MODELING EXCHANGE RATES: LONG-RUN DEPENDENCE VERSUS CONDITIONAL HETEROSCEDASTICITY

Michael A. HAUSER*
Robert M. KUNST
Erhard RESCHENHOFER**

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* University of Economics and Business Administration, Vienna
** University of Vienna

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ABSTRACT

Indications for two different features not captured by low-order linear time series models can be found in day-to-day changes of exchange rates: long memory and conditional heteroscedasticity. These characteristics have inspired the development of ARFIMA and GARCH models. By means of Monte Carlo simulation, it is demonstrated that either of the two features stands a non-negligible chance of being detected spuriously in the presence of the other one. A table of explicit empirical small sample quantiles for identification of long-memory structures in the presence of GARCH effects is included.

ZUSAMMENFASSUNG

Zwei verschiedene Phänomene treten in Änderungsraten täglicher Wechselkurs-Zeitreihen auf: langes Gedächtnis und bedingte Heteroskedastie. Diese Erscheinungen, die durch lineare Zeitreihenmodelle niederer Ordnung nicht erklärt werden können, haben die Entwicklung von ARFIMA und GARCH inspiriert. Wir zeigen daß jede der beiden Eigenheiten in Gegenwart der anderen empirisch gefunden wird, obwohl sie in Wahrheit nicht da ist. Zur Erläuterung verwenden wir Zufallszahlen-Simulation.

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Michael A. Hauser, Robert M. Kunst, and Erhard Reschenhofer

1. INTRODUCTION

Following the breakdown of the Bretton-Woods system, empirical analysis of exchange rates suddenly has become more interesting. Accounting for the fact that changes in exchange rates cannot be reconciled with the normal model, observed empirical distributions being much too leptokurtic, Westerfield (1977) supported the stable Paretian model, which had been so controversially used on stock prices. Other authors suggested other fat-tailed distributions. This strand of literature is surveyed in Boothe and Glassman (1987) who favor Student distributions. In recent years attention has shifted towards analyzing the conditional heteroscedasticity in the series on the basis of autoregressive conditionally heteroscedastic (ARCH, see Engle, 1982) or generalized ARCH (GARCH, see Bollerslev, 1987) models. The unconditional distributions implied by these models can display considerable leptokurtosis but do not have closed forms. Hols and deVries (1991) address the discrimination problem of these heteroskedastic models versus other leptokurtic laws.

The present paper considers another discrimination problem, that of conditional heteroskedasticity versus long-term dependence or, more precisely, long-term autocorrelation. In the next subsection the possibility of long-term dependence in economic time series is discussed. Subsections 1.2 and 1.3 introduce parametric models for long-term dependence and conditional heteroscedasticity, respectively. Section 2. presents the results of the fitting of these models to time series of daily exchange rates. In section 3. the problem of testing for long-term dependence under a heteroscedastic null as well as that of testing for conditional heteroscedasticity under a strongly dependent null are considered. In addition, tables of critical values for tests of serial correlation under heteroscedastic nulls are given. Section 4. concludes.

1.1 LONG-TERM DEPENDENCE IN ECONOMIC TIME SERIES

Economic growth does not proceed in a smooth, monotonic fashion. It may rather be characterized by recurrent waves of acceleration and deceleration after the effects of primary trends and short cycles have been eliminated. In the frequency domain the most noticeable characteristic of the majority of economic time series is the overpowering importance of the low frequency components (see Adelman, 1965, Granger, 1966). For this sort of behavior Mandelbrot and Wallis (1968) have coined the term "Joseph effect", a reference to the Old Testament prophet Joseph who foretold the seven years of plenty followed by the seven years of famine.

Significant long-term correlation is inconsistent with the common assumption of time series analysis that observations separated by a long time span are nearly uncorrelated. Strong autocorrelation has been characterized by an autocorrelation function decaying hyperbolically or by a range over standard deviation (R/S) statistic decaying hyperbolically with an exponent different from 1/2. The latter characterization is also known as the Hurst phenomenon. Strong dependence in this sense is well documented in hydrology, meteorology, and geophysics. Perhaps the most celebrated example occurs in hydrology. For the annual discharges of the Nile at Aswan, Hurst (1951) found that the log of the R/S-statistic depends linearly on the log of the number of observations in the range-term with a slope considerably greater than 1/2. One argument in favor of strong dependence in economic time series is that many economic variables (e.g. agricultural production, tourism etc.) are directly related to climatological variables.

Mandelbrot (1971) considered the possibility of strong dependence in financial time series. Using the R/S-technique (see Hurst, 1951, Mandelbrot and Wallis, 1968, 1969, Mandelbrot, 1972, 1975) Greene and Fielitz (1977) claimed to have found long-term dependence in stock return series. Lo (1991) criticized that the R/S-statistic is not robust to short-range dependence. In view of the fact that stock returns appear to display substantial short-range dependence (Lo and MacKinlay, 1988) this is indeed a severe shortcoming. Therefore Lo (1991) robustified the R/S-test and applied this modified test to stock return data. He found no evidence of long-range dependence once the effects of short-range dependence are accounted for.

However, for our data set, which consists of nominal exchange rates against the Swiss franc, evidence of short-range dependence is poor (see 2.1) and therefore we concentrate on the discrimination problem of long-range dependence versus conditional heteroscedasticity. As parametric models for long-range dependence we consider autoregressive fractionally integrated moving average (ARFIMA) processes (see Granger and Joyeux, 1980, Hosking, 1981) and as parametric models for conditional heteroscedasticity we consider GARCH processes. We fit these models to our series of exchange rates (see section 2.) and examine the behavior of the estimation and testing methods under heteroscedastic nulls and under strongly dependent nulls (see section 3.).

1.2 ARFIMA MODELS

Conventional ARMA processes (of moderate order) are not appropriate for the modeling of long-term dependence because their autocorrelation functions decay exponentially as the lag increases. Therefore Granger and Joyeux (1980) and Hosking (1981) introduced the family of ARFIMA processes which offer a greater flexibility in the modeling of the long-term behavior of a time series.

An ARFIMA(p,d,q) process is defined as a stochastic process (y_t) which may be represented as

$$A(L)(1-L)^d y_t = B(L)\varepsilon_t,$$

where (ε_t) is a white noise process, $A(L)=1+\alpha_1 L+\ldots+\alpha_p L^p$ and $B(L)=1+\beta_1 L+\ldots+\beta_q L^q$ are polynomials in the backward-shift operator, and the fractionally integrating operator $(1-L)^d$ is defined as an infinite binomial series expansion in integer powers of L: $(1-L)^d = 1 - dL + \frac{d(d-1)}{2!}L^2 - \frac{d(d-1)(d-2)}{3!}L^3 + \ldots$

The process (y_t) is stationary if $d<1/2$ and invertible if $d>-1/2$. For any d, (y_t) can be integrated or differenced a finite integer number of times until d lies in the interval $[-1/2,1/2)$. For $d\neq 0$ the autocorrelation function ρ decays hyperbolically, i.e. $\rho(k)\sim Ck^{2d-1}$. For $d>0$ the autocorrelation function is not summable. Processes with non-summable autocorrelation function are called long memory processes.

Diebold and Rudebusch (1989) fitted ARFIMA models to a number of first differenced macroeconomic time series and throughout found negative estimates of d. For estimation they used the two-step procedure suggested by Geweke and Porter-Hudak (1983).

1.3 GARCH MODELS

Many recent empirical studies of exchange rates use the following GARCH(1,1) model which is, originally, due to Bollerslev (1986). The log differences of the original exchange rates

$$y_t = \log E_t - \log E_{t-1}$$

are uncorrelated with a small, theoretically zero, mean. Their conditional variances obey

$$E(y_t^2 | y_{t-1}, y_{t-2}, \ldots) = h_t = \alpha_0 + \alpha_1 y_{t-1}^2 + \beta h_{t-1}.$$

Commonly, the conditional distribution of the y_t is assumed as normal. As long as the (generally non-negative) parameters meet the condition $\alpha_1+\beta<1$ the process is weakly stationary. If $\alpha_1+\beta=1$, the process still has a stationary distribution, but the second moment does not exist. Such a process is called an integrated GARCH (IGARCH) process. Putting $\beta=0$ recovers the original ARCH model by Engle (1982). For all exchange rates in our sample, this restriction is safely rejected.

2. EMPIRICAL RESULTS

Our objects are (first-differences of log) nominal exchange rates against the Swiss franc. The data are taken from the ODAS data base of the Swiss National Bank. These exchange rates are available on a daily basis, starting on January 1st, 1970 and ending on April 12, 1989. All missing data due to public holidays were eliminated, hence differences represent changes between business days. However, the influence of the treatment of the holidays is small and very similar results can be obtained by interpolating them in some reasonable way. The total sample size (without holidays) is almost 5000, the Yen series being slightly shorter as it starts on January 1st, 1972. The analysis by Bärlocher (1990) of the U.S. and Deutschmark exchange rates relied on the same sample.

2.1 THE FITTING OF GARCH MODELS

For estimation the sample was split into three subsamples of 1500 observations each and GARCH(1,1) models were estimated for each subsample. Estimation was performed via a FORTRAN program due to Ng which does not allow for more than 1500 observations. The basic results are given in Table 1. This table allows for some general statements. Most means are negative, expressing a tendency for depreciation against the Swiss franc. The sum of $\alpha_1+\beta$ is always close to one, even surpassing one in some cases. β always dominates, which further enhances the persistence of variance shocks. α_0 and hence the unconditional variance is slightly higher for the Dollar currencies and the British Pound.

A summary of diagnostics for the GARCH(1,1) model is given in Table 2. Whereas skewness appears to be a minor problem, kurtosis of the adjusted data is considerable. It is doubtful, however, whether kurtosis is high enough to invalidate the conditionally normal model and to take up the suggestion of Bollerslev (1987) to consider conditional t-distributions. Note that kurtosis is highest in the first part of the sample and then gradually falls to almost normal levels. We calculated the statistics Q, which is the Ljung-Box statistic for serial correlation (up to lag 12) in the normalized residuals, and Q^2, which is the analogous statistic for the squares of the normalized residuals. Autocorrelation in the data is scarcely significant. Autocorrelation patterns are too weak and unsystematic to allow for formal ARMA models. Residual autocorrelation in the variance equation is even less significant and hence the GARCH(1,1) model suffices for an accurate description of the conditional heteroskedasticity structure.

Finally note that for 12 of the 21 (sub)series the condition

$$3\alpha_1^2+2\alpha_1\beta+\beta_1^2<1$$

for the existence of the fourth-order moment is not fulfilled. In particular, this condition is implied by the heteroscedastic null hypothesis H^* of no serial correlation, under which Lo and MacKinlay (1988) have derived the asymptotic distribution of their test statistic, and hence this test does not appear to be appropriate for our data.

2.2 THE FITTING OF ARFIMA MODELS

Due to the lack of evidence of short-range dependence in our series we restricted ourselves to ARFIMA(0,d,0) processes, i. e. to fractional noise processes. The parameter d was estimated by regressing the log periodogram ordinates $I(\omega_k)$ at the Fourier frequencies ω_k on a constant and the deterministic quantities $\log(4\sin^2(\omega_k/2))$. The estimator of d is just the slope coefficient in this least squares regression (see Geweke and Porter-Hudak, 1983). The estimates obtained for the series of exchange rates are given in Table 3. Some estimates differ significantly from zero. Only one of the significant estimates is positive. However, this positive estimate, which has been obtained for a subperiod, is challenged by a significant, negative estimate in the preceding subperiod.

3. MONTE CARLO STUDIES

3.1 MISSPECIFICATION OF ARFIMA PROCESSES AS GARCH PROCESSES

150 replications of fractional noise processes were generated, each sample containing 1000 observations. We considered the following values of the parameter d: -0.1, 0.1, -0.2, 0.2, -0.3. First we supposed that an imaginary investigator wants to test whether the synthetic series are white noise against simple alternatives. To this end, an LM-test against the alternative of an ARCH(1) process is performed. The LM-test statistic has a chi-square distribution with one degree of freedom. Sample skewness and kurtosis are also listed. Finally, the tests Q and Q^2 for autocorrelation in the linear sense (which we know to exist) and in the ARCH sense, respectively, are applied.

Results are shown in Table 4. This table shows that empirical higher moments are largely unaffected by long-memory. It is therefore not surprising that, in most cases, the null hypothesis of no ARCH cannot be rejected as ARCH models would demand for non-Gaussian higher moments. Only if the parameter d deviates substantially from 0, rejection of the null becomes more frequent.

A positive value of 0.2 suffices for this effect which can be explained primarily by the increased serial correlation which is recognized by the Q-test and affects the LM-ARCH-test and, to a lesser extent, the Q^2-statistic. Note that the results indicate a minor amount of platykurtosis, which is inconsistent with the considerable leptokurtosis prescribed by ARCH models.

3.2 MISSPECIFICATION OF GARCH PROCESSES AS ARFIMA PROCESSES

One thousand replications of various GARCH processes were generated, each sample containing 1500 observations. For each sequence we estimated the parameter d in the same way as above. In Table 5 the arithmetic means of these estimates as well as the portions of estimates outside the 95% confidence interval around zero are given. Under realistic forms of conditional heteroscedasticity the danger of erroneously assuming the existence of long-range dependence is quite large. Therefore we performed a simulation study in order to examine the distribution of the estimator of d under various GARCH nulls. 1000 replications were generated for each heteroscedastic null and for each sample size.

5. CONCLUSION

Both autoregressive fractionally integrated moving average models and generalized autoregressive conditionally heteroscedastic models are fitted to long time series of daily exchange rates against the Swiss franc. The discrimination problem of long-range autocorrelation versus conditional heteroscedasticity is discussed. Monte Carlo studies suggest that heteroscedastic series may appear erroneously as long-term dependent and, to a smaller degree, also vice versa. In order to facilitate testing for strong dependence in case of heteroscedastic nulls, critical values for the estimator of the fractional integration parameter are given for a number of sample sizes and GARCH nulls.

Table 1. GARCH(1,1) models for nominal exchange rates: Estimated GARCH parameters and mean.

Currency	Sub-period	$\hat{\alpha}_1$	$\hat{\beta}$	$\hat{\alpha}_0$	$\hat{\mu}$	$\hat{\alpha}_1+\hat{\beta}$
öS	1	.24	.77	$3x10^{-7}$	$-5x10^{-5}$	1.01
	2	.36	.63	$1x10^{-6}$	$-4x10^{-5}$	0.99
	3	.13	.79	$6x10^{-7}$	$-4x10^{-5}$	0.92
Can $	1	.24	.70	$3x10^{-6}$	$-4x10^{-5}$	0.90
	2	.22	.76	$2x10^{-6}$	$-2x10^{-3}$	0.98
	3	.11	.84	$3x10^{-6}$	$-1x10^{-5}$	0.95
DM	1	.25	.71	$8x10^{-7}$	$-2x10^{-4}$	0.97
	2	.33	.67	$7x10^{-7}$	$-8x10^{-6}$	1.00
	3	.14	.78	$6x10^{-7}$	$-2x10^{-5}$	0.92
FF	1	.21	.71	$3x10^{-6}$	$-2x10^{-4}$	0.92
	2	.29	.72	$9x10^{-7}$	$-2x10^{-4}$	1.00
	3	.15	.83	$4x10^{-7}$	$-2x10^{-4}$	0.97
£	1	.28	.66	$3x10^{-6}$	$-2x10^{-4}$	0.93
	2	.20	.73	$4x10^{-6}$	$-8x10^{-5}$	0.93
	3	.15	.81	$1x10^{-6}$	$-8x10^{-5}$	0.96
Yen	1	.19	.83	$4x10^{-7}$	$-3x10^{-5}$	1.02
	2	.15	.84	$1x10^{-6}$	$7x10^{-5}$	0.99
	3	.13	.82	$1x10^{-6}$	$3x10^{-4}$	0.95
US-$	1	.31	.63	$3x10^{-6}$	$1x10^{-4}$	0.94
	2	.23	.77	$2x10^{-6}$	$-1x10^{-4}$	1.00
	3	.08	.89	$2x10^{-6}$	$7x10^{-5}$	0.97

Table 2. GARCH(1,1) models for nominal exchange rates: diagnostic tests (Q and Q^2 measure residual autocorrelation in the mean and variance equation and are both distributed as chi-square with 12 degrees of freedom under the null)

Currency	Sub-period	skewness	kurtosis	Q	Q^2
öS	1	-1.62	24.0	34.8	1.1
	2	-0.37	7.7	22.9	7.6
	3	-0.14	4.5	18.9	6.6
Can $	1	0.62	76.7	10.8	0.3
	2	-0.24	5.0	17.0	11.2
	3	-0.23	4.8	10.6	9.8
DM	1	-3.14	42.4	4.6	0.4
	2	-0.52	8.5	41.9	6.7
	3	-0.10	4.7	20.6	6.2
FF	1	-2.91	82.6	14.9	0.4
	2	-0.44	6.7	18.0	11.4
	3	-2.33	33.3	13.5	0.8
£	1	-4.38	67.7	17.8	0.1
	2	-0.80	9.7	18.0	3.3
	3	-0.19	4.1	12.9	18.4
Yen	1	0.94	19.0	13.6	4.3
	2	0.14	5.0	20.0	5.7
	3	-0.05	4.8	15.6	3.4
US-$	1	-0.39	85.4	16.1	0.3
	2	-0.35	5.7	27.6	12.5
	3	-0.22	4.4	12.6	6.4

Table 3. Estimation of fractional noise models

Currency	Sub-period	n	Estimate of d	Asymptotic 95% Conf. Int.
öS		4840	-0.0557	+/- 0.0284
	1	1500	-0.1930	+/- 0.0518
	2	1500	-0.0205	+/- 0.0518
	3	1500	-0.0041	+/- 0.0518
Can $		4845	0.0105	+/- 0.0284
	1	1500	-0.0334	+/- 0.0518
	2	1500	0.0289	+/- 0.0518
	3	1500	0.0293	+/- 0.0518
DM		4849	0.0193	+/- 0.0284
	1	1500	-0.0587	+/- 0.0518
	2	1500	0.0317	+/- 0.0518
	3	1500	0.0056	+/- 0.0518
FF		4854	-0.0031	+/- 0.0284
	1	1500	-0.0519	+/- 0.0518
	2	1500	0.0110	+/- 0.0518
	3	1500	0.0056	+/- 0.0518
£		4845	0.0122	+/- 0.0284
	1	1500	0.0074	+/- 0.0518
	2	1500	-0.0109	+/- 0.0518
	3	1500	0.0263	+/- 0.0518
Yen		4332	0.0179	+/- 0.0301
	1	1500	-0.0838	+/- 0.0518
	2	1500	0.0645	+/- 0.0518
	3	1332	0.0170	+/- 0.0550
US-$		4849	0.0049	+/- 0.0284
	1	1500	-0.0326	+/- 0.0518
	2	1500	0.0221	+/- 0.0518
	3	1500	0.0152	+/- 0.0518

Table 4. Misspecification of ARFIMA(0,d,0) as GARCH processes: Empirical 95% quantiles and higher moments statistics (150 replications, sample size=1000).

d	-0.1	0.1	0.2	-0.2	-0.3
95 % quantiles:					
LM-test	3.3	2.9	6.9	4.2	7.6
theoretical	3.84	3.84	3.84	3.84	3.84
Q-test	34.3	64.5	268.0	59.7	88.5
Q^2-test	18.1	19.9	29.5	20.1	25.2
theoretical	21.0	21.0	21.0	21.0	21.0
quartiles:					
skewness	-.06,.05	-.06,.06	-.06,.05	-.06,.05	-.05,.05
kurtosis	2.8,3.1	2.8,3.1	2.8,3.1	2.8,3.0	2.8,3.1

Table 5. Misspecification of GARCH processes as ARFIMA(0,d,0) processes (1000 replications, sample size=1500).

GARCH process			mean	portion outside
α_0	α_1	β	of $\hat{d}$	of 95% conf.int.
0.000001	0.90	0.00	-0.0031	68%
0.000001	0.30	0.60	0.0005	44%
0.000001	0.20	0.78	-0.0003	46%
0.000001	0.20	0.79	-0.0005	49%
0.000001	0.10	0.89	0.0009	40%

Table 6. Distribution of the estimator of d under various GARCH nulls (1000 replications).

Sample size	GARCH param. α_1	β	mean of $\hat{d}$	$\sigma(\hat{d})$	Asymptotic st.dev.under white noise	Quantiles 2.5%	5%	95%	97.5%
100	.1	.00	-.01	.13	.12	-.27	-.22	.19	.22
100	.3	.00	-.01	.14	.12	-.29	-.24	.21	.25
100	.5	.00	-.01	.15	.12	-.31	-.28	.24	.28
100	.7	.00	-.02	.18	.12	-.38	-.30	.27	.31
100	.9	.00	-.02	.20	.12	-.44	-.35	.31	.36
100	.2	.70	-.01	.14	.12	-.28	-.23	.20	.24
100	.3	.60	-.01	.15	.12	-.29	-.25	.22	.26
100	.4	.50	-.01	.16	.12	-.32	-.28	.24	.28
100	.2	.75	-.01	.14	.12	-.29	-.24	.20	.24
100	.3	.65	-.01	.15	.12	-.30	-.26	.23	.26
100	.4	.55	-.01	.16	.12	-.33	-.28	.24	.28
100	.2	.79	-.01	.14	.12	-.30	-.24	.21	.24
100	.3	.69	-.01	.15	.12	-.32	-.26	.23	.26
100	.4	.59	-.01	.16	.12	-.34	-.28	.24	.29
100	.3	.70	-.01	.15	.12	-.32	-.27	.23	.26
500	.1	.00	.00	.05	.05	-.10	-.08	.08	.10
500	.3	.00	.00	.06	.05	-.11	-.09	.10	.11
500	.5	.00	.00	.07	.05	-.13	-.11	.11	.14
500	.7	.00	.00	.09	.05	-.18	-.15	.15	.17
500	.9	.00	.00	.12	.05	-.25	-.20	.20	.25
500	.2	.70	.00	.06	.05	-.11	-.09	.10	.11
500	.3	.60	.00	.07	.05	-.13	-.11	.11	.13
500	.4	.50	.00	.08	.05	-.16	-.13	.12	.15
500	.2	.75	.00	.06	.05	-.12	-.10	.10	.12
500	.3	.65	.00	.07	.05	-.14	-.11	.11	.14
500	.4	.55	.00	.08	.05	-.16	-.13	.13	.15
500	.2	.79	.00	.07	.05	-.14	-.12	.11	.13
500	.3	.69	.00	.08	.05	-.16	-.13	.13	.15
500	.4	.59	.00	.09	.05	-.17	-.14	.15	.17
500	.3	.70	.00	.08	.05	-.17	-.13	.13	.16
1000	.1	.00	.00	.03	.03	-.07	-.06	.05	.06
1000	.3	.00	.00	.04	.03	-.08	-.06	.06	.07
1000	.5	.00	.00	.05	.03	-.09	-.08	.08	.09
1000	.7	.00	.00	.07	.03	-.14	-.11	.11	.14
1000	.9	.00	.00	.11	.03	-.23	-.16	.17	.21
1000	.2	.70	.00	.04	.03	-.08	-.07	.06	.08
1000	.3	.60	.00	.05	.03	-.10	-.08	.07	.09
1000	.4	.50	.00	.06	.03	-.11	-.09	.09	.10
1000	.2	.75	.00	.04	.03	-.09	-.08	.07	.09
1000	.3	.65	.00	.05	.03	-.11	-.09	.08	.10
1000	.4	.55	.00	.06	.03	-.13	-.11	.10	.12
1000	.2	.79	.00	.05	.03	-.11	-.09	.08	.09
1000	.3	.69	.00	.06	.03	-.13	-.10	.10	.12
1000	.4	.59	.00	.07	.03	-.14	-.12	.12	.13
1000	.3	.70	.00	.07	.03	-.13	-.11	.10	.13

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