejected across all covariance matrices at the 5% significance level (with the exception of the non-overlapping regressions). In contrast, the U.S. data accept the null hypothesis, $\beta = 0$, at the 5% significance level regardless of the covariance matrix utilised (with the exception of one non-overlapping case), although at the 10% significance level this null hypothesis is rejected by HAN (m=3), NWB (m=3), NWB (m=6) and NWQ (m=3).

Across all three empirical examples we find that the conclusions from hypothesis testing are dependent upon the choice of the estimation method used. In all cases the non-overlapping regressions yield larger standard error estimates (and smaller t-ratios) compared with the GMM estimation methods. For both the exchange rate and the UK stock return examples the use of non-overlapping regressions actually leads us to accept the null hypothesis, while the alternative covariance matrices in general lead us to reject the null hypothesis. Given the simulation results show that the GMM standard errors reject the null hypothesis too frequently compared with the non-overlapping regressions, tests of rationality, efficiency or mean-reverting behaviour using equations similar to (1) or (3) ought not to rely heavily on any one covariance matrix. Rather, results from an array of alternative covariance matrices ought to be presented in an attempt to appeal to robustness arguments.

IV Concluding Remarks

This paper investigates the performance of alternative estimation methods for models with over-lapping data. A number of alternative GMM estimation methods due to Hansen (1982), Newey and West (1987) (with Bartlett and QS weights and different bandwidth parameter) and Andrews and Monahan (1991) are compared. For highly correlated explanatory variables the GMM estimators of Hansen (1982) and Andrews and Monahan (1991) perform the best, although these still perform worse than the non-overlapping regressions. For all procedures there exists a strong tendency to over-reject the true null hypothesis even for large sample sizes, $T = 200$. While asymptotically these estimation procedures do yield consistent standard errors, in finite samples the standard errors can be markedly misleading. The empirical illustrations support the finding that the choice of the method and the bandwidth can affect the decision rule and that researchers ought to be wary of reporting results based on just one of the alternative covariance matrix calculations presented in this paper. Consequently, researchers should eschew reliance on just a single covariance matrix estimator; rather, they ought to report the range of possible test statistics (based on alternative covariance matrix calculations) and discuss the robustness of their findings. Recently, researchers have moved away from focussing attention on standard error calculations and conduct inference based on the empirical distribution of the regression coefficients derived from bootstrapping the data, see, for example, Kim, Nelson and Startz (1991) and McQueen (1992).

Table 1: Empirical 5% Size Results For Alternative Estimation Procedures

		Methods						
φ	T	OLS	N-O	NWB	NWAB	NWAQ	HAN	A-M
0.0	50	5.74	7.62	9.28	7.84	7.86	14.68	9.94
	75	5.40	6.34	8.54	8.08	8.08	11.14	9.16
	100	4.52	5.92	7.52	7.20	7.28	10.40	8.34
	150	4.56	6.00	6.36	6.18	6.50	7.94	7.34
	200	5.44	5.96	6.48	6.74	6.82	6.78	7.12
0.1	50	7.06	7.52	10.80	9.46	9.24	15.34	10.44
	75	7.96	6.10	9.50	9.10	9.08	11.70	9.42
	100	7.20	5.74	8.16	7.98	7.94	10.46	8.68
	150	6.70	5.98	7.08	7.26	7.38	7.86	7.50
	200	7.48	5.88	6.98	7.58	7.52	7.00	7.26
0.2	50	9.92	7.46	11.92	11.34	10.90	15.50	10.70
	75	10.84	6.08	10.48	10.58	10.14	12.04	9.54
	100	9.56	5.66	9.34	9.44	9.14	10.60	8.76
	150	8.80	5.88	7.84	8.02	7.76	7.96	7.42
	200	9.72	5.92	7.60	8.28	7.78	7.02	7.28
0.3	50	12.12	7.58	13.28	12.76	11.90	15.82	11.12
	75	13.50	6.32	11.42	11.80	11.10	12.12	9.98
	100	12.26	5.88	10.74	10.86	10.10	11.08	9.18
	150	11.72	5.74	8.80	8.92	8.54	8.12	7.44
	200	12.36	5.88	8.32	8.54	7.94	7.02	6.94
0.4	50	15.06	7.52	14.62	14.28	13.36	16.50	12.10
	75	16.00	6.40	12.66	12.80	11.82	12.72	10.18
	100	15.46	6.02	12.12	12.06	11.34	11.92	9.64
	150	14.62	5.62	9.70	9.70	8.96	8.34	7.74
	200	14.92	6.06	9.04	8.82	8.10	7.18	6.84
0.5	50	18.32	7.64	16.12	16.30	15.08	16.82	13.02
	75	19.74	6.52	13.82	13.84	12.90	12.90	10.38
	100	18.54	5.98	13.32	13.30	12.30	12.36	9.88
	150	18.08	5.46	10.82	10.42	9.46	8.60	7.78
	200	18.04	6.10	9.82	9.32	8.36	7.64	7.36
0.6	50	21.74	7.90	17.90	18.14	16.80	17.36	13.94
	75	22.54	6.48	15.06	14.76	13.58	13.56	11.02
	100	22.12	5.72	14.54	14.16	12.86	12.46	10.68
	150	21.62	5.52	11.80	10.92	9.80	8.78	7.90
	200	21.42	6.38	10.74	9.74	8.80	8.04	7.38
0.7	50	25.18	7.98	19.14	19.14	18.16	17.88	14.76
	75	25.64	6.28	16.86	16.06	14.92	13.78	11.00
	100	24.54	6.12	15.88	15.24	14.02	12.84	10.62
	150	25.82	5.80	12.62	11.70	10.28	8.82	7.88
	200	24.84	6.06	11.62	10.46	9.16	8.02	7.30
0.8	50	28.32	7.66	20.16	20.58	19.86	18.32	15.58
	75	29.20	6.32	17.40	17.00	16.12	14.30	11.06
	100	28.46	5.96	16.26	15.66	14.56	12.80	11.04
	150	28.86	5.80	13.34	12.22	11.16	9.56	8.76
	200	28.50	6.14	12.70	11.20	10.30	8.34	7.66
0.9	50	29.94	7.56	21.68	22.52	22.40	19.04	18.86
	75	32.40	6.62	17.68	17.78	17.64	13.08	10.38
	100	31.88	6.30	16.74	16.78	15.74	11.86	10.86
	150	31.46	5.66	14.52	13.18	12.30	9.40	9.00
	200	31.34	6.10	13.28	11.76	10.84	8.34	8.08

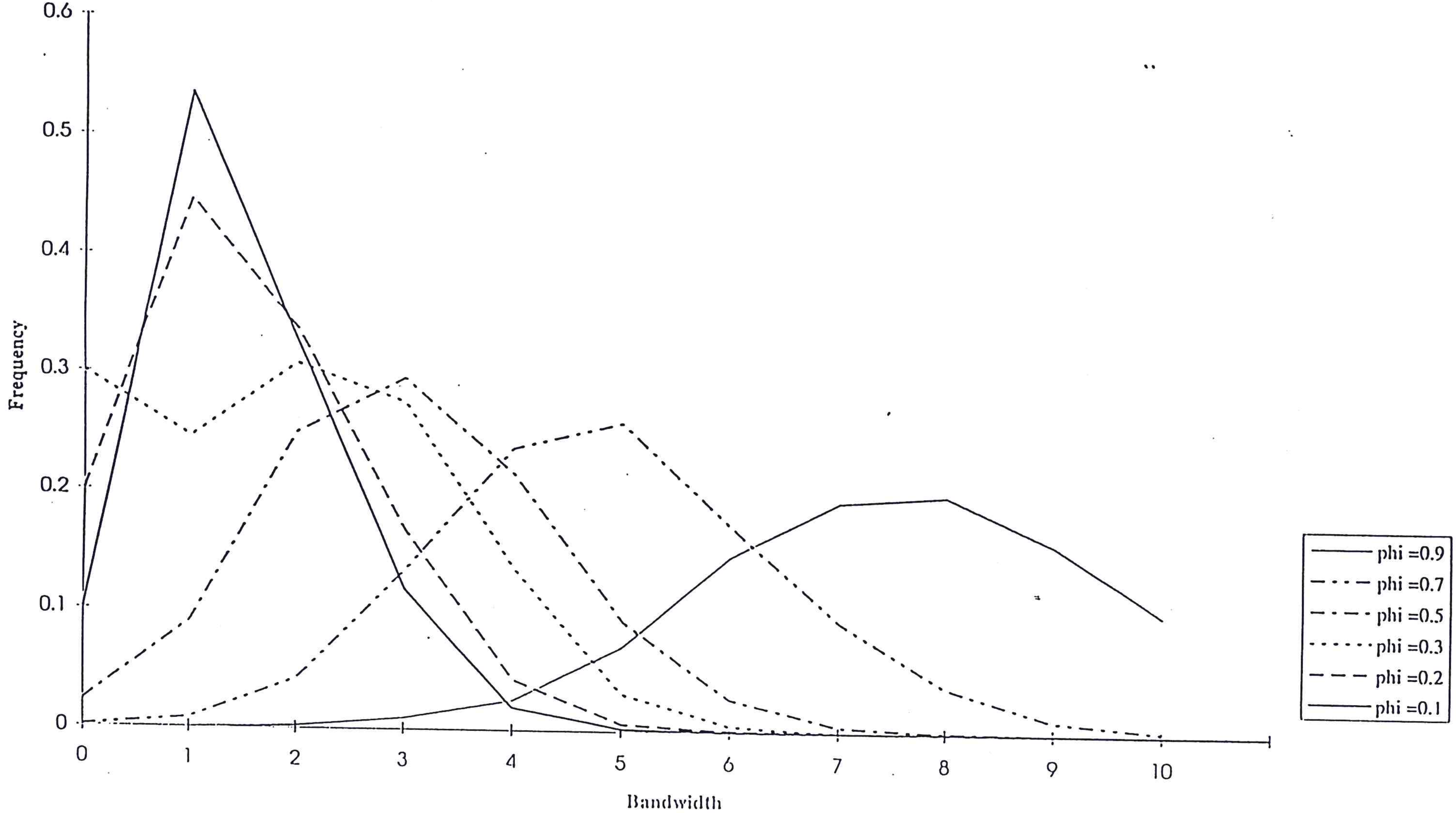
Table 2: Efficiency in the Foreign Exchange Market and Mean Reversion Tests

Method	Exchange Rate Equation α [1]	Exchange Rate Equation β [2]	U.K. Stock Market α [1]	U.K. Stock Market β [1]	U.S. Stock Market α [1]	U.S. Stock Market β [1]
OLS	-0.044 (-3.63)	-6.18 (-4.30)	0.070 (8.43)	-0.24 (-3.30)	0.54 (11.22)	-0.31 (-3.44)
N-O[3]	0.038 (1.53)	-5.41 (-1.91)	0.063 (3.59)	-0.16 (-1.01)	0.41 (4.30)	-0.02 (-0.10)
N-O	0.059 (2.40)	-8.09 (-2.73)	0.065 (3.89)	-0.19 (-1.26)	0.51 (5.35)	-0.26 (-1.05)
N-O	0.048 (1.82)	-6.60 (-2.12)	0.076 (5.07)	-0.34 (-2.38)	0.63 (9.39)	-0.55 (-3.24)
N-O	0.034 (1.39)	-4.80 (-1.72)	0.074 (4.21)	-0.29 (-1.95)	0.48 (5.13)	-0.13 (-0.68)
HAN (m=3)	-0.044 (-1.97)	-6.18 (-2.64)	0.070 (5.42)	-0.24 (-2.44)	0.54 (6.86)	-0.31 (-1.68)
HAN (m=6)	-0.044 (-1.87)	-6.18 (-2.48)	0.070 (5.23)	-0.24 (***)	0.54 (5.77)	-0.31 (-1.40)
NWB (m=3)	-0.044 (-2.39)	-6.18 (-3.20)	0.070 (6.41)	-0.24 (-2.51)	0.54 (7.99)	-0.31 (-1.91)
NWB (m=6)	-0.044 (-2.13)	-6.18 (-2.84)	0.070 (5.84)	-0.24 (-3.04)	0.54 (6.87)	-0.31 (-1.66)
NWAB[4]	-0.044 (-1.92)	-6.18 (-2.58)	0.070 (5.69)	-0.24 (-3.68)	0.54 (6.54)	-0.31 (-1.58)
NWQ (m=3)	-0.044 (-2.19)	-6.18 (-2.93)	0.070 (5.93)	-0.24 (-2.41)	0.54 (7.49)	-0.31 (-1.80)
NWAQ[5]	-0.044 (-1.81)	-6.18 (-2.42)	0.070 (5.37)	-0.24 (-4.20)	0.54 (6.13)	-0.31 (-1.49)
NWAQ[5,6]	-0.044 (-1.82)	-6.18 (-2.45)	0.070 (5.45)	-0.24 (-4.08)	0.54 (6.19)	-0.31 (-1.50)
A-M[5]	-0.044 (-0.77)	-6.18 (-0.92)	0.070 (4.59)	-0.24 (-3.82)	0.54 (5.82)	-0.31 (-1.38)

Notes:

1. Coefficient estimate and t-ratio for testing $H_0: \alpha = 0$ or $H_0: \beta = 0$.
2. Coefficient estimate and t-ratio for testing $H_0: \beta = 1$.
3. The number of observations used by the N-O method is 32 for exchange rate, 45 for the UK stock market equation and 27 for the US stock market equation. White's (1980) heteroscedasticity consistent standard errors are used.
4. $\hat{Z}_T = 13.54$ for exchange rate equation, $\hat{Z}_T = 9.94$ for UK stocks and $\hat{Z}_T = 9.37$ for US stocks.
5. $\hat{Z}_T = 12.91$ for exchange rate equation, $\hat{Z}_T = 8.47$ for UK stocks and $\hat{Z}_T = 8.68$ for US stocks.
6. This uses covariance terms up to $\Omega_{[\hat{Z}_T]}$.

Figure 1: Bandwidth Parameter Chosen By Andrews Procedure for MA(3) Model, T = 100



Notes

1. The QS weighting scheme uses covariance matrix terms up to Ω_{n-1}. We also consider the QS estimator when only terms up to $\Omega_{[\hat{Z}_T]}$ were $[\hat{Z}_T]$ is the integer part of $\hat{Z}_T$.

2. Frankel and Froot (1987) only report standard errors corresponding to a bandwidth equal to twice the order of the moving average process as these were larger.

3. The number of observations used for N-O are T = 12, 18, 25, 37, and 50.

4. Similar results are obtained from the A-M procedure when only weighted sums of $\Omega_j + \Omega'_j$, j = 1, 2, .., $[Z_T]$, where [.] refers to the integer component are used.

5. While results are only presented for the MA(3) process, higher ordered MA processes yield empirical size probabilities even further from their theoretical values. However, the ranking of the alternative estimators remains the same irrespective of the assumed MA process.

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