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Discussion Paper Series

Testing for Volatility Changes in US Macroeconomic Time Series

By

Marianne Sensier[†] and Dick van Dijk[*]

[†]Centre for Growth and Business Cycle Research, School of Economic Studies, University of Manchester, Manchester, M13 9PL, UK
[*]Econometric Institute, Erasmus University Rotterdam, The Netherlands

September 2003
Number 036

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Marianne Sensier†
Centre for Growth and Business Cycle Research
School of Economic Studies
University of Manchester

Dick van Dijk‡
Econometric Institute
Erasmus University Rotterdam

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Abstract

We test for a change in the volatility of 214 US macroeconomic time series over the period 1959-1999. We find that about 80% of these series have experienced a break in unconditional volatility during this period. Even though more than half of the series experienced a break in conditional mean, most of the reduction in volatility appears to be due to changes in conditional volatility. Our results are robust to controlling for business cycle nonlinearity in both mean and variance. Volatility changes are more appropriately characterized as an instantaneous break rather than as a gradual change. Nominal variables such as inflation and interest rates experienced multiple volatility breaks and witnessed temporary increases in volatility during the 1970s. Based upon this evidence, we conclude that the increased stability of economic fluctuations is a wide-spread phenomenon.

Keywords: volatility, structural change tests, business cycle nonlinearity.

JEL Classification Codes: C52, E32.

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*Financial support from the Leverhulme Trust, the ESRC (grant no. L138251030) and the Netherlands Organization for Scientific Research (N.W.O.) is gratefully acknowledged. Part of this work was completed while the second author was visiting the Department of Economics, University of California at San Diego. The hospitality and stimulating research environment provided are gratefully acknowledged. We thank Clive Granger, James Hamilton, John Haywood, Denise Osborn, Alessandra Pelloni, Allan Timmermann, three anonymous referees and the editor James Stock for helpful comments and discussion. Any remaining errors and shortcomings are ours.

†Centre for Growth and Business Cycle Research, School of Economic Studies, University of Manchester, Manchester M13 9PL, United Kingdom, `email: marianne.sensier@man.ac.uk`

‡Econometric Institute, Erasmus University Rotterdam, P.O. Box 1738, NL-3000 DR Rotterdam, The Netherlands, `email: djvandijk@few.eur.nl` (corresponding author)

1 Introduction

The volatility of US output growth has shown a substantial decline in the early 1980s, as uncovered by Kim and Nelson (1999) and McConnell and Perez-Quiros (2000). Subsequent research has detected similar volatility reductions in other important macroeconomic variables such as employment, consumption and income,[1] suggesting that business cycle fluctuations in the US have dampened considerably over the last two decades.

In this paper, we further investigate the extent of the change in the variability of economic fluctuations by testing for a change in the volatility of 214 monthly US macroeconomic variables over the period 1959-1999. We find that about 80% of these series have experienced a break in unconditional volatility during this period, with most breaks occurring after 1980. We demonstrate that, even though more than half of the series experienced a break in conditional mean, most of the reduction in volatility appears to be due to changes in conditional volatility. We also document that our results are robust to controlling for business cycle nonlinearity in both mean and variance, and that the volatility changes are more appropriately characterized as instantaneous breaks rather than as gradual changes. Finally, we find that nominal variables such as inflation and interest rates experienced multiple volatility breaks and witnessed temporary increases in volatility during the 1970s. Based upon this evidence, we conclude that the increased stability of economic fluctuations is a widespread phenomenon.

Our analysis is similar in spirit to independently conducted research by Stock and Watson (2002), examining a data set of 168 quarterly US macroeconomic time series. Their emphasis is more on exploring the different explanations for the reduction in volatility that have been put forward. Here we confine ourselves mainly to documenting the prevalence and robustness of the decline in volatility, although we provide some links to its possible causes. Our results do not provide unequivocal support for a single explanation for the reduction in macroeconomic volatility. The finding that changes in conditional volatility are remarkably similar to changes in unconditional volatility does suggest, however, that a large part of the reduction is due to "good luck" in the form of a reduction in volatility of exogenous shocks.

[1]See Ahmed, Levin and Wilson (2002), Blanchard and Simon (2001), Chauvet and Potter (2001), Herrera and Pesavento (2003), McConnell, Mosser and Perez-Quiros (1999), and Stock and Watson (2002), among others.

2 Structural Change in Unconditional Volatility

We examine a data set originally compiled by Stock and Watson (1999), consisting of 214 monthly US macroeconomic time series, where we extend the sample period to January 1959-December 1999. The series are conveniently grouped in categories as shown in Table 1, with the number of series in each category in parentheses. A detailed description of the data set can be found in Stock and Watson (1999).

We start our analysis by testing for a one-time instantaneous structural change in the unconditional volatility of monthly growth rates of the series, denoted as y_t. This is implemented by testing for a break in the mean of the absolute value of the demeaned growth rates. Let $W_T(\tau_v)$ denote the heteroskedasticity and autocorrelation-consistent (HAC) Wald test of the null hypothesis $H_0 : \delta_1 = \delta_2$ in the regression

$$\sqrt{\frac{\pi}{2}}|y_t - \hat{\mu}| = \delta_1(1 - \mathtt{I}(t > \tau_v)) + \delta_2\mathtt{I}(t > \tau_v) + \varepsilon_t, \qquad t = 1, \ldots, T, \tag{1}$$

where $\hat{\mu}$ denotes the sample mean of y_t, T is the sample size, τ_v is the specified break date, and $\mathtt{I}(A)$ is an indicator function for the event A.[2] We treat the break date τ_v as unknown and use the sup-Wald statistic developed by Andrews (1993), given by[3]

$$\text{SupW} = \sup_{\tau_1 \leq \tau_v \leq \tau_2} W_T(\tau_v). \tag{2}$$

We require both pre- and post-break periods to contain at least 15 % of the available observations, that is we set $\tau_1 = [\pi T]$ and $\tau_2 = [(1 - \pi)T] + 1$ with $\pi = 0.15$, where $[\cdot]$ denotes integer part. We use the method of Hansen (1997) to obtain approximate asymptotic p-values and employ a 5% significance level throughout. The value of τ_v that minimizes the sum of squared residuals in (1) is taken to be the estimate of the break date, confidence intervals for which are computed using the methods developed in Bai (1997a).[4]

Results from the SupW test are summarized in the first two columns of Table 1 and in Figure 1. Cross-plots of the break dates against the percent change in

[2] If y_t follows a normal distribution with mean μ, $\sqrt{\frac{\pi}{2}}|y_t - \hat{\mu}|$ is a unbiased estimator of the standard deviation of y_t.

[3] Average and exponential statistics, computed as $\text{AveW} = \frac{1}{\tau_2 - \tau_1 + 1}\sum_{\tau_v=\tau_1}^{\tau_2} W_T(\tau_v)$ and $\text{ExpW} = \ln\left(\frac{1}{\tau_2 - \tau_1 + 1}\sum_{\tau_v=\tau_1}^{\tau_2} \exp\left(\frac{1}{2}W_T(\tau_v)\right)\right)$, respectively, render qualitatively similar results. The same holds for Lagrange Multiplier and Likelihood Ratio based tests. Details are available upon request.

[4] When computing these confidence intervals we take into account the fact that, in the presence of a structural change, the variance of the error term in the test regression (1) is different before and after the break, cf. Stock and Watson (2002). This results in asymmetric confidence intervals, with less uncertainty about the break date in the high than the low volatility period.

standard deviation, including 90% confidence intervals for both, are shown in Figure 2 for selected groups of series. Detailed results for individual series are available upon request.

A significant change in unconditional volatility is detected for 168 or 78.5% of the series, with a median change in standard deviation equal to –32.6%. In fact, almost three-quarters of the significant changes concern a reduction in volatility, as can be seen from Figure 1(a). More than 70% of the volatility changes are dated in the 1980's and the first half of the 1990's, with a particularly large number of breaks occurring in 1984, see Figure 1(b). The scatter in Figure 1(c) reveals a pronounced negative relationship between the timing and magnitude of the volatility breaks. For example, of the 48 (120) volatility changes dated before (after) January 1980, 38 (8) are positive and 10 (112) are negative. We also find a marked contrast between real variables (production, employment, wages and salaries, construction, trade, inventories, orders, consumption and miscellaneous) and nominal variables (money and credit, stock prices, dividends and volume, interest rates, exchange rates, producer and consumer prices): Of the 115 (out of 131) real series for which a significant volatility break is detected, the change is negative (positive) for 101 (14) series. By contrast, volatility has declined (increased) for 21 (32) of the 53 (out of 83) nominal variables with significant volatility changes.

These overall results mask interesting differences occurring across and within groups of series. We highlight some of these below. First, total industrial production growth experienced a decline in standard deviation of more than 40%, where the break is dated in March 1984 with the corresponding 90% confidence interval running from August 1983 to December 1986.[5] This is consistent with the break in volatility of GDP occurring in the first quarter of 1984, as documented by McConnell and Perez-Quiros (2000). Most series in the production category experienced declines in volatility of similar magnitude around the same time. Notable exceptions are production and capacity utilisation for utilities, which saw volatility increasing by 70% and 43% in 1980 and 1982, respectively, following the second OPEC oil price shock.

Second, volatility declines are dated in 1984 for production and capacity utilisation of durable consumer goods and durable manufacturing, while for the analogous series for nondurables these occurred only in 1990. This is in line with McConnell and Perez-Quiros (2000) that the break in output volatility originates from a reduc-

[5] In general, the span of the confidence intervals varies widely, ranging from a few months to more than a decade.

tion in volatility of durable goods production.

Third, the reduction in volatility of inventories is dated in 1986 (both for durable and non-durable manufacturing goods), with the lower limit of the 90% confidence intervals placed at the end of 1984, that is after the reduction in production volatility. This goes against the explanation put forward by Kahn, McConnell and Perez-Quiros (2002) that change in inventory management is the driving force behind reductions in output volatility (via reduced volatility of durable goods inventories). Also in contrast with Kahn *et al.* (2002), we do find a substantial decline in durable goods trade volatility (–40%), albeit it is dated in 1990 only. On the other hand, volatility of unfilled orders decreased by 40% in 1979 and 1984 for durable and non-durable manufacturing goods, respectively. This provides somewhat more positive evidence for the hypothesis that reduced output volatility is due to better business practice, especially in the durable goods sector.

Fourth, the main employment and unemployment series experienced a decline in volatility around 1984. We find similar reductions around the same time for all sectors of the economy, in contrast to Warnock and Warnock (2000) who found that only employment in (durable goods) manufacturing has become more stable. These conflicting results can be attributed to major differences in methodology.

Fifth, the results for the monetary/financial variables also reveal several interesting features. All significant volatility changes in the money and credit series are positive, with break dates varying widely from 1968 until 1991. Results for interest rate series are in line with Watson (1999). Medium- and long-term rates have experienced increases in volatility at the end of the 1960s or 1970s, while short-term interest rates, including the Federal Funds rate and the 3- and 6-month Treasury Bills, have declines in volatility between 1983 and 1985. This would support the explanation advocated by Clarida, Galí and Gertler (2000), Kim, Nelson and Piger (2003) and Herrera and Pesavento (2003), that the reduction in output volatility is due to improved monetary policy. Finally, the volatility changes in consumer and producer prices clearly fall into two groups: substantial increases in the early 1970s on the one hand, and decreases in the early 1980s. This is in line with the hypothesis of Blanchard and Simon (2001) that falls in inflation volatility after the temporary increases in the 1970s are an important determinant of output volatility reductions.

3 Structural Change in Conditional Mean and Volatility

The changes in unconditional volatility documented above may be due to changes in the conditional mean or in the conditional variance, or in both. For example, Kim and Nelson (1999) argue that a smaller gap between mean growth rates during expansions and contractions is more important than the decline in the volatility of shocks in explaining the increased stability of US output after 1984. Overwhelming evidence for structural change in the conditional mean dynamics of US macroeconomic variables is provided in Stock and Watson (1996).

To explore this issue, we consider a linear autoregressive (AR) model with a single structural change at time τ_m,

$$y_t = (\phi_{10} + \phi_{11}y_{t-1} + \ldots + \phi_{1p}y_{t-p})(1 - \mathtt{I}(t > \tau_m)) + (\phi_{20} + \phi_{21}y_{t-1} + \ldots + \phi_{2p}y_{t-p})\mathtt{I}(t > \tau_m) + \varepsilon_t, \quad (3)$$

where ε_t is a martingale difference sequence with time-varying conditional variance $\mathsf{E}[\varepsilon_t^2|\Omega_{t-1}] = \sigma_t^2$, where

$$\sigma_t = \sigma_1(1 - \mathtt{I}(t > \tau_v)) + \sigma_2\mathtt{I}(t > \tau_v). \quad (4)$$

Note that we allow the break date τ_m for the conditional mean to be different from the break date in conditional volatility τ_v. Our testing strategy in this case is to first test for a structural change in the conditional mean, and estimate the parameters in (3) using the value of τ_m that minimizes the sum of squared residuals as the estimate of the break date. We then proceed with testing for a structural change in the conditional standard deviation using the SupW procedure described in the previous section, but instead of the demeaned growth rates now using $\sqrt{\frac{\pi}{2}}|\hat{\varepsilon}_t|$ as the dependent variable in (1), where $\hat{\varepsilon}_t$ are the residuals from (3).

In total 59% of the series show evidence of structural change in the conditional mean, as shown in the third column of Table 1. A (relatively) large number of changes in mean are found in interest rates, producer and consumer prices, consumption, and production. The histogram of estimated mean break dates shown in Figure 3 shows that most breaks are dated in a few particular short episodes: 1973-4, 1980-1982 and 1984. Obviously, many breaks in conditional mean can be attributed to the OPEC oil price shocks.

Significant conditional volatility breaks are detected for 80% of the series, with a median change in standard deviation of –33.5%, see the final two columns of Table

1. This corresponds rather closely with the results from tests for changes in unconditional volatility. The main effect of allowing for a structural change in mean appears to be that for quite a few series the break in volatility is dated somewhat later, in particular in the early 1990s, as shown in Figure 4(b). The distribution of percent changes in standard deviation is largely unaffected (see Figure 4(a)), while the negative relationship between timing and magnitude of the volatility break continues to emerge from the scatter in Figure 4(c). Comparing the relevant columns in Table 1 in fact shows that for most groups the test results for changes in unconditional volatility and for conditional volatility are remarkably similar. Substantial differences are found only for orders and money and credit groups, for which the numbers of significant changes in conditional volatility are considerably higher and lower, respectively.

In sum, even though changes in the conditional mean dynamics appear to be a relevant feature of the majority of US macroeconomic time series, they do not account at all for the observed changes in volatility. This provides quite strong support for the "good luck" hypothesis that the reduced output volatility is primarily accounted for by a reduction in the variance of exogenous shocks hitting the economy, cf. Ahmed, Levin and Wilson (2002) and Stock and Watson (2002). In the remainder of this section we summarize results from additional tests, which are performed to examine the robustness of the results discussed above.

3.1 Nonlinearities in Conditional Mean and Volatility

Next we examine whether the observed reductions in volatility may be due to neglected business cycle asymmetry in the (conditional) mean or variance. The volatility of macroeconomic variables typically is higher during recessions than during expansions (Brunner, 1992; French and Sichel, 1993), while mean growth rates and conditional mean dynamics also tend to be quite different during these different business cycle phases (Acemoglu and Scott, 1997; Lundbergh, Teräsvirta and van Dijk, 2003). Given that after the trough of November 1982 only eight months (August 1990-March 1991) are coined as "recession" by the NBER as opposed to 59 months before this trough, it may be that the apparent reduction in volatility may simply be due to the "lack of recessions" during the second half of our sample period.

For our data set, we find that 62% and 68% of all series exhibit significant business cycle asymmetry in conditional mean dynamics and in conditional variance, respectively, where we use NBER turning points to define expansions and recessions. A high incidence of nonlinearity occurs in production, employment, trade, orders, consumption, stock prices (volatility only) and interest rates. Allowing for nonlinearity in the conditional mean dynamics (with or without allowing for structural change during expansions[6]) has very little effect on subsequent tests for structural change in conditional volatility. Similarly, allowing for nonlinearity in (un)conditional volatility and testing for structural change in volatility during expansions renders results that are qualitatively identical and quantitatively similar to those discussed before. Results are not shown here to save space, but are available upon request.

3.2 Smooth changes in Conditional Mean and Volatility

There has been some discussion whether the reductions in volatility of US output and other macroeconomic variables are best characterized as instantaneous breaks or as gradual ("smooth") changes, see Blanchard and Simon (2001) and Stock and Watson (2002). We examine this issue by replacing the indicator function $\mathtt{I}(t > \tau_v)$ in (1) and (4) by the logistic function

$$F(t;\gamma,\tau_v) = \frac{1}{1+\exp(-\gamma(t/T-\tau_v))}, \qquad \gamma > 0, \tag{5}$$

which changes smoothly from 0 to 1 as t increases, while $F(\tau_v;\gamma,\tau_v) = 0.5$ such that τ_v represents the mid-point of the change in volatility and hence can still be interpreted as the "break date". The parameter γ controls the degree of smoothness in the transition of $F(t;\gamma,\tau_v)$ from 0 to 1. In particular, as $\gamma \to \infty$, the logistic function approaches the indicator function $\mathtt{I}(t > \tau_v)$.

When estimating the resulting smooth transition model, we find significant differences between pre- and post-change volatility for 75% and 83% of the series for unconditional and conditional volatility, respectively. For the large majority of series, the estimates are such that volatility declines over time. In general, the estimate of γ in (5) is rather large, such that the change of $F(t;\gamma,\tau_v)$ from 0 to 1 is almost instantaneous. Hence, it appears that the volatility changes are best characterized as discrete breaks rather than as gradual changes, cf. Stock and Watson (2002). Again, detailed results are not shown but are available upon request.

3.3 Multiple Breaks in Volatility

As a final robustness check, we examine the possibility of multiple breaks in volatility. This is partly motivated by the previous results for producer prices and other

[6] We do not allow for structural change in the conditional mean dynamics during contractions given the limited number of recession months during our sample period. For the same reason, we only test for structural change in (un)conditional volatility during expansions below.

nominal variables, where for some series a significant increase early in the sample period is found, while for others a reduction in volatility at a later date is detected. This suggests the possibility that the increase in volatility may have been a temporary phenomenon, and that the volatility of these variables has undergone multiple breaks. Further motivation is given by the observed negative relationship between the timing and magnitude of the volatility break: this pattern would also be observed in the presence of two structural changes where the first break is an increase in volatility and the second a decrease.

We employ the sequential procedure of Bai (1997b) to test for multiple changes in (un)conditional volatility; see also Bai and Perron (1998).[7] We apply this sequential testing procedure both to the absolute value of demeaned growth rates and to the residuals from an AR(p) model with multiple structural changes for the conditional mean, to test for multiple changes in unconditional and conditional volatility, respectively. The number and timing of the breaks in the AR-parameters are determined by an analogous sequential procedure. As the results are qualitatively similar, we only report results from the procedure for testing for multiple breaks in conditional volatility.

Of the 126 series for which at least one significant change in the conditional mean is found, almost half have experienced multiple breaks, in particular production series, wages, interest rates and producer and consumer prices; see the first four columns of Table 2. A considerable number of money series and producer and consumer price series have experienced two changes in volatility, see the next four columns of Table 2. A notable difference is that, on average, volatility for the money series increases at both breaks, whereas volatility of the price series generally shows a hump-shaped pattern, with an increase in volatility at the first break (generally in the early 1970s) followed by a decrease of roughly similar absolute magnitude at the second break (in the early 1980s). To some extent this can be seen from the final four columns of Table 2 which shows the number of breaks and median percent change in volatility for breaks dated before and after January 1980. For money series, the median percent changes in volatility is positive for both sub-periods, while for producer and consumer price series the median change is positive (negative) for

[7]After detecting a first volatility break, the procedure is to split the sample at that date and to perform another break test separately on each sub-sample. This procedure is repeated until no further significant volatility breaks are detected, or until a maximum of five breaks is detected, or until the subsamples become too small for further splitting. Finally, the dates of each of the m detected breaks are re-estimated one by one, conditional on the dates of the remaining $m-1$ breaks obtained in the sequential procedure. Throughout these procedures, a minimum of 15% of the sample is required to lie between consecutive breaks.

breaks occurring before (after) 1980. More generally, these columns demonstrate the marked difference between breaks occurring before and after January 1980, where early breaks meant an increase in volatility on average, while later breaks generally reduced volatility. The large majority of interest rate series experienced three changes in volatility, showing a similar hump-shaped pattern as the producer and consumer price series. Multiple changes also are not uncommon in real series such as construction, orders and consumption, although most real series show evidence of only a single volatility break.

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Table 1: Tests for structural change in unconditional volatility, conditional mean and conditional volatility

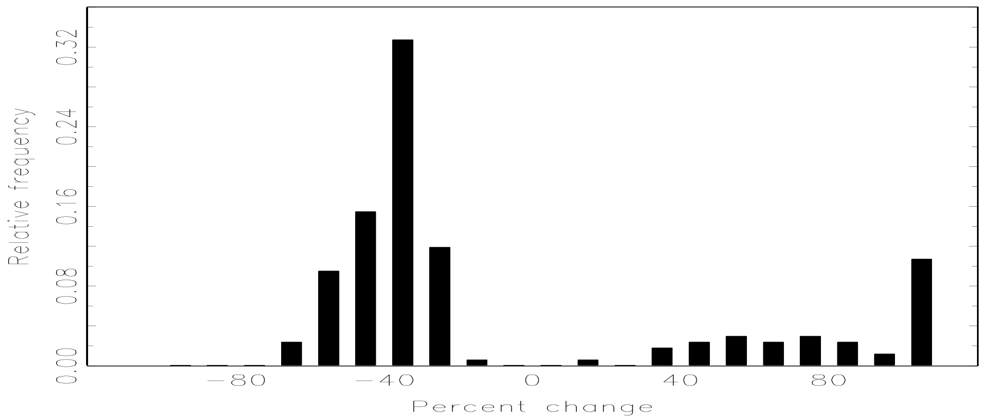
	UV		CM	CV	
Group	#R	$\Delta\sigma$	#R	#R	$\Delta\sigma$
Production (24)	21	−40.9	18	21	−37.6
(Un)Employment (29)	27	−39.5	20	29	−37.4
Wages and salaries (7)	7	−36.2	5	7	−44.4
Construction (21)	14	−31.6	5	13	−34.9
Trade (10)	9	−34.7	5	10	−35.5
Inventories (10)	10	−32.4	5	9	−29.4
Orders (14)	13	−28.3	9	7	−27.9
Consumption (5)	5	−37.1	4	5	−38.2
Money and credit (20)	11	99.8	7	16	66.8
Stock Prices (11)	3	−32.5	1	4	−27.8
Dividends and volume (3)	1	−60.7	2	1	−50.9
Interest rates (11)	11	152.8	10	11	107.9
Exchange rates (6)	3	54.3	0	3	53.1
Producer prices (16)	12	66.0	13	13	−23.9
Consumer prices (16)	12	−40.9	16	13	−39.5
Miscellaneous (11)	9	−35.4	6	9	−34.7
Total (214)	168	−32.6	126	171	−33.5

The table contains results of SupW tests for a single structural change in (un)conditional volatility and conditional mean in 214 monthly US macroeconomic time series over the period 1959-1999. Columns headed "UV" contain results of tests for change in unconditional volatility. The column headed "CM" concerns results of tests for change in the conditional mean (that is in the parameters in the linear autoregressive model (3)). Columns headed "CV" contain results of tests for change in conditional volatility (while allowing for a change in conditional mean). Columns headed "#R" contain the number of rejections of the null hypothesis of constant (un)conditional volatility or conditional mean at the 5% nominal significance level, where the procedure of Hansen (1997) is used to obtain approximate asymptotic p-values. Columns headed "$\Delta\sigma$" contain the median percent change in the (un)conditional standard deviation for those series for which the SupW test statistic is significant. Numbers in parentheses following the series type denote the number of series tested.

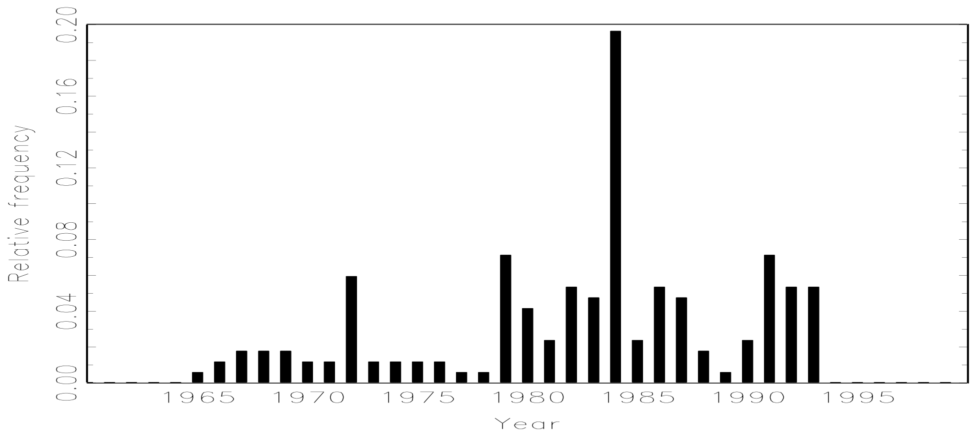
Table 2: Tests for multiple structural changes in conditional volatility

	m CM changes				m CV changes					Before 1980		After 1980	
	1	2	3	#R	1	2	3	#R	$\Delta\sigma$	#B	$\Delta\sigma$	#B	$\Delta\sigma$
Production (24)	9	9	0	18	18	3	0	21	−37.5	4	52.3	20	−38.9
(Un)Employment (29)	13	5	2	20	23	4	1	28	−37.8	12	−33.4	22	−40.1
Wages and salaries (7)	0	5	0	5	7	0	0	7	−46.0	0	–	7	−46.0
Construction (21)	5	0	0	5	9	6	0	15	−31.1	9	45.6	12	−35.0
Trade (10)	5	0	0	5	7	3	0	10	−41.9	3	41.7	10	−42.3
Inventories (10)	3	2	0	5	7	3	0	10	−29.3	4	38.3	9	−33.4
Orders (14)	8	1	0	9	5	3	1	9	−21.3	6	54.9	8	−34.2
Consumption (5)	3	1	0	4	1	4	0	5	−37.7	2	133.9	7	−38.7
Money (20)	7	0	0	7	10	5	2	17	47.1	15	93.1	11	38.0
Stock Prices (11)	1	0	0	1	3	1	0	4	−29.8	3	−29.1	2	−32.0
Dividends and volume (3)	1	1	0	2	0	1	0	1	−70.4	1	−41.6	1	−49.3
Interest rates (11)	2	3	5	10	1	1	9	11	27.2	16	176.3	14	−50.9
Exchange rates (6)	0	0	0	0	2	1	0	3	63.6	2	67.6	2	−2.1
Producer prices (16)	4	4	5	13	6	8	1	15	21.6	16	87.4	9	−33.4
Consumer prices (16)	1	3	12	16	3	12	0	15	−22.9	13	60.7	14	−43.9
Miscellaneous (11)	5	1	0	6	7	3	0	10	−33.9	5	45.6	8	−35.8
Total (214)	67	35	24	126	109	58	14	181	−29.5	111	63.1	156	−38.2

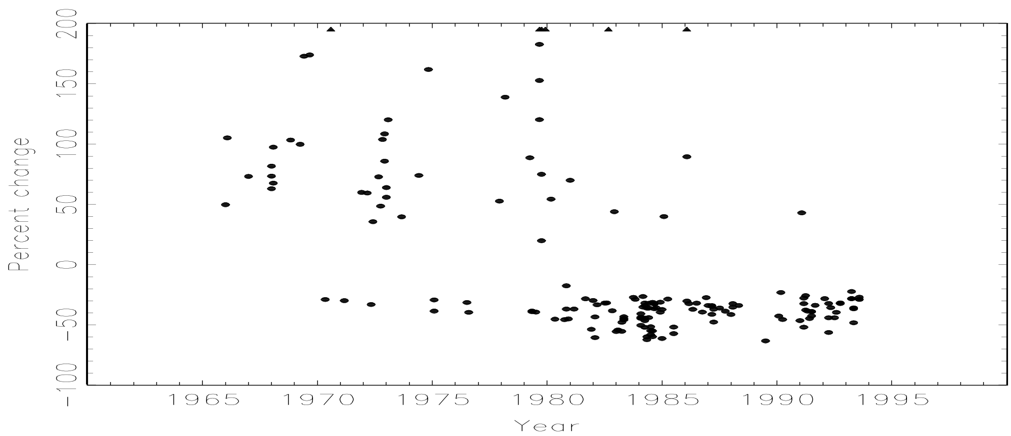
The table contains results of sequential tests for multiple structural changes in conditional mean or in conditional volatility. Columns headed "m CM (CV) changes", $m = 1, 2, 3$ contain the number of series for which m changes in conditional mean (conditional volatility) are found based upon the sequential testing procedure of Bai and Perron (1998). Columns headed $\#R$ contain the number of series for which at least one change is detected. The column headed "$\Delta\sigma$" contain the median percent "net" change in the standard deviation (that is the difference between the standard deviations after the final structural change and before the first change) across all series for which at least one change in volatility is found. In the blocks headed "Before (After) 1980", columns headed "$\#B$" contain the number of breaks dated before (after) January 1980, while columns headed "$\Delta\sigma$" contain the median percent change in the standard deviation across these breaks.



(a) Histogram of percent change in unconditional volatility

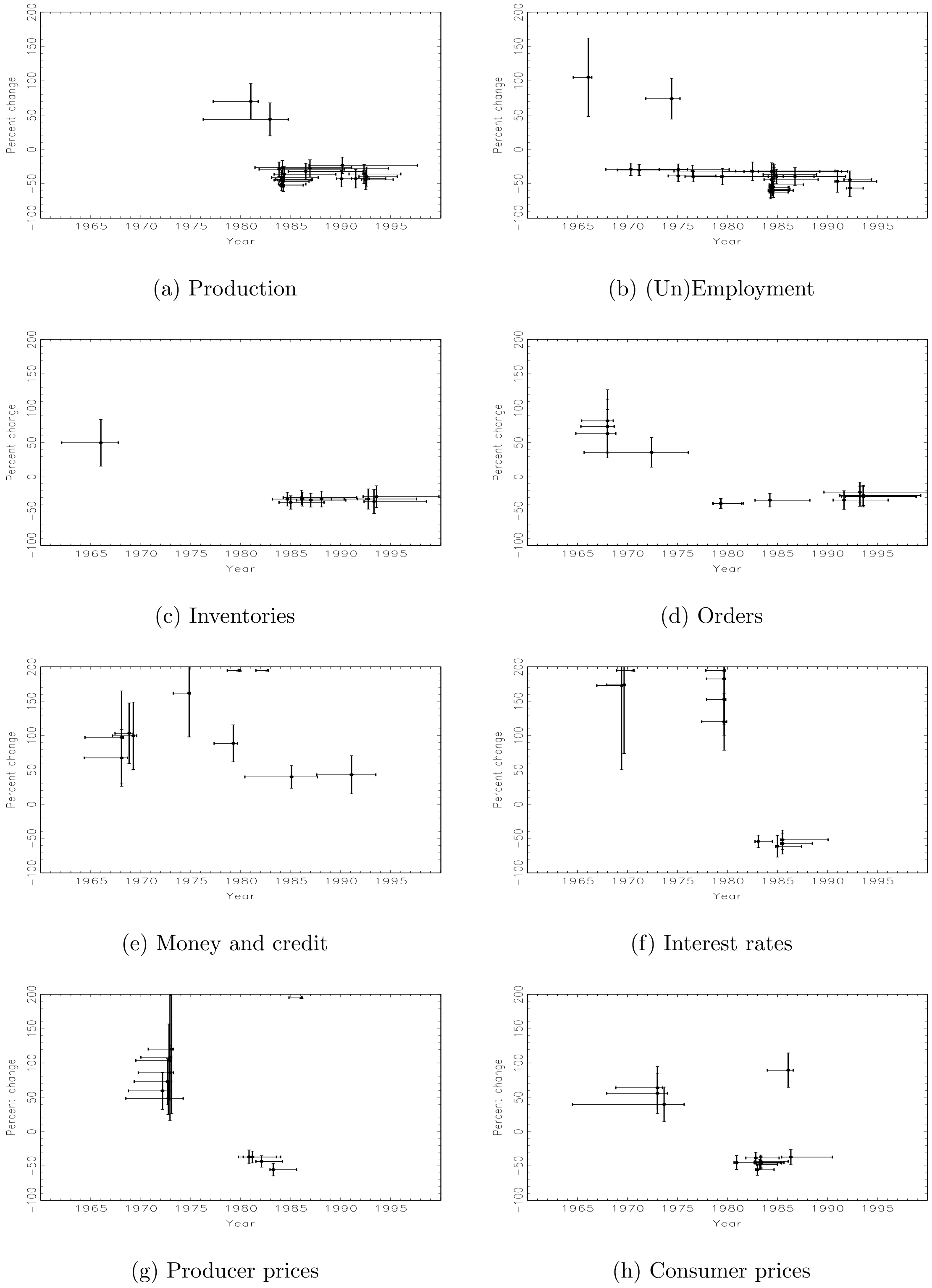


(b) Histogram of estimated break dates



(c) Scatter of break dates against percent change in standard deviation

Figure 1: Characteristics of unconditional volatility breaks for series for which the SupW statistic is significant at the 5% level (168 series). In panel (a), series for which the standard deviation more than doubles are collected in the right-most category. In panel (c), series for which the standard deviation more than triples are shown as triangles.



(a) Production

(b) (Un)Employment

(c) Inventories

(d) Orders

(e) Money and credit

(f) Interest rates

(g) Producer prices

(h) Consumer prices

Figure 2: Scatter plots of volatility break dates against percent change in unconditional standard deviation for series for which the SupW statistic is significant at the 5% level. 90% Confidence intervals for the break date and the percent change in standard deviation are included. Series for which the standard deviation more than triples are shown as triangles.

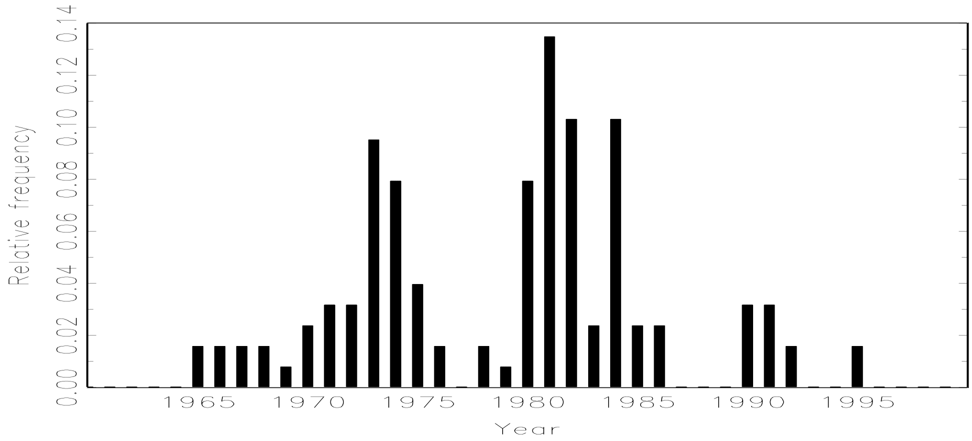
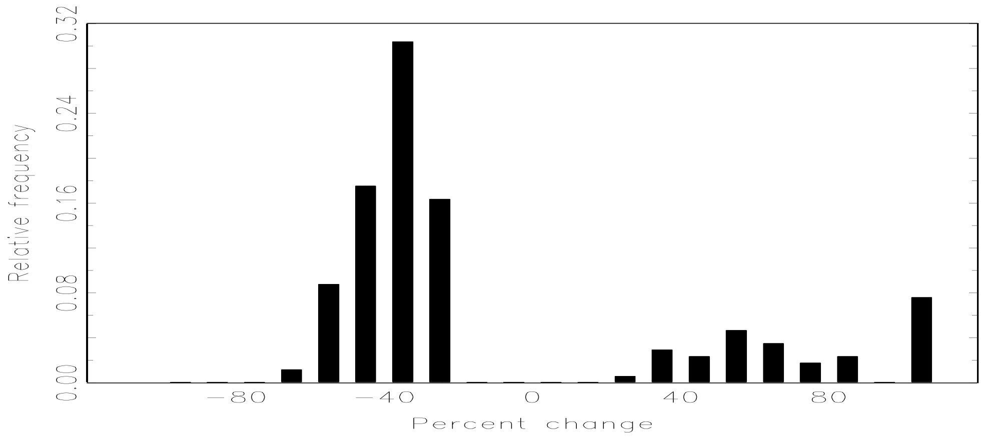
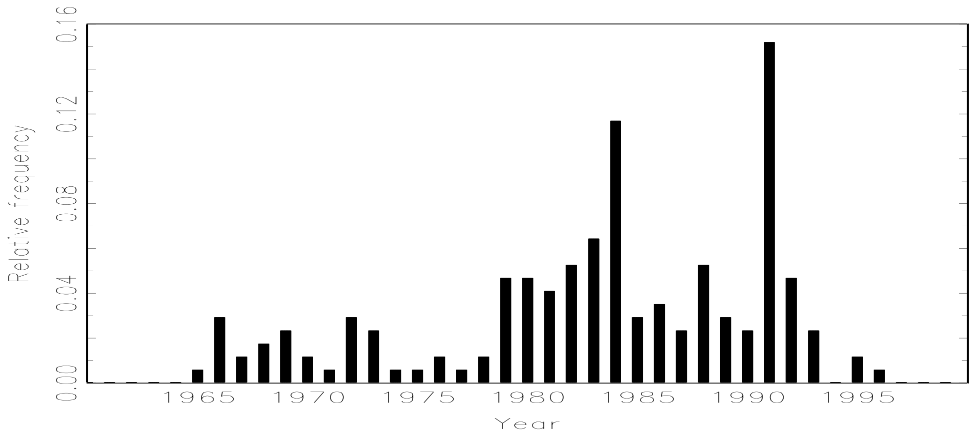


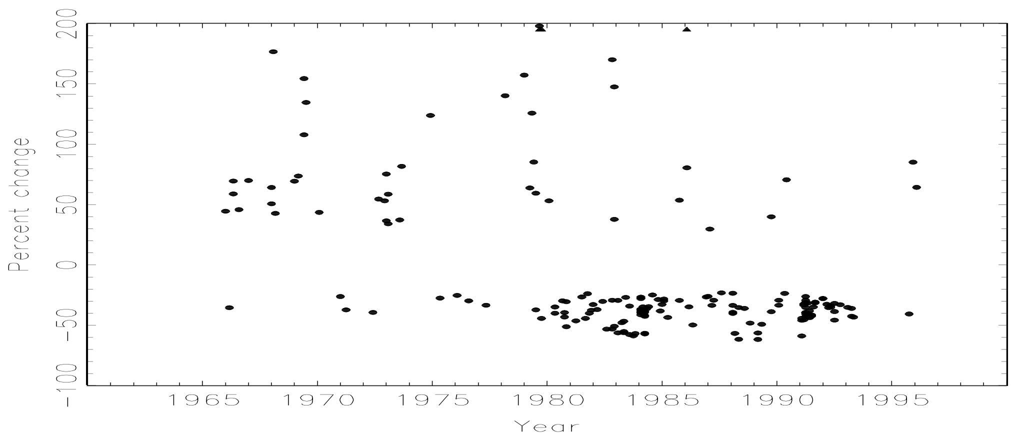
Figure 3: Histogram of estimated break dates for series for which the SupW statistic for a structural change in conditional mean (that is the parameters in the linear model (3)) is significant at 5% level (126 series).



(a) Histogram of percent change in conditional standard deviation



(b) Histogram of break dates



(c) Scatter of break dates against percent change in standard deviation

Figure 4: Characteristics of conditional volatility breaks for series for which the SupW statistic is significant at the 5% level (171 series). In panel (a), series for which the standard deviation more than doubles are collected in the right-most category. In panel (c), series for which the standard deviation more than triples are shown as triangles.