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Was There a Regime Change in the German Monetary Transmission Mechanism in 1983?*

by

Bertrand Candelon and Helmut Lütkepohl
Institut für Statistik und Ökonometrie, Wirtschaftswissenschaftliche Fakultät,
Humboldt-Universität, Spandauer Str. 1, 10178 Berlin, GERMANY

Abstract

Recent investigations of the transmission mechanism of German monetary policy arrive at quite different conclusions regarding its stability during the period of monetary targeting by the Bundesbank. In this study small dynamic models for the monetary sector of the German economy are analyzed in detail to determine the sources for the contrasting results found in the literature. It turns out that instabilities detected in previous work in the 1980s are possibly spurious. Thus, it appears that the monetary transmission mechanism was reasonably stable and, hence, one important precondition for a monetary targeting policy was satisfied.

Key Words: Cointegration analysis, Markov regime switching analysis, monetary policy, money demand, vector error correction model

JEL classification: C32, E52, E41

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1 Introduction

In a couple of articles, Juselius (1996, 1998) (henceforth J) constructs small dynamic models for the monetary sector of the German economy and finds that the transmission mechanism of German monetary policy has changed around 1983. In her view possible reasons for this change are the implementation of the more rigid exchange rate mechanism (ERM) in March 1983, different macroeconomic regimes due to a change in government in 1982 and an increase in international capital movements or financial liberalization. Using statistical tools, Juselius clearly confirms the change in regime in a small dynamic model for quarterly money (M3), income, prices and interest rates for the period 1975 - 1994. Based on her results she argues that the money supply could not be controlled after 1983. Clearly, such a finding is not in line with the claim of the Deutsche Bundesbank (DB) that it has controlled inflation via a monetary targeting strategy since the middle of the 1970s. The question whether or not the monetary targeting in Germany worked or not is of some importance because the new European Central Bank (ECB) uses a similar monetary policy strategy.

In contrast to Juselius' results, other researchers found models for the monetary sector with supposedly stable relations for similar variables and observation periods (see, e.g., Lütkepohl & Wolters (1998), henceforth LW, and Hubrich (1999)). Moreover, a number of authors have found a stable M3 money demand function for a period covering the 1980s (e.g., Hansen & Kim (1995), Issing & Tödter (1995), Scharnagl (1996), Wolters & Lütkepohl (1997), Wolters, Teräsvirta & Lütkepohl (1998)). Such a relation is an important prerequisite for a successful monetary targeting strategy and its existence for all of the 1980s is questioned by Juselius. Given the importance of the issue for the current monetary policy of the ECB it is of interest to investigate the reasons for the contradictory findings in the different studies.

One objective of empirical dynamic modeling is to establish a time invariant model for the observation period. Thus, if in one study a stable model is found and in another study such a model is not found, the former study apparently achieves its goal in a superior way and one could simply go with the results of those authors who have established a time invariant specification. In the present case, however, J's results and her far reaching conclusions are quite surprising because her variables and modeling approach are very similar to that of LW, for example. Therefore it is of interest to study the differences in more detail and to determine the reasons for the contradictory findings.

We will do so in the present investigation by comparing the data and models of J and LW in some detail. Different tests for model stability and Markov regime switching (MS) models will be used in the comparison. The latter models explicitly allow for different regimes in the sampling period. The data are used to attach probabilities to the different regimes in each period. Using these techniques, we hope to get a better picture of possible regimes and changes in regimes than with previously used means for checking the time invariance of a model. Giving the data a chance to decide for themselves which periods are likely to be in the same regime if two regimes are allowed for, it is of interest if they partition the sample period in a similar way as J.

We focus on a comparison of the variables, data and models considered by J and LW, respectively, because these authors based their analyses on very similar systems of variables and they also give sufficiently detailed information on the data and techniques used so that their results can be replicated. In the next section we compare the data and variables of the two studies. In Sec. 3 their models are briefly described and contrasted. Using standard parameter constancy tests in the framework of vector error correction models, a preliminary stability analysis is performed in Sec. 4. A descriptive MS analysis is reported in Sec. 5 and conclusions are given in Sec. 6.

2 The Data

The sets of variables, observation periods and basic data characteristics used in J and LW are listed in Table 1. Both studies use quarterly, unadjusted seasonal data. While J considers the observation period 1975(3) - 1994(4), LW use data for 1976(1) - 1996(4) plus presample values for lagged variables which are necessary for the statistical analysis. Hence, they effectively use data from 1975 onwards. German monetary unification (GMU) on July 1, 1990, is included in both observation periods and requires special modeling efforts. The end of the sample period is supposedly determined by data availability at the time of the analyses. The sample beginnings roughly coincide with the time when the DB started its policy of monetary targeting. In fact, in 1974 it announced a money growth target for the first time for 1975. Thus, the monetary targeting strategy started in 1975.

Obviously, the endogenous variables used in the two studies are very similar. In Figure

Table 1: Variables Used in Juselius (1996, 1998) and Lütkepohl & Wolters (1998)

		Juselius	Lütkepohl & Wolters
Data characteristics		quarterly, seasonally unadjusted	quarterly, seasonally unadjusted
Sampling period		1975(3) - 1994(4)	1976(1) - 1996(4) plus presample values
Endogenous variables	m_t	log M3	log M3
	y_t	log real GDP	log real GNP
	p_t	log GDP deflator	log GNP deflator
	r_t	yearly rate on private bank deposits	annual own rate of M3
	R_t	yearly rate of the effective yield on bonds in circulation	annual average bond rate ('Umlaufsrendite')
Exogenous variables	pm_t	not included	log import price index
	$d_t(R-r)_t$	not included	$R-r$ for 1994(3) - 1995(4), zero elsewhere
Deterministic variables		constant	constant
		linear trend	
		seasonal dummies	seasonal dummies
		GMU step dummy $S90q3_t$	GMU step dummy $S90q3_t$
		impulse dummy $I90q2_t$	$I90q3_t$, $I92q4_t$, $I93q3_t$
		post GMU seasonal dummies	

1 we have plotted the actual data used and their first differences for the common period 1975(4) - 1994(4). The graphs reveal some differences in the series.* First of all, there are obvious differences in the two M3 series. It is not fully clear to us where these differences come from because both series should be based on the official data of the DB although J does not explicitly give the data source. Of course, there are different ways to extract a quarterly series from the monthly series given in the DB's 'Monatsberichte'. For instance, data for one particular month from each quarter or an average of the monthly values may be used. LW explicitly state that they used the end of quarter values. A related information is not available in J. Obviously, her M3 data are much smoother than LW's series. As a consequence, the real M3 series $(m-p)$ also differ.

– Figure 1 about here –

Differences in the series representing real activity are minor. J uses Gross Domestic Product (GDP) whereas LW use Gross National Product (GNP). Notice, also, that the similarity of the corresponding series of first differences is remarkable. There are some

*The data and details on their sources are available from the internet at http://wotan.wiwi.hu-berlin.de/oekonometrie/engl/data.html.

differences in the inflation series ($\Delta p_t = p_t - p_{t-1}$), however. Surprisingly, the differenced series $\Delta^2 p_t$ are virtually identical after the GMU. In particular, the apparent differences in the seasonal pattern before the GMU are noteworthy. Of course, the differences in the price series also contribute to the differences in the real money series ($m-p$). The long-term (R_t) and short-term (r_t) interest rates are quite similar despite the differences in the definitions of the variables. In particular, the two R_t series are almost identical. Note, however, that in their actual analysis LW use the interest rate spread ($R-r$) only and not the two separate series as in J. Because including the interest rate spread amounts to imposing a restriction on the model, removing it should not weaken the stability properties of the system. Specifically, the vectors of endogenous variables used by J and LW are $z_t^J = [m-p, y, \Delta p, R, r]_t$ and $[m-p, y, \Delta p, R-r]_t$, respectively.

In addition to the endogenous variables, LW also use two variables which they treat as unmodeled or exogenous. The import price inflation rate (Δpm_t) is used to account for exchange rate effects and a further variable is included which is meant to capture a period of unusually slow growth of the money stock due to a large substitution into short-term interest bearing assets not included in M3. It is denoted by $d_t(R-r)_t$ in Table 1 and it is active only during the period 1994(3) - 1995(4). In other words, the interest rate spread is multiplied by a dummy variable which is 1 during the period 1994(3) - 1995(4) and zero elsewhere. Strictly speaking this variable is endogenous because it involves the interest rate spread. However, it is convenient to treat it as exogenous because it is assumed to be activated by an exogenous event and it is included for a limited period only. The following analysis is based on data up to 1994(4) only to ensure a fair comparison with J's models. Therefore, the variable $d_t(R-r)_t$ will not be used in LW's system in our subsequent analysis.

A major difference in the dummy variables used by J and LW is the extra set of seasonal dummies in J's model for the post-GMU era. Otherwise, there are a few impulse dummies denoted by $I**q*_t$ in both models which take care of specific events in the latter part of the observation period. They assume the value 1 for the period indicated and are zero elsewhere. For example, $I90q2_t$ is 1 for the second quarter of 1990 and zero otherwise. Furthermore, there is a shift dummy $S90q3_t$ which is zero before the GMU and one from there onwards. In both studies this dummy is confined to the long-run cointegration relations as discussed in the next section. Thus, in conclusion the variables used in the two studies are in principle

quite similar while some of the actual data series differ a bit. In the next section the models used in the two studies will be discussed.

3 The Models Used by J and LW

In both studies vector error correction models (VECMs) are used as baseline models. They are of the general form

$$\Gamma_0 \Delta z_t = \alpha\beta' z^*_{t-1} + \Gamma_1 \Delta z_{t-1} + \cdots + \Gamma_p \Delta z_{t-p} + \Phi x_t + \Xi D_t + u_t, \tag{3.1}$$

where z_t is a vector of endogenous variables, x_t is a vector of exogenous or unmodeled variables, D_t includes all deterministic terms and u_t is the error vector which is assumed to be white noise (WN) with zero mean and nonsingular covariance matrix Σ, $u_t \sim \mathrm{WN}(0, \Sigma)$. The Γ_i matrices ($i = 0, \ldots, p$) contain structural coefficients if Γ_0 is not a priori assumed to be an identity matrix (denoted by I in the following). In the latter case we have a reduced form which was actually used by J. The first term on the right-hand side of (3.1) is the error correction (EC) term, $\beta' z^*_{t-1}$ represents the r cointegration relations and α is the loading matrix which determines the weights of the cointegration relations in the equations of the system. The vector z^*_{t-1} contains the endogenous variables z_{t-1} and possibly deterministic terms in the cointegrating relations. For instance, z^*_{t-1} may contain a constant and a shift dummy variable.

J uses reduced forms with $\Gamma_0 = I$ and just one lag of Δz_t. She does not use unmodeled or exogenous variables so that $\Phi = 0$. Moreover, she finds three cointegration relations. She argues that a recursive analysis shows clear evidence of a regime change in 1983. Therefore she tests for a break in that year and rejects time homogeneity (Juselius (1998)). Of course, such a procedure may be problematic because the test is preceded by a descriptive pretest which may distort the outcome of the overall procedure. For example, a stability test at some other point in the sample may produce even stronger evidence for a regime shift or rejection of the time homogeneity may not be found if the break date is not assumed to be known in advance. Nevertheless, given her test results, J proceeds with separate models for 1975 - 82 and 1984 - 94 leaving out the critical year 1983. In the first period a constant term, a linear trend and seasonal dummies are the only deterministic terms and further dummy variables including a second set of seasonals are used in the model for the latter subperiod

mainly to account for changes due to the GMU. The step dummy $S90q3_t$ is confined to the cointegration relations. Thus, it is used to capture a shift in the intercept term of the cointegration relations.

LW use the exogenous and deterministic terms given in Table 1 and construct a single model for the full observation period with cointegrating rank 1. The only cointegration relation represents a money demand function and the step dummy $S90q3_t$ is confined to this relation. LW's model is a structural form in the sense that $\Gamma_0 \neq I$. They allow for four lags of Δz_t and Δpm_t and place a number of zero restrictions on the coefficient matrices. Moreover, they do not actually enter $(R-r)_t$ in differenced form because they treat this variable as stationary in levels which does not require differencing. Of course, the model could be reparameterized to include $\Delta(R-r)_t$ or both ΔR_t and Δr_t. The variable $(R-r)_t$ may be viewed as an additional cointegration relation so that there are two cointegration relations in a model where R_t and r_t enter separately as in J. In terms of J's set of variables, LW impose a further restriction on the EC term by considering a smaller cointegrating rank. Overall LW's model may be regarded as a restricted version of (3.1). Moreover, it may be transformed to a reduced form by multiplying with Γ_0^{-1}. Furthermore, defining $z_t^{LW} = [m-p, y, \Delta p, R, r]_t$, the LW model can be written in precisely the reduced form version of (3.1). Provided the unmodeled variable Δpm_t is actually stationary, dropping it does not introduce an instability in the unconditional process. Hence, we may focus on the unconditional DGP in which the set of stochastic variables used by J and LW are basically the same.

In conclusion, the models used in the two studies are special cases of (3.1). Ignoring the restrictions imposed by LW should not result in an unstable model if the original model is really stable for the full observation period. On the other hand, restricting the J models further may induce additional inhomogeneity and is therefore undesirable in the context of our analysis.

In the next section, some stability checks will be performed based on reduced form models for z_t^J and z_t^{LW} to investigate the impact of the data on the stability properties of the systems. In Sec. 5 a further stability analysis based on MS models will be reported.

4 Stability Analysis of the System

A preliminary approach to investigate the possible rupture of the transmission mechanism of German monetary policy in 1983 consists of performing stability tests. We have performed a range of such tests based on VECMs with two lags without imposing a rank restriction or, equivalently, on vector autoregressive (VAR) models in levels with three lags for z_t^J and z_t^{LW}. Thus, with respect to the dynamic structure the models are even less restricted than J's models. In both models, we include the endogenous variables plus all deterministic terms used in the two studies to facilitate a comparison. In other words, in both models we include an intercept, a deterministic linear trend, seasonal dummies for the full sample period as well as extra seasonals for the post GMU period, the impulse dummy $I90q2_t$ and the shift dummy $S90q3_t$. The models are estimated in reduced form based on a sample period 1976(3) - 1994(4) plus presample values for lagged variables. Hence, we use the intersection of the observation periods from J and LW to allow a fair comparison.

Following J, we first perform LR type tests based on the test statistic

$$(T-3)\log\det\hat{\Sigma} - T_1\log\det\hat{\Sigma}_1 - T_2\log\det\hat{\Sigma}_2,$$

where $\hat{\Sigma}_1$ is the ML covariance matrix estimator based on the T_1 first observations whereas $\hat{\Sigma}_2$ is based on the last T_2 observations of our sample. As advocated by Juselius (1998), the sample has been split taking into account the 3 lags included in the VAR model. Thus, samples used to test a break in period t are based on observations from 1976(3) to t and from $t+4$ to 1994(4). Therefore, the three observations between the first and second sample period also have to be ignored in the parameter estimators on which $\hat{\Sigma}$ is based. Table 2 gathers results for selected values of t. As the number of restrictions placed on the constant coefficient model is 140 (75 parameters associated with VAR coefficients, 15 covariance parameters and 50 parameters associated with deterministic terms) and the 95% quantile of a $\chi^2(140)$ distribution is 168, parameter constancy is rejected for every t and both models. However, the test values for 1983 are not particularly large in comparison to other years. In fact, the 1983 values are even smaller than in some of the other years. Hence, the evidence for a break is no greater in 1983 than in other years during the 80s.

The actual distribution of the test statistics under the stability assumption may be quite different from a χ^2 distribution, however, because of the small sample size for each subperiod

Table 2. LR Tests for Parameter Constancy

t	1982(4)	1983(1)	1983(2)	1983(3)	1983(4)	1984(1)	1985(1)	1986(1)
z_t^J	252.6	235.4	206.7	245.2	233.7	232.4	231.2	307.2
z_t^{LW}	293.2	271.6	247.6	228.4	204.4	203.5	226.5	296.2

Table 3. Simulation Results for Stability Tests Based on Sample Size $T = 75$

		assumed break point						
		26	28	30	31	33	35	37
J	mean of test statistic	358.5	317.3	303.0	300.4	305.9	322.2	358.6
	empirical 95% quantile	455.0	393.6	373.9	369.7	377.3	398.5	451.3
LW	mean of test statistic	358.3	318.2	303.9	302.2	305.9	322.4	359.0
	empirical 95% quantile	454.8	393.2	375.1	372.4	377.6	399.8	452.4

and the dummy variables added in the latter part of the sample. To investigate the finite sample properties of the tests we have performed a small simulation study. For this purpose we have used the estimated models based on J's and LW's data for the full sample period and we have simulated 10 000 multiple time series of length $T = 75$. In other words, we have performed simulations for models without a structural break. Then we have applied stability tests for different break points corresponding roughly to those in Table 2. The means and empirical 95% quantiles of the test statistics are given in Table 3. Clearly, the actual distributions are quite different from the asymptotic χ^2 distributions. They are shifted to the right. The 95% quantiles exceed the assumed critical value of 168 dramatically. In fact, the simulated quantiles are substantially larger than the corresponding values of the test statistics in Table 2. Hence, the virtue of these stability tests is doubtful in small samples. Overall the present stability tests provide no evidence for a break in 1983 or in any of the other years.

We have also used recursive methods based on One-Step Chow and Break-Point Chow tests as described in Doornik & Hendry (1997, Sec. 10.8) to investigate the stability of the models. Note that the Chow tests may be computed by including impulse dummy variables

for the period where stability is tested. Therefore it is not meaningful to compute these tests for the GMU year because additional dummies are added in 1990. Hence, test values until the end of 1989 are computed only. Also, in order to produce forecasts, the models have to be estimated with data prior to the forecast period. Degrees of freedom restrictions allow us to start the one-step tests in 1983(3) and the break-point tests in 1983(2) only. Figure 2 shows the results. In the figure the test values are normalized in such a way that the 95% critical value is 1. Clearly, constancy of the models is not rejected by the Chow tests, except close to the GMU. Of course, this outcome may be due to low power of the Chow tests. Still, the tests do not support a break in 1983. In the next section we will further analyze the stability issue in the framework of MS models.

– Figure 2 about here –

5 Markov Regime Switching Models

Using the reduced form version of (3.1) as our point of departure, a general form of an MS-VECM is defined as

$$\Delta z_t = \alpha(s_t)\beta(s_t)' z^*_{t-1} + \Gamma_1(s_t)\Delta z_{t-1} + \cdots + \Gamma_p(s_t)\Delta z_{t-p} + \Phi(s_t)x_t + \Xi(s_t)D_t + u_t, \quad (5.1)$$

with $u_t \sim \mathrm{WN}(0, \Sigma(s_t))$. Here s_t is a discrete Markov process with states $1, \ldots, K$ and a $(K \times K)$ transition matrix P. Thus, in the general form (5.1) there can be K different regimes and all the coefficients may vary from one regime to the next. In other words, the model is considerably more flexible than the constant coefficient VECM. In practice, models that allow for two regimes only ($K = 2$) are often considered. Moreover, the set of coefficients which are allowed to vary may be restricted to a subset of all the coefficients. For example, only the intercept term may vary or the covariance of the residual process etc..

The analysis usually aims at estimating the conditional probabilities of the different states given the observations. For instance, $p_{kt} \equiv Pr(s_t = k | z_1, \ldots, z_T)$ may be of interest. Assuming that the conditional distributions, given the states, are Gaussian, it is easy to formulate the likelihood function. Maximization algorithms and inference procedures are available which also allow to estimate the regime probabilities of interest. In practice, the estimation of a MS-VECM is based on a two-step procedure (see Krolzig (1997, 1998)). First,

cointegration relationships are tested and estimated via the Johansen-Juselius methodology. Then, they are introduced in the model as 'exogenous variables' whose coefficients may be different in different regimes. In the next step the corresponding MS model is estimated with the traditional EM algorithm (see Dempster, Laird & Rubin (1977) and Hamilton (1990)) using the cointegration relations as given variables.† The procedure consists of estimating the conditional probabilities by maximizing the log likelihood function based on conditional normality without actually assuming that the true distribution is conditionally Gaussian. Instead we view the estimation algorithm as a descriptive tool which allows the data to assign weights to the different states and thereby partition the observation period in different regimes. If a regime has probability close to one in a specific period, it is attached to that period. Thereby a partitioning of the sample period in different regimes recommended by the data may be obtained.

In our analysis we consider a Markov process with two regimes only, because J finds that there are two regimes and performs her analysis under this assumption. We allow all coefficients of the short-term dynamics, the intercept terms and the residual covariance matrix to vary in the two regimes. Because such a model is very flexible, the estimation may not be very reliable and the analysis may produce spurious results. Therefore, we have also experimented with models where the coefficients of the short-term dynamics are fixed over the full sample period and, hence, are not allowed to vary with the regimes. We use $p = 2$ lags in the VECM. Hence, we allow for one more lag than J whereas LW use up to four lags. Moreover, we consider the cointegrating rank $r = 3$ suggested by J and we include all the dummies that were also included by J in her model for the second period, that is, seasonal dummies for the full period and an extra set for the post GMU period plus $S90q3_t$ confined to the cointegration relations and $I90q2_t$ are included. In addition we also include $I90q3_t$ which is used by LW. The cointegration relations are estimated in a preliminary step from a model which does not allow for regime switching. The resulting cointegration relations are then used as additional variables in the MS analysis. If fixing the estimates of the cointegration parameters is unjustified given the data properties, e.g., if a split in 1983 is necessary, this should show up in the subsequent MS analysis. In other words, restricting some coefficients

†Computations have been performed with PC GIVE 9.1, for the cointegration analysis and OX 2.1 and the MSVAR package for the estimation of the MS-VECM.

to be constant, the MS model should still bring out the split period and perhaps even more clearly, because the overall estimation uncertainty is reduced by restricting the parameter space. We use data from 1976(3) - 94(4) plus presample values for lagged variables as in the previous section.

In Figures 3 and 4 the estimated probabilities p_{1t} of Regime 1 are plotted for a number of different models. The corresponding probabilities of Regime 2 are, of course, $p_{2t} = 1 - p_{1t}$. In Figure 3, the probabilities for J's data are depicted. They are mostly 0 or 1 so that a clear association of regimes with time periods is obtained. However, allowing the data to partition the sample period in two regimes does not result in a split in 1983 as suggested by J. In contrast, based on the estimated probabilities, several changes in regime are observed during the sample period. In particular, the same regime is assigned to some quarters before and after 1983. Against this background, splitting the data in 1983 as in J appears to be somewhat arbitrary.

– Figure 3 about here –

In Figure 4, the corresponding probabilities for LW's data are depicted. In order to simplify a comparison, we use the same models as for J's data and thereby we clearly give an advantage to her analysis. The model for LW's data is less restrictive than in LW's original analysis in the sense explained in Sec. 3, except that the lag order is smaller than in LW and the impulse dummies $I92q4_t$ and $I93q3_t$ are not included now.

– Figure 4 about here –

It turns out that the partitioning based on LW's data is somewhat different from that seen in Figure 3. In particular, the changes in the regimes in the first two panels are more volatile now. The sensitivity of the estimated probabilities to changes in characteristics of the model such as the number of varying coefficients and the trend characteristics is substantial. This outcome may be indicative of the fact that a partitioning in different regimes is not necessary at all because the probabilities are estimated under the assumption that there are actually two regimes. If the data can be described well by a time homogenous linear model for the full observation period, one would expect the partitioning in two regimes to be fairly arbitrary and unsystematic as in Figure 4. Overall the results in Figure 4 cast doubt on the

need to partition the sample period in two regimes because relatively small changes in the models lead to substantial changes in the regime split.

6 Conclusions

In a couple of articles Juselius questions the stability of the monetary transmission mechanism in Germany during the 1980s. If her finding is correct one may question the usefulness of a monetary targeting strategy. Such a conclusion may also have important implications for the present monetary strategy of the new ECB. Therefore we have compared Juselius' models and analyses to a model developed by Lütkepohl & Wolters which supported a stable transmission mechanism in the 1980s. In the comparison we have used a range of stability tests as well as a detailed Markov regime switching analysis.

In conclusion, it appears that the two regimes found by J are an artefact of her choice of data and analysis. Even with her data set her partitioning of the sample period is not imperative. Of course, this also means that the events blamed for the change in regime may not have had the important impact on the monetary transmission mechanism assumed by Juselius. Hence, her arguments against a successful monetary targeting strategy of the DB appear to be on soft grounds.

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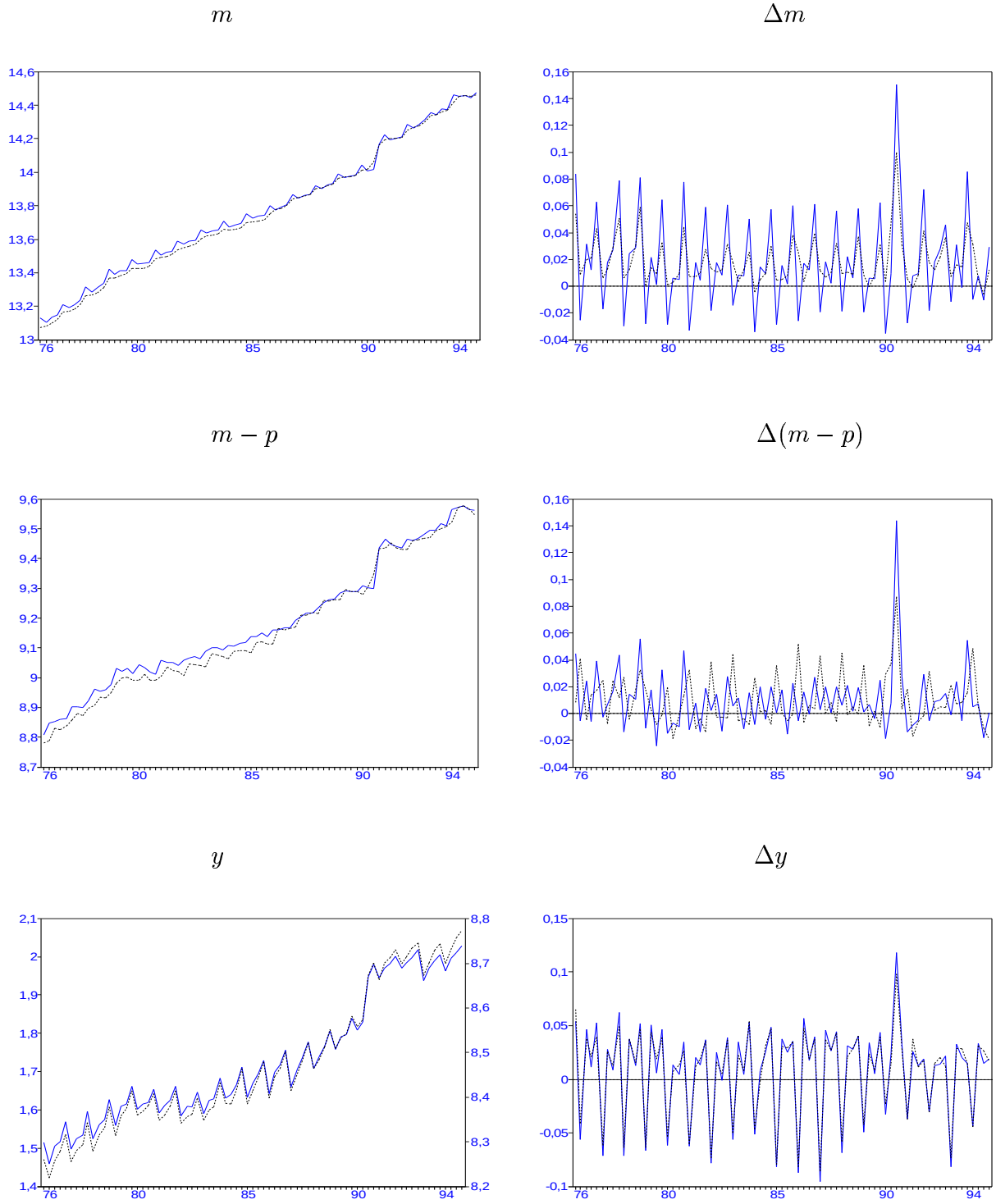
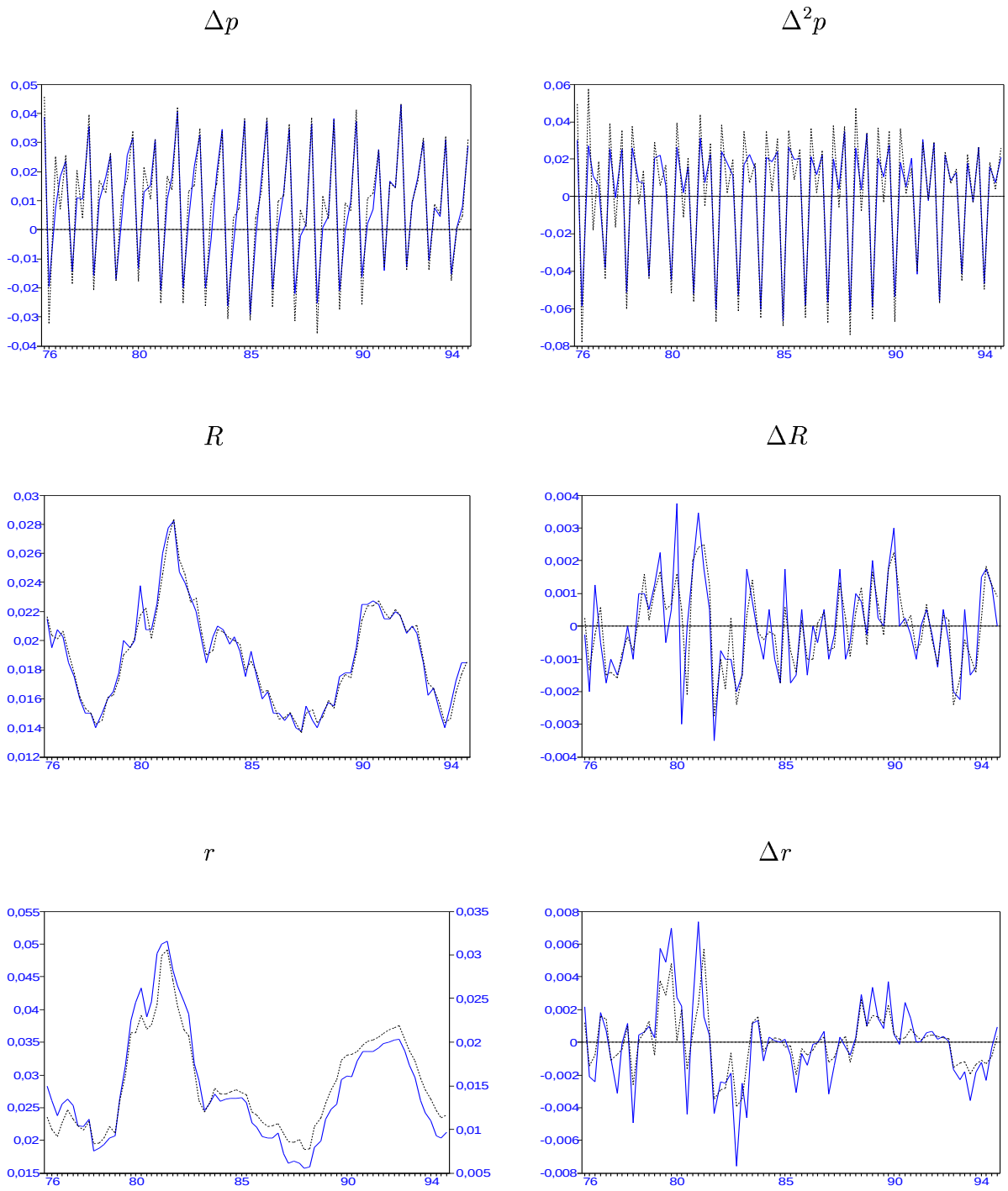


Figures 1 : Data (LW full line, J dotted line)



Figures 1 (continued): Data (LW full line, J dotted line)

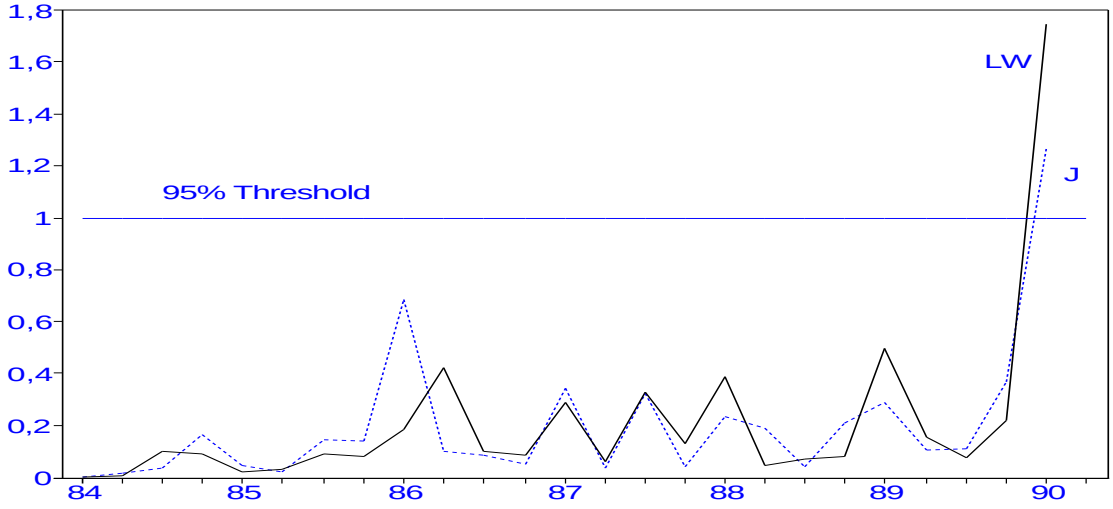


Figure 2(a) : One-Step Chow Test

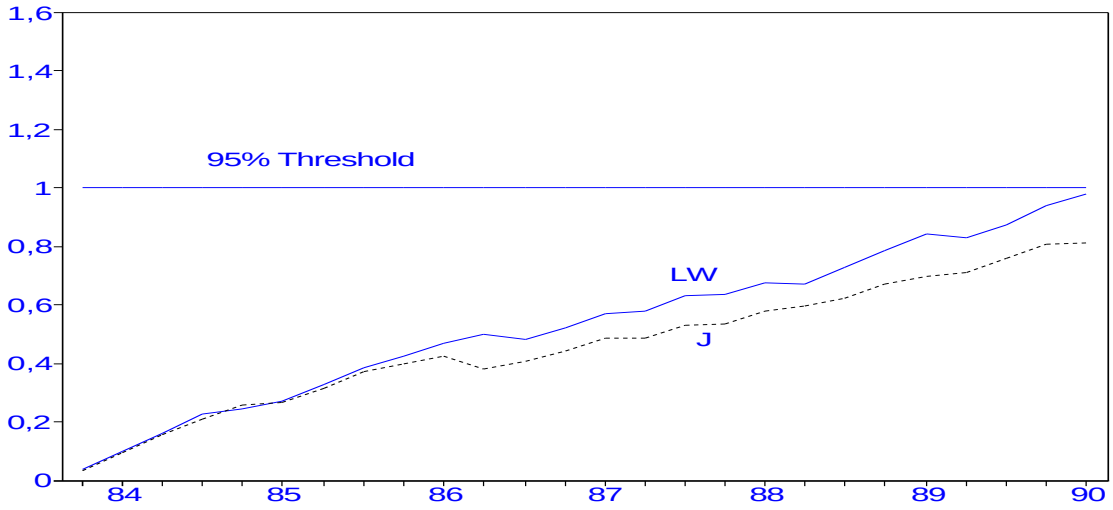
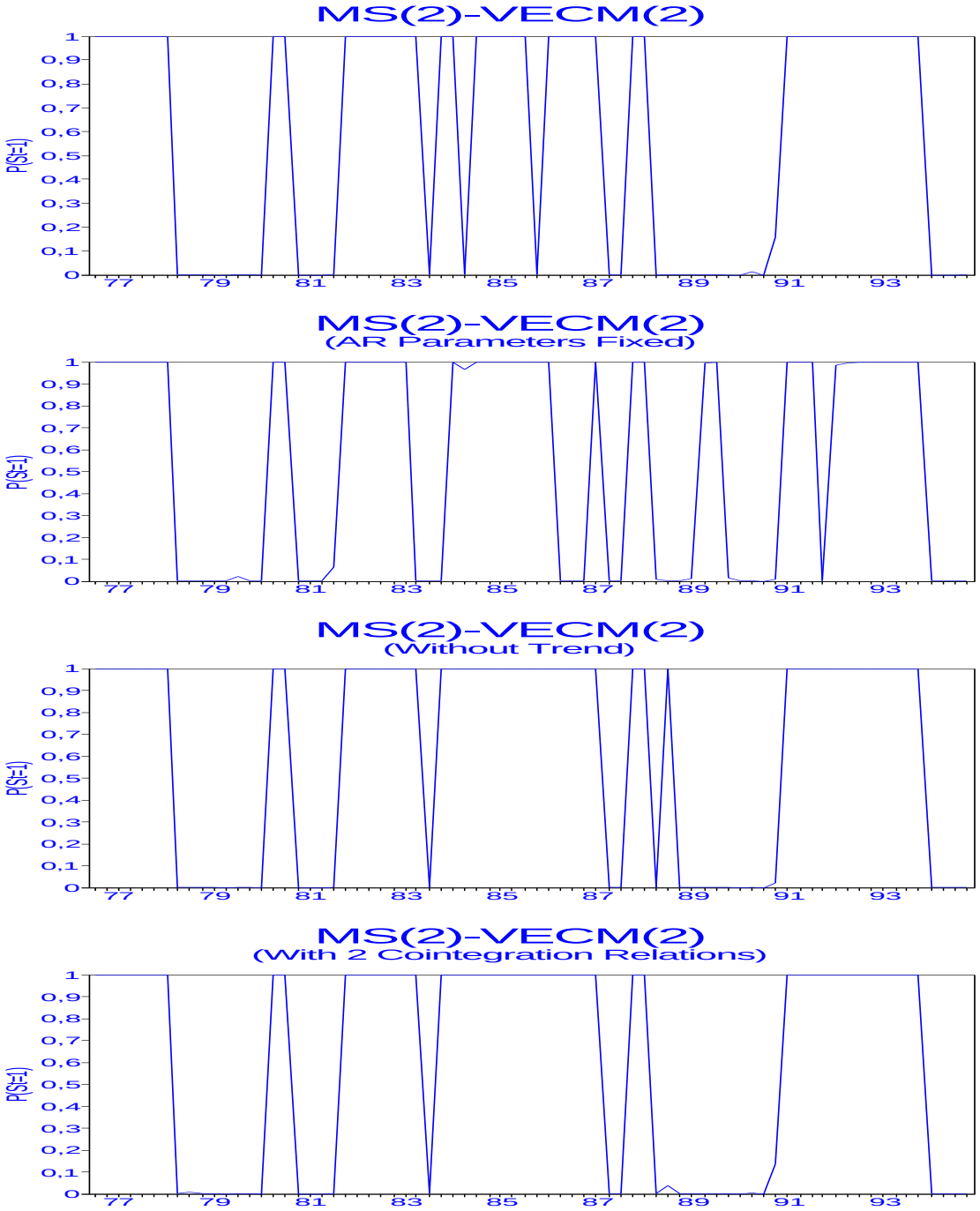
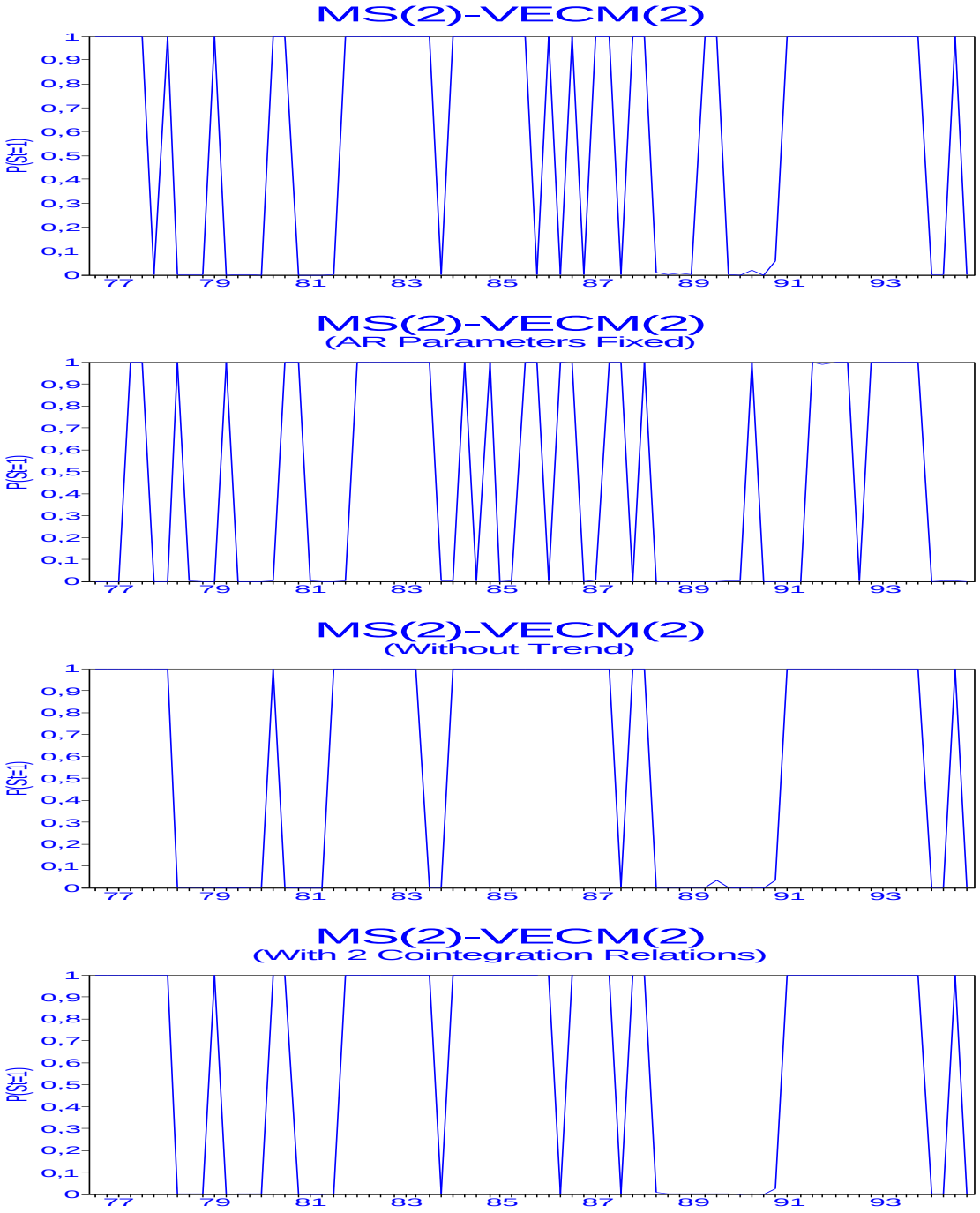


Figure 2 (b) : Break-Point Chow Test



Figures 3 : Estimated regime 1 probabilities for Juselius' model



Figures 4 : Estimated regime 1 probabilities for LW's model