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Are Stock Returns Predictable from Industrial Production? Evidence from the USA, Japan and some European Countries.

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Abstract

A model of predictable stock returns which allows technical progress to follow a stochastic trend with fixed drift is derived. The predictability of stock returns is not inconsistent with market efficiency. As rational investors try to smooth consumption over time the prediction of a higher return is offset by the disadvantage of more volatile consumption.

When testing the model on monthly data, current production is a significant predictor of stock returns in nine of eleven countries: the USA, Japan, Germany, the UK, Italy, Spain, Belgium, the Netherlands and Denmark. With annual data, current production is a significant predictor of stock returns in five of eight countries: the USA, Japan, Germany, the UK and Spain. A longer return horizon increases the level of predictability from around 5-10 percent (monthly data) to 15-35 percent (annual data).

In most countries a deterministic trend model performs better than the stochastic trend model. However, for Japan the stochastic trend model is the preferred alternative. One possible interpretation of this result is that it is due to a more pronounced productivity slowdown in Japan since 1989, which did not occur in other countries.

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1. Introduction

There are evidence that stock returns can be predicted by financial and macroeconomic variables, both across international stock markets and over different time horizons , see, for instance, the articles by Breen, Glosten and Jagannathan (1990), Campbell (1987), Cochrane (1991), Fama and French (1989), Ferson and Harvey (1993) and Pesaran and Timmermann (1994).

Modern equilibrium models used to explain the pricing of assets suggest that the expected return on any stock depends on the sensitivity of the stock's return to *unexpected* changes in the macro economy. One fundamental implication of these models is that a security earns an extra expected return due to its sensitivity to macroeconomic factors, e.g. the unexpected changes in industrial production, unexpected changes in inflation, the return on the market portfolio and the term structure of interest rates.

One major problem with the Intertemporal Capital Asset Pricing Model, ICAPM, by Merton (1973) or the Arbitrage Pricing Theory, APT, by Ross (1976), which both are used to motivate much of the empirical work in this area, is that they are not general equilibrium models. One disquieting implication of this fact is that empirical tests cannot distinguish among the suggested theories. There are basically two methods, reported in the literature, that can be used to test asset price models.

The first method is to set up a pricing equation given from theory and replace unknown random factors with observed maroeconomic variables; standard hypotheses tests are then used to pick out the relevant factors. One implicit motivation for this type of work is probably the following: As

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we do not know which general equilibrium model gives the best description of the linkage between the real and financial sectors we may choose any (partial) equilibrium model.

The second possibility is to develop a parsimonious intertemporal general equilibrium model of capital asset pricing with an explicit relation between asset prices and one (or more) macroeconomic factor(s) and then implement a statistical test of this relation. This is the route that we shall follow in this paper.

Brock (1982) integrated stochastic growth theory and the theory of finance in such a way as to preserve the empirical tractability of the ICAPM and at the same time determine the risk prices in the APT. Balvers, Cosimano and McDonald (1990), (referred to as BCM in the following) extended Brock's model by allowing production to become endogenous. BCM derived a model where aggregate output is serially correlated around a time trend and share returns vary over time due to the desire of consumers to smooth consumption. Since aggregate output is serially correlated and hence predictable, the theory suggests that stock returns can be predicted based on rational forecasts of output in a context that is consistent with efficient markets. To maximize utility, investors smooth consumption by adjusting their required rate of return for financial assets: a lower return is accepted in a period with low output as long as there exists a possiblity to transfer wealth to this period.

The central testable relation in the BCM model shows how future stock returns are related to current aggregate output and a time trend. What does the trend represent? The time trend is a stand-in for constant technological progress. There is, however, no a priori reason to believe that technological progress can be proxied by a deterministic trend. On the contrary, a stochastic-trend model seems to be more plausible as a deterministic trend model for productivity may have unreasonable consequences in the long run, see Stock and Watson(1988). Shocks to productivity have permanent effects, i.e. the effect of, say an oil shock, will have an impact on the level of productivity in all future quarters. In the trend stationary model by contrast, the effect of shocks to the trend die out.

In Berg (1993) I derived a version of the Brock-BCM model which results in a statistical formulation flexible enough to allow the trend component to respond to general changes in the direction of the series. When the model was tested on Swedish monthly data for the time period 1973-1987 the explanatory power of a deterministic-trend model was better than that of a stochastic-trend model. Wilkens (1994) tested the model on Swedish annual data for the period 1919-1989 with basically the same results.

In this paper I shall perform tests of the basic model on stock market and industrial production indices for USA, Japan, Germany, UK, France, Italy, Spain, Sweden, Belgium, Netherlands and Denmark. The analysis is based on both monthly and annual data. For most countries the series cover the period 1970-1996.

2. The Model

2.1 *The Timing of Events*

There is one representative firm and one representative consumer. The timing of events is as follows:
First, the firm observes current stochastic productivity, λ_t.
Second, output, y_t, is produced with a Cobb-Douglas production function: $y_t = \lambda_t k_t^{\alpha}$, where k_t is the capital stock and $\alpha<1$.
Third, investment, i_t, dividends, d_t, and consumption, c_t, is determined. Dividends satisfy: $d_t = y_t - i_t$. The consumer has a logarithmic utility function: $u(c_t) = \ln(c_t)$. Consumption, c_t, equals dividends in the representative firm, when the number of shares is normalized to one. Fourth, the simple time-to-build technology implies that investment at time t, i_t, results in the next period's capital stock, k_{t+1}. (Capital depreciates fully each period.)

2.2 *The Firm's Maximization Problem*

R_t, one plus the discount rate, is endogenously determined in the following maximization problem:

$$(1)\quad \text{Max}\ E_0 \sum_{t=0}^{\infty}\left[\prod_{i=0}^{t} R_i^{-1}\right] d_t$$

subject to

(2) $d_t = y_t - i_t$

(3a) $y_t = \lambda_t k^{\alpha}{}_t, \alpha < 1$

(3b) $\lambda_t = \lambda_{t-1} \exp(\mu + \eta_t)$

where the stochastic trend of technical progress, λ_t, is modeled as a first order Markov process with a constant slope, μ. η_t is a normally distributed independent white-noise process with zero mean and variance σ^2_η. The Euler condition of the maximization problem is:

(4) $E_t\{R^{-1}_{t+1}\alpha(y_{t+1}/k_{t+1})\} = 1$

and has a straightforward interpretation: the expected value of $\alpha(y_{t+1}/k_{t+1})$, the marginal product of investment, discounted by R_{t+1} must equal the one unit of capital which is invested rather than consumed.

2.3 *The Consumers Maximization Problem*

Given a logarithmic utility function the consumer maximizes:

(5) $E_0 \sum_{t=0}^{\infty} \beta^t \ln c_t$

subject to

(6) $c_t + p_t(y_t)s_{t+1} = [p_t(y_t) + d_t(y_t)]s_t$

where β is the discount factor for utility. $p_t(y_t)$ is the price per share after dividends, $d_t(y_t)$, are paid. s_t is the number of shares held at the beginning of period t.

The Euler condition for the consumer's maximization problem can be written:

(7) $p_t \dfrac{1}{c_t} = \beta E_t\left\{[p_{t+1} + d_{t+1}]\dfrac{1}{c_{t+1}}\right\}$

which again has a straightforward interpretation: utility sacrified at time t (the price of a share times the marginal utility of consumption) equals the utility gained at time t+1 (the expected value of the return times the marginal value of consumption at t+1).

Solving equation (7) forwards and normalizing the supply of shares to one (which by (6) implies $c_t = d_t$) yields:

$$(8) \qquad p_t = E_t \sum_{i=0}^{\infty} \beta^i d_t = \frac{\beta d_t}{1-\beta}$$

Defining returns as $R_{t+1} = [p_{t+1} + d_{t+1}]/p_t$ we then get:

$$(9) \qquad R_{t+1} = \left(\frac{1}{\beta}\right)\left(\frac{d_{t+1}}{d_t}\right)$$

Equation (9) can be interpreted in the following way. We take expectations conditional on information at time t. When dividends at time t+1 are expected to be lower than dividends at time t, investors/consumers are willing to accept a lower return in order to have the possibility to transfer purchasing power from t to t+1 and thus smoth consumption over time.

2.4 *Solution*

The model is easily solved using the method of undetermined coefficients. The solution is given by:

$$(10) \qquad R_{t+1} = \left(\frac{1}{\beta}\right)\left(\frac{y_{t+1}}{y_t}\right),$$

$$(11) \qquad y_{t+1} = (\alpha\beta)^{\alpha} \lambda_{t+1} y_t^{\alpha}.$$

Equation (10) shows that output at time t+1 relative to output at time t determines the rate of return. From equation (11) it is obvious that output at time t+1 can be predicted, given current output at time t. The reason is that technical progress at time t+1 can be predicted, due to the assumption of stochastic technical progress following a first order Markov process. Excess profit opportunities, however, are not available: the prediction of a lower return is compensated exactly by the possibility to smooth consumption. Equivalently the prediction of a higher return is offset by the disadvantage of more volatile consumption.

3. The Data and Results for the Basic Model

3.1 *The Data*

We studied the relation between industrial output (seasonally adjusted) and the total return on Morgan Stanley Capital Index. The stock index was deflated by the consumer price index. The model was tested on monthly data for 11 industrial countries: USA, Japan, Germany, United Kingdom, France, Italy, Spain, Sweden, Belgium, Netherlands and Denmark. The sample period is 1970:2 - 1997:1. For eight countries the model was also tested using annual data for the period 1971-1996: USA, Japan, Germany, United Kingdom, France, Italy, Spain and Sweden.

3.2 *The Empirical Equation*

The empirical relation we tested is derived from equations (10) and (11). Taking logs of both equations and then inserting equation (11) in equation (10) results in:

$$\text{(12a)}\quad \ln R_{t+1} = b_0 + \ln \lambda_{t+1} + b_1 \ln y_t + \varepsilon_t,$$

$$\text{(12b)}\quad \ln \lambda_{t+1} = \ln \lambda_t + \mu + \eta_t,$$

where $b_0 = \alpha \ln \alpha + \ln \beta(\alpha - 1)$ and $b_1 = \alpha - 1$. We shall test three different propositions of the model: first, current production should be significant in predicting future stock returns; second, the coefficient b_1 on the log of current output should be negative; third, technical progress should exhibit a stochastic trend.

In order to evaluate the stochastic trend model we also tested directly the deterministic-trend model, as derived by BCM (1990):

$$\text{(12')}\quad \ln R_{t+1} = c_0 + c_1 \ln y_t + c_2 t + \varepsilon_t$$

We report the results from estimating equations (12) in tables 1 (monthly data) and 3 (annual data). The results from equation (12′) are in tables 2 (monthly data) and 4 (annual data).

Some goodness-of-fit measures are also given. The conventional measure of goodness of fit, R^2, is obtained by dividing the residual sum of squares by the sum of squares of the observations about the mean and subtracting from unity. A better measure for non- stationary time-series data, R_d^2, is obtained by replacing the observations by their first differences.

When searching for a preferred model one may also base the comparisons on the prediction-error variance (p.e.v.), which has to be minimized.

3.3 *Monthly Data*

Using monthly data, current production is significant in predicting future stock returns for eight of the eleven countries in the stochastic trend model, as can be seen in table 1. The countries are USA, Japan, Germany, UK, Italy, Belgium, Netherlands and Denmark. In addition, as predicted the coefficient estimate, b_1, on the log of current output is negative. However, for France, Spain and Sweden the coefficent estimate is not significantly different from 0 at the 5 percent level.

Column 5 shows the estimate of the standard deviation of the disturbance affecting stochastic technical growth. If this hyperparameter is positive, the trend is stochastic. If it is zero, the trend becomes deterministic . It can thus be concluded from table 1 that the stochastic-trend model is rejected for the USA, Germany, UK, Sweden and Belgium using monthly data. The deterministic-trend model fits the data relatively well in the USA, Germany, UK, Spain and Belgium. R^2 is between 0.043 and 0.096, while R_d^2 ranges between 0.455 and 0.506. (In Sweden, the coefficient estimate on industrial production is only significant at the 20 percent level of significance.)

In contrast, the stochastic-trend specification is not rejected for six of the countries: Japan, France, Italy, Spain, Netherlands and Denmark. As can be seen from column five of table 1, the estimate of the standard deviation of the disturbance is different from zero for these countries.

In order to assess the performance of the stochastic trend specification for Japan, France, Italy, Spain, Netherlands and Denmark a deterministic-trend equation was also specified and estimated according to equation (12´). The results are reported in table 2.

For Japan, the stochastic-trend model is the preferred one. R^2 is 0.036 and R_d^2 is 0.479. The coefficient estimate on industrial production is significant and negative. Using a deterministic trend with japanese data, the coefficient estimate on industrial production is not significant at the 5 percent level. R^2 and R_d^2 are also lower than with a stochastic trend, 0.029 and 0.478 respectively.

For France, the coefficient estimate on industrial production is still insignificant at the 5 percent level, when using the deterministic trend model.

For Italy, the coefficient estimate on industrial production is not significant at the 5 percent level with a deterministic trend. The prediction error variance is higher than with a stochastic trend. However, the trend coefficient estimate is significant with a deterministic trend, while in significant (at the 5 percent level) with a stochastic trend. Data are hence inconclusive when attempting to discriminate between the models with italian data.

For Spain, the deterministic-trend model performs better than the stochastic-trend model. The coefficient estimate on industrial production and the trend coefficient estimate are both significant at the 5 percent level with a deterministic trend. R^2 and R_d^2 are higher than whith a stochastic trend.

For the Netherlands and Denmark, both models perform well. The coefficient estimate on industrial production and the trend coefficient estimate are significant at the 5 percent level in both specifications. In addition, goodness of fit measures are higher for these countries than for the other countries. With a stochastic trend R^2 is 0.142 and R_d^2 is 0.509 for Denmark.

In conclusion, with monthly data, current production is a significant predictor of stock returns in nine of the eleven countries. However, in most of these countries a deterministic-trend model performs better than the stochastic trend model. Only for Japan is the stochastic-trend model the preferred alternative. The deterministic-trend model fits the data relatively well in USA, Germany, UK, Spain and Belgium. For the Netherlands and Denmark, a stochastic-trend model performs equally well as a deterministic-trend model.

Figure 1 depicts the deterministic-trend component for the USA, while figure 3 shows the stochastic trend component for Japan. A slowdown in productivity growth since 1989 may be the main factor explaining why a stochastic trend model is the preferred alternative for Japan.

3.4 *Annual Data*

In BCM (1990), alternative return horizons were tested on US data. With annual instead of monthly data, the level of predictability increases from 3 percent to 20 percent. Table 3 and 4 report results from estimations in eight countries for which annual data were available for the time period 1971-1996. With annual data, current production is a significant (at the 5 percent level) predictor of stock returns in five of the eight countries: USA, Japan, Germany, UK and Spain. For Sweden it is significant at the 10 percent level. Goodness-of-fit measures are generally better than with monthly data. (For France and Italy, both the trend coefficient estimates and the coefficient estimates on industrial productions are not significant.)

For the USA, Germany, UK and Spain the deterministic-trend option is the preferred alternative. The coefficient estimates are clearly significant. R^2 is between 0.308 and 0.349, while R_d^2 ranges between 0.132 and 0.689.

For Japan, the stochastic trend model performs better than the deterministic trend specification in terms of goodness of fit. With a stochastic trend, R^2 is 0.158 and R_d^2 is 0.489, with a deterministic trend they are 0.094 and 0.451, respectively.

In conclusion, with annual data current production is a significant predictor of stock returns in five of the eight countries investigated. A longer return horizon increases the level of predictability from around 5-10 percent (monthly data) to 15-35 percent (annual data).

The deterministic-trend model fits the data well in the USA, Germany, UK and Spain. As with monthly data, the stochastic trend model is the preferred alternative only for Japan.

3.5 Diagnostics

Tests for normality (Bowman-Shenton (BS) and Doornik-Hansen (DH) heteroscedacity (H), and serial correlation (Box-Ljung) are reported in the lower part of each table. The normality test is based on the third and fourth moments of the distributions of the errors and has a χ^2 distribution with 2 degrees of freedom when the model is correctly specified. The 5 percent critical value is thus 5.99. With monthly data this statistic is high for all countries using the BS-statistic. The DH-test has better small-sample properties that the BS-test. Although the DH-test gives lower values than the BS-test, they are still above the 5 per cent critical value. High values are often caused by outliers. The model should not necessarily be rejected but further investigation is required.

A test for skewness and excess kurtosis was performed separately. The main reason for the high normality-test statistic for all countries except Italy was a very high value on the excess kurtosis test statistic. One weakness with the excess kurtosis test statistic is that it approaches normality very slowly when the sample size is increased.

A search for large residual values, residuals which have an absolute value exceeding two, was also performed for monthly data. In the estimations reported in table 1, the number of outliers was 18 for the USA (the largest value, -5.6, appeared in October 1987), 15 for Germany (-5.3 in October 1987) , 13 for the UK (6.4 in January 1975), 17 for Japan (-3.6 in September 1990), 11 for Sweden (4.7 in November 1992), 15 for France (-4.3 in October 1987), 16 for Italy (3.5 in October 1980), 16 for Spain (-5.4 in October 1987), 11 for Belgium (-5.8 in October 1987), 18 in the Netherlands (-5.7 in October 1987), and 18 for Denmark (-3.3 in October 1987).

The high values for the Bowman-Shenton tests with monthly data are thus mainly caused by outliers. Disregarding from excess kurtosis the distributions of the residuals are similar to a normal distribution. With annual data, the assumption of normality is not rejected for any country, except the UK.

The heteroscedacity test statistic, $H(h)$, is the ratio of the sum of the squares of the last h residuals to the sum of squares of the first h residuals, where h is set to the closest integer of $T/3$. It has an F distribution with (h,h) degrees of freedom. A high value indicates change in the variance. $F(103,103)$ is 1.4 at the 5 percent level. For most countries there is no evidence of heteroscedacity in the regressions with monthly data as reported in tables 1 and 2. However, for Sweden, Germany and Japan the null hypothesis of homoscedacity is rejected. With annual data, (tables 3 and 4), the null hypothesis of homoscedasticity is not rejected for any country as the critical value is $F(8,8) = 3.4$

The test for autocorrelation, $Q(p,q)$, is the Box-Ljung statistic based on the first p autocorrelations; it is distributed as a χ^2-variable with monthly data with q degrees of freedom. For Sweden, Germany and Japan a heteroscedacity consistent version of the test is used, see Milhøj (1985). χ^2 (14) is 23.7 at the 5 percent level, therefore, the null hypothesis of no serial correlation is rejected only for Spain and the UK. With annual data, the null hypothesis of no serial correlation is rejected only for Spain (χ^2 (6) is 12.6 at the 5 percent level).

3.6 *Predictive Testing*

In order to study the predictive properties of the model for the USA and Japan, predictions are made within the sample as one-step ahead forecasts with monthly data for the period 1994:6-1997:1. For the USA the deterministic-trend model was used. The logarithm of stock returns and the deterministic trend component are shown in figure 1. A stochastic trend model was fitted to data from Japan, as shown in figure 3.

In figure 2, fitted values, residuals and the CUSUM are depicted for USA. The residuals are well inside the band which is twice the RMSE. The CUSUM graph is far from crossing the two boundary lines, which are based on a significance level of 10 percent. There is a slight tendency for the model to overpredict the stock returns. A formal Chow test was performed and gave the value 0.413 (0.998). This statistic is approximately distributed as $F(32,279)$, indicating a stable forecasting model.

In figure 4, fitted values, residuals and the CUSUM are depicted for Japan. The residuals are well inside the bands, except for one month by the end of 1995. The CUSUM graph is far from crossing the two boundary lines, which are based on a significance level of 10 percent. There is a slight tendency for the model to underpredict stock returns. The Chow test is 0.884 (0.711), which does not reject stability.

4. Conclusions

I derived a version of the model by Balvers, Cosimano and McDonald (1990) which allows technical progress to follow a stochastic trend with fixed drift. As in the BCM model, stock returns are predictable. The future capital stock is a linear function of actual output. Future output is a function of the future capital stock and future productivity. As future productivity can be predicted from current productivity, stock returns can also be predicted. The predictability of stock returns is not inconsistent with market efficiency. As rational investors try to smooth consumption over time the prediction of a higher return is offset by the disadvantage of more volatile consumption.

When testing the model on monthly data, current production is a significant predictor of stock returns in nine of eleven countries: the USA, Japan, Germany, the UK, Italy, Spain, Belgium, the Netherlands and Denmark. With annual data, current production is a significant predictor of stock returns in five of eight countries: the USA, Japan, Germany, the UK and Spain. A longer return horizon increased the level of predictability from around 5-10 percent (monthly data) to 15-35 percent (annual data).

In most countries a deterministic trend model performs better than the stochastic trend model. However, for Japan the stochastic trend model is the preferred alternative. One possible interpretation of this result is that it is due to a more pronounced productivity slowdown in Japan since 1989, which did not occur in other countries.

Table 1 a
Test of the relation between output and share returns. The return on shares is measured as one plus the return on the MSCI gross index minus the change in the CPI. The data for inflation and industrial production are taken from the ECOWIN database. Data are monthly. Stochastic-trend specification. t-statistics appear within parentheses.

Country	b_0	b_1	μ	σ_η	R^2	R^2_d	p.e.v.	Interval
USA	0.833	-0.172	0.0004	0.0000	0.062	0.506	0.0018	70:2-97:1
	(3.17)	(-3.12)	(3.47)					
JAP	0.688	-0.151	0.0003	0.0027	0.036	0.479	0.0029	70:2-97:1
	(2.40)	(-2.42)	(1.51)					
GER	0.743	-0.159	0.0002	0.0000	0.043	0.481	0.0025	70:2-97:1
	(2.35)	(-2.32)	(2.64)					
UK	0.915	-0.194	0.0003	0.0000	0.067	0.481	0.0036	70:2-97:1
	(2.42)	(-2.39)	(2.7)					
FRA	0.669	-0.142	0.0002	0.0012	0.057	0.476	0.0034	70:2-97:1
	(1.74)	(-1.71)	(1.73)					
ITA	0.885	-0.186	0.0004	0.0046	0.082	0.484	0.0046	70:2-97:1
	(2.02)	(-2.00)	(1.35)					
SPA	0.326	-0.064	0.0002	0.0033	0.073	0.455	0.0032	70:2-97:1
	(1.03)	(-0.95)	(0.93)					
SWE	0.356	-0.072	0.0001	0.0000	0.079	0.468	0.0035	70:2-97:1
	(1.34)	(-1.28)	(1.99)					
BEL	0.714	-0.154	0.00009	0.0000	0.096	0.456	0.0021	75:2-97:1
	(2.86)	(-2.81)	(2.29)					
NET	0.764	-0.159	0.0003	0.0006	0.126	0.513	0.0021	70:2-97:1
	(2.62)	(-2.57)	(3.01)					
DEN	1.151	-0.236	0.0006	0.0036	0.142	0.509	0.0016	74:2-97:1
	(3.21)	(-3.16)	(2.35)					

Table 1 b Diagnostics

Country	Normality BS	DH	Heteroscedasticity	Autocorrelation
USA	218.4	76.5	H (103)=0.58	Q(17,14)=12.87
JAP	23.1	18.8	H(103)=1.75	Q(17,14)=13.89
GER	143.8	44.7	H(103)=1.57	Q(17,14)=13.94
UK	1003	239	H(103)=0.33	Q(17,14)=21.78
FRA	31.31	21.8	H(103)=0.64	Q(17,14)=15.94
ITA	13.83	13.6	H(103)=0.99	Q(17,14)=13.77
SPA	117.2	54.9	H(103)=1.30	Q(17,14)=24.05
SWE	90.7	56.9	H(103)=2.18	Q(17,14)=9.61
BEL	237.8	107.2	H(83)=1.18	Q(15,12)=17.12
NET	159.0	70.6	H(103)=0.76	Q(17,14)=18.06
DEN	17.9	9.4	H(87)=1.41	Q(15,12)=20.38

Table 2 a

Test of the relation between output and share returns. The return on shares is measured as one plus the return on the MSCI gross index minus the change in the CPI. The data for inflation and industrial production are taken from the ECOWIN database. Data are monthly. Deterministic-trend specification. t-statistics appear within parentheses.

Country	c_0	c_1	c_2	R^2	R^2_d	p.e.v.	Interval
JAP	0.315	-0.066	0.00015	0.029	0.478	0.0029	70:2-97:1
	(1.51)	(-1.51)	(1.26)				
FRA	0.516	-0.108	0.00017	0.065	0.481	0.0034	70:2-97:1
	(1.48)	(-1.45)	(1.73)				
ITA	0.461	-0.096	0.002	0.087	0.487	0.0046	70:2-97:1
	(1.36)	(-1.33)	(1.86)				
SPA	0.427	-0.088	0.0002	0.077	0.457	0.0033	70:2-97:1
	(2.18)	(-2.10)	(2.94)				
NET	0.752	-0.157	0.00026	0.133	0.517	0.0021	70:2-97:1
	(2.67)	(-2.60)	(3.01)				
DEN	0.878	-0.181	0.0004	0.147	0.512	0.0021	74:2-97:1
	(3.09)	(-3.06)	(2.35)				

Table 2 b Diagnostics

Country	Normality BS	DH	Heteroscedasticity	Autocorrelation
JAP	25.1	15.7	H(103)=1.75	Q(17,14)=16.12
FRA	31.47	21.9	H(103)=0.65	Q(17,16)=15.92
ITA	26.71	11.7	H(103)=1.07	Q(17,16)=19.45
SPA	98.3	50.4	H(103)=1.33	Q(17,16)=26.66
NET	161.1	71.5	H(103)=0.76	Q(17,16)=17.89
DEN	15.9	10.9	H(87)=1.51	Q(15,14)=24.94

Table 3 a
Test of the relation between output and share returns. The return on shares is measured as one plus the return on the MSCI gross index minus the change in the CPI. The data for inflation and industrial production are taken from the ECOWIN database. Data are annual: 1971-1996. Stochastic-trend specification. t-statistics appear within parentheses.

Country	b_0	b_1	μ	σ_η	R^2	R_d^2	p.e.v.
USA	8.477	-1.762	0.054	0.0000	0.349	0.689	0.016
	(3.09)	(-3.04)	(3.42)				
JAP	10.296	-2.24	0.063	0.1317	0.158	0.489	0.039
	(3.54)	(-3.52)	(1.93)				
GER	10.683	-2.302	0.038	0.0000	0.337	0.623	0.016
	(3.39)	(-3.36)	(3.57)				
UK	9.778	-2.076	0.035	0.0000	0.308	0.561	0.021
	(3.00)	(-2.96)	(3.34)				
FRA	4.798	-1.026	0.005	0.0000	-0.149	0.399	0.051
	(0.95)	(-0.94)	(0.19)				
ITA	4.887	-1.042	0.0303	0.1146	-0.072	0.281	0.094
	(0.85)	(-0.85)	(0.86)				
SPA	6.114	-1.277	0.039	0.1881	0.264	0.166	0.053
	(1.38)	(-1.34)	(0.86)				
SWE	6.388	-1.333	0.022	0.0000	0.138	0.534	0.043
	(1.88)	(-1.83)	(2.12)				

Table 3 b Diagnostics

Country	Normality BS	Heteroscedasticity	Autocorrelation
USA	1.40	H(8)=0.82	Q(8,6)=6.34
JAP	3.02	H(8)=0.83	Q(8,6)=4.24
GER	0.18	H(8)=1.24	Q(8,6)=10.93
UK	6.78	H(8)=0.20	Q(8,6)=3.98
FRA	0.42	H(8)=0.49	Q(8,6)=8.86
ITA	1.24	H(8)=0.59	Q(8,6)=7.71
SPA	1.86	H(8)=0.64	Q(8,6)=14.15
SWE	0.58	H(8)=2.75	Q(8,6)=5.06

Table 4 a

Test of the relation between output and share returns. The return on shares is measured as one plus the return on the MSCI gross index minus the change in the CPI. The data for inflation and industrial production are taken from the ECOWIN database. Data are annual:1971-1996. Deterministic-trend specification. t-statistics appear within parentheses.

Country	c_0	c_1	c_2	R^2	R^2_d	p.e.v.
JAP	5.000	-1.064	0.032	0.094	0.451	0.042
	(1.74)	(-1.73)	(1.56)			
FRA	2.975	-1.615	0.015	0.043	0.499	0.043
	(0.61)	(-0.58)	(1.00)			
ITA	2.066	-0.42	0.018	0.046	0.360	0.083
	(0.38)	(-0.36)	(0.77)			
SPA	7.154	-1.502	0.041	0.234	0.132	0.055
	(2.19)	(-2.14)	(2.72)			

Table 4 b Diagnostics

Country	Normality BS	Heteroscedasticity	Autocorrelation
JAP	3.13	H(8)=1.29	Q(6,6)=10.06
FRA	0.44	H(8)=0.64	Q(6,6)=2.82
ITA	1.41	H(8)=0.90	Q(6,6)=3.33
SPA	1.60	H(8)=1.08	Q(6,6)=13.77

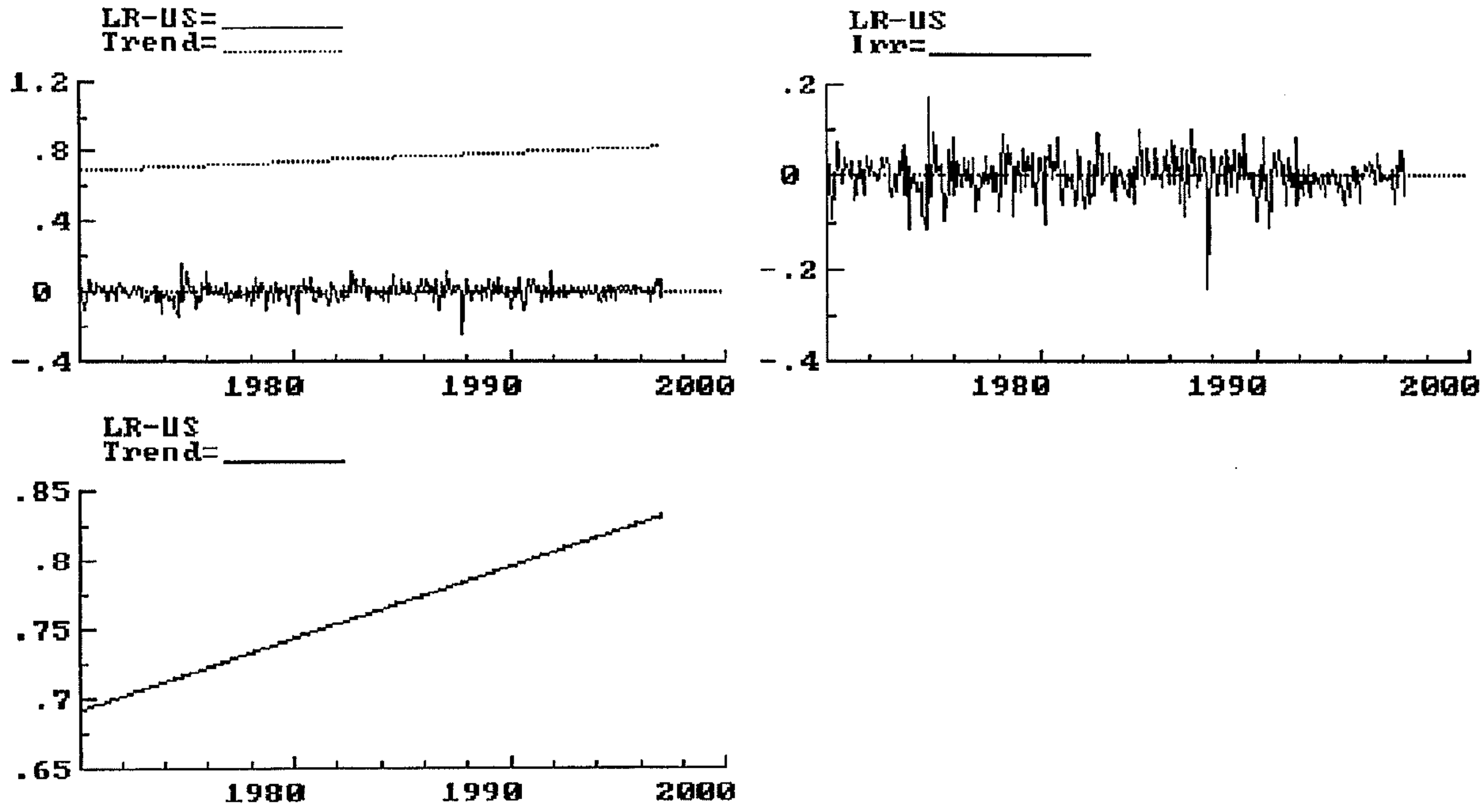

Figure 1. USA, logarithm of stock returns and trend component, irregular component, trend component. Monthly data.

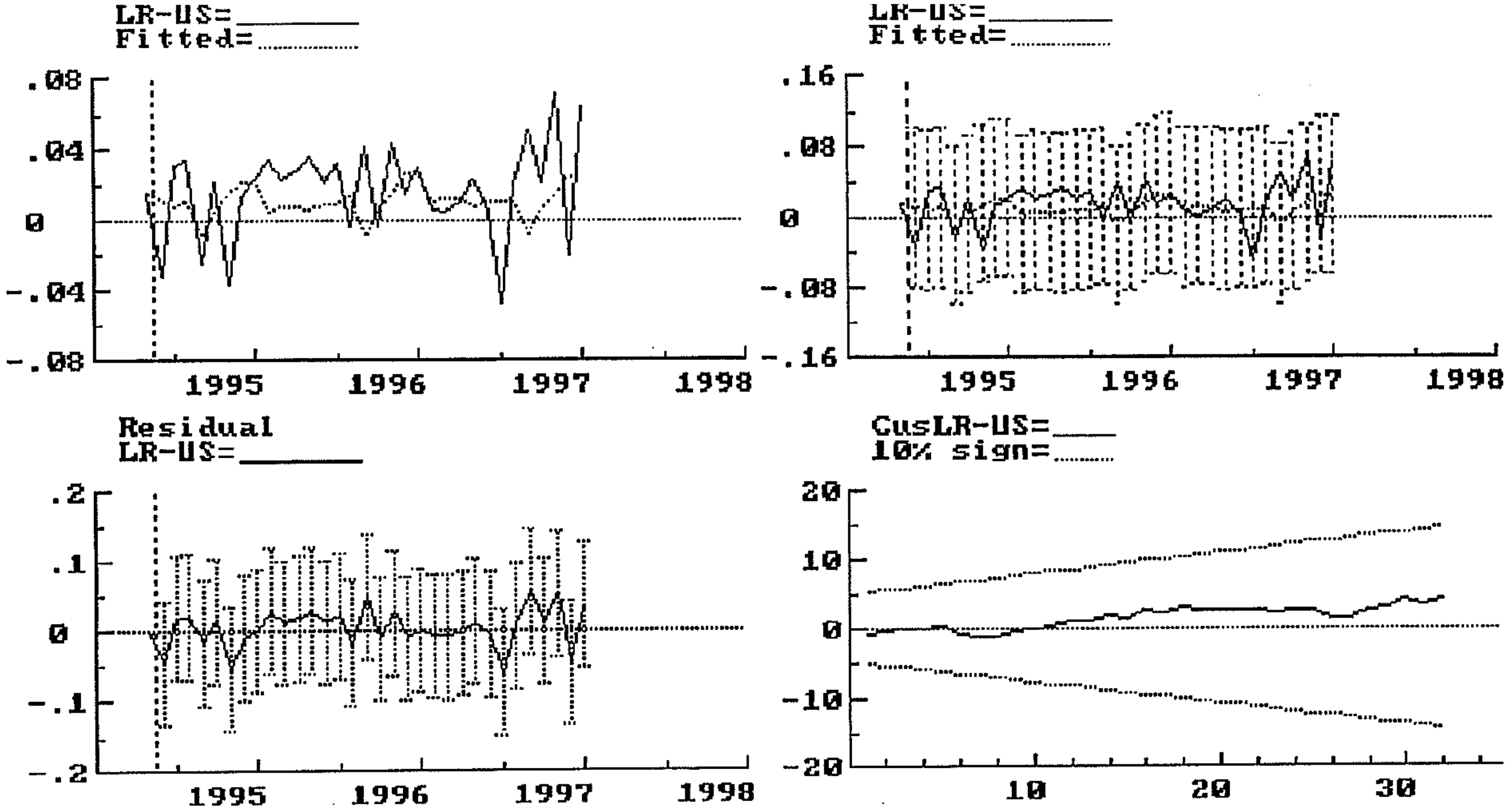

Figure 2. USA, one-step ahead predictions within sample. Fitted values, fitted values with 2 RMSE, residuals with 2 RMSE, CUSUM. Monthly data.

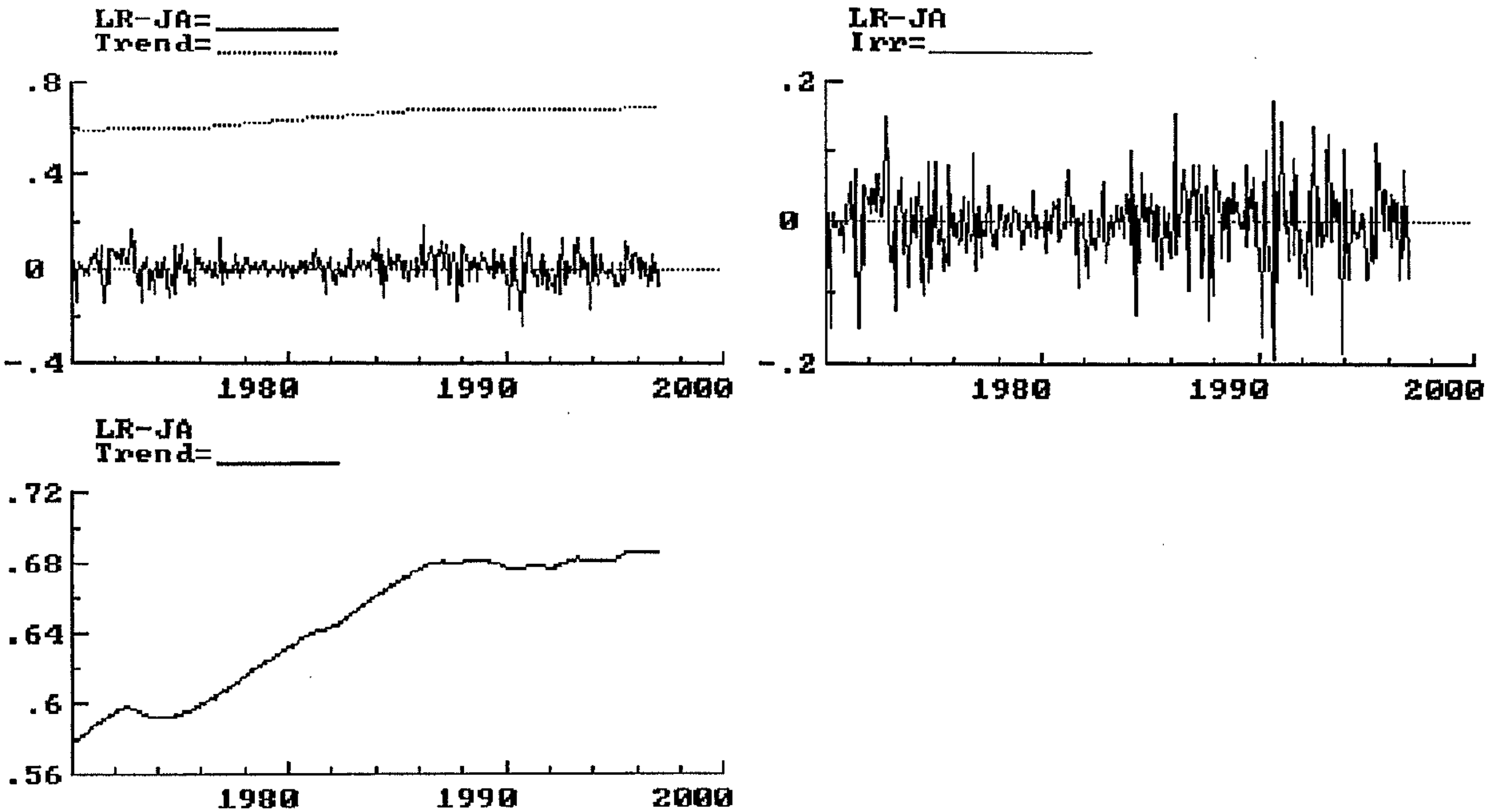

Figure 3. Japan, logarithm of stock returns and trend component, irregular component, trend component. Monthly data.

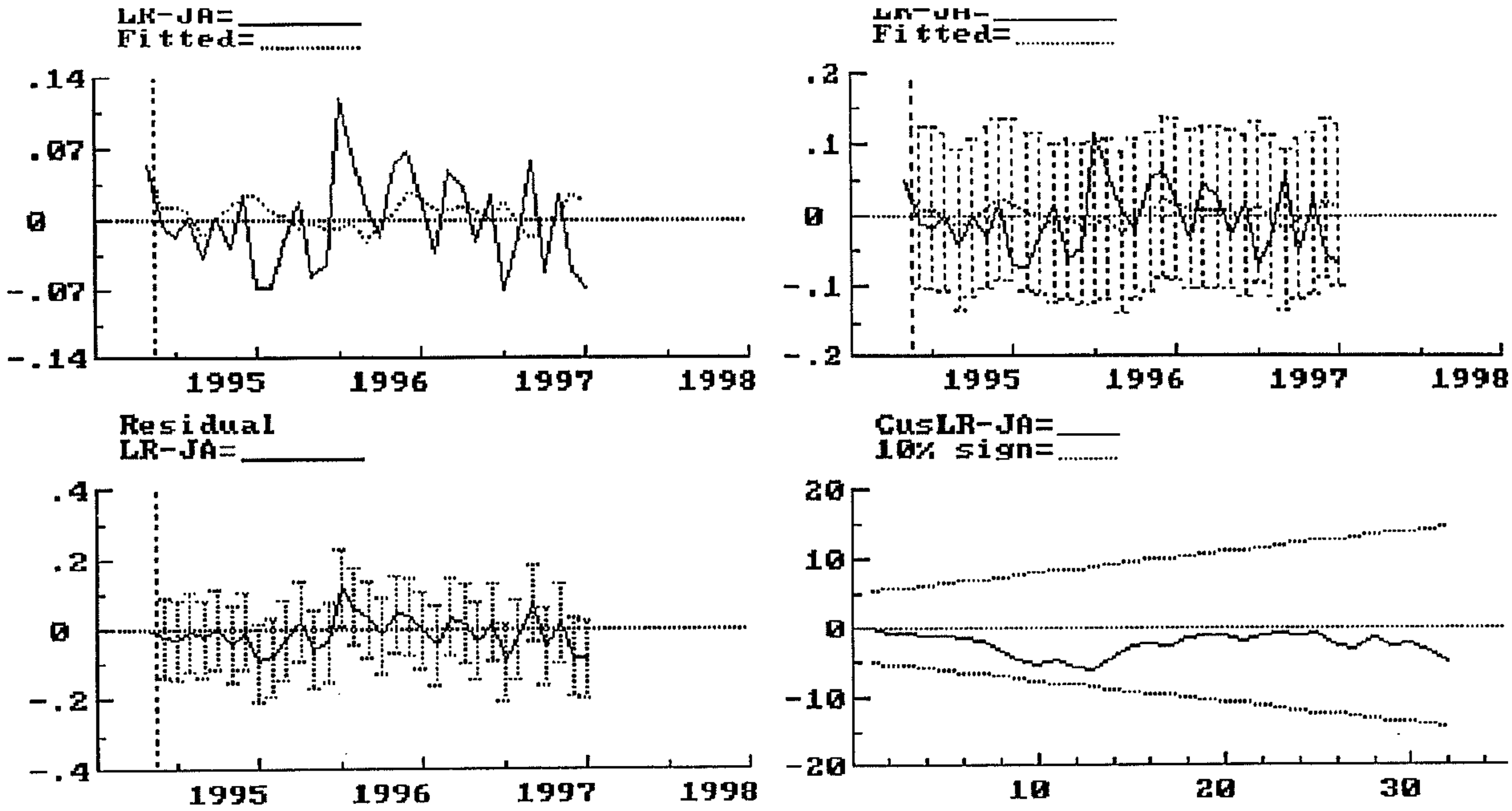

Figure 4. Japan, one-step ahead predictions within sample. Fitted values, fitted values with 2 RMSE, residuals with 2 RMSE, CUSUM. Monthly data.

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