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MONITORING MACROECONOMIC VOLATILITY

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ABSTRACT

In this paper we develop testing procedures for monitoring the stability of the variance of a time series. While the traditional approach to testing for structural change is retrospective, applying a single test to a historical time series of given length, we consider testing stability in a prospective framework, where the time series are observed online and monitored continuously. The proposed testing procedures have controlled asymptotic size, in that the probability of a false alarm during an infinitely long monitoring period is fixed. A Monte Carlo study is performed to evaluate the test statistics with respect to size and power under different circumstances. We apply our methods to US GDP and its major components in order to investigate when the documented decline in volatility of the US economy during the latter part of the twentieth century could have been detected in real time.

Key Words: *Structural change, monitoring, variance, stability, robust, moving window, cumulative sum.*

1 INTRODUCTION

In many areas in economics and finance, correct and timely detection of structural changes in the statistical properties of time series variables is of utmost importance. Examples include detection of business cycle turning points and changes in volatility of financial asset returns. The reasons for desiring accurate and fast detection of structural changes are obvious as well. For example, if a time series model is not updated to be in accordance with changing properties of the data, forecasts generated from the model will be misleading.

The traditional approach to testing for structural change in, for example, the mean or variance of time series employs retrospective tests, where a historical data set of given length is analyzed and tests for structural change are applied only once. In this setting tests have been developed both for confirming a hypothesized (fixed) change-point for the (conditional) mean of a time series as in Chow (1960), and for an unknown change-point. For the latter case, Andrews (1993) and Andrews and Ploberger (1994) developed tests under the assumption of a specific alternative, whereas others have proposed tests, sometimes referred to as fluctuation tests, that do not assume a particular pattern of deviation from the null hypothesis, see Kuan and Hornik (1995). A similar classification can be made for retrospective tests for changes

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The outline of the paper is as follows. In section 2, we describe our notation and some further specifications. Criteria of optimality and measures of evaluation are also briefly discussed in this section. In section 3 the monitoring test procedures are described, both for a Gaussian process and procedures robust against deviations from that assumption. In section 4 we perform extensive Monte Carlo experiments in order to examine the empirical performance of the different test statistics. The empirical application to U.S. macroeconomic data appears in section 5 and we conclude with some remarks in section 6.

2 NOTATION AND SPECIFICATIONS

Consider the linear time series representation

$$y_t=\mu+u_t, \qquad t=1, 2, \ldots, \tag{1}$$

where u_t is an independent and identically distributed process with zero mean and variance σ_t^2. The observations $Y^{(n)}=\{ y_t;\ t \leq n\}$ form the historical data set. The assumptions of a constant conditional mean μ is made only for ease of exposition. It is straightforward to extend the analysis presented below to the situation of a general nonlinear model for the conditional mean, by replacing μ in (1) with $G(x_t;\theta)$ for some nonlinear function $G(\cdot;\cdot)$, where x_t is a vector of explanatory variables containing lagged values of y_t and possibly exogenous variables $z_{1t},\ldots, z_{kt}$, and θ is a vector of parameters. Furthermore, without loss of generality, we impose $\mu=0$.

Our purpose is to test the null hypothesis that the variance of y(t) is constant, that is $\sigma_t^2=\sigma_0^2 < \infty$ for all t, where σ_0^2 is unknown. In this paper we will restrict ourselves to the alternative hypothesis where there is a single change at an unknown point in time, denoted by τ, that is under the alternative

$$\sigma_t^2=\begin{cases}\sigma_0^2, & t<\tau\\ \sigma_1^2, & t\geq\tau\end{cases}$$

where also σ_1^2 is unknown.

In a retrospective setting, this hypothesis would be examined with "one-shot" tests: given observations $y_1, y_2,\ldots,y_n$, where the length of the time series n is fixed, the tests aim to detect a structural break within this given time series. In a prospective or monitoring context, the situation is completely different. In such situations, we start with the historical data set consisting of observations $Y^{(n)}=\{ y_t;\ t \leq n\}$, but continue to observe the time series after $t=n$. Assuming that the variance of the time series was constant, and equal to σ_0^2, for all $1\leq t \leq n$, we now would like to test the null hypothesis that the variance remains constant during the so-called monitoring period, that is

$$\mathbf{H_0}\text{: } \sigma_t^2 = \sigma_0^2 \text{ for all } t > n,$$

against the alternative hypothesis

$$\mathbf{H_a}: \sigma_t^2 \text{ changes at some unknown time } \tau > n.$$

3.1 Two tests based on cumulative sums

Inclan and Tiao (1994) use a centered cumulative sum of squared observations for retrospective testing for a change of the variance of an independent and identically distributed sequence of random variables. At time $m \leq n$, let

$$D_m = \frac{C_m}{C_n} - \frac{m}{n} \tag{2}$$

where $C_n = \sum_{t=1}^{n} y_t^2$ and n is the number of observations in the historical data set. Under the null hypothesis and the assumptions regarding the process outlined in section 2, D_m has zero mean (see Inclan and Tiao (1994), Appendix A). A rejection of the null hypothesis is made when $\sqrt{n/2}\max_{1 \leq m \leq n}|D_m|$ exceeds a critical value. Inclan and Tiao (1994) show that under the null hypothesis, $\sqrt{n/2}\, D_{[n \cdot t]}$, where $t=m/n$, converges weakly to a Brownian bridge

$$W^0(t) = W(t) - t \cdot W(1)$$

where W is a standard Wiener process. The boundary is determined from this asymptotic result. Inclan and Tiao (1994) prove this result for $t \in [0,1]$, but it can be extended to $t \in [0, \infty)$, that is to a monitoring framework where $m > n$. Note that, under the assumption of normality of the time series y_t, the statistic $\sqrt{n/2}D_m$ is in fact based on the estimated cumulative score process

$$\rho_m(\hat{\sigma}_n^2) = \sum_{t=1}^{m}\left\{\frac{1}{2\hat{\sigma}_n^2}\left(\frac{y_t^2}{\hat{\sigma}_n^2} - 1\right)\right\}$$

where $m \leq n$ and $\hat{\sigma}_n^2 = \frac{1}{n}\sum_{t=1}^{n} y_t^2$ is the maximum likelihood estimator of the variance.

Here we use a (centered) cumulative sum of squared observations for monitoring stability of the variance, that is for $m>n>2$. Define

$$D_m = \frac{C_m}{C_n} - \frac{m-2}{n-2}. \tag{3}$$

where $(m-2)/(n-2)$ is the expected value of C_m/C_n under the null hypothesis, and the assumption that y_t has an **iid** Gaussian distribution. In order to guarantee that the probability of a false alarm during an infinitely long monitoring period is not larger than α, that is $\lim_{i \to \infty} P(t_A < i \mid H_0) \leq \alpha$, we use Theorem 3.4 in Chu et al. (1996). The theorem states that if our test statistic converges in law to a standard Wiener process, $\lim_{i \to \infty} P(t_A < i \mid H_0)$ is approximately equal to the probability that the absolute value of a Wiener process $W(t)$, $t>1$ crosses at least once the path of a boundary function $b(t)$. One such function is $b(t)=\sqrt{t\left(\lambda^2 + \ln(t)\right)}$ where λ is a chosen constant. Values of λ

The statistic (7) is used together with the boundary in (4) and is hereafter referred to as CUSUMQes, where "es" is an abbreviation for empirical scaling.

3.2 *A test based on moving sums*

Chu et al. (1996) found that their test gets increasingly insensitive for detecting changes that occur late in the monitoring period. Leisch et al. (2000) explained this by the shape of the boundary function given in (4), which is said to grow too fast. In Zeileis et al. (2004) it was shown that the empirical density of the time points where the null hypothesis is incorrectly rejected actually has its peak at early time points. Two ways to remedy this effect have been suggested. In Zeileis et al. (2004) a different boundary function was suggested for the test, yielding a more uniformly shaped density compared to when (4) is used. Leisch et al. (2000) proposed a monitoring statistic based on a moving window of observations instead of a cumulative sum. Zeileis et al. (2004) showed that for a CUSUM based test converging to a Brownian bridge, a moving sum (MOSUM) version of the test converges to the increments of a Brownian bridge. More precisely, the test statistic with a window of width p has a limiting behavior characterized by the increments

$$W^0(t)- W^0(t-h)$$

where $h=p/n$ is the window width expressed as a fraction of the number of observations in the historical data set. A test referred to as MOSUMQes that uses observations from a moving window of fixed length p is here proposed for detecting a change in the variance. The test statistic, denoted by $M_{m,\,p}$, is calculated by taking the p-th difference of the statistic S_m in (5) but where the scaling coefficient given a Gaussian distribution is replaced by the empirical scaling coefficient given in the previous section;

$$S_m\text{-}S_{m\text{-}p} = \sqrt{n/\left(\hat{k}_0-1\right)}\,(D_m\text{-}D_{m\text{-}p}),$$

which is equal to

$$\frac{1}{\sqrt{n\left(\hat{k}_0-1\right)}}\sum_{t=m-p+1}^{m}\left(\frac{y_t^2}{\hat{\sigma}_n^2}-\frac{n}{n-2}\right). \tag{8}$$

Based on the argument above, since S_m converges to a Brownian bridge, $M_{m,\,p}$ in (8) converges to the increments of a Brownian bridge. A boundary function for the increments of a Brownian bridge that, at least approximately, yields a fixed asymptotic size is given in Theorem 4.2 in Leisch et al. (2000). For $t=m/n>1$, the function has the form

$$b_2(z(h),\ t)=\begin{cases} z(h)\sqrt{2} & t\leq e, \\ z(h)\sqrt{2\log\ t} & \text{otherwise} \end{cases} \tag{9}$$

and the boundary function (4) such that we have the stopping rule

$$t_A = \min\{m \geq n: |R_m| > b_1(\lambda, m, n)\}.$$

4 MONTE CARLO STUDY

We want to investigate the properties of the proposed test procedures from different aspects. First, we wish to see whether the empirical size is close to the asymptotic controlled size. We do it for three situations, namely when the process that is being monitored has a Gaussian distribution with or without isolated additive outliers and when it has a t distribution. The two latter processes are of interest to look at since economic time series data often have outliers and the distributions often have tails that are thicker than those of a Gaussian distribution. Here we will use a t distribution with six degrees of freedom in order to ensure the existence of the fourth moment. We then evaluate the power for different situations under the alternative hypothesis. First, we evaluate the behavior of the empirical power for different sizes of the shift. Second, we study the power for different time points of the change during the monitoring period. In addition, we look at the aspect of timeliness of the methods in terms of the time required to detect a change.

In theory, the monitoring period is infinite. However, in order to assess the properties of the procedures empirically by Monte Carlo simulations, or to simulate certain critical values, the monitoring period must obviously be finite and we have a finite number of decisions to make regarding the acceptance or rejection of the null hypothesis. For the MOSUMQes test we will use the simulated asymptotic critical values given in Leisch et al. (2000). For them to be valid we will use the same combinations of lengths of the historical and monitoring period as in Leisch et al. (2000). In that paper the number of observations in the historical period (n) is 1000 and the total lengths of the historical period and the monitoring periods, hereafter denoted by T, are set to 4000, 6000, 8000 and 10 000. The properties of the methods for smaller samples can be found in section 5.3 and for CUSUMQ also in Carsoule and Franses (1999).

4.1 Size properties

In this subsection, we present results on the size properties of the tests. The size when the observations come from a Gaussian distribution with or without isolated additive outliers and a t distribution with six degrees of freedom has been estimated by calculating the rejection frequencies in 100,000 replications. The total length of the historical period and the monitoring period, denoted by T are given in the first column from the left in the tables below. The variance under the null hypothesis is $\sigma_0^2 = 1$.

In Table 1 we see that at a 5% significance level, all procedures but the robust (RCUSUMQ) are more or less over-sized. The shorter the window width is, that is used in MOSUMQes, the larger is the empirical size. At the 10% significance level (Table 2), all methods are conservative except for the MOSUMQes tests, which are slightly over-sized.

Table 6. Empirical size for different values of T given an asymptotic size of 10%. IID Gaussian distribution with isolated additive outliers.

10%	CUSUMQ	CUSUMQes	RCUSUMQ	MOSUMQes h=0.25	MOSUMQes h=0.50	MOSUMQes h=1
4000	0.463	0.465	0.076	0.659	0.603	0.562
6000	0.499	0.501	0.081	0.706	0.647	0.607
8000	0.517	0.519	0.083	0.724	0.667	0.627
10000	0.527	0.529	0.086	0.734	0.678	0.639

We simulate a Gaussian distributed process with isolated additive outliers using the model $y_t = u_t + \zeta d_t$ where $u_t \sim$ **iid** $N(0, 1)$, $\zeta = 3$ and d_t is an **iid** process with density $P(d_t = 0) = 1-p$ and $P(d_t = 1) = P(d_t = -1) = p/2$ for $p = 0.01$. The rejection frequencies of the test under the null hypothesis are given in Table 5 and 6. The empirical scaling coefficient seems to be of no use here and all tests but RCUSUMQ appear to be very sensitive to isolated additive outliers.

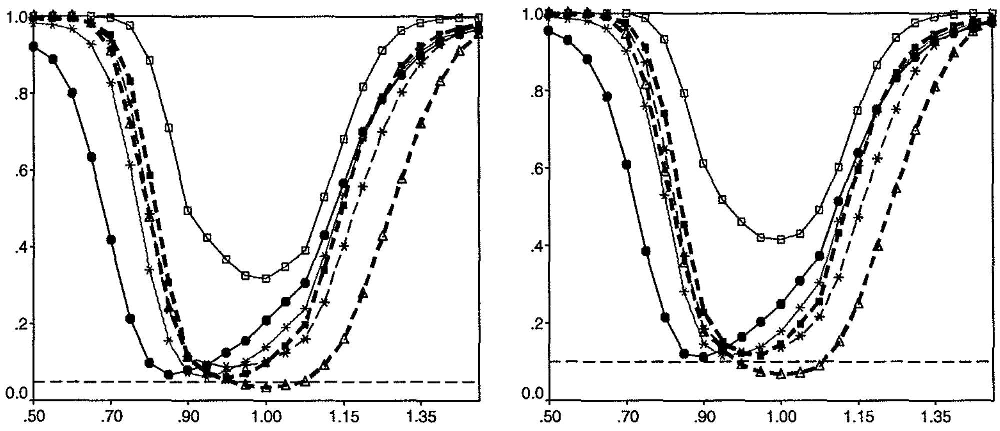
4.2 Power properties

Evaluating the methods ability to detect a change in the process can be made for numerous situations. In order to keep the computational burden moderate, we only consider a limited number. In real data we expected that the conditional mean will change as well as the variance. Here however, we assume that the expected value of the process remains constant. The power functions below were estimated by calculating rejection frequencies from 10,000 replications of an **iid** Gaussian distributed process and a process that has a t distribution with six degrees of freedom. The total length of the historical period and the monitoring period considered below is T=4000 and the variance under the null hypothesis is $\sigma_0^2 = 1$.

4.2.1 The effect of the size of the shift

We look at the power of rejecting the null hypothesis for different values of the variance under the alternative when the change occurs at different time-points τ. More precisely, in Figures 1 to 3 below the estimated probability $P(t_A < T \mid \mathrm{H_a})$ is shown for τ=1100, τ=3000 and different magnitudes of the shift. The results of CUSUMQ and CUSUMQes are identical when the process is **iid** Gaussian distributed. Therefore CUSUMQes is omitted in Fig. 1 and 2.

All curves are more or less symmetric for the length of the historical and monitoring period that is used here. CUSUMQ appears however to have a slightly steeper curve when there is an increase in the variance compared to a decrease, which confirms the results of Carsoule and Franses (1999). RCUSUMQ is asymmetric in the opposite way; the power is lower for detecting an increase than a decrease. MOSUMQes, h=0.25, is slightly biased, i.e. the power under the alternative hypothesis can be less than the size. For an increase in the variance, the power curves are almost identical for the different window widths. However, for a decrease, MOSUMQes, h=0.25, has almost as low power as RCUSUMQ though it is the most over-sized method of them all (see Table 1 and 2). For a very small decrease, it has in fact lower power than RCUSUMQ. Carsoule and Franses (1999) investigated the time required by CUSUMQ for rejecting the null hypothesis for different values of the variance under the alternative. They found that the relation between the time of



a b

Fig. 3. τ=1100. Vertical axis: Values of the power. Horizontal axis: Values of σ_1^2. IID t distribution with 6 degrees of freedom. Asymptotic size: Panel a: 5%, Panel b: 10%. The asymptotic size level is marked with a dashed horizontal line. CUSUMQ (—□), CUSUMQes (– – – *), RCUSUMQ (▬ ▬ △), MOSUMQes, h=0.25 (—— ●), MOSUMQes, h=0.50 (—— *), MOSUMQes, h=1 (▬ ▬ ■).

4.2.2 The effect of the time of the structural change

We consider different time-points τ where a change in the variance occurs. Given the research question on stability in this paper, we first examine the case where the variance decreases. We also examine the situation of an increase. More precisely, in Figures 4 and 5 below the estimated probability $P(t_A < T \mid \mathrm{H_a})$ is shown for $\sigma_1^2 = 0.5$, $\sigma_1^2 = 1.5$ and different values of τ. The results of CUSUMQ and CUSUMQes are identical when the process is **iid** Gaussian distributed. Therefore CUSUMQes is omitted in Fig. 4 and 5.

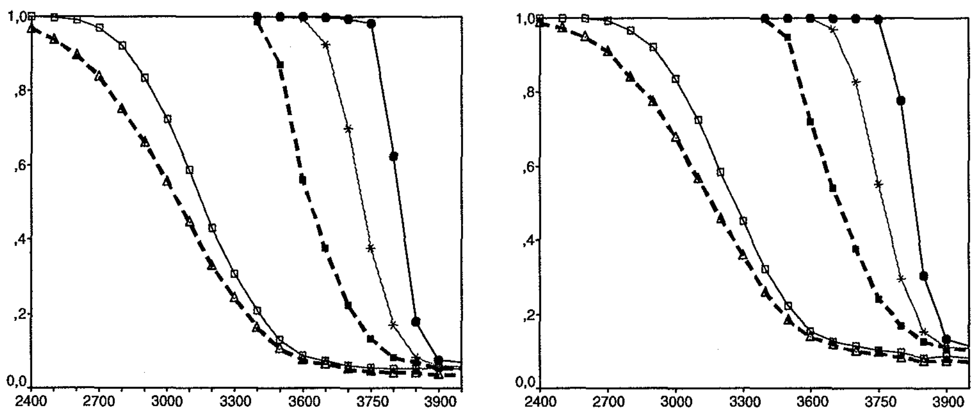


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Fig. 4. σ_1^2 = 0.5. Vertical axis: Values of the power. Horizontal axis: Different values of τ. IID Gaussian distribution. Asymptotic size: Panel a: 5%, Panel b: 10%. CUSUMQ (—□), RCUSUMQ (▬ ▬ △), MOSUMQes, h=0.25 (—— ●), MOSUMQes, h=0.50 (—— *), MOSUMQes, h=1 (▬ ▬ ■).

In the Figures above we see that for all methods the power becomes lower the later the change occurs. The reason for this is that as the change point time gets closer to the end of the monitoring period, the fewer are the time points after the shift where we

Fig. 6 below shows the median time required to correctly reject the null hypothesis at the 5% level, given the rejection is made during the remaining monitoring period after τ. It is shown for different values of τ and for both a decrease and an increase in the variance. The total length of the historical period and the monitoring period considered below is T=4000 and the variance under the null hypothesis, σ_0^2 = 1. The number of replications used in the simulations are 50,000. The results of CUSUMQ and CUSUMQes are identical when the process is iid Gaussian distributed. Therefore CUSUMQes is omitted in Fig. 6.

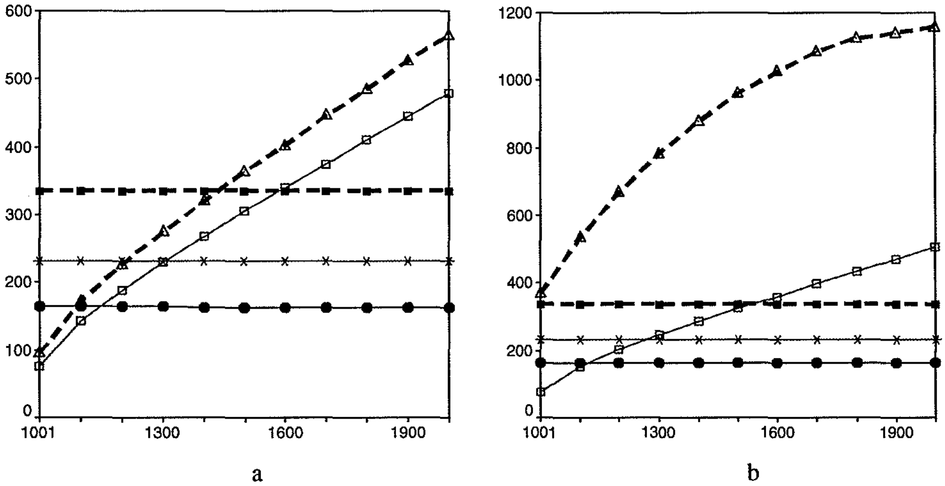

Fig. 6. Asymptotic size: 5% level. Vertical axis: Values of the median time required to correctly reject the null hypothesis given the rejection is made during the remaining monitoring period after τ. Horizontal axis: Different values of τ. IID Gaussian distribution. Panel a: decrease in the variance to σ_1^2 = 0.5, Panel b: increase in the variance to σ_1^2 = 1.5. CUSUMQ (—□), RCUSUMQ (- - △), MOSUMQes, h=0.25 (——●), MOSUMQes, h=0.50 (—— *), MOSUMQes, h=1 (- - ■).

We confirm what was pointed out by several authors; the later a change occurs, the longer the (median) time required to detect the change for methods using the boundary (4). These methods outperform window based methods for early changes but the relation is reverse for later changes because window based methods have a constant detection delay as was also noticed by Zeileis et al. (2004). The asymmetry of RCUSUMQ with respect to the direction of the change is easily seen here.

Zeileis et al. (2004) pointed out that a possible solution to the choice of boundary function is to base it on a specified prior distribution for the timing of the shift. The advantage is that the detection power is concentrated to those time points where is the change is most likely to occur. However the obvious disadvantage is that the ability to detect a change that takes place at an unexpected time point is poor.

5 MONITORING U.S. MACROECONOMIC TIME SERIES

The stability of the U.S. economy is a topic of much recent research. The two key questions, which are common to most studies on stability, concern the selection of the appropriate variables and the choice for the most insightful statistical method or econometric model. Examples of studies with a specific focus on the first question are

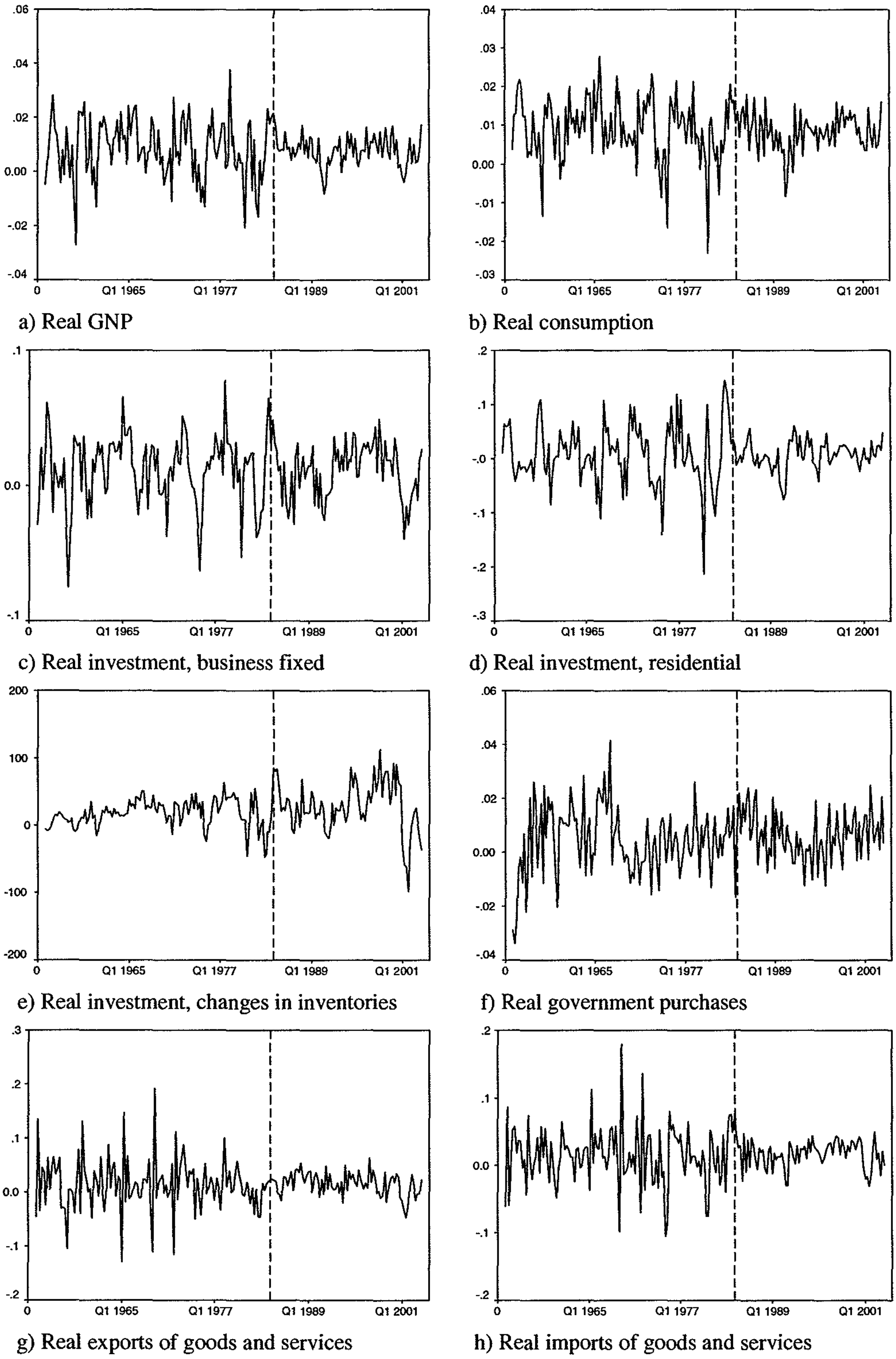

Fig. 7. Growth rates of the variables for the period 1954Q1 – 2003Q3. Vertical axis: Values of the growth rates. Horizontal axis: Time. The start of the monitoring period 1984Q1is marked with a dashed vertical line.

In most of the cases where the null hypothesis is rejected, it is made in favor of a smaller alternative that is a decrease in the volatility. CUSUMQ tends to be the method that mostly give the earliest rejections followed by RCUSUMQ and the MOSUMQes tests. The time of rejection differs a lot between CUSUMQ and CUSUMQes and unreported results show that when $\left(\hat{k}_0 - 1\right)$ is replaced by 2 in the MOSUMQes statistic, the rejections are also made earlier. As the residuals of the estimated models have more or less excess kurtosis, this is not surprising because the simulations showed that a seriously misspecified scaling coefficient generate too frequent rejections of the null hypothesis. Given the estimated change-point time 1984Q1 and the revised data being used, it could have been detected in the late 1980s using the proposed methods.

5.2 Monitoring growth contributions

In this section the variances of the growth contributions of the components of GNP are monitored. With growth contributions we measure by what magnitude the components contribute to the relative growth rate of GNP. We compute the growth contributions by dividing the first differences of the variables by the lagged value of the Real GNP. For the the Real GNP the relative growth is monitored. We use the same time periods as in the previous section. Figure 9, panel a to h, plots the growth contributions of the variables.

In order to deal with the problem of serial correlation, we proceed in the same way as we did in the previous section. We test for structural change in the variance in the monitoring period with a controlled asymptotic size of 10%. For MOSUMQes, the simulated critical values used in the previous section are used.

The results of the monitoring of the period 1984Q1 – 2003Q3 by the testing procedures are given in Table 8.

Table 8. Date of rejection of the null hypothesis when monitoring growth contributions. ↑ and ↓ indicate that the null hypothesis is rejected in favour of an increase and a decrease in the variance, respectively. No rejection of the null hypothesis of stability is denoted by NR. Variables are in real quantities.

Variable	CUSUMQ	CUSUMQes	RCUSUMQ	MOSUMQes h=0.25	MOSUMQes h=0.50	MOSUMQes h=1
GNP	1989Q1 ↓	1994Q1 ↓	1987Q2 ↓	NR	1996Q1 ↓	1999Q3 ↓
Consump.	NR	NR	NR	NR	NR	NR
Invest, bus. fixed	NR	NR	NR	NR	NR	NR
Invest, residential	1988Q3 ↓	1991Q3 ↓	1987Q2 ↓	2000Q1 ↓	1995Q1 ↓	1997Q1 ↓
Invest, inventories	NR	NR	NR	NR	NR	NR
Government purchases	1998Q4 ↓	1999Q4 ↓	NR	NR	1993Q3 ↓	1990Q1 ↓
Exports	2001Q2 ↑	2001Q4 ↑	2002Q4 ↑	2000Q1 ↑	2001Q1 ↑	2001Q2 ↑
Imports	NR	NR	NR	2002Q4 ↑	NR	NR

The relation between the methods with respect to time of rejection is more or less the same as for the growth rates. Like the growth rates, in most of the cases where the null hypothesis is rejected, it is made in favor of a smaller alternative that is a decrease in the volatility. There are slightly fewer cases where the null hypothesis is rejected compared to growth rates.

Compared with growth rates, the times of rejection in favor of stability are made earlier for Real investment, residential and more frequently for the variable Real government purchases of goods and services. We find the opposite to hold for Real investment, changes in inventories and Real imports of goods and services where growth rates appear to give a clearer indication of stability. Given the estimated change-point time 1984Q1 and the revised data being used, it could have been detected in the late 1980s using the proposed methods.

5.3 Small sample properties of the tests

A drawback with a Monte Carlo study is that the model used in the simulations might not be representative of the process we want to study. Though an actual data set is certainly representative of the specific time period and situation at hand, it might deviate randomly from the process of interest. However, it is impossible to know whether an outcome is extreme or not if not several examples are available or if the process is replicated.

To assess the sample behavior of the tests in the case study above, we investigate their properties for a historical data set and a monitoring period of length 120 and 79 respectively. For an IID Gaussian distributed process and a controlled asymptotic size

Though size distortions and the ability to detect structural changes that occur late can be coped with, we find that the performance of some of the suggested solutions are highly dependent on the size and direction of the change.

In the empirical illustration of the methods on a set of macroeconomic variables of the U.S. economy, we found that in most of the cases where stability is rejected, it is made in favor of a decrease in the volatility. Given the estimated change-point time 1984Q1 of the volatility drop and the revised data being used, the change could have been detected in the late 1980s using the proposed methods.

Not all relevant factors influencing the tests have been examined here. The question remains what effect e.g. autocorrelation, skewed distributions, temporary changes and smooth transition between the alternatives have on the tests. Also the properties of the tests for smaller samples than those used here is worth receiving more attention. Furthermore, considering a moving window based version of the proposed robust test might be a scope for further study.

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Research Report

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