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von

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1. Introduction

This is an empirical study on the exchange rate between the Swiss Franc and the Deutsche Mark. We are using a priori theoretical reasoning[1] in order to determine a set of variables which appear capable of explaining real exchange rate changes. These variables may themselves be to some extent determined by changes in the exchange rate. A priori, the direction of causality is left open and brought to our knowledge by a search process for Granger-causality[2] among this set of variables.

This study tries to back up or refute, as the case may arrive, pieces of economic theory. We consider the theory of measurement, the methodology of measurement and the data as given for the time being. Any result that may be obtained in this way is thus limited in its stability as it is valid only relative to the above implicit assumptions.

Section 2 contains a detailed description of the variables. In section 3 we describe the system identification. The results are in section 4 and some final remarks are in section 5.

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1 The monetary approach to the determination of exchange rates is the dominant theory here. For an elaboration of the theoretical base see Reinhard Fürstenberg, "The Portfolio Effect", 1981, unpublished manuscript.

2 The concept of Granger-causality is from the contribution of Granger, C.W.J., Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. Econometrica, Vol. 34, 1966, pp. 424-438.
A less formal summary of the main ideas is in Granger, C.W.J., Testing for Causality. Journal of Economic Dynamics and Control, 2 (1980), pp. 329-352.

2. Description of the Variables

The empirical tests have been carried out with three synthetical variables. The definitions are as follows:

1. $$ER1(t) := (1-L)\ \ln\left(\frac{BW(t)}{PPP(t)}\right) \quad \text{with}$$

$$PPP(t) := \frac{CPIDT(t)}{CPICH(t)} * F$$

2. $$M1(t) := (1-L)\ \ln\left(\frac{MDT(t)}{MCH(t)}\right)$$

3. $$TB1(t) := (1-L)\ \ln\left(\frac{EXP(t)}{IMP(t)}\right)$$

where

BW the exchange rate of the Swiss Franc and the Deutsche Mark as quoted in Germany (Deutsche Mark per 100 Swiss Franc).

CPINN the consumer price index for Germany (DT) and Switzerland (CH)

F time invariant level adjustment

MNN the money supply M1 in Germany (DT) and Switzerland (CH)

EXP the nominal exports of goods from Germany to Switzerland

IMP the nominal imports of goods of Germany from Switzerland

L the lag operator

ln the natural logarithm

The terms on the left hand side of the equations are explained below. The data sources are exclusively from the monthly reports of the central banks, i.e. the Bundesbank in Frankfurt and the Swiss Nationalbank. The period of observation is January 1974 to December 1981, monthly data have been used in order to have as many observations as possible. The choice of the period was largely determined by the exchange rate regime. The analysis is restricted to floating exchange rates on theoretical grounds. Since the introduction of such a system after an extended period of time with a fixed exchange rate may lead to movements in exchange rates which are purely a reflection of this change, the time prior to 1974 was excluded. All time series consist of raw data in the sense that no seasonal adjustment has been applied to them at the source.

The first variable, ER1(t), is a proxy for a real exchange rate change in the following sense: If the exchange rate changes from one month to the next with exactly the same percentage rate as the corresponding PPP rate it takes a value of zero. ER1(t) is positive (negative) if the Deutsche Mark devalues (revalues) in real terms against the Swiss Franc, i.e. it goes up (down) by more than is compatible with PPP.

The second variable, M1(t), behaves very similarly: If the rates of expansion for the two money supplies do not change from one month to the next, it remains at the previous month's value. The rates of expansion need not be the same in both countries. M1(t) is rising (falling) if the money supply in Germany accelerates (decelerates) relative to that in Switzerland.

The third variable, TB1(t), behaves completely analogous to the second variable.

3. System Identification

3.1. Achieving Stationarity

Any sequence of data which is subjected to time series analysis must have the important property of (covariance) stationarity. This is a basic and crucial precondition for any further treatment of the time series. Stationarity should explicitly be tested for. A simple differencing or mechanical application of some filter[1] cannot be considered sufficiently careful.

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[1] Compare Kirchgässner, Gebhard, Einige neuere statistische Verfahren zur Erfassung kausaler Beziehungen zwischen Zeitreihen, Göttingen, 1981, p. 47: "Nun gibt es jedoch, entgegen der Meinung von C.A. Sims, viele ökonomische Zeitreihen, die mit Hilfe dieses speziellen Filters nicht zu white-noise transformiert werden." Reference is made in the quotation to the following filter: $(1-0.75L)^2$, the Nerlove universal filter.

From among the various tests we have selected the two standard deviationserror[2] criterion. The autocorrelations of the residuals of the filtered series have to be within an interval of the length $2/(T-\tau)^{1/2}$ with T number of observations and τ number of the autocorrelation. In addition it is considered "desirable" that not too many autocorrelations have the same sign in succession.

3.2. The Univariate Case

Consider a stationary autoregressive process $x_1(n)$ which is generated in the following way:

$$x_1(t) = \alpha_1 + \sum_{k=1}^{m} a_{1,k} x(t-k) + \varepsilon_1(t)$$

with $\varepsilon_1(t)$ white noise, i.e. mutually independent and identically distributed random variables with $E(\varepsilon_1(t))) = 0$ and $E(\varepsilon_1^{\,2}(t)) = \sigma_{\varepsilon 1}^{\,2}$. We wish to determine a predictor $\hat{x}_1(t)$ for $x_1(t)$ by way of identifying an optimal lag structure for a least squares estimate of the autoregressive process.

For an optimality criterion we might use the final prediction error (FPE) which was introduced by Akaike.[1] The definition is:

$$\text{FPE}(k) = \frac{T+q}{T-q} \cdot \frac{1}{T} \cdot \text{SSR}(k)$$

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1 Henceforth "two standard deviations error" is abbreviated by 2SE.

2 Akaike, Hirotugu, Fitting Autoregressive Models for Prediction, Ann. Inst. Stat. Math., 21, 1969, pp. 243-247. For a more detailed description of the FPE measure see Akaike, Statistical Predictor Identification, Ann. Inst. Stat. Math. 22, 1970, pp. 203-217.

with q = p+m. The symbols are:

T number of observations

p number of coefficients which are lag invariant ("deterministic")

k number of lags of $x_1(t)$ in the regression

SSR(k) sum of squared residuals

Akaike[1] suggests the following procedure: if m can be considered an upper limit for the order of the autoregressive model calculate successively least squares estimates with k ranging from 1 in the first step to m in the last step. Calculate the FPE(k) for all k. If FPE(m_o), $1 \leq m_o \leq m$ is the minimum of all FPE values choose m_o for the order of the autoregressive model.

The conventional alternative to this procedure is generally to apply an F-test in order to discriminate between different orders for the autoregressive model. The significance level for the F-test would have to be chosen ad hoc prior to carrying out the calculations. The procedure described above has been praised[2] exactly because the ad hoc choice of the significance level can be avoided. This argument has some validity. It may happen that the estimated structure changes dramatically as a function of the a priori chosen significance level. If the order of the autoregressive model is selected by the minimum FPE criterion this is equivalent to applying an approximate F-test with varying significance levels.[3]

This observation, of course, implies in particular that the order of the autoregressive model is maybe increased although the probability of committing an error is very high indeed.[4]

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[1] Akaike, opt. cit., p. 245.

[2] See e.g. Hsiao, Cheng, Autoregressive Modelling and Money-Income Causality Detection. Journal of Monetary Economics 7(1981), on p. 90.

[3] See Hsiao, opt.cit., p. 89.

[4] The maximum possible probability to make such an error depends on the ratio

$$\frac{2T}{T+q}.$$

Clearly it increases to what appear to be intolerable levels as q rises relative to T. In particular, the significance level may fall to less than 50%. The probability that an error is committed with applying the higher parameterized system then is more than 50 percent.

If the FPE value for a larger number of lags is only marginally smaller than some other FPE value associated with fewer lags the larger model is not automatically accepted. The FPE is used but as a convenient technical device.[1] Ultimately the decision on the order of the autoregressive model is based on an appropriate F-test.

3.3. The Multivariate Case

Consider a further stationary autoregressive process $x_2(t)$ which is generated in the following way:

$$x_2(t) = \alpha_2 + \sum_{k=i}^{m} a_{2,k} x_2(t-k) + \varepsilon_2(t)$$

with $\varepsilon_2(t)$ white noise.

This process is treated analogously to the case which was described above. Assume that the optimal lag is w_o.

We now search for causality from one process to the other.[2] This is accomplished by holding the first autoregressive process fixed and by increasing successively the number of lags for the other process. At every step we calculate the FPE value. If a lower value is found as compared to the value for just the first autoregressive process the second process is called Granger-causal for the first. Similar to the univariate

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1 This "detour" is a computational short cut because the automatic calculation of the FPE value has been rendered possible. The comparison of different regressions then is very comfortable.

2 Instantaneous causality is excluded from the search process. The reason is both technically and theoretically motivated. The theoretical reason is that a priori it cannot be excluded that between any two autoregressive processes there is unidirectional causality only, i.e. no feedback. In this case the one (other) process qualifies as endogenous (exogenous) with respect the other (one). That cannot happen, however, with instantaneous causality. It can be shown (see: Gebhard Kirchgässner, opt.cit., p. 22) that if $x_1(n)$ is instantaneously causal for $x_2(n)$ then necessarily $x_2(n)$ is instantaneously causal for $x_1(n)$. A technical reason is that the structural form of a model with instantaneous causality cannot be identified (see Kirchgässner, opt.cit., page 42).

case an F-test is calculated in order to find some assurance that the two FPE values are "significantly" different. Again the FPE value is used only as a token. Very marginal differences - in complete analogy to the univariate case - between the relevant FPE values may indicate causality with an unacceptably low level of probability. The probability that the two systems are not significantly different may be much higher than 50 percent while at the same time the corresponding FPE values are different.

If a third autoregressive process $x_3(t)$ is included into the analysis the procedure is extended systematically. First determine the order of the autoregressive process for the variable chosen to be the dependent variable. Thereafter add the first independent variable and check for causality. Keep the optimal lag fixed. Add the second independent variable step by step increasing the number of lags by one with every step. Check for causality as in the case with two variables. Then reverse the order of sequence with which the independent variables are analyzed. It may be that the lag structure which was found before is not reproduced. The reason is that in principle one would have to test every lag of the first independent variable with every lag of the second independent variable to be sure to find the best system. This is not done, however, for two reasons: first, the probability to get close to the best system appears to be rather high using the short cut procedure[1]. Second, the computer time would readily go beyond acceptable limits with the calculation of thousands of equations which take a long time to be calculated for each single one and which at the same time, if the above reason one applies, are never used for anything afterwards except for a quick check. This checking can be considered close to superfluous in almost all cases. In this way one can handle also larger systems and test for mutual causality and/or feedback relationships between the time series under observation.

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1 This procedure is inspired by Hsiao, opt.cit.

3.4. Some Criticism

The above procedure has the advantage of allowing for different orders for different autoregressive processes. It is thus hoped that a significant share of the information that is contained in the time series and their various lags has been utilized. In our view it is only in this case that it is legitimate to speak of Granger causality. In case the number of lags is fixed a priori the test for causality - be it with the pure comparison of FPE values or by an F-test - may be misleading. "Causality" apparently detected in this way, may vanish as the number of lags in the univariate autoregressive process is optimized. The FPE value may fall substantially as the information set (i.e. the number of lags) is increased.

As we have mentioned above there is an ad hoc element in the search process for the lag structure due to the choice of the significance level. If the pure FPE procedure is used this issue can be bypassed but possibly at the cost of choosing overly parameterized models. But also in this case one is not saved from being involved with a high degree of arbitrariness. Any autoregressive process which is analyzed in this way must be covariance stationary.

In particular any deterministic component that may be contained in the process must be eliminated. Various procedures to achieve this result are described in the literature. Many of the authors concerned with time series methods, however, appear to be dealing with this crucial condition rather generously. It is at this point that arbitrariness cannot be eliminated. One must choose one or more tests to decide whether the series is stationary or not. The decision on the significance levels for these tests is of course ad hoc.

A further disadvantage of the above procedure is that it is not universally applicable. Three reasons for this observation are:

1. It may not be possible to obtain a stationary time series by applying an appropriate filter in all cases. Even if

each time series under observation can be rendered stationary separately with an individual filter one cannot be sure that it is always possible to make all series stationary with an identical filter.

2. Even if this process is successfully completed - all time series' residuals exhibit stationarity, after the application of an identical filter - it may happen that given the number of observations the order of some autoregressive process is so large that one runs out of degrees of freedom when working on the multivariate cases.

3. Even if the selection of optimal lag structures has successfully been completed it need not be that the residuals - at least from the "best" regressions - are white noise. In this case another very basic assumption is violated. In particular one cannot hope to get meaningful results if the system is transferred into a moving average form. There is clearly an element of luck in passing through the various stages of the procedure.

4. Results

4.1. Stationarity

At this stage we have before us three time series which all are as close to stationary as one may hope to get after the application of an identical filter, namely first differences of logarithmic values, and regression on identical variables, a constant, seasonal dummies and a trend in order to remove the deterministic components. We may now enter the second step and determine the optimal lag structure.

The second variable, M1(t) was regressed on a constant, 11 dummies for the seasonal pattern and a trend. 9 out of 11 dummies are individually highly significant revealing a strong seasonal pattern. The residuals of the filtered series show autocorrelations that are all within the 2SE band except for the first one which may always be "neglected". They are acceptably distributed around zero (see Graph 1). M1(t) is considered stationary.

The first variable, ER1(t), is expected to have no seasonal pattern at all. The seasonal pattern in the price indices can be expected to be rather similar and maybe cancel out and the remaining variable, namely the exchange rate cannot have a seasonal pattern: If it did one could exploit it in the forward markets to make a safe gain.[1] It turns out that none of the coefficients is statistically significant. The residuals of the filtered series are all well behaved with respect to the 2SE criterion. They are somewhat skewed to the negative (see Graph 2). The series passes as stationary.

The third variable, TB1(t), is clearly stationary once it has been filtered (see Graph 3). Only one autocorrelation, number 22, is slightly bigger than it should be.

4.2. The Optimal Lag Structure

All variables are regressed on their own lagged values over the period February 1975 until December 1981. The number of observations has decreased from 95 in the stationarity tests to 83 because we need room for the introduction of lags without leaving the period for which we know the time series to be stationary. Step by step up to 12 lags can be introduced.[2]

When this is completed the other variables are introduced one after the other. A selection of results is presented in Table 1.

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[1] Such gains, however, can be excluded by axiomatic assumption.

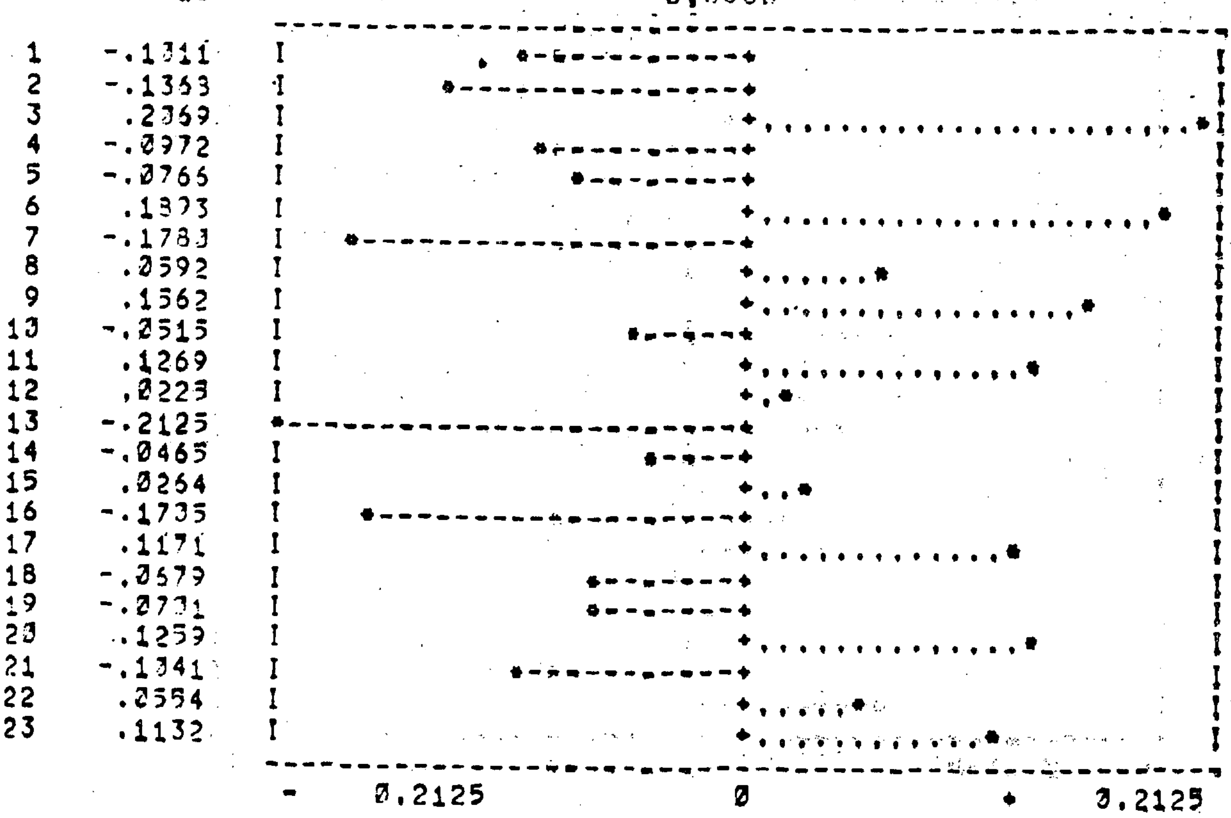
[2] Since it is not clear a priori that the true order of the autoregressive process is less than 13 we have also calculated univariate autoregressions with up to 24 lags for all these variables and have started in February 1976. In all cases the optimal lags for the longer series were reproduced by the shorter series. Under very conservative assumptions for the stability of the process one may assume that also the longer time series' true orders for the autoregressive model have been detected.

Graph 1:

URSPRUENGLICHE REIHE

ANZAHL AUTOKOV. UND AUTOKORR.	:	23
ANZAHL BEOBACHTUNGEN	:	95
MITTELWERT	:	-0.0000
VARIANZ	:	0.0003
BOX PIERCE STAT.	:	0.3447

LAG	AUTOKOVARIANZEN	AUTOKORRELATIONEN
1	-Ø,ØØØØ	-Ø.1Ø11
2	-Ø,ØØØØ	-Ø.1368
3	Ø,ØØØ1	Ø,2Ø69
4	-Ø,ØØØØ	-Ø.Ø972
5	-Ø,ØØØØ	-Ø.Ø766
6	Ø,ØØØ1	Ø.1893
7	-Ø,ØØØ1	-Ø.178Ø
8	Ø,ØØØØ	Ø,Ø592
9	Ø,ØØØØ	Ø.1562
10	-Ø,ØØØØ	-Ø.Ø515
11	Ø,ØØØØ	Ø.1269
12	Ø,ØØØØ	Ø,Ø225
13	-Ø,ØØØ1	-Ø,2125
14	-Ø,ØØØØ	-Ø,Ø465
15	Ø,ØØØØ	Ø,Ø264
16	-Ø,ØØØ1	-Ø,17Ø5
17	Ø,ØØØØ	Ø,1171
18	-Ø,ØØØØ	-Ø,Ø679
19	-Ø,ØØØØ	-Ø.Ø7Ø1
20	Ø,ØØØØ	Ø,1259
21	-Ø,ØØØØ	-Ø.1Ø41
22	Ø,ØØØØ	Ø.Ø554
23	Ø,ØØØØ	Ø.1132



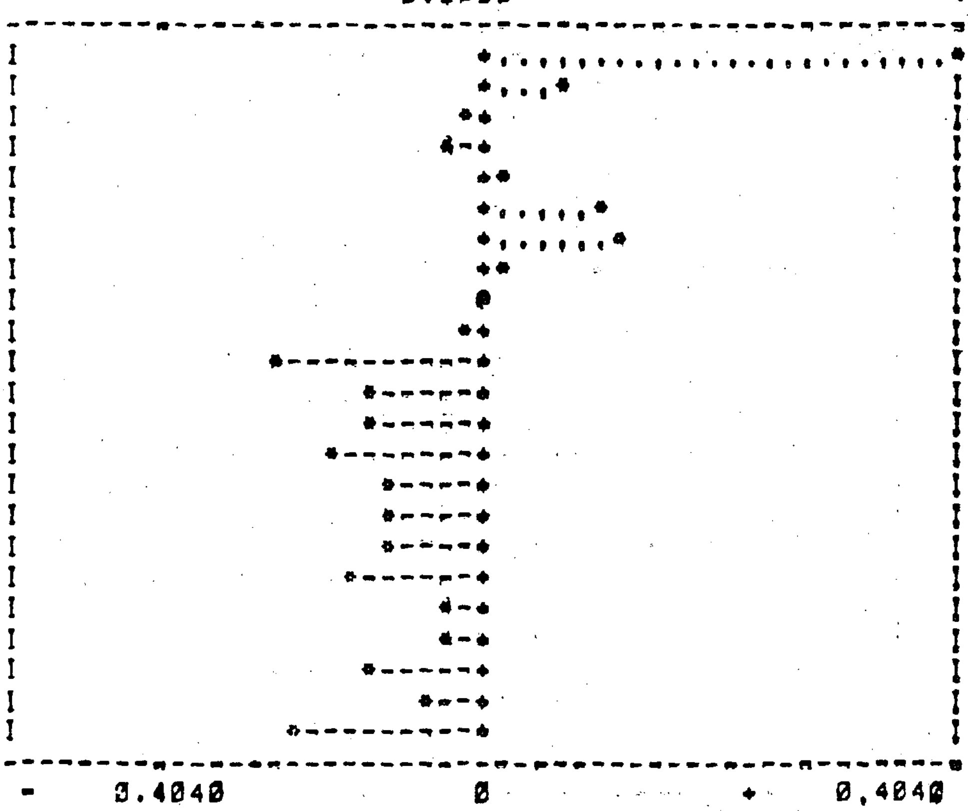
Graph 2:

URSPRUENGLICHE REIHE

ANZAHL AUTOKOV. UND AUTOKORR.	:	23
ANZAHL BEOBACHTUNGEN	:	95
MITTELWERT	:	0.0000
VARIANZ	:	0.0003
BOX PIERCE STAT.	:	0.3487

LAG	AUTOKOVARIANZEN	AUTOKORRELATIONEN
1	0.0001	0.4040
2	0.0000	0.0664
3	-0.0000	-0.0225
4	-0.0000	-0.0410
5	0.0000	0.0281
6	0.0000	0.0991
7	0.0000	0.1178
8	0.0000	0.0260
9	-0.0000	-0.0113
10	-0.0000	-0.0244
11	-0.0000	-0.1807
12	-0.0000	-0.0957
13	-0.0000	-0.1046
14	-0.0000	-0.1386
15	-0.0000	-0.0938
16	-0.0000	-0.0921
17	-0.0000	-0.0852
18	-0.0000	-0.1114
19	-0.0000	-0.0317
20	-0.0000	-0.0418
21	-0.0000	-0.1064
22	-0.0000	-0.0496
23	-0.0000	-0.1662

1	.4040
2	.0664
3	-.0225
4	-.0410
5	.0281
6	.0991
7	.1178
8	.0260
9	-.0113
10	-.0244
11	-.1807
12	-.0957
13	-.1046
14	-.1386
15	-.0938
16	-.0921
17	-.0852
18	-.1114
19	-.0317
20	-.0418
21	-.1064
22	-.0496
23	-.1662



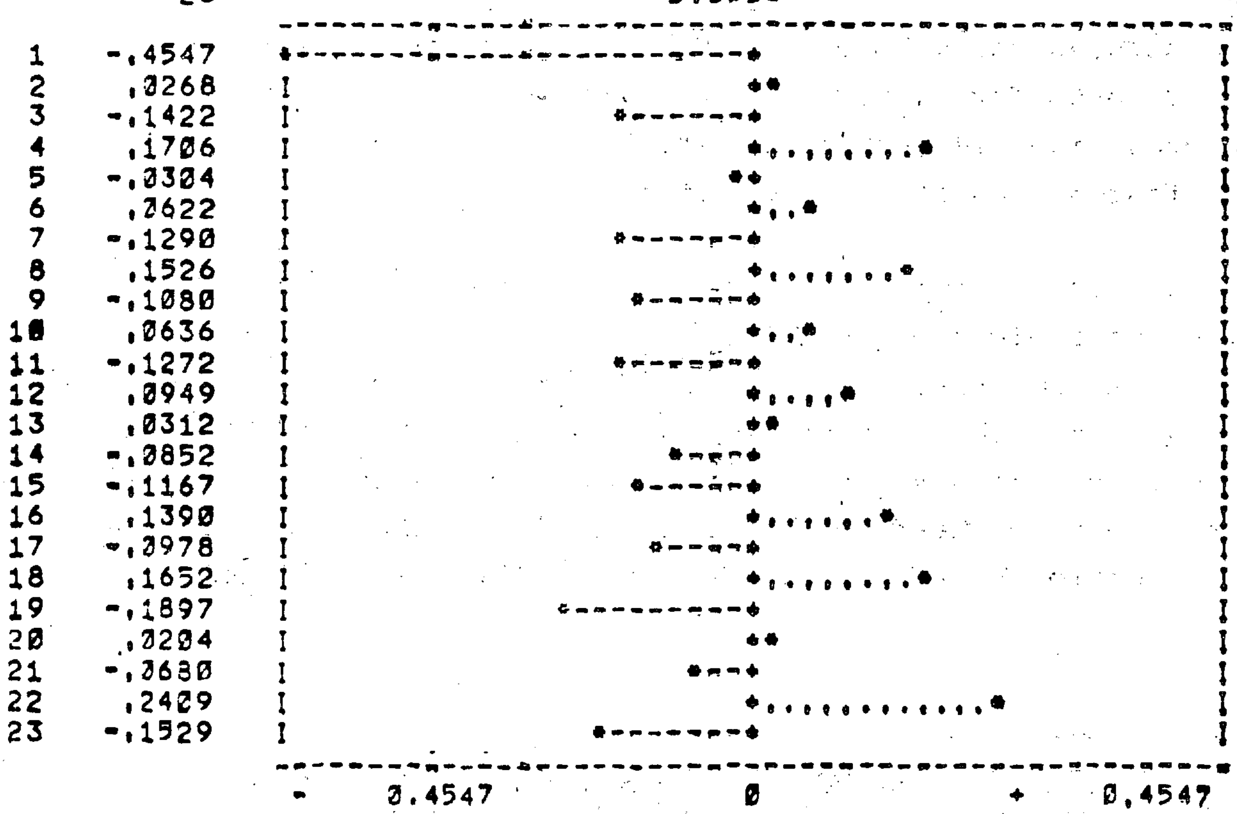
Graph 3:

1. VARIABLE : TB1 — 5-APR-82 23:54

URSPRUENGLICHE REIHE

ANZAHL AUTOKOV. UND AUTOKORR.	:	23
ANZAHL BEOBACHTUNGEN	:	95
MITTELWERT	:	-0.0008
VARIANZ	:	0.0053
BOX PIERCE STAT.	:	0.5429

LAG	AUTOKOVARIANZEN	AUTOKORRELATIONEN
1	-0.0024	-0.4547
2	0.0001	0.0268
3	-0.0007	-0.1422
4	0.0009	0.1706
5	-0.0002	-0.0304
6	0.0003	0.0622
7	-0.0007	-0.1290
8	0.0008	0.1526
9	-0.0006	-0.1080
10	0.0003	0.0636
11	-0.0007	-0.1272
12	0.0005	0.0949
13	0.0002	0.0312
14	-0.0004	-0.0852
15	-0.0006	-0.1167
16	0.0007	0.1390
17	-0.0005	-0.0978
18	0.0009	0.1652
19	-0.0010	-0.1897
20	0.0001	0.0204
21	-0.0004	-0.0680
22	0.0013	0.2409
23	-0.0008	-0.1529



Consider the Variable ER1.
The optimal lag for the univariate autoregression is two. The trade balance variable, TB1, is Granger-causal at the one percent level. The sum of the coefficients is negative, -0.1441. The sign is in accord with what one would expect. If the trade balance improves for Germany the Deutsche Mark revalues in real terms. One can find an explanation arguing in real terms.[1] The trade balance improves because the demand for German goods has increased relative to Swiss goods. Swiss (German) economic subjects are willing to pay higher relative prices for German goods as compared to Swiss goods in Swiss Francs (Deutsche Marks). Part of this relative price change is likely to spill over to the exchange market and lead to a real appreciation of the Deutsche Mark: The Deutsche Mark is granted a higher value.

If the relative money supply, M1, is taken separately it is not Granger-causal. That may appear surprising at first sight but will find a rather simple explanation a little later. It is Granger-causal, however, together with TB1.[2] The sum of coefficients for M1 is positive, 0.2444. Clearly this is the expected sign. If the Deutsche Mark is inflated at a relatively faster pace it devalues in real terms.

Consider the variable M1. Since this variable is a classic policy variable one may interprete statistically significant results as a policy reaction function of the monetary authorities. The exchange rate variable is Granger-causal, the sum of coefficients has the expected sign. It is negative (-0.6259). If the Deutsche Mark devalues in real terms the relative money expansion for this currency decreases. The trade balance is

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1 If contrary to our interpretation the change in the demand/supply relationship does not result from a change in demand but from a change in supply the correltion would have the opposite sign.

2 The sum of coefficients for TB1 remains negative (-0.1999).

Table 1: S w i t z e r l a n d

No.	Dependent Variable (Lag)	Independent Variable 1 (Lag)	Independent Variable 2 (Lag)	FPE value* 10^{-6}	Significance Level	F-test	Granger Causality
1.1.	ER1(2)	-	-	280	72	-	-
1.2.	ER1(2)	M1(1)	-	286	65	-	NO
1.3.	ER1(2)	TB1(2)	-	258	81	4.69*	YES
1.4.	ER1(2)	TB1(2)	M1(9)	240	86	2.24*	YES
1.5.	ER1(2)	RES22(8)	-	261	87	2.37*	YES
2.1.	M1(1)	-	-	428	36	-	-
2.2.	M1(1)	ER1(11)	-	385	92	2.48*	YES
2.3.	M1(1)	TB1(1)	-	438	38	-	NO
2.4.	M1(1)	ER1(11)	TB1(1)	394	94	-	NO
3.1.	TB1(3)	-	-	4441	80	-	-
3.2.	TB1(3)	ER1(1)	-	4531	84	-	NO
3.3.	TB1(3)	M1(1)	-	4040	96	8.41*	YES
3.4.	TB1(3)	M1(1)	ER1(11)	3920	98	1.86+	yes

The F-test values for the choice of the number of lags for a variable are not reported (the critical level is 10 percent) because a number of comparisons were carried out in general.
A "*" indicates that the F-test is significant at the 5 percent level, a "+" is associated to the 10 percent level.
The Durbin-Watson statistic is not reproduced because it is within 2.00 ± 0.10 in all regressions.
The R^2 is not reported because is does not carry important information in this context.

not Granger-causal, the coefficient for TB1(1) is not significantly different from zero. In the next equation, number 2.4., the trade balance variable was added to the exchange rate variable. Also in this combination it is not Granger-causal. The sum of coefficients for the exchange rate variable remains negative (-0.6317).

Consider again equation 2.2., the "central bank reaction function". Clearly, this equation is very much partial in character; maybe one would not expect it to yield a basis for predicting the relative monetary policies in Germany and Switzerland. There are many other variables which one would expect[2] to have yet more important influences like price level developments, unemployment "targets", interest rate "targets", the government budget deficit and so on.

Simple as the structure of equation 2.2. certainly is, we cannot exclude the possibility that it is used by economic subjects to de facto formulate a forecast for M1. This forecast is then used to change the exchange rate according to an unknown mechanism[1] prior to the time that this influence can be mirrored by equation 1.2.: M1 is not Granger-causal for ER1. Since the forecast for M1 on the basis of equation 2.2. will in general not be correct, the difference between the forecast and the actual value (i.e. the residual) might have a measurable influence on ER1. The above interpretation would certainly be substantiated if the residuals would prove to be Granger-causal for ER1. This is the case. The residuals from equation 2.2. are significant at the 5 percent level as can be seen in equation 1.5. It is very much in accord with a priori expectations that the sum of coefficients is

[1] These expectations are deeply rooted certainly also due to the fact that respective statements are almost ubiquitous. On the other hand equation 2.2. is rather well behaved and thus throughs a more complex structure into some tentative doubt: Equation 2.2. has a R^2 of .82, a Durbin-Watson of 2.00 and a significance level of 92. We can be rather sure that the residuals are white noise and in particular, the equation is probably not misspecified due to a missing variable.

[2] This change of the exchange rate is likely to occur instantaneously, i.e. during the current period.

positive (0.2656). If the rate of relative money expansion in Germany has been underestimated the real value of the Deutsche Mark falls.

One may venture the interpretation that economic subjects are discovered to behave rationally in these circumstances. They know that the relative money supply (M1) is important information for the one step ahead prediction of the real exchange rate (ER1). Therefore they predict M1 as good as they can (on the basis of equation 2.2.) and immediately react upon this forecast in an appropriate albeit unobservable way. The unavoidable mistake of the forecast for M1 leads as soon as it becomes known to a further change of ER1 in order to have it more perfectly in line with equation 2.2. and the (unobservable) desired relationship between ER1 and M1.

Consider the variable TB1. The optimal lag for the univariate autoregression is three. When the exchange rate is tested for causality we get a negative result. This is so in spite of the fact that the trade balance is Granger-causal for the exchange rate (equation 1.3.). There is unidirectional causality but no feedback between these two variables if only the exchange rate variable is included. Elasticity considerations might have led to a different expectation. So far as Germany and Switzerland are concerned, and to the extent that the competitive position of international traders can be mirrored by the trade balance variable one may say that the importance of the real exchange rate does not seem to go far. This observation is probably in some contrast to the interpretation[1] of real exchange rate changes by the Swiss Nationalbank.

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[1] A recent statement of the view of the Nationalbank is available from its president (see Leutwiler, opt.cit., p. 2): "Veränderungen des realen Wechselkurses bedeuten aber, daß sich die Wettbewerbsfähigkeit der eigenen Wirtschaft ändern kann. Da solche Schwankungen nicht nur von kurzer Dauer sind, sondern über ein oder zwei Jahre anhalten können, stellt sich geldpolitisch die Frage, bis zu welchem Ausmaß der Wirtschaft derart massive Veränderungen des realen Wechselkurses zugemutet werden können..." Similar explicit statements do not seem to be readily available from the Bundesbank.

The following interpretation carries a small speculative element. Remember that M1 contains both the Swiss and the German money supply. It is therefore theoretically possible - though not likely[2] - that it is predominantly the behaviour of the Bundesbank which is responsible for the existence of equation 2.2. With this caveat in mind we believe that the Nationalbank is inclined to carry out an activist monetary policy - as mirrored by equation 2.2. - in order to protect primarily the competitive position of Swiss exporters.

In so far as the competitive position of this group is influenced by changes in the real exchange rate equation 1.4. tells us that - given a passive role of the Bundesbank - the Swiss central bank in fact can have some impact on real exchange rate changes via changes in the Swiss money supply.

In equation 3.3. we have tested the money supply variable M1 for Granger causality on the trade balance variable in exclusivity. The equation 3.3. reveals that there is a Granger-causal relationship. The coefficient for M1 is negative (-1.0551). If the expansion of the money supply in Germany is accelerated relative to that in Switzerland the trade performance of Germany worsens.[2]

To complete the analysis the exchange rate variable ER1 was tested for Granger causality together with the money supply variable M1. The optimal lag for M1[3] is known from equation 3.3.; it is one. The exchange rate variable ER1 becomes

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[1] The importance of the exchange rate between the Swiss Franc and the Deutsche Mark seems to be bigger for the Nationalbank as compared to the Bundesbank. Certain statements of Bundesbank officials seem to indicate that the exchange rate vis-a-vis the US dollar is given a larger weight in arriving at a certain monetary policy.

[2] It may be that the expectation of relatively more inflation in Germany at a later time leads to increased imports now in order to profit from the now relatively expensive own currency.

[3] In equation 3.4. the coefficient for M1 remains negative, it is -1.3169.

Granger-causal for TB1 in this specification.[1] The sum of coefficients for ER1(11) is negative, -1.3545.

The coefficients for the trade balance variable in equations 1.3. and 1.4. were also negative. So there is some consistency in the results.

There is an almost puzzling consistency[2] between the interpretation of the results that we have obtained and what we believe is the interpretation by the Nationalbank of its own policies with respect to the ability of the Nationalbank to improve the competitive position of Swiss exporters. One must bear in mind, however, that the above analysis does not show the consequences of an expansionary monetary policy for the rate of inflation. The rate of inflation will go up if the money supply is expanded over an extended period of time[3] irrespective of the reasons for the expansionary policy.

The cost of deviating from a path for monetary policy which is consistent with price level stability, however, may be very large indeed and ask for a change in monetary policy in its own right.

4.3. The Moving Average Form

In the above section we have described some equations in terms of a comparison of the coefficients for certain variables some of which were found to be Granger-causal for some other

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[1] Similar to M1 in equations 1.2. and 1.4. we achieve causality if the specification is changed. The only too obvious interpretation that the misspecification is due to a missing variable, however, is indicated somewhat more clearly in equation 1.2. as compared to equation 3.2. In the former case the significance level is only 65 but in the latter it is 84. Notice that it jumps to 98 as the specification is improved with equation 3.4.

[2] We continue to assume that the Bundesbank plays a rather passive role.

[3] Compare the analysis in Reinhard Fürstenberg, Monetary Policy in Switzerland, Working Paper No. 106, Kiel, May 1980.

variables. There is a convenient method of familiarising oneself with some dynamic aspects of the behaviour of a system consisting of several regression equations which yields a comparatively deeper insight than the naked study of the relative sizes of coefficients.

We are given a system of three multivariate autoregressive equations which we write as a vector equation

$$x(t) = \alpha + \sum_{j=1}^{m} A_j \cdot x(t-j) + \varepsilon(t)$$

One can now solve this vector difference equation by recursive substitution for x(t) in terms of the ε(t) to get

$$x(t) = \alpha' + \sum_{j=0}^{\infty} C_j \cdot \varepsilon(t-j).$$

In general x(t), ε(t), α and α' are nx1 vectors, A_j and C_j are nxn matrices. In our case n = 3. In the last equation x(t) is represented as a function of the least squares disturbances only. This is the process of innovations which cannot be predicted from the m lags in x(t).

Now let ε(t-j) be zero except for the i-th component. The elements in the i-th column of C_j can be considered the sequence of responses of the n components of x(t) to an innovation in the i-th component of x(t). These responses can be traced over a user determined number of periods. They are interpreted as the dynamic response of the vector autoregressive system. The ordering of the components is irrelevant in this context.[1]

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[1] Compare the preconditions for a decomposition of variance where the ordering of the components does have some impact on the results (see section 4.4. below).

This procedure cannot be meaningfully applied to a system of two equations with two variables in the absense of feedback. Consider equation 2.2. ER1 is Granger-causal for M1. But in equation 1.2. M1 is not Granger-causal for ER1. The coefficients of M1 are not significantly different from zero. The significance level is rather low at 65. The technically possible moving average representation is not carried out. The result would be biased because the residuals are probably not white-noise and it would be based on pure coincidence.

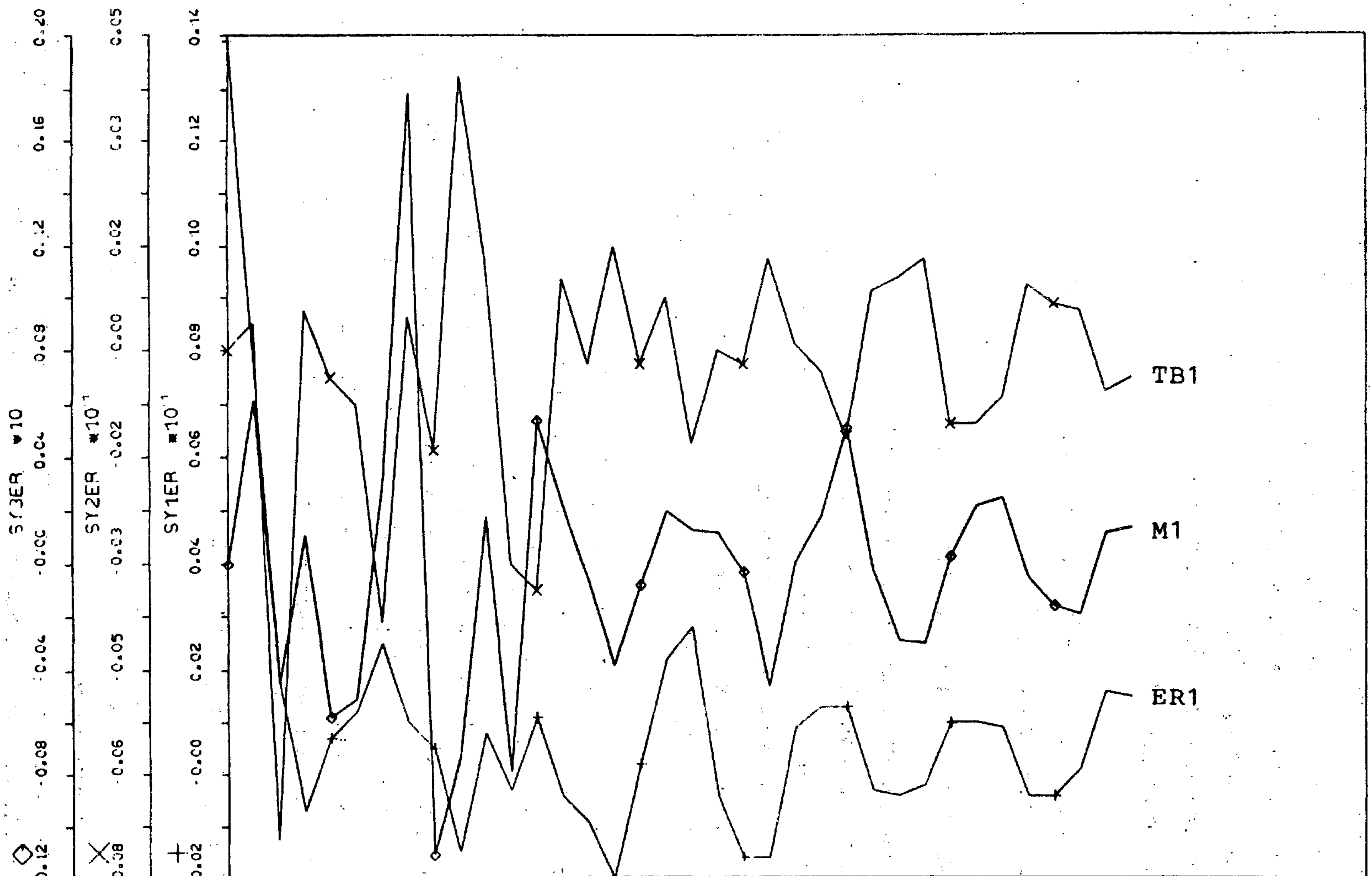
Instead we use the three by three system, namely equations 1.4., 2.4. and 3.4. All these equations have white-noise residuals with a high degree of probability. The significance levels are 87,94 and 98, respectively. All of the independent variables are Granger-causal with the single exception of TB1(1) in equation 2.4. The coefficient for TB1(1) is small, 0,01 and not significant (T-test is 0.52). We therefore assume that the overall picture is not disturbed too much as a result of this small deficiency.

This system of equations is now subjected to innovations in ER1, M1 and TB1. The responses are in Graphs 4, 5 and 6. These graphs show the movement of the corresponding variables over 36 periods; in this context one period is one month. It is important to constrain oneself in the efforts of interpretation. It appears to be easy to go too far. In particular one should avoid affording the time path too much attention. The main interest is in the sign of the cumulative change of a variable over the entire 36 periods. In order to measure this effect we have formed the sum of the deviations over the 36 periods. Abstracting from a very minor incorrectness due to some level effects this sum indicates the position of the respective variable after 36 periods have elapsed as compared to the initial position. It should be noted that of course such movements of the variables can never be observed in reality because by the time that one "shock" for some variable has just started to work through the system the next shock for the same variable or another one is certainly scheduled to arrive. What one observes in reality is the sum of reactions of the system to various shocks for many variables arriving successively, one after the other. In the graphs we have the laboratory situation of the effects of a single shock for just one variable.

Graph 4 contains the effect of a positive innovation of one standard error in the real exchange rate variable, ER1. After 36 periods the real exchange rate remains at a real depreciation. The dynamics of the system lead the money supply variable M1 to a value of -0.0109.

We afford this number the following interpretation. Remember that M1 is the difference in the monthly growth rates of the money supplies in Germany and in Switzerland. This difference has an initial value of zero in the above exercise. In the first period after the shock has occurred it starts changing. After one period the value is 0.00036. The money supply in Germany was expanded relatively faster in comparison to Switzerland. In the second period the value is -0.0074. The situation has changed. These values are reproduced in Graph 4. The sum of the effects in the first two periods is negative, -0.0070. It remains negative all the way until the period 36 is reached. In this period the sum of all the differences in the rates of money supply expansion has the above value: -0.0109. If the relative rate of expansion would have been -0.0109/36 one would have obtained the same value (abstracting again from level effects although all values have the same sign) for the overall effect. It is in this limited sense that one can speak of a cumulative effect here. A positive innovation in the real exchange rate variable leads the money supply in Germany to be expanded relatively less fast as compared to the money supply in Switzerland. The trade balance dives into the negative also, the value is -0.0049.

Graph 4: Innovation in ER1



Graph 5 shows the responses of the three variables to a shock in the relative money supplies. Again the trade balance becomes negative (-0.0124). The interesting question which may find a first tentative answer is: is it true that a purely monetary innovation does lead to a real exchange rate change over an extended period of time? Our equations answer this question in a positive way. The cumulative effect is 0.0073. Even after 36 periods there remains a real depreciation for the Deutsche Mark.

Graph 6 shows the effects of an innovation in the trade balance variable, TB1.

4.4. Decomposition of Variance

In the above section we have considered the moving average representation for an analysis of the behavior of the system subject to an innovation. A yet different way to look at the relationships among the components (our "variables") of the vector x(t) is to analyse the decomposition of the variance of a k-step ahead prediction error componentwise.

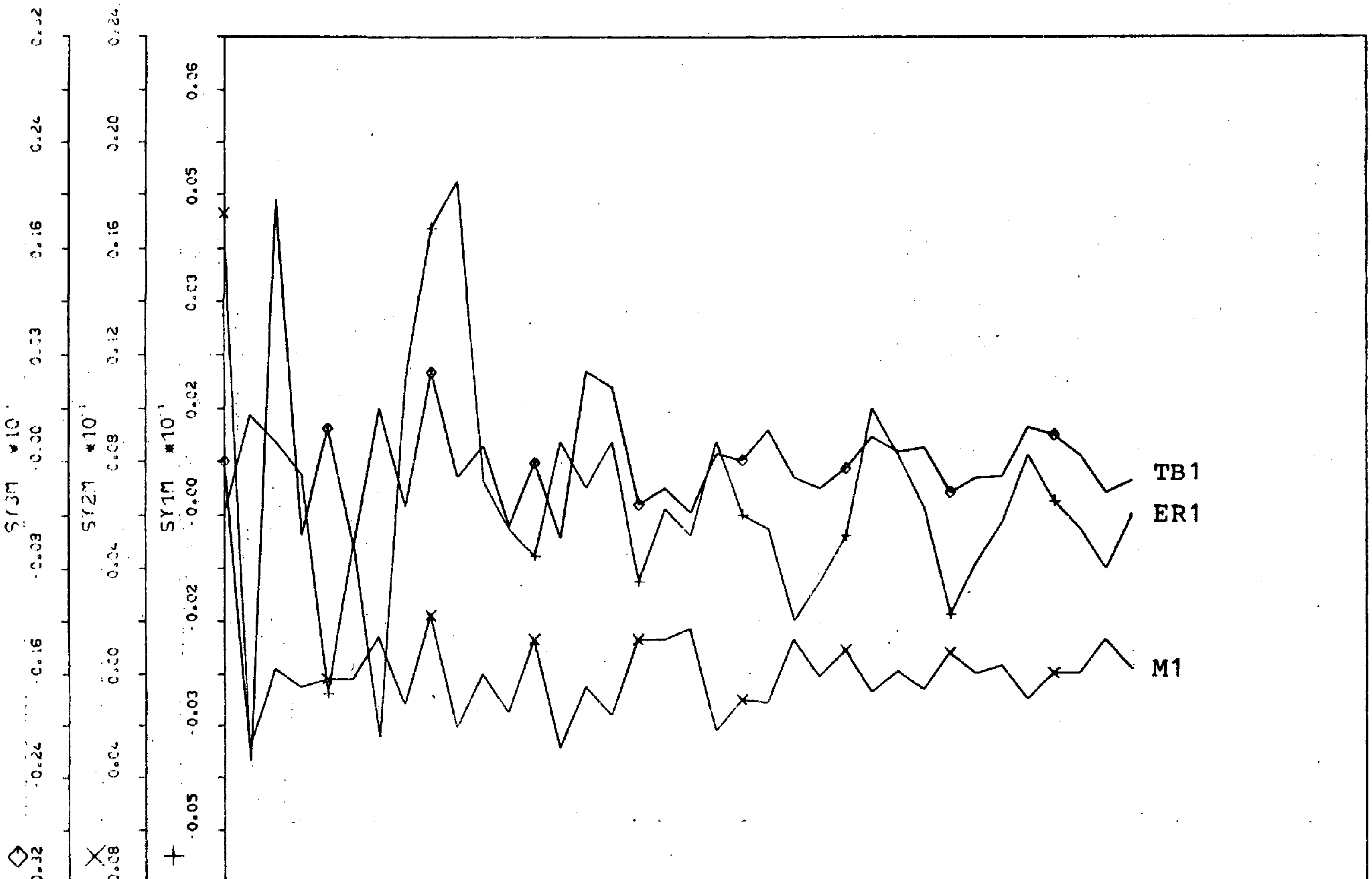
In order to do this it is necessary to arrive at a disturbance process which is orthogonal contemporaneously as well as at all lags. This will guarantee a diagonal variance-covariance matrix for $\varepsilon(t)$. This can always be achieved, but some entries in the matrix F which relates $\varepsilon(t)$ to the new process u(t), with $\varepsilon(t) = F \cdot u(t)$, will in general depend on the order of the components of the vector x(t) and correspondingly $\varepsilon(t)$.[1] The moving average representation then becomes

$$x(t) = \alpha' + \sum_{j=0}^{\infty} C_j F u(t-j)$$

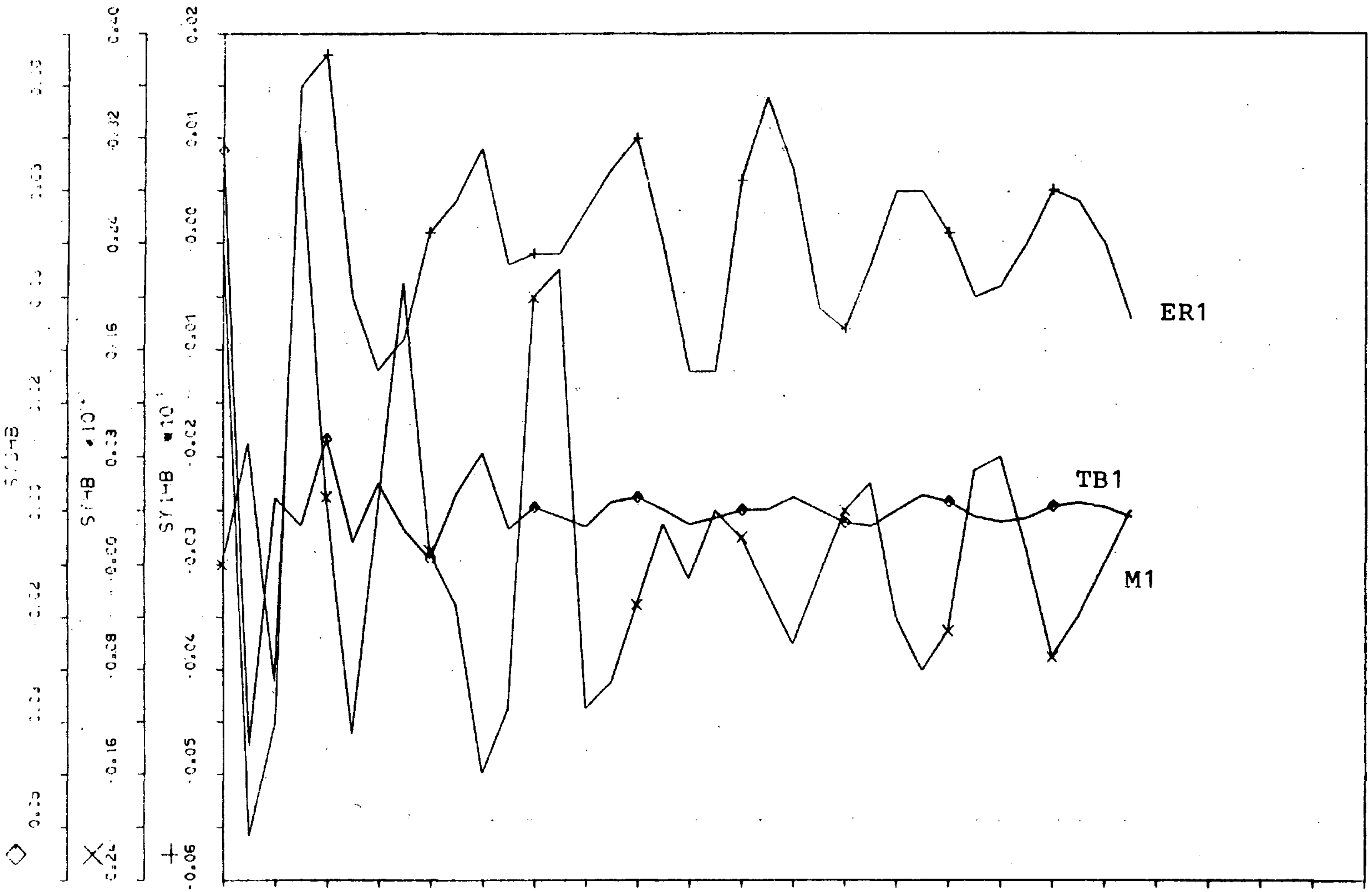
$$= \alpha' + \sum_{j=0}^{\infty} D_j u(t-j)$$

[1] For the case n = 2, e.g., one alternatively considers the part of $\varepsilon_2(t)$ that is orthogonal to $\varepsilon_1(t)$ or vice versa. For more details see the Appendix of Thomas J. Sargent, Estimation of Dynamic Labour Demand Schedules under Rational Expectations, Journal of Political Economy, 1978, Vol. 86, No. 6.

Graph 5: Innovation in M1



<u>Graph 6:</u> Innovation in TB1



The variance of the k-step ahead prediction error for x(t) can now be calculated to yield the desired decomposition. Let E(t-k)x(t) be the linear least squares forecast for x(t) given x(t-k), x(t-k-1), etc.

$$\text{var}\ (x(t) - E(t-k)x(t))$$

$$= \text{var}\ (D_o \cdot u(t) + \ldots + D_{k-1} \cdot u(t-k+1))$$

$$= D_o D_o' + \ldots + D_{k-1} \cdot D_{k-1}'$$

Consider the variance of the first variable of x(t), namely $x_1(t)$. The variance can be calculated as the sum of the elements (1,1) of the matrix products $D_o D_o'$, $D_1 D_1'$,..., $D_{k-1} D_{k-1}'$. Every such element represents the corresponding lag component and is itself the sum of contributions belonging to all variables involved by definition of the matrix product. The contribution of the i-th variable is found by summing over all its lag components and thereafter dividing this sum by the total variance. This reads as follows: Let $d_{l,i,j}$ be the element (i,j) in matrix D_l.

Then $\text{var}\ x_1(t) = \sum_{l=o}^{k-1} \sum_{j=1}^{n} d_{l,1,j}^2$.

The contribution of the i-th variable to the above variance is $\frac{\omega_i}{\text{var}\ x_1(t)}$ with $\omega_i = \sum_{l=o}^{k-1} d_{l,1,i}^2$. It is these numbers which can be found in Tables 2, 3 and 4 for the respective variables.

Being given a system of three equations there are six possible ways of ordering the equations. As one must expect the results do change to a small extent as one moves from one order of the equations to the next. The changes, however, are small enough in order not to question the thrust of the informations which one can obtain from any one ordering.[1] We have represented the results associated with the ordering of equations 1.4., 2.4., 3.4. as first, second and third equation.

[1] The fact that the decomposition does not change much is welcome because "If the covariance matrix of innovation Σ is nearly diagonal, the decomposition will be relatively robust to changes in the order of factorization." The quotation is from the manual for RATS 4.0 page 11.7.

What do these tables show? In the first column there is the standard error for a k-step ahead forecast of the variable after the term "series" (in Table 2 it is ER1). The forecast error is zero in case all innovations affecting variables which were used to make ten forecast are zero. In general that will not be the case. There will be innovations different from zero. If the historical pattern of the occurrance of these innovations continues into the future the number in one of the following columns is the average contribution of the innovations of the respective variable to the total forecast error.

In all three cases the own innovations have the largest share in explaining the total variance. About 65% of the total variance for ER1 can be explained in this way. For M1 and TB1 the figures are 68% and 69% respectively.

These figures are reached already after the steps 12 to 15. Thereafter also the division of the remaining variance among the two remaining variables does not change any more.

If we remember the pattern of Granger-causality from Table 1 it is not surprising to see that the only variable which is not Granger-causal, namely TB1 in equation 2.4. has the smallest figure (Table 3) of all cases. It contributes only 6.5 percent to the total variance of M1.

Since all three variables' covariances of the forecast errors are not very much affected by innovations in other variables that may indicate that one try to define an univariate ARMA (or ARIMA) model for these variables.

4.5. Robustness of Results

In economics it is generally considered necessary for a particular hypothesis to pass a number of independent empirical tests[1]

[1] The validity of empirical evidence, of course, depends on the state of the art of statistical theory. What is considered acceptable today may well be regarded as "spurious" tomorrow.

Table 2:

DECOMPOSITION OF VARIANCE, SERIES 1 ER1

STEP	STAN ERR	ER1	M1	TB1
1	0.112142D-01	100.000000	0.000000	0.000000
2	0.138862D-01	87.987199	1.457794	10.555007
3	0.144929D-01	81.987609	2.066979	15.945412
4	0.145762D-01	81.481422	2.100387	16.418191
5	0.148468D-01	78.547280	4.629304	16.823416
6	0.148695D-01	78.517501	4.649594	16.832906
7	0.152187D-01	75.870840	7.675069	16.454091
8	0.153511D-01	74.805698	8.795540	16.398761
9	0.157594D-01	71.119383	13.314648	15.565969
10	0.163174D-01	66.729351	18.704742	14.565908
11	0.163384D-01	66.599029	18.690934	14.710037
12	0.163512D-01	66.634960	18.670678	14.694362
13	0.163670D-01	66.600919	18.727641	14.671439
14	0.164013D-01	66.412558	18.975545	14.611897
15	0.164380D-01	66.512477	18.924753	14.562770
16	0.165810D-01	66.678280	18.880363	14.441357
17	0.166280D-01	66.340323	19.070663	14.589014
18	0.166936D-01	66.603486	18.921819	14.474695
19	0.168449D-01	66.880488	18.595532	14.523980
20	0.169055D-01	66.475939	18.791291	14.732769
21	0.169954D-01	66.743084	18.594679	14.662237
22	0.171263D-01	66.794562	18.339793	14.865645
23	0.171950D-01	66.271533	18.860926	14.867541
24	0.172305D-01	66.141423	18.969665	14.888912
25	0.172597D-01	66.111634	18.918654	14.969712
26	0.173167D-01	65.717492	19.403436	14.879071
27	0.173475D-01	65.601422	19.509862	14.888717
28	0.173607D-01	65.592619	19.481077	14.926304
29	0.174092D-01	65.269246	19.885843	14.844911
30	0.174274D-01	65.207986	19.930909	14.861104
31	0.174346D-01	65.203741	19.915386	14.880873
32	0.174587D-01	65.124153	20.035688	14.840160
33	0.174755D-01	65.141171	20.000055	14.858774
34	0.174825D-01	65.117460	19.995250	14.887290
35	0.175160D-01	65.121558	20.047941	14.830501
36	0.175486D-01	65.159058	19.974990	14.865952

Table 3: DECOMPOSITION OF VARIANCE, SERIES 4 M1

STEP	STAN ERR	ER1	M1	TB1
1	0.143472D-01	1.826447	98.173553	0.000000
2	0.145780D-01	1.772839	97.984173	0.242988
3	0.157957D-01	16.111220	83.475341	0.413438
4	0.160227D-01	15.676892	81.308847	3.014260
5	0.160347D-01	15.714406	81.203332	3.082263
6	0.160791D-01	15.767968	80.757063	3.474970
7	0.164428D-01	18.968694	77.677566	3.353741
8	0.165738D-01	18.676201	76.957160	4.366639
9	0.167053D-01	18.748820	76.950688	4.300492
10	0.171038D-01	21.502857	74.373342	4.123802
11	0.172008D-01	21.818637	73.542087	4.639277
12	0.174758D-01	23.559165	71.702470	4.738365
13	0.178169D-01	25.364591	69.263087	5.372322
14	0.180897D-01	24.654309	69.180352	6.165339
15	0.181125D-01	24.596304	69.031898	6.371797
16	0.182079D-01	24.775590	68.766759	6.457651
17	0.182397D-01	24.689893	68.859521	6.450586
18	0.182879D-01	24.750907	68.816534	6.432559
19	0.183663D-01	24.842619	68.779029	6.378352
20	0.184625D-01	24.611282	69.049276	6.339441
21	0.184830D-01	24.575986	69.093763	6.330251
22	0.185340D-01	24.742906	68.955053	6.302042
23	0.185735D-01	24.653623	69.007255	6.339121
24	0.185758D-01	24.668502	68.992697	6.338801
25	0.186185D-01	24.828422	68.832844	6.338734
26	0.186460D-01	24.862779	68.748832	6.388389
27	0.186731D-01	25.044950	68.551963	6.403087
28	0.187242D-01	25.283323	68.227393	6.489284
29	0.187566D-01	25.367937	68.118360	6.513703
30	0.187865D-01	25.526245	67.902493	6.571262
31	0.188088D-01	25.577555	67.751878	6.670568
32	0.188409D-01	25.637144	67.712598	6.650258
33	0.188581D-01	25.687308	67.589396	6.723296
34	0.188680D-01	25.727833	67.519963	6.752204
35	0.189003D-01	25.673327	67.597500	6.729173
36	0.189068D-01	25.690045	67.555977	6.753978

Table 4: DECOMPOSITION OF VARIANCE, SERIES 5 TB1

STEP	STAN ERR	ER1	M1	TB1
1	0.440749D-01	0.683522	0.956999	98.359479
2	0.552886D-01	1.263155	8.844159	89.892686
3	0.575960D-01	1.245482	15.843852	82.910666
4	0.577893D-01	1.242182	16.302501	82.455317
5	0.586688D-01	1.992930	15.857590	82.149480
6	0.591697D-01	2.577337	16.247879	81.174784
7	0.594005D-01	2.764772	16.373117	80.862111
8	0.612701D-01	8.290580	15.564562	76.144859
9	0.623527D-01	9.652772	15.986892	74.360336
10	0.627214D-01	10.560581	15.834820	73.604599
11	0.631099D-01	10.459111	15.642273	73.898616
12	0.636333D-01	11.463341	15.732750	72.803909
13	0.637906D-01	11.893507	15.655595	72.450898
14	0.639713D-01	11.865548	16.082265	72.052187
15	0.642595D-01	11.763231	16.744189	71.492581
16	0.644763D-01	11.844686	17.111862	71.043452
17	0.645699D-01	11.844195	17.247989	70.907816
18	0.646083D-01	11.879486	17.295307	70.825207
19	0.646997D-01	11.861351	17.457556	70.681093
20	0.647158D-01	11.884396	17.456859	70.658745
21	0.647165D-01	11.885476	17.456661	70.657863
22	0.648416D-01	12.136989	17.476151	70.386860
23	0.648737D-01	12.126231	17.490189	70.383580
24	0.649068D-01	12.150309	17.537600	70.312090
25	0.650656D-01	12.530589	17.453947	70.015464
26	0.651144D-01	12.513121	17.498549	69.988330
27	0.651610D-01	12.626698	17.484457	69.888845
28	0.652410D-01	12.744186	17.452741	69.803073
29	0.652814D-01	12.728630	17.526729	69.744641
30	0.653143D-01	12.787076	17.528194	69.684729
31	0.653644D-01	12.887198	17.517044	69.615757
32	0.654067D-01	12.850739	17.609302	69.539958
33	0.654383D-01	12.870397	17.648365	69.481238
34	0.654659D-01	12.919799	17.635906	69.444295
35	0.654997D-01	12.918917	17.702304	69.378779
36	0.6552[illegible]7D-01	12.938653	17.717069	69.344278

prior to it approaching the status of a widely accepted piece of economic theory.

In order to afford the above results some stability one may test the hypothesis for the same country and different intervals of time or for different countries over an identical period of time.

We have chosen the second alternative. Three more countries have been analysed in exactly the same way as was Switzerland. These three countries are the United States of America (US), the United Kingdom (UK), and Italy. The US and the UK were considered interesting cases bacause of very dramatic swings in their real exchange rates vis-à-vis the Deutsche Mark.[1] The monetary policy in the US as well as in the UK had turned to a more restrictive stance prior to the occurrence of the large real exchange rate changes. Italy was included into the sample because it is an European country which had a good deal more inflation over the period under consideration and may therefore be an interesting country to study contrasting the comparatively low inflation case Germany.[2]

The data for the US and the UK tell a rather unexpected story. The difference between the results for Switzerland and these two countries could hardly be more expressed. Italy is an in-between case. The results for Italy are analysed below. Tables 5, 6 and 7 contain a summary of the findings.

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1 Between January 1980 and August 1981 the US dollar appreciated in real terms against the Deutsche Mark by an unprecedented 54 percent. During the same period the pound showed a real appreciation of 29 percent.

2 From January 1975 to December 1981 The consumer price index went up 183 percent in Italy and 36 percent in Germany.

Table 5: I t a l y

No.	Dependent Variable (lag)	Independent Variable 1 (lag)	Independent Variable 2 (lag)	FPE*10^{-6}	Significance level	F-Test	Granger Causality
5.1.1.	ER1 (3)	-	-	334	95	-	-
5.1.2.	ER1 (3)	M1 (11)	-	307	55	2.27*	YES
5.1.3.	ER1 (3)	TB1 (2)	-	286	75	7.70*	YES
5.1.4.	ER1 (3)	M1 (11)	TB1 (2)	270	48	5.50*	YES
5.2.1.	M1 (1)	-	-	312	68	-	-
5.2.2.	M1 (1)	ER1 (1)	-	320	68	-	NO
5.2.3.	M1 (1)	TB1 (2)	-	275	22	6.53*	YES
5.2.4.	M1 (1)	TB1 (2)	ER1 (1)	280	18	-	NO
5.3.1.	TB1 (1)	-	-	3970	63	-	-
5.3.2.	TB1 (1)	M1 (1)	-	4070	59	-	NO
5.3.3.	TB1 (1)	ER1 (2)	-	3910	57	-	NO

The F-Test values for the choice of the number of lags for a variable are not reported (the critical level is 5 percent) because a number of comparisons were carried out in general. A "*" indicates that the F-Test is significant at the 5 percent level.
The Durbin-Watson statistic is not reproduced because it is within 2.00 ± 0.14 in all regressions.
The R^2 is not reported because it does not carry important information in this context.

Table 6: United Kingdom (UK)

No.	Dependent Variable (lag)	Independent Variable 1 (lag)	Independent Variable 2 (lag)	FPE 10^{-6}	Significance level	F-Test	Granger Causality
6.1.1.	ER1(1)	-	-	570	75	-	-
6.1.2.	ER1(1)	M1(1)	-	576	74	-	NO
6.1.3.	ER1(1)	TB1(1)	-	583	78	-	NO
6.2.1.	M1(10)	-	-	392	98	-	-
6.2.2.	M1(10)	ER1(1)	-	402	99	-	NO
6.2.3.	M1(10)	TB1(1)	-	394	98	-	NO
6.3.1.	TB1(2)	-	-	14300	98	-	-
6.3.2.	TB1(2)	ER1(1)	-	14300	97	-	NO
6.3.3.	TB1(2)	M1(1)	-	14700	98	-	NO

For explanations see Table 5.

Table 7: U n i t e d S t a t e s (US)

No.	Dependent Variable (lag)	Independent Variable 1 (lag)	Independent Variable 2 (lag)	FPE*10^{-6}	Significance level	F-Test	Granger Causality
7.1.1.	ER1(1)	-	-	693	98	-	-
7.1.2.	ER1(1)	M1(1)	-	710	98	-	NO
7.1.3.	ER1(1)	TB1(1)	-	706	98	-	NO
7.2.1.	M1(1)	-	-	164	51	-	-
7.2.2.	M1(1)	ER1(1)	-	167	54	-	NO
7.2.3.	M1(1)	TB1(1)	-	166	59	-	NO
7.3.1.	TB1(1)	-	-	21700	45	-	-
7.3.2.	TB1(1)	ER1(1)	-	22100	42	-	NO
7.3.3.	TB1(1)	M1(1)	-	21600	51	-	NO

For explanations see Table 5.

The Italian case is characterised by an apparently exogenous trade balance while on the other hand this variable has a highly significant influence on both the exchange rate variable and the money supply variable. In addition also the money supply variable plays an exogenous role with respect to the exchange rate variable. The sum of coefficients for M1 in equation 5.1.2. is negativ: -0.121. The last three coefficients for lags 9, 10 and 11 are rather large and bring about what appears to be an implausible result: if the German money supply is inflated relatively more the exchange rate variable falls indicating a real appreciation for the Deutsche Mark. The sum of coefficients for the TB1 in equation 5.1.3. is negative, -0.163, reproducing the sign we had found for Switzerland in equation 1.3. in Table 1. If the order of independent variables is changed in equation 5.1.4. the same lag structure is obtained. Again the sum of coefficients is negative for both variables (M1: -0.182; TB1: -0.142).

While in the case for Italy it is possible to detect some Granger causal relationships, this is not the case for the two remaining countries, namely the UK and the US. The results are in Tables 6 and 7 and speak for themselves: they are suggesting that the set of variables which was utilized here is mutually totally independent from oneanother. One is tempted to ascribe this situation to the fact that what matters is but the unexpected share in the total change of a variable. Given our equations we have assumed that expectations are formed on the basis of equations 6.1.1., 6.2.1. and 6.3.1. for the UK and, respectively, 7.1.1., 7.2.1. and 7.3.1. for the US. We have therefore treated the residuals from these equations as new independent variables and have estimated a corresponding set of regressions for the US and the UK. The results for both countries coincide perfectly: not a single residual is Granger-causal for any variable. The case for rather far reaching independence of the variables involved is thus enhanced. One may speculate on the reasons for this independence. It does not seem to be very likely that the estimating method is biased very strongly in favour of not accepting Granger-causality because in the cases of Switzerland and Italy such a relationship was detected in some situations. It may be that the true number of lags is larger than 12 for the trade balance variable. While in the cases of the financial variables 12 months may be considered a sufficiently long period of time for an innovation in the one variable to influence the other, this need not be so with the trade balance variable. It may make more than 12 months for trade flows to show the thrust of the impact stemming from a real exchange rate change.

The lag structure was determined on the basis of an F-test. The significance level was set at 5 percent. If this level was shifted to 10 percent, it may be that a different lag structure is selected and that on the basis of this new lag structure Granger-causality can be found.

To start with the UK there is no change at all for the lags in the univariate cases (equations 6.1.1., 6.2.1. and 6.3.1. in Table 6). Given the relative seizes of the FPE values there can be no Granger causality.

For the US, in equation 7.2.1. the optimal lag for the money supply variable is two given a significance level of ten percent for the F-test. Recalculating equations 7.2.2. and 7.2.3. with this lag for M1, however, it is true that the lags for ER1 and TB1 are both reestablished. In addition there is no Granger causality in either case.[1]

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1 Also in the Italian case the only change is an optimal lag of three for the trade balance variable in equation 5.2.3. Subsequent reestimation of equation 5.2.4. brings no change: the exchange rate variable does not become Granger causal.

These findings justify the conclusion that the ad hoc choice of the significance level is not very important for the stability of the results for the US and the UK.

The three countries, US, UK and Italy were analysed in our striving for robustness of the results we obtained for Switzerland. It is to be acknowledged that the negative responses do not reinforce the Swiss case.

5. Final remarks

In this paper we have presented some results which are interpreted as answers to very specific questions. Thos questions were formulated on the basis of a priori theorizing. The expected answers have been obtained in most cases.

It was possible to detect some causal relationships between a real exchange rate variable and two other variables one of which relates to the nominal sphere while the other one can also reflect changes in real economic conditions. It would be of interest to see whether these results have some stability across countries or whether it is possible to reproduce them for different periods of floating exchange rates.

Any economic reasoning is ultimately concerned with improving our ability to forecast. Be it that one is directly working on making a superior forecast be it that one is concerned with the detection of structural relationships again for the only purpose to integrate this work into the amelioration of the forecast.

If one deals with variables which are lacking an institutionalized forward market the task is comparatively easy: Make a better forecast than individual competitors. In the alternative case one has to beat the market! The forecast that one makes must be systematically better in a very puristically defined ex-ante sense. It is not clear in our mind whether such a thing is theoretically possible. If it is not, the advice to a curious economic subject is simple enough: Turn to the forward market. The forward market may be a poor predictor but is still the best there is. The theoretical possibility to make forecasts which are systematically better than the forward market will exist only for a very limited period of time. It will be possible as long as it takes the market to attach a high degree of credibility to those forecasts.

After this period the once superior forecasts lose this quality because they are integrated into the "market" forecast, namely the forward market, in a prominent way. A model which yields such forecasts - if it can exist at all - must include some variable which was neglected so far or interpret the old set of variables (information) in a superior fashion.

If there is an innovation in this paper with respect to the information set it is the radical smallness of it on the one hand and the maximal exploitation of the information on the other hand. Superior forecasts from the source "superior set of information" are thus only partly excluded. What remains is the interpretation of the data. We do not venture to assume this analysis to be totally alien to the markets. However, we did gain some insight into structural relationships which seem to be at work in the real world. It does seem to be sufficiently rewarding to continue the empirical work towards competing[1] with the forward markets. It would be interesting also to see, in addition, whether forecasts for the real exchange rate variable, ER1, based on these equations are able competitors with optimally fitted univariate ARMA or ARIMA models for this variable.

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1 The a priori feeling is that forward markets will prove to be superior. The competition would be limited to getting close to the predictive power of the forward markets.