Modelling UK Inflation Uncertainty: The Impact of News and the Relationship with Inflation

by

*M A S Joyce**
Bank of England

April 1995

* The views expressed are those of the author and do not necessarily reflect those of the Bank of England. I am grateful to an anonymous referee and several colleagues at the Bank for helpful comments. In particular, I would like to thank Francis Breedon, Andrew Derry and Bahram Pesaran. The usual disclaimer applies.

ISSN 0142-6753

Contents

Abstract

This paper estimates UK quarterly inflation uncertainty over 1950-94, conditional on a univariate specification of mean inflation, using a variety of ARCH-related volatility models. To discriminate between these models, we employ the partially non-parametric methodology of Engle and Ng (1993), which focuses on measuring the 'news impact curve'. Our results reject the symmetry restriction imposed in standard ARCH and GARCH models, suggesting that inflation uncertainty is much more sensitive to 'bad news' than 'good news'. Our preferred estimates of the conditional variance of inflation are found to be positively associated with the level of inflation.

1 Introduction

Uncertainty about future inflation is often claimed to be one of the most important costs of inflation, since it distorts the workings of the price system and leads to allocational inefficiencies. Moreover, starting with Okun (1971) and Friedman (1977), it has been argued that high inflation itself leads to greater uncertainty about the path of future inflation rates.[1] But, although high rates of inflation have often been shown to be associated with greater inflation variability (eg as measured by the unconditional standard deviation or variance), this need not imply a link with greater inflation uncertainty. The latter depends on inflation's forecastability, which may be invariant to its level.

A natural framework for measuring inflation uncertainty is the class of autoregressive heteroscedasticity (ARCH) models originally introduced by Engle (1982), which allow the conditional variance to change over time according to past forecasting errors.[2] Indeed, although the use of ARCH models is more commonly associated with the finance literature, the first applications of ARCH and its subsequent generalised version (GARCH) were to modelling quarterly inflation [see Engle (1982), Engle (1983), Engle and Kraft (1983) and Bollerslev (1986)].

More recent extensions of the ARCH framework - motivated primarily by the inability of these simple models to explain important features of financial data[3] - have resulted in a variety of models which allow the conditional variance to be affected asymmetrically by positive and

---

1 For a more recent formalisation of this view, see Ball (1992). A number of other models generate a relationship between the level and variability of inflation; eg Tsiddon (1993), Devereux (1989) and Cukierman and Meltzer (1986). For further discussion of the costs of inflation see Driffill, Mizon and Ulph (1990).

2 The uncertainty measures produced by such models are obviously conditional on the specifications of the mean and variance equations. See discussion in Section 2.

3 In particular, the so-called 'leverage' effect, whereby an unexpected stock price fall produces a bigger increase in volatility than a similar rise.

negative shocks. The 'news impact curve', recently proposed by Engle and Ng (1993), provides a convenient means of comparing these models. This curve is simply the relationship between current volatility and the previous period's news, holding other information constant. Engle and Ng (*op cit*) suggest several diagnostic tests (termed sign and size bias tests) based on the news impact curve to evaluate how well volatility models capture asymmetries in the data and they also propose a partially non-parametric ARCH model, which provides a more direct means of estimating the relationship between news and volatility.

These developments have obvious implications for measuring inflation uncertainty which this paper attempts to explore. Following on from the arguments of Okun (*op cit*), Friedman (*op cit*), and others, it seems plausible that higher-than expected inflation ('bad news') will generate more uncertainty about future inflation than lower-than-expected inflation ('good news'). When inflation rises unexpectedly, the authorites are, for example, more likely to come under pressure to change policy than when inflation is lower than expected. If there is greater uncertainty about future policy, then uncertainty about future inflation is also likely to increase. Another reason for expecting asymmetries follows if agents use good and bad inflation shocks to infer the preferences of the authorities towards inflation. Evidently, bad shocks are more likely to raise doubts over the authorities' commitment to fight inflation, thereby increasing inflation uncertainty. Whatever their source, if such asymmetries exist, then conventional, symmetric ARCH and GARCH models will provide misleading estimates of inflation uncertainty.

This paper has two main objectives. First, using Engle and Ng's methodology, we examine several common asymmetric volatility models and attempt to identify the best parsimonious ARCH representation of inflation uncertainty. This is obviously important in its own right since inflation uncertainty might be expected to explain other economic behaviour (eg, the inflation risk premium attached to equities may be a function of the conditional variance of inflation). The second objective of the paper is to examine whether any relationship exists between measured inflation uncertainty and the level of inflation. Using a slightly different framework and US data, Brunner and Hess (1993) have recently shown that once news asymmetries are allowed for there is a much stronger relationship between the level of inflation and its conditional variance. We try to establish whether the same holds true for UK retail price inflation over the postwar period.

The paper is structured as follows. Section 2 introduces the ARCH framework followed in the paper. Section 3 describes the data used and some of the stylised facts about UK inflation variability over the post-war period. In Section 4 we estimate univariate models of quarterly RPI, RPIX and RPIY inflation and test for ARCH effects. Then in Section 5 we estimate several ARCH models of inflation uncertainty, including a partially non-parametric specification, and compare them in terms of their implied news impact curves. In Section 6 we investigate the association between our preferred measures of the conditional variance of inflation and the level of inflation. Conclusions are presented in Section 7.

2 Empirical Framework

The framework we adopt for measuring inflation uncertainty can be described in the following general terms. Suppose π_t is the rate of price inflation in period t and Ω_{t-1} is the information set available in period t-1, then the conditional mean and conditional variance of inflation in period t may be defined as

$$m_t = E(\pi_t \mid \Omega_{t-1})$$

$$h_t = Var(\pi_t \mid \Omega_{t-1})$$

A necessary condition for inflation expectations to be rational must be that

$$\pi_t = m_t + \epsilon_t$$

where ϵ_t is a random error which can be thought of as a measure of inflation 'news' arriving at time t. Thus a positive realisation of ϵ_t implies that inflation is worse than expected, whereas a negative realisation implies that it is better than expected.

In principle, the information set available at period t-1 (ie Ω_{t-1}) should include everything that might be relevant to forecasting inflation. In this paper, however, we shall restrict it to past inflation rates and quarterly seasonal factors. Thus we estimate m_t using the following specification

$$\pi_t = \alpha_o + \sum_{i=1}^{n} \alpha_i \pi_{t-i} + seasonals + \epsilon_t$$

In the absence of an accepted structural model, this seems a useful benchmark to adopt, but it obviously means that we need to be cautious in interpreting the resulting measures of the conditional variance as measuring 'inflation uncertainty' in the strict sense. Nevertheless, we shall use the words volatility and uncertainty interchangeably for convenience.

In Engle's ARCH model, h_t is specified purely as a function of lagged ϵ_t terms. This was generalised by Bollerslev (1986) to include terms in the lagged conditional variance to allow for longer memory processes. Thus in the well-known GARCH(1,1) model, h_t has the following specification:

$$h_t = \gamma_o + \gamma_1 \epsilon^2_{t-1} + \delta_1 h_{t-1}$$

The presence of the lagged h_t term means that the impact of inflation shocks declines geometrically over time. The conditional mean and variance are estimated jointly under the assumption that

$$\epsilon_t \mid \Omega_{t-1} \sim N\ (0,\ h_t)$$

Although we find that the GARCH(1,1) model appears to measure inflation volatility reasonably well, the symmetry restriction - implying that good and bad news have identical effects on volatility - appears questionable on *a priori* grounds. We shall therefore also examine several other volatility models, originally developed in the context of measuring stock return volatility, which specifically allow for asymmetric effects.

In their recent study Engle and Ng (1993) compare a variety of such models in terms of the implied 'news impact curve': the relationship between the conditional variance, h_t, and the lagged error term, ϵ_t, holding everything else constant. In the case of an ARCH or GARCH process, the news impact curve will be a quadratic (and hence symmetric) function centred on $\epsilon_{t-1}=0$. But, for the asymmetric models they consider, the implied news impact curves are distinguished by either not being centred at the origin or by having different slopes on their positive and negative sides. Bearing this distinction in mind, we also estimate the following three asymmetric volatility models: the asymmetric ARCH model of Engle (1990), henceforth the AGARCH model; the exponential GARCH (EGARCH) model of Nelson (1990); and the model originally proposed by Glosten, Jagannathan and Runkle (1989) and Zakoian (1990), henceforth the GJR model. These are represented by the following equations:

AGARCH

$$h_t = \gamma_o + \gamma_1 \left(\epsilon_{t-1} + \gamma_2 \right)^2 + \delta_1 h_{t-1} \qquad (2.1)$$

EGARCH

$$\log h_t = \gamma_o + \gamma_1 \frac{\epsilon_{t-1}}{h_{t-1}^{1/2}} + \gamma_2 \left[\frac{|\epsilon_{t-1}|}{h_{t-1}^{1/2}} - \left(\frac{2}{\Pi} \right)^{1/2} \right] + \delta_1 \log h_{t-1} \qquad (2.2)$$

GJR

$$h_t = \gamma_o + \gamma_1 \epsilon_{t-1}^2 + \gamma_2 D_{t-1} \epsilon_{t-1}^2 + \delta h_{t-1} \qquad (2.3)$$

where $D_t = 1$ if $\epsilon_t > 0$ and $D_t = 0$ if $\epsilon \leq 0$

These models were chosen because between them they allow the news impact curve to be centred away from the origin (AGARCH) or to have different slopes on their positive and negative sides (EGARCH and GJR). For the AGARCH model, it is easy to show that the news impact curve will be centred at the point where $\epsilon_{t-1} = -\gamma_2$. Thus if bad news on inflation has a disproportionate effect on inflation uncertainty then we expect γ_2 to be positive. In the case of the EGARCH model, the term in the level of $\epsilon_{t-1} / \sqrt{h_{t-1}}$ allows the slopes of the news impact curve to be asymmetric; for $\gamma_2 > 0$, we expect $\gamma_1 > 0$. The GJR model captures asymmetry in a similar way to EGARCH; the γ_2 parameter acts to reinforce or offset the γ_1 parameter, thus we expect $\gamma_2 > 0$ if $\gamma_1 > 0$.

Following Engle and Ng (*op cit*), we compare these models by computing diagnostic statistics for sign and size bias which test how adequately they pick up asymmetries in the data. As a further test, we compare the implied news impact curves based on their parameter estimates with the curve revealed by the data using a partially non-parametric procedure. More precisely, we estimate the following linear spline model of the conditional variance of inflation

$$h_t = \gamma_o + \sum_{i=0}^{n} \gamma_{1i} D^{+}_{it-1} (\epsilon_{t-1} - \tau_i) + \sum_{i=0}^{n} \gamma_{2i} D^{-}_{it-1} (\epsilon_{t-1} + \tau_i) + \delta_1 h_{t-1}$$

$$D^{+}_{it} = 1 \text{ if } \epsilon_t > \tau_i \text{ and } D^{+}_{it} = 0 \text{ if } \epsilon_t \leq \tau_i$$

$$D^{-}_{it} = 1 \text{ if } \epsilon_t < \tau_i \text{ and } D^{-}_{it} = 0 \text{ if } \epsilon_t \geq \tau_i$$

where the knot points are the τ_i's. The implied news impact curve from this model is contrasted with the curves from the estimated GARCH, AGARCH, EGARCH and GJR models, in order to choose the best, parsimonious representation of the data.

Finally, we investigate whether there is an association between our preferred measure of inflation uncertainty and the level of inflation, by looking at correlations between lagged inflation and h_t, as well as by directly including lagged inflation terms in the h_t function itself to see whether they are statistically significant.

3 Preliminary Data Analysis

(a) Measuring inflation

As our measure of aggregate UK inflation, we use three measures of retail prices: RPI, RPIX and RPIY. The RPI has been published monthly since 1947, allowing us to derive results for the entire post-war period. As is well known, however, the inclusion of mortgage interest payments in the index (since 1974) causes movements in this measure to be distorted by interest rate changes. The measure of retail prices known as RPIX gets round this problem by excluding mortgage interest payments, but at the expense of excluding any measure of the cost of housing. Although data on RPIX are only available from 1974, we have spliced this series together with the RPI series before 1974 to allow us to extend our sample back to the immediate post-war period.

Both RPI and RPIX are sensitive to the short-run impact effect of changes in indirect taxes. In the empirical work described below (see Section 4), we made further adjustments to allow for particularly large Budget changes. A more systematic attempt to take out the direct impact effect of Budget changes has been made to produce the measure of retail prices known as RPIY [see Beaton and Fisher (1995)], which we also examine. However, this series is not available before 1976, severely restricting the degrees of freedom available in using it. Our estimation results therefore use all three measures of prices. (For precise data sources see Annex 1.)

(b) Descriptive statistics and time series properties

Quarterly percentage growth rates of RPI, RPIX and RPIY are shown in Chart 3.1 and summary descriptive statistics and time series properties for these series are shown in Tables 3.1 and 3.2 respectively. Here and throughout the rest of this paper, quarterly price inflation data are calculated from the logarithmic changes of the end-month figures, in order to avoid well-known problems of spurious correlations which can be induced by averaging [see Working (1960)].

One striking thing to emerge from Table 3.1 is that over the longest common sample period (1976 Q2 - 1994 Q1), RPIY inflation, as well as being lower, also exhibits less variation than either RPI or RPIX, suggesting that indirect tax plays an important role in amplifying short term inflation variability. Another, perhaps surprising, finding is that RPIX exhibits slightly greater positive skewness and greater excess kurtosis (fatter tails) than RPI. This would seem to suggest that the inclusion of mortgage interest payments acts to smooth the RPI series.

The unit root tests reported in Table 3.2 suggest that quarterly inflation is stationary over the longer sample periods since 1947 Q3 and 1974 Q2. However, over the shorter sample period since 1976 Q2 the Augmented Dickey-Fuller test is unable to reject the unit root null. Given, that these tests are known to have lower power and the short sample periods involved, we treat inflation as a stationary throughout the analysis reported here.

Chart 3.1: Quarterly Price Inflation, 1947 Q3 - 94 Q1 (End Quarter Figs)

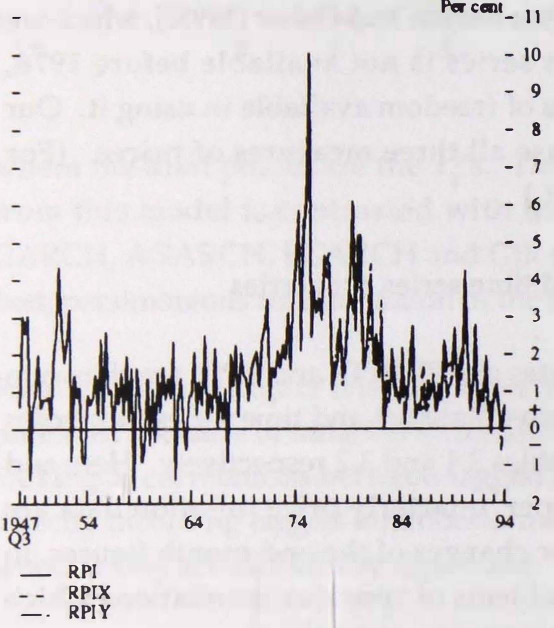


TABLE 3.1: QUARTERLY PRICE INFLATION DESCRIPTIVE STATISTICS (END QUARTER)

	Sample	Max	Min	Mean	Standard deviation	Skewness	Kurtosis-3
RPI	1947 Q3-94 Q1	9.80	-1.65	1.59	1.53	1.37	4.28
	1974 Q2-94 Q1	9.80	-0.14	2.13	1.77	1.54	3.28
	1976 Q2-94 Q1	6.01	-0.14	1.83	1.40	0.99	0.47
RPIX	1947 Q3-94 Q1⁺	10.07	-1.65	1.58	1.54	1.48	4.84
	1974 Q2-94 Q1	10.07	0.00	2.11	1.78	1.68	3.76
	1976 Q2-94 Q1	6.17	0.00	1.80	1.38	1.14	0.61
RPIY	1976 Q2-94 Q1	4.67	-0.60	1.67	1.13	0.78	0.13

⁺ Longer sample derived by splicing together data on RPI and RPIX.

TABLE 3.2: QUARTERLY PRICE INFLATION UNIT ROOT STATISTICS

	Sample Statistic	Dickey-Fuller Statistic	Augmented Dickey-Fuller (4 lags)
RPI	1947 Q3-94 Q1	-8.22*	-3.07*
	1974 Q2-94 Q1	-4.97*	-3.74*
	1976 Q2-94 Q1	-4.49*	-2.64
RPIX	1947Q3-94 Q1+	-8.53*	-2.95*
	1974 Q2-94 Q1	-5.35*	-3.86*
	1976 Q2-94 Q1	-5.10*	-2.66
RPIY	1976 Q2-94 Q1	-3.93*	-2.76

+ Longer sample derived by splicing together data on RPI and RPIX.

* Significant at 5% level; no trend case.

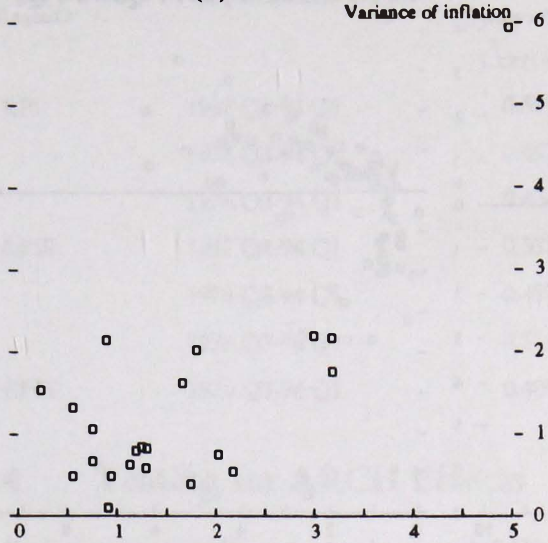
(c) Stylised facts on the level of inflation and its variability

The relationship between the level and variability of inflation is often examined by looking at the relationship between average inflation and its variance or the relationship between average inflation and its rate of change.[4]

Chart 3.2 plots the variance of quarterly RPI inflation against the average inflation rate for non-overlapping eight quarter periods since 1950. The positive relationship between the two appears to support the inflation-uncertainty hypothesis, although the strength of the positive correlation rests in large part on one observation (the 1974-75 period).

4 For a review of the early empirical literature examining the relationship between the level and variability of inflation, see Fischer (1981) and Taylor (1981).

Chart 3.2: The Variance and Level of RPI Inflation (a)



(a) Calculated for non-overlapping eight quarter averages using end-quarter data, 1950 - 93.

Scatter plots of the relationship between inflation and its rate of change are shown in Charts 3.3, 3.4 and 3.5 for RPI, RPIX and RPIY respectively, and again seem to confirm the existence of a positive relationship. But this relationship is much less apparent when the absolute value of the change in inflation is substituted on the vertical axis, when the positive correlation coefficient either falls significantly or, for RPIY, disappears (see Table 3.3). This certainly provides grounds for suspecting that there may be asymmetries in the inflation uncertainty relationship, but (unconditional) variability measures may be poor proxies for uncertainty.

Chart 3.3: Level and Change in Quarterly RPI Inflation, 1947 Q4 - 94 Q1

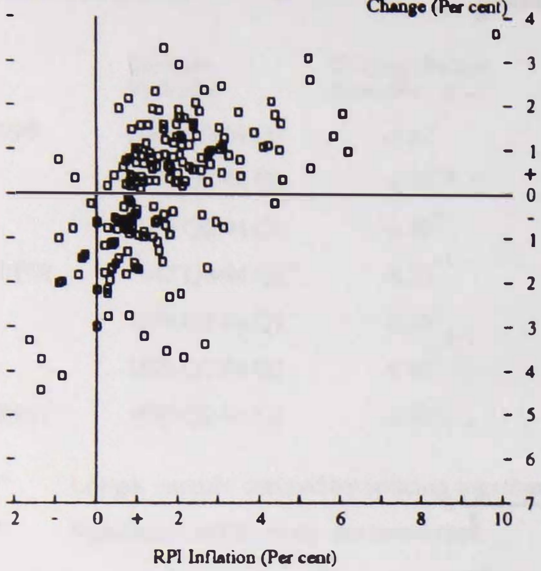


Chart 3.4: Level and Change in Quarterly RPIX Inflation, 1974 Q3 - 94 Q1

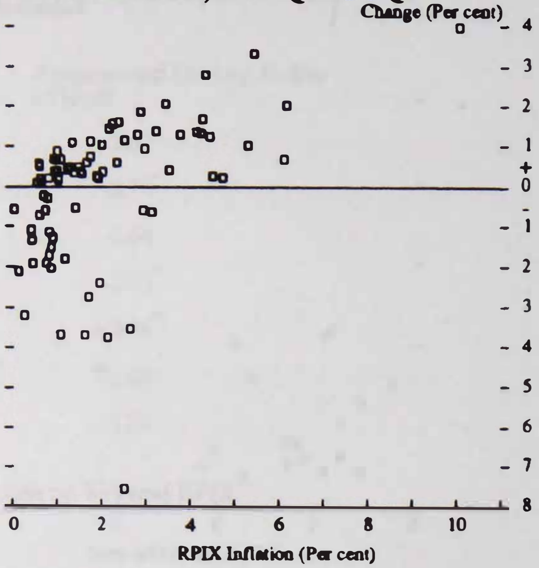


Chart 3.5: Level and Change in Quarterly RPIY Inflation, 1976 Q3 - 94 Q1

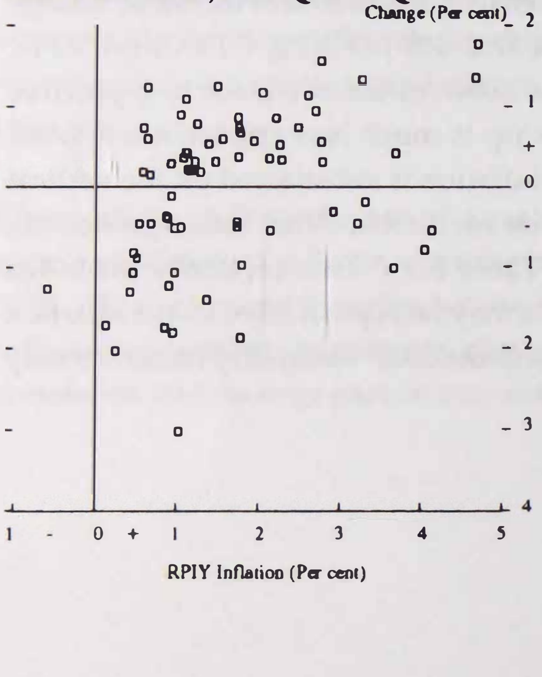


TABLE 3.3: CORRELATIONS BETWEEN AVERAGE INFLATION AND ITS ACTUAL AND ABSOLUTE RATE OF CHANGE

		$Corr(\pi,\Delta\pi)$	$Corr(\pi,\lvert\Delta\pi\rvert)$
RPI	1947 Q4-94 Q1	0.519	0.038
	1974 Q3-94 Q1	0.457	0.250
	1976 Q3-94 Q1	0.470	0.130
RPIX	1947 Q4-94 Q1	0.532	0.067
	1974 Q3-94 Q1	0.483	0.264
	1976 Q3-94 Q1	0.516	0.159
RPIY	1976 Q3-94 Q1	0.409	-0.023

4 Testing for ARCH Effects

Before proceeding to estimate ARCH representations of inflation uncertainty, we need to estimate a model for the conditional mean, in order to test first for the presence of ARCH effects. In the absence of an accepted structural model, we modelled each of our three measures of quarterly inflation as autoregressive processes of the following form:

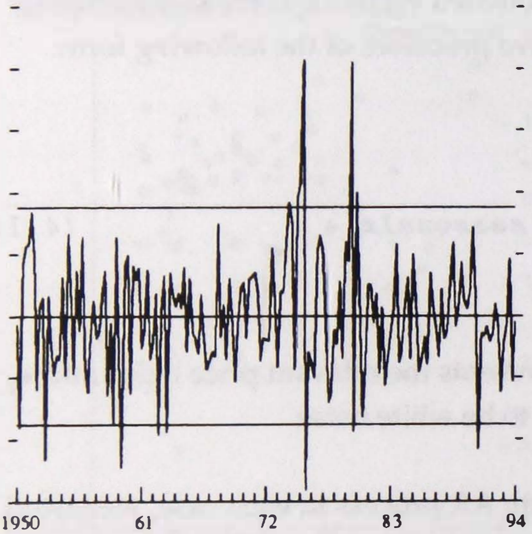
$$\pi_t = \alpha_o + \sum_{i=1}^{n} \alpha_i \pi_{t-i} + seasonals + e_t \qquad (4.1)$$

where $\pi_t = 100 * \ln(P_t/P_{t-1})$, P_t represents the relevant price index and e_t is an error term assumed initially to be white noise.

In order to choose the appropriate AR process in each case, we tested down from an AR(8), using a variety of model selection criteria, including absence of serial correlation, goodness of fit and the Akaike and Schwarz information criteria. The resulting OLS estimates for both the full sample and the largest common sample period are shown in Tables 4.1, 4.2 and 4.3.

In the case of RPI and RPIX, we found that using the unadjusted data produced a number of large outliers associated with Budget changes in indirect taxes, notably the extension of VAT in 1975 and its doubling in 1979 (see Chart 4.1). Rather than attempting to remove these outliers using dummy variables, which would imply there was no aggregate inflation uncertainty during these periods, we pre-adjusted the data to allow for the published impact effects on RPI inflation of the 1975 and 1979 Budgets.[5] Thus we are assuming that agents were rational and fully discounted these pre-announced effects. This can be questioned on a number of grounds, but there would seem no obvious way of dealing with indirect tax effects satisfactorily other than by excluding them, which we effectively do by also modelling the RPIY measure. For completeness, however, we report the results for both unadjusted and adjusted data in what follows.

Chart 4.1: Residuals from RPI AR(4) Model with Unadjusted Data



Error bands signify +/- 2xSEE

---

5 These adjustments were 2.5% in 1975 Q2 and 3.0% in 1979 Q3. These were the (rounded) Budget impact effects on RPI in May 1975 and July 1979, reported in the *Department Employment Gazette* (June 1975 and July 1979 issues).

For both the unadjusted and adjusted data, we found that a 4th-order AR process was sufficient to satisfy most conventional model selection criteria. Using adjusted data, the RPI and RPIX equations also satisfy tests for normality (column 3 in Tables 4.1 and 4.2), but the equations still show signs of heteroscedasticity over the full sample period. This in itself is not surprising if there are ARCH effects (neither is non-normality), but it means that conventional *t*-ratios will be biased and we therefore report White (1980) heteroscedasticity corrected figures. Note that in both equations there are no signs of autocorrelation. This is important because if the errors of the mean equation are correlated, this is likely to result in the squared residuals also being correlated, confounding the usual tests for ARCH disturbances [see Cosimano and Jansen (1988)].

In the case of RPIY, we found that an AR(3) representation was adequate to satisfy conventional model selection criteria. As might have been expected, this equation exhibited no signs of non-normality, although there is some weak evidence of heteroscedasticity.

TABLE 4.1: AUTOREGRESSIVE QUARTERLY RPI INFLATION EQUATIONS, OLS ESTIMATES

	Dependent Variable:				
	1 Unadjusted	2 Unadjusted	3 Adjusted	4 Unadjusted	5 Adjusted
Constant	0.265	0.329	0.153	0.690	0.483
	(1.2)	(1.5)	(0.7)	(2.1)	(1.6)
π_{t-1}	0.460	0.458	0.529	0.497	0.704
	(3.8)	(3.8)	(6.3)	(4.1)	(5.8)
π_{t-2}	0.173	0.174	0.065	0.259	-0.063
	(1.7)	(1.8)	(0.7)	(1.9)	(0.4)
π_{t-3}	0.058	0.064	0.131	0.035	0.088
	(0.6)	(0.6)	(1.3)	(0.3)	(0.6)
π_{t-4}	0.121	0.119	0.110	-0.048	0.053
	(1.2)	(1.3)	(1.4)	(0.4)	(0.4)
π_{t-5}	-0.046				
	(0.6)				
π_{t-6}	0.007				
	(0.1)				
π_{t-7}	0.065				
	(1.0)				
π_{t-8}	-0.012				
	(0.2)				
Q2	0.898	0.791	0.969	0.889	0.847
	(2.8)	(2.8)	(3.2)	(2.1)	(2.0)
Q3	-1.119	-1.190	-1.156	-1.270	-1.437
	(3.7)	(4.7)	(4.8)	(3.2)	(4.1)
Q4	0.263	0.258	0.601	-0.804	-0.085
	(0.7)	(0.8)	(2.1)	(2.0)	(0.2)
R^2	0.588	0.585	0.636	0.631	0.713
SEE	1.02	1.01	0.889	0.876	0.720
NORM(2)	71.9	61.6	0.1	70.1	9.9
HET(1)	30.0	32.6	8.2	1.2	0.2
LM(1)	0.2	0.05	0.3	1.3	0.9
LM(4)	3.3	0.9	1.9	7.8	3.6
LM(8)	9.2	4.8	6.5	11.0	8.0
Sample	50 Q1-94 Q1	50 Q1-94 Q1	50 Q1-94 Q1	77 Q1-94 Q1	77 Q1-94 Q1

T statistics are in parentheses.
For columns 1, 2 and 3 *t*-statistics have been calculated using White (1980) heteroscedasticity consistent standard errors.

TABLE 4.2: AUTOREGRESSIVE QUARTERLY RPIX INFLATION EQUATIONS, OLS ESTIMATES

Dependent Variable:

	1 Unadjusted	2 Unadjusted	3 Adjusted	4 Unadjusted	5 Adjusted
Constant	0.141	0.254	0.067	0.619	0.553
	(0.6)	(1.2)	(0.3)	(1.8)	(1.8)
π_{t-1}	0.453	0.452	0.522	0.447	0.627
	(3.7)	(3.7)	(5.9)	(3.6)	(5.2)
π_{t-2}	0.142	0.137	0.036	0.262	0.049
	(1.5)	(1.5)	(0.4)	(1.9)	(0.3)
π_{t-3}	0.087	0.093	0.160	0.048	-0.002
	(0.8)	(0.9)	(1.5)	(0.4)	(0.0)
π_{t-4}	0.136	0.138	0.128	-0.005	0.132
	(1.3)	(1.4)	(1.5)	(0.0)	(1.1)
π_{t-5}	-0.004				
	(0.1)				
π_{t-6}	-0.059				
	(0.7)				
π_{t-7}	0.051				
	(0.8)				
π_{t-8}	0.025				
	(0.4)				
Q2	1.078	0.960	1.147	1.152	0.844
	(2.9)	(3.1)	(3.5)	(2.6)	(1.8)
Q3	-1.060	-1.174	-1.143	-1.330	-1.685
	(3.5)	(4.6)	(4.8)	(3.1)	(4.6)
Q4	0.488	0.340	0.688	-0.828	-0.328
	(1.3)	(1.1)	(2.2)	(1.9)	(0.7)
R^2	0.597	0.595	0.655	0.662	0.774
SEE	1.01	1.00	0.864	0.834	0.632
NORM(2)	138.1	126.3	0.1	353.6	1.5
HET(1)	26.5	28.7	12.2	0.3	1.3
LM(1)	0.0	0.0	0.3	2.2	1.5
LM(4)	2.1	0.9	4.8	7.3	8.1
LM(8)	7.8	5.1	8.5	9.2	9.1
Sample	50 Q1-94 Q1	50 Q1-94 Q1	50 Q1-94 Q1	77 Q1-94 Q1	77 Q1-94 Q1

T statistics are in parentheses.
For columns 1, 2 and 3 *t*-statistics have been calculated using White (1980) heteroscedasticity consistent standard errors.

TABLE 4.3: AUTOREGRESSIVE QUARTERLY RPIY INFLATION EQUATIONS, OLS ESTIMATES

	Dependent Variable:		
	1	2	3
Constant	0.385	0.383	0.627
	(1.6)	(2.1)	(2.7)
π_{t-1}	0.480	0.470	0.523
	(3.5)	(3.7)	(4.4)
π_{t-2}	0.222	0.214	0.169
	(1.1)	(1.2)	(1.2)
π_{t-3}	0.205	0.199	0.094
	(1.7)	(1.7)	(0.8)
π_{t-4}	-0.047		
	(0.4)		
π_{t-5}	-0.025		
	(0.2)		
π_{t-6}	0.009		
	(0.1)		
π_{t-7}	-0.074		
	(0.7)		
π_{t-8}	0.127		
	(1.3)		
Q2	0.347	0.462	0.290
	(1.0)	(1.6)	(1.1)
Q3	-0.994	-0.998	-1.239
	(2.8)	(3.3)	(4.6)
Q4	-0.497	-0.464	-0.487
	(1.1)	(1.3)	(1.7)
R^2	0.708	0.701	0.710
SEE	0.590	0.571	0.597
NORM(2)	0.4	0.3	1.6
HET(1)	3.2	4.0	1.2
LM(1)	0.8	0.1	0.1
LM(4)	3.2	1.0	2.9
LM(8)	9.7	1.7	3.3
Sample	78 Q2-94 Q1	78 Q2-94 Q1	77 Q1-94 Q1

T statistics are in parentheses.
For columns 1 and 2 *t*-statistics have been calculated using White (1980) heteroscedasticity consistent standard errors.

LM Test Results

In order to test for the presence of ARCH effects, the residuals from each model were squared and regressed on their lagged values. The associated LM tests for the presence of ARCH disturbances (calculated as the product of the number of observations and the R^2) are reported for each inflation measure in Table 4.4, both for the full sample 1950 Q1-1994 Q1 and a sub-sample from 1977 Q1 to 1994 Q1.

For the longer sample period, the results show that the RPI and RPIX equations (using both adjusted and unadjusted data) exhibit strong signs of ARCH disturbances. But when the sample is truncated at 1977, there is much less evidence of ARCH effects, although the equation using adjusted RPIX data still shows strong signs of ARCH disturbances. It is difficult to know what to make of this result, because it is difficult to justify excluding the earlier period.[6] The lack of evidence of ARCH over this period does mean, however, that we do not attempt to model the RPIY series - which is only available over the shorter sample period - as an ARCH process.[7] All the model results reported in Sections 5 and 6 were estimated over the full sample period.

---

6 We also tested for ARCH over the 1950 Q1 - 1970 Q1 period to see whether the presence of ARCH errors might be due to a structural break in the 1970s. However, we again found evidence of significant ARCH effects, suggesting that ARCH effects over the full sample period cannot be explained by a discrete change in the variance of inflation.

7 It is worth noting that in the case of RPIY, we did find evidence of very high order ARCH (at lags 10 and above). Such high levels of ARCH seem implausible and we treated these results as spurious.

TABLE 4.4: LM TESTS FOR ARCH

	Variable:				
	RPI Unadjusted AR(4)	**RPI Adjusted AR(4)**	**RPIX Unadjusted AR(4)**	**RPIX Adjusted AR(4)**	**RPIY AR(3)**
Sample: 1950 Q1-94 Q1					
ARCH(1)	16.0**	1.0	11.5**	4.4*	n/a
ARCH(2)	18.2**	6.2*	12.8**	14.2**	n/a
ARCH(4)	18.5**	12.1*	13.0*	23.7**	n/a
ARCH(8)	18.7**	12.9	13.3	23.4**	n/a
Sample: 1977 Q1-94 Q1					
ARCH(1)	0.2	2.2	0.1	1.9	0.4
ARCH(2)	3.1	5.5	0.2	15.3**	2.4
ARCH(4)	3.5	5.6	0.4	16.8**	5.3
ARCH(8)	4.5	7.2	1.6	21.9**	9.4

* significant at 5%; ** significant at 1%

5 ARCH Model Results

(a) Symmetric Model Results

To allow for time-varying heteroscedasticity, we first re-estimated the equations for RPI and RPIX (using both adjusted and unadjusted data), assuming that the error terms followed particular ARCH and GARCH processes. Thus the models were respecified in general terms as:

$$\pi_t = \alpha_o + \sum_{i=1}^{4} \alpha_i \pi_{t-i} + seasonals + \epsilon_t \qquad (5.1)$$

$$\epsilon_t \mid \Omega_{t-1} \sim N\left(o, h_t \right) \qquad (5.2)$$

$$h_t = \gamma_o + \sum_{j=1}^{q} \gamma_j \epsilon^2_{t-j} + \sum_{k=1}^{p} \delta_k h_{t-k} \qquad (5.3)$$

where the error term in the mean equation (equation 5.1) is now specified as normal conditional on the information set available at t-1 (Ω_{t-1}), with time-varying variance h_t a function of lagged squared forecast errors and lagged conditional variance terms.

We experimented with various ARCH and GARCH processes, but found that in each case the GARCH(1,1) model was sufficient to eliminate ARCH effects. Maximum likelihood results for the latter are shown below in Table 5.1;[8] since our interest is in inflation uncertainty, only the results for the parameters in the conditional variance model are reported. As can be seen from the Table, the terms in the GARCH process are at least weakly significant in all the equations. In each case, there is no sign of any residual ARCH effects in the scaled residuals, nor is there any sign of serial correlation. The sum of γ_1 and δ_1 averages 0.82, suggesting there is considerable persistence in the conditional variance equation, so that the effect of inflation shocks takes time to die away.

---

8 The maximum likelihood estimation results were derived from the Berndt, Hall, Hall and Hausman algorithm (1974) using RATS 4.10. Note that the initial starting values of e^2_0 and h_0 were set equal to the squared value of the OLS equation standard error in deriving these results.

TABLE 5.1: RESULTS FOR GARCH(1, 1) MODELS[1]

Model:

$$\pi_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i \pi_{t-i} + \text{seasonals} + \epsilon_t$$

$$\epsilon_t \mid \Omega_{t-1} \sim N\left(0, h_t\right)$$

$$h_t = \gamma_0 + \gamma_1 \epsilon_{t-1}^2 + \delta_1 h_{t-1}$$

Parameter	RPI Unadjusted	RPI Adjusted	RPIX Unadjusted	RPIX Adjusted
γ_0	0.243	0.171	0.184	0.115
	(2.4)	(1.2)	(2.9)	(1.7)
γ_1	0.478	0.143	0.489	0.189
	(3.5)	(1.4)	(3.7)	(1.8)
δ_1	0.326	0.626	0.391	0.647
	(2.2)	(2.4)	(3.4)	(3.9)
Log-likelihood	-70.001	-59.623	-65.044	-50.962
ARCH ($\chi^2(4)$)[2]	2.6	2.5	2.2	2.7
ARCH ($\chi^2(8)$)[2]	4.6	5.5	4.2	4.9
Q ($\chi^2(8)$)[2]	4.8	1.5	5.8	4.1

T statistics in parentheses.

(1) Parameters from the mean equation are not reported.

(2) Tests refer to scaled residuals, ie $\epsilon_t / h_t^{1/2}$.

(b) Allowing for Asymmetries

Although the GARCH(1,1) model seems adequate in terms of dealing with ARCH, in that neither the scaled residuals nor their squared values are autocorrelated, we have already argued that the implied symmetric restriction on the impact of inflation shocks seems implausible *a priori*. To investigate this further, we ran three additional asymmetric volatility models on the same RPI/RPIX inflation data: the AGARCH model, the EGARCH model and the GJR model (details of these models were given in Section 2 above). The estimation results are set out in Tables 5.2, 5.3 and 5.4.

Each of these asymmetric models also satisfies the tests for autocorrelation and ARCH effects, and in each case the value of the log-likelihood function is higher than the corresponding GARCH model. More interestingly, the parameter estimate of γ_2 in the AGARCH model, γ_1 in the EGARCH model and γ_2 in the GJR model are all positive and, at least weakly, statistically significant (see discussion in Section 2). In each case therefore the results suggest that bad news on inflation results in a bigger increase in inflation uncertainty than good news, suggesting that the symmetry restriction implicit in the GARCH model is not accepted by the data. Indeed, in the case of the GJR model the estimate of the γ_1 parameter, while statistically insignificant for the most part, is negative, suggesting that lower than expected inflation reduces inflation uncertainty.

TABLE 5.2: RESULTS FOR AGARCH MODEL[1]

Model: $\pi_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i \pi_{t-i} + \text{seasonals} + \epsilon_t$

$$\epsilon_t \mid \Omega_{t-1} \sim N\left(0,\ h_t\right)$$

$$h_t = \gamma_0 + \gamma_1 \left(\epsilon_{t-1} + \gamma_2\right)^2 + \delta_1 h_{t-1}$$

	RPI Unadjusted	RPI Adjusted	RPIX Unadjusted	RPIX Adjusted
Parameter				
γ_0	0.157 (1.8)	0.091 (0.7)	0.129 (2.2)	0.097 (1.7)
γ_1	0.275 (2.1)	0.110 (1.1)	0.372 (3.3)	0.165 (1.7)
γ_2	0.775 (2.3)	1.183 (1.5)	0.492 (3.1)	0.528 (1.9)
δ_1	0.364 (2.2)	0.554 (2.6)	0.415 (3.6)	0.624 (4.2)
Log-likelihood	-62.713	-55.076	-59.426	-48.254
ARCH ($\chi^2(4)$)[2]	2.6	4.8	3.4	4.4
ARCH ($\chi^2(8)$)[2]	4.5	8.9	5.7	6.5
Q ($\chi^2(8)$)[2]	2.8	1.5	6.0	4.3

T statistics are in parentheses.

(1) Parameters from the mean equation are not reported.

(2) Tests refer to scaled residuals, ie $\epsilon_t / h_t^{1/2}$

TABLE 5.3: RESULTS FOR EGARCH MODEL[1]

Model: $\pi_t = \alpha_o + \sum_{i=1}^{4} \alpha_i \pi_{t-i} + seasonals + \epsilon_t$

$$\epsilon_t \mid \Omega_{t-1} \sim N(o, h_t)$$

$$\log h_t = \gamma_o + \gamma_1 \frac{\epsilon_{t-1}}{h_{t-1}^{1/2}} + \gamma_2 \left[\frac{|\epsilon_{t-1}|}{h_{t-1}^{1/2}} - \left(\frac{2}{\pi}\right)^{1/2} \right] + \delta_1 \log h_{t-1}$$

Parameter	RPI Unadjusted	RPI Adjusted	RPIX Unadjusted	RPIX Adjusted
γ_0	-0.138	-0.138	-0.109	-0.099
	(1.6)	(1.8)	(1.6)	(1.6)
γ_1	0.467	0.312	0.383	0.193
	(3.5)	(2.2)	(3.7)	(1.8)
γ_2	0.426	0.200	0.453	0.255
	(2.0)	(1.1)	(2.9)	(1.8)
δ_1	0.594	0.656	0.685	0.802
	(4.3)	(4.3)	(6.6)	(8.2)
Log-likelihood	-60.809	-54.724	-58.052	-48.182
ARCH ($\chi^2(4)$)[2]	3.5	5.4	5.2	6.4
ARCH ($\chi^2(8)$)[2]	6.3	10.1	7.7	8.7
Q ($\chi^2(8)$)[2]	3.1	2.1	5.1	4.2

T statistics are in parentheses.

(1) Parameters from the mean equation are not reported.

(2) Tests refer to scaled residuals, ie $\epsilon_t/h_t^{1/2}$

TABLE 5.4: RESULTS FOR GJR MODEL(1)

Model: $\pi_t = \alpha_o + \sum_{i=1}^{4} \alpha_i \pi_{t-i} + \text{seasonals} + \epsilon_t$

$$\epsilon_t \mid \Omega_{t-1} \sim N\left(o, h_t\right)$$

$$h_t = \gamma_o + \gamma_1 \epsilon_{t-1}^2 + \gamma_2 D_{t-1} \epsilon_{t-1}^2 + \delta_1 h_{t-1}; \quad D_t = 1 \text{ if } \epsilon_t > 0, \quad D_t = 0 \text{ if } \epsilon_t \leq 0$$

Parameter	**RPI Unadjusted**	**RPI Adjusted**	**RPIX Unadjusted**	**RPIX Adjusted**
γ_o	0.353	0.273	0.282	0.166
	(3.4)	(2.4)	(3.4)	(2.4)
γ_1	-0.068	-0.067	-0.051	-0.004
	(1.6)	(1.4)	(1.2)	(0.1)
γ_2	1.037	0.537	0.916	0.394
	(2.9)	(1.8)	(3.4)	(1.6)
δ_1	0.214	0.447	0.308	0.559
	(1.6)	(2.4)	(2.4)	(3.7)
Log-likelihood	-59.798	-54.768	-57.515	-48.037
ARCH ($\chi^2(4)$)(2)	7.2	6.3	6.1	6.9
ARCH ($\chi^2(8)$)(2)	9.6	10.7	7.4	8.3
Q ($\chi^2(8)$)(2)	4.6	2.6	5.2	4.9

T statistics are in parentheses.

(1) Parameters from the mean equation are not reported.
(2) Tests refer to scaled residuals, ie $\epsilon_t/h_t^{1/2}$.

Unfortunately, discriminating between these models is difficult, because (apart from the GARCH and AGARCH models) they are not nested. However, Engle and Ng (1993) have proposed some tests which aim to detect whether the asymmetries in the data are being adequately picked up. The tests are constructed from the t-ratios on the b coefficient in the following regressions:

$$v_t^{*2} = a + b D_{t-1}^{+} + \beta' z^*_{0t} + e_t \qquad (5.4)$$

$$v_t^{*2} = a + b D_{t-1}^{-} \epsilon_{t-1} + \beta' z^*_{0t} + e_t \qquad (5.5)$$

$$v_t^{*2} = a + b D_{t-1}^{+} \epsilon_{t-1} + \beta' z^*_{0t} + e_t \qquad (5.6)$$

$$\text{and } D_t^{+} = 1 \text{ if } \epsilon_t > 0 \text{ and } D_t^{-} = 1 \text{ if } \epsilon_t < 0$$

where $v^*{}_t^2$ are adjusted, scaled residuals (ie residuals from a regression of the squared scaled residuals - ie ϵ_t^2/h_t - on the variables included in the volatility model), a and b are constant parameters, β is a constant parameter vector, z^* is a vector of variables dependent on the volatility model being tested, and e_t is the residual.[9]

The positive sign bias test statistic is defined as the t-ratio on the b coefficient in the regression equation (5.4); the negative size bias test statistic is the t-ratio on the b coefficient in the regression equation (5.5) and the positive size bias test statistic is the t-ratio on the b coefficient in the regression equation (5.6). The intuition behind these tests is simply that if the squared normalised residuals can be explained by the D_{t-1} terms then the volatility model must be mis-specified. We also report a

9 For further details, the interested reader is referred to Engle and Ng (1993). The details behind the results reported in Table 5.5 are set out in Annex 2.

joint test derived from the $t R^2$ statistic of the following regression, which is distributed as $X^2(3)$ under the null that the volatility model is correct.

$$v_t^{*2} = a + b_0 D_{t-1}^{+} + b_1 D_{t-1}^{-} e_{t-1} + b_2 D_{t-1}^{+} e_{t-1} + \beta' z_{0t}^{*} + e_t$$

TABLE 5.5: SIGN AND SIZE BIAS TEST RESULTS

Model	Positive Sign Bias	Negative Size Bias	Positive Size Bias	Joint Test
GARCH				
RPI unadjusted	2.09**	2.33**	1.92**	5.72*
RPI adjusted	0.94	1.30*	1.31*	1.78
RPIX unadjusted	1.24	1.96**	1.44*	4.15
RPIX adjusted	1.44*	1.29*	1.13	2.35
AGARCH				
RPI unadjusted	1.47*	1.56*	1.07	4.87*
RPI adjusted	0.93	0.99	0.66	2.07
RPIX unadjusted	-0.41	1.17	0.35	3.46
RPIX adjusted	0.21	0.94	0.05	1.78
EGARCH				
RPI unadjusted	0.83	1.51*	0.27	3.70
RPI adjusted	0.35	0.90	-0.30	1.95
RPIX unadjusted	-0.28	1.32	0.61	2.34
RPI adjusted	-1.06	0.72	-0.07	2.19
GJR				
RPI unadjusted	-0.90	-0.01	-0.08	1.59
RPI adjusted	-0.22	0.34	-0.19	1.39
RPIX unadjusted	-0.27	0.14	-0.01	0.50
RPIX adjusted	-0.75	0.57	-0.50	2.87

*/** indicates significance at the 20%/10% level.

The test results reported in Table 5.5 provide some tentative evidence that the GARCH model of inflation volatility is mis-specified, with the positive sign bias and size bias results suggesting that it understates the uncertainty resulting from a positive shock to inflation and correspondingly overstates the effects of a negative shock. But, apart from the results for the model using unadjusted RPI, the test results are only weakly statistically significant, probably reflecting the low power of these tests in small samples. In the case of the asymmetric models, the tests do not indicate the presence of any significant sign or size bias. Thus it is difficult to determine from these tests which of the asymmetric models provides the best representation of asymmetries in the data, although we may note that the *t*-ratios for the EGARCH and GJR model tend to be smaller than those for the AGARCH model.

To cast some further light on this question, we estimated a version of the partially non-parametric model (PNP) advocated by Engle and Ng (1993). This model of volatility contains a linear spline specification in the lagged forecast errors. It is termed partially non-parametric because it includes a GARCH term (the lagged conditional variance) to pick up long memory. Experimentation with different specifications led us to adopt three equally spaced breakpoints corresponding to 0, $\pm 0.5\sigma$, and $\pm \sigma$, where σ is the OLS standard error from the appropriate conditional mean equation. Thus the precise model we estimated had the following form:

$$h_t = \gamma_o + \sum_{i=0}^{2} \gamma_{1i} D^{+}_{it-1} (\epsilon_{t-1} - i\sigma/2) + \sum_{i=0}^{2} \gamma_{2i} D^{-}_{it-1} (\epsilon_{t-1} + i\sigma/2) + \delta_1 h_{t-1}$$

$$D^{+}_{it} = 1 \text{ if } \epsilon_t > i\sigma/2 \text{ and } D^{+}_{it} = 0 \text{ if } \epsilon_t \leq i\sigma/2$$

$$D^{-}_{it} = 1 \text{ if } \epsilon_t < i\sigma/2 \text{ and } D^{-}_{it} = 0 \text{ if } \epsilon_t \geq i\sigma/2$$

The results from this model are reported in Table 5.6. A symmetric news impact curve would imply that the (positive) γ_{1i}'s were equal in absolute size to the (negative) γ_{2i}'s. The results evidently do not support this, with the conditional variance much more sensitive to positive shocks across most of the specifications.

This is brought out more clearly in Table 5.7 which shows the implied relationship between current inflation volatility and the value of the previous period's inflation shock, holding the lagged conditional variance fixed at σ^2, for each of the estimated models. In the case of the PNP model, the implied news impact curve is very asymmetric, with uncertainty an increasing function of the size of positive inflation shock (bad news), but much less responsive or invariant to negative inflation shocks (good news).

TABLE 5.6: RESULTS FOR PARTIALLY NON-PARAMETRIC MODEL WITH 3 BREAK-POINTS(1)

Model: $\pi_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i \pi_{t-i} + \text{seasonals} + \epsilon_t$

$$\epsilon_t \mid \Omega_{t-1} \sim N\left(0, h_t\right)$$

$$h_t = \gamma_0 + \sum_{i=0}^{2} \gamma_{1i} D^{+}_{it-1}(\epsilon_{t-1} - i\sigma/2) + \sum_{i=0}^{2} \gamma_{2i} D^{-}_{it-1}(\epsilon_{t-1} + i\sigma/2) + \delta_1 h_{t-1}$$

$$D^{+}_{it-1} = 1 \text{ if } \epsilon_t > i\sigma/2 \text{ and } D^{+}_{it-1} = 0 \text{ if } \epsilon_t \leq i\sigma/2$$

$$D^{-}_{it-1} = 1 \text{ if } \epsilon_t < i\sigma/2 \text{ and } D^{-}_{it-1} = 0 \text{ if } \epsilon_t \geq i\sigma/2$$

Parameter	RPI Unadjusted	RPI Adjusted	RPIX Unadjusted	RPIX Adjusted
γ_0	0.344 (2.2)	-0.039 (0.3)	-0.034 (0.3)	-0.050 (0.4)
γ_{10}	1.773 (2.1)	1.876 (2.2)	1.546 (2.5)	1.236 (2.3)
γ_{11}	-4.209 (2.6)	-2.052 (1.2)	-0.970 (0.7)	-1.124 (0.9)
γ_{12}	11.771 (2.7)	0.967 (0.5)	2.313 (1.0)	0.564 (0.3)
γ_{20}	0.044 (0.1)	-0.636 (1.1)	-1.213 (2.6)	-0.518 (1.0)
γ_{21}	-0.976 (1.1)	0.594 (0.5)	1.755 (1.9)	0.514 (0.5)
γ_{22}	1.601 (2.2)	0.296 (0.4)	-0.243 (0.3)	0.008 (0.0)
δ_1	0.076 (1.2)	0.462 (2.7)	0.294 (2.7)	0.570 (3.9)
Log-likelihood	-51.986	-51.759	-53.961	-46.706
ARCH ($\chi^2(4)$)(2)	4.1	5.3	7.9	4.0
ARCH ($\chi^2(8)$)(2)	10.0	11.5	9.4	6.2
Q ($\chi^2(8)$)(2)	4.2	1.5	7.8	5.5

T statistics are in parentheses.

(1) Parameters from the mean equation are not reported.
(2) Tests refer to scaled residuals, ie $\epsilon_t/h_t^{1/2}$.

In contrast to the PNP results, the GARCH model tends to understate h_t for positive values of ϵ_t and to overstate them for negative values. The AGARCH allows for asymmetry and is therefore much closer to the PNP model, but it still tends to understate the impact of large positive shocks and to exaggerate the impact of negative ones. Of the models considered, the EGARCH and GJR models come closest to replicating the shape of the PNP news impact curve and, using the adjusted data (the results we wish to put most emphasis on), it is difficult to choose between them. While the GJR model comes closest to matching the PNP curve for negative shocks, it shows a slight tendency to overpredict the impact of positive shocks. On the other hand, the EGARCH model seems to give a more accurate representation for positive shocks, but shows a slight tendency to overstate the impact of negative shocks.

TABLE 5.7: INFLATION VOLATILITY NEWS IMPACT CURVES

ϵ_{t-1}	PNP	GARCH	AGARCH	EGARCH	GJR
Unadjusted RPI results					
-2.0	0.21	2.49	0.94	0.58	0.30
-1.5	0.54	1.65	0.67	0.59	0.42
-1.0	0.86	1.05	0.54	0.61	0.50
-0.5	0.40	0.70	0.55	0.62	0.56
0.0	0.42	0.58	0.70	0.63	0.57
+0.5	1.31	0.70	0.98	0.98	0.81
+1.0	0.11	1.05	1.40	1.52	1.54
+1.5	4.66	1.65	1.95	2.36	2.75
+2.0	9.32	2.49	2.65	3.67	4.45
Adjusted RPI results					
-2.0	0.34	1.23	0.60	0.49	0.36
-1.5	0.47	0.98	0.54	0.53	0.48
-1.0	0.59	0.81	0.53	0.56	0.56
-0.5	0.61	0.70	0.58	0.60	0.61
0.0	0.32	0.66	0.68	0.64	0.63
-0.5	1.14	0.70	0.84	0.85	0.74
+1.0	1.17	0.81	1.05	1.13	1.10
+1.5	1.56	0.98	1.32	1.51	1.68
+2.0	1.96	1.23	1.65	2.01	2.51
Unadjusted RPIX results					
-2.0	0.30	2.53	1.40	0.72	0.39
-1.5	0.45	1.68	0.93	0.70	0.48
-1.0	0.60	1.07	0.65	0.68	0.54
-0.5	0.87	0.70	0.55	0.65	0.58
0.0	0.26	0.58	0.64	0.63	0.59
+0.5	1.04	0.70	0.92	0.96	0.81
+1.0	1.33	1.07	1.38	1.45	1.46
+1.5	2.76	1.68	2.03	2.19	2.54
+2.0	4.21	2.53	2.86	3.32	4.05
Adjusted RPIX results					
-2.0	0.60	1.35	0.92	0.67	0.60
-1.5	0.60	1.02	0.72	0.65	0.59
-1.0	0.60	0.79	0.60	0.63	0.59
-0.5	0.60	0.64	0.57	0.61	0.59
0.0	0.38	0.60	0.61	0.59	0.59
+0.5	0.92	0.64	0.74	0.76	0.69
+1.0	1.05	0.79	0.95	1.00	0.98
+1.5	1.39	1.02	1.24	1.30	1.48
+2.0	1.73	1.35	1.62	1.69	2.18

6 Inflation Uncertainty and the Level of Inflation

The presence of ARCH effects in inflation does not in itself establish whether inflation uncertainty is associated with the level of inflation, since the conditional variance (our proxy for uncertainty) is being modelled as a function of past forecast errors rather than inflation itself [see Brunner and Hess (1993)].

In order to test for the link between the level of inflation and inflation uncertainty, we re-estimated each of the volatility models reported in Section 5 including additional lagged inflation terms to see if they were statistically significant. We experimented with a variety of specifications, but we report only the results from including an additional four lags in quarterly inflation (Tables 6.1 - 6.4). The results are slightly mixed: for virtually all the models, we found that the additional inflation terms were jointly statistically significant according to likelihood ratio tests, but for the asymmetric models often the most significant effects were negative rather than positive.

The main problem with including additional inflation terms into the volatility model is that, the two kinds of effects - inflation shocks and inflation levels - appear to be closely correlated, as Brunner and Hess (1993) note. This point seems to be confirmed by plotting our preferred estimates of inflation uncertainty against inflation. Charts 6.1 and 6.2 show that the conditional standard deviations from the EGARCH and GJR models (estimated on adjusted data) track RPI inflation remarkably closely throughout the postwar period (Chart 6.3 provides a comparison with the GARCH model). Thus inflation uncertainty was particularly high in the mid-1970s, at the same time as inflation peaked.

However, it is noteworthy that, inflation uncertainty reached similar levels in the early 1980s (a conditional standard deviation of around 2%), at a time when a change in policy regime made inflation difficult to predict.[10]

10 The spikes in the conditional standard deviation series are likely to reflect the impact of tax changes associated with annual Budgets which are only partly dummied out in the mean equation. This highlights the sensitivity of the results to the specification of the mean equation.

TABLE 6.1: RESULTS FOR GARCH(1,1) MODELS AUGMENTED BY LAGGED INFLATION[1]

Model: $\pi_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i \pi_{t-i} + seasonals + \epsilon_t$

$$\epsilon_t \mid \Omega_{t-1} \sim N\left(0, h_t\right)$$

$$h_t = \gamma_0 + \gamma_1 \epsilon_{t-1}^2 + \delta_1 h_{t-1} + \sum_{j=1}^{4} \lambda_j \pi_{t-j}$$

Parameter	RPI Unadjusted	RPI Adjusted	RPIX Unadjusted	RPIX Adjusted
γ_0	0.159	0.189	0.079	0.095
	(1.9)	(1.9)	(0.7)	(0.8)
γ_1	0.262	0.148	0.105	0.103
	(2.5)	(1.3)	(1.5)	(1.0)
δ_1	0.467	0.547	0.414	0.556
	(3.3)	(2.8)	(1.4)	(1.5)
λ_1	0.276	0.204	0.260	0.173
	(3.7)	(2.4)	(5.6)	(2.5)
λ_2	0.050	0.069	-0.068	-0.039
	(0.6)	(0.9)	(0.6)	(0.4)
λ_3	-0.214	-0.152	-0.237	-0.171
	(2.8)	(1.5)	(3.4)	(1.9)
λ_4	-0.051	-0.088	0.271	0.129
	(0.7)	(1.2)	(3.2)	(1.6)
Log-likelihood	-55.928	-50.920	-54.795	-46.588
ARCH ($\chi^2(4)$)[2]	2.7	1.8	5.9	8.3
ARCH ($\chi^2(8)$)[2]	8.9	4.9	8.6	12.1
Q ($\chi^2(8)$)[2]	3.1	2.0	6.5	4.9

T statistics are in parentheses.

(1) Parameters from the mean equation are not reported.
(2) Tests refer to scaled residuals, ie $\epsilon_t/h_t^{1/2}$

TABLE 6.2: RESULTS FOR AGARCH MODEL AUGMENTED BY LAGGED INFLATION[1]

Model: $\pi_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i \pi_{t-i} + seasonals + \epsilon_t$

$$\epsilon_t \mid \Omega_{t-1} \sim N\left(0, h_t\right)$$

$$h_t = \gamma_0 + \gamma_1 \left(\epsilon_{t-1} + \gamma_2\right)^2 + \delta_1 h_{t-1} + \sum_{j=1}^{4} \lambda_j \Pi_{t-j}$$

Parameter	RPI Unadjusted	RPI Adjusted	RPIX Unadjusted	RPIX Adjusted
γ_0	0.185	0.203	0.017	0.102
	(1.7)	(1.8)	(0.1)	(1.0)
γ_1	0.222	0.145	0.088	0.112
	(1.8)	(1.3)	(1.4)	(1.1)
γ_2	0.075	1.146	-0.401	0.489
	(0.2)	(0.2)	(0.5)	(0.6)
δ_1	0.482	0.540	0.476	0.586
	(2.2)	(2.6)	(1.9)	(1.7)
λ_1	0.250	0.176	0.275	0.106
	(1.7)	(1.3)	(3.5)	(1.0)
λ_2	0.029	0.074	-0.069	-0.050
	(0.3)	(0.9)	(0.8)	(0.5)
λ_3	-0.246	-0.143	-0.248	-0.146
	(2.7)	(1.4)	(3.6)	(1.6)
λ_4	0.015	-0.080	0.276	0.138
	(0.2)	(1.1)	(3.4)	(1.6)
Log-likelihood	-56.246	-50.789	-54.122	-46.328
ARCH $(\chi^2(4))$[2]	4.3	1.9	4.8	7.2
ARCH $(\chi^2(8))$[2]	9.8	5.1	7.3	10.9
Q $(\chi^2(8))$[2]	3.7	2.1	5.9	4.8

T statistics are in parentheses.

(1) Parameters from the mean equation are not reported.
(2) Tests refer to scaled residuals, ie $\epsilon_t/h_t^{1/2}$.

TABLE 6.3: RESULTS FOR EGARCH MODEL AUGMENTED BY LAGGED INFLATION(1)

Model: $\pi_t = \alpha_0 + \sum_{i=1}^{4} \alpha_i \pi_{t-i} + seasonals + \epsilon_t$

$$\epsilon_t \mid \Omega_{t-1} \sim N\left(0, h_t\right)$$

$$\log h_t = \gamma_0 + \gamma_1 \frac{\epsilon_{t-1}}{h_{t-1}^{1/2}} + \gamma_2 \left[\frac{|\epsilon_{t-1}|}{h_{t-1}^{1/2}} - \left(\frac{2}{\Pi}\right)^{1/2} \right] + \delta_1 \log h_{t-1} + \sum_{j=1}^{4} \lambda_j \Pi_{t-j}$$

	RPI Unadjusted	RPI Adjusted	RPIX Unadjusted	RPIX Adjusted
Parameter				
γ_0	-0.083	0.049	-0.114	0.027
	(0.8)	(1.1)	(0.5)	(1.1)
γ_1	0.198	0.194	0.301	0.170
	(1.4)	(1.2)	(1.9)	(1.6)
γ_2	0.417	-0.056	0.350	0.014
	(2.2)	(0.6)	(1.6)	(0.3)
δ_1	0.682	0.932	0.700	0.912
	(8.2)	(10.8)	(6.3)	(13.9)
λ_1	0.200	0.006	0.122	0.046
	(1.6)	(0.1)	(1.0)	(0.5)
λ_2	0.006	-0.002	-0.133	-0.012
	(0.1)	(0.0)	(1.5)	(0.1)
λ_3	-0.234	-0.172	-0.166	-0.182
	(2.7)	(2.1)	(1.9)	(4.3)
λ_4	0.050	0.125	0.200	0.114
	(0.6)	(2.0)	(2.4)	(1.8)
Log-likelihood	-54.395	-49.234	-53.912	-40.538
ARCH ($X^2(4)$)(2)	5.1	2.9	7.0	6.9
ARCH ($X^2(8)$)(2)	10.6	6.4	10.0	12.4
Q ($X^2(8)$)(2)	2.0	12.8	8.3	4.9

T statistics are in parentheses.

(1) Parameters from the mean equation are not reported.

(2) Tests refer to scaled residuals, ie $\epsilon_t / h_t^{1/2}$

TABLE 6.4: RESULTS FOR GJR MODEL AUGMENTED BY LAGGED INFLATION(1)

Model:
$$\pi_t = \alpha_o + \sum_{i=1}^{4} \alpha_i \pi_{t-i} + seasonals + \epsilon_t$$

$$\epsilon_t \mid \Omega_{t-1} \sim N\left[o, h_t\right]$$

$$h_t = \gamma_o + \gamma_1 \epsilon_{t-1}^2 + \gamma_2 D_{t-1} \epsilon_{t-1}^2 + \delta h_{t-1} + \sum_{j=1}^{4} \lambda_j \Pi_{t-j}; \quad D_t = 1 \text{ if } \epsilon_t > 0, \; D_t = 0 \text{ if } \epsilon_t \leq 0$$

Parameter	RPI Unadjusted	RPI Adjusted	RPIX Unadjusted(3)	RPIX Adjusted
γ_0	0.311	0.122	0.059	0.054
	(3.5)	(1.6)	(0.8)	(0.6)
γ_1	-0.013	-0.130	-0.048	0.248
	(0.2)	(1.9)	(0.5)	(1.4)
γ_2	0.575	0.286	0.665	-0.205
	(2.0)	(1.7)	(3.0)	(1.3)
δ_1	0.423	0.666	0.473	0.591
	(3.0)	(2.7)	(4.3)	(2.4)
λ_1	0.131	0.100	0.100	0.231
	(1.4)	(1.3)	(2.0)	(3.3)
λ_2	-0.014	0.082		-0.111
	(0.2)	(0.9)		(1.3)
λ_3	-0.183	-0.138		-0.198
	(2.3)	(1.6)		(2.8)
λ_4	0.043	0.017		0.187
	(0.6)	(0.3)		(2.4)
Log-likelihood	-55.501	-47.019	-56.123	-43.916
ARCH $(\chi^2(4))$(2)	5.4	3.3	7.3	8.3
ARCH $(\chi^2(8))$(2)	9.4	8.0	10.0	13.1
Q $(\chi^2(8))$(2)	4.8	2.8	6.0	7.9

T statistics are in parentheses.

(1) Parameters from the mean equation are not reported.
(2) Tests refer to scaled residuals, ie $\epsilon_t / h_t^{1/2}$.
(3) Results for the model with one lagged inflation term are reported because the model failed to converge with four lagged inflation terms.

Chart 6.1: RPI Inflation and Estimated Inflation Uncertainty from EGARCH Model

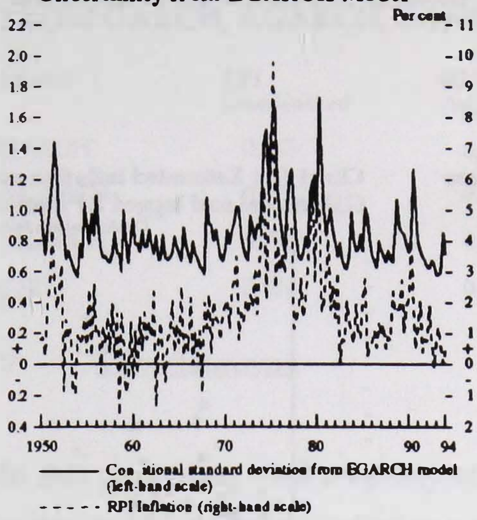


Chart 6.2: RPI Inflation and Estimated Inflation Uncertainty from GJR Model

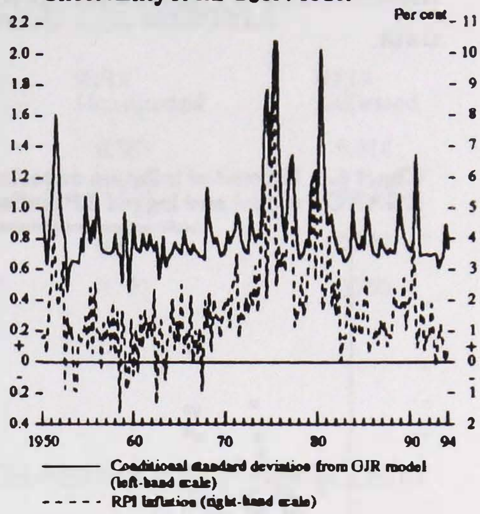
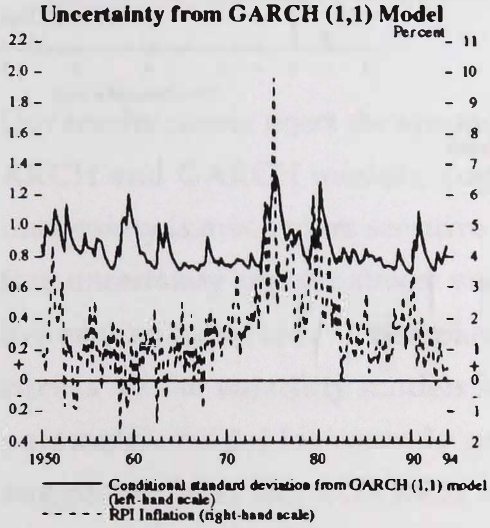


Chart 6.3: RPI Inflation and Estimated Inflation Uncertainty from GARCH (1,1) Model



The close correlation between inflation and estimated uncertainty is much less apparent using the conditional standard deviation from the symmetric, GARCH model, as can be seen from the scatter plots in Charts 6.4, 6.5 and 6.6. This finding, which exactly mirrors that of Brunner and Hess (1993) for the United States, emphasises the importance of allowing for asymmetric news effects. The correlations summarised in Table 6.5 show that this pattern is also repeated for the models of RPIX inflation and for the models estimated on unadjusted data.

Chart 6.4: Estimated inflation uncertainty from EGARCH model and lagged RPI inflation

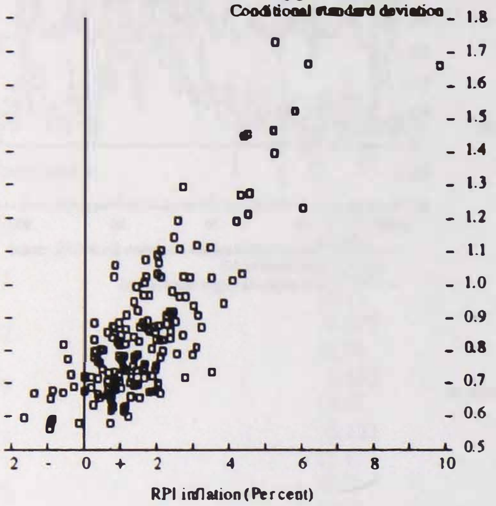


Chart 6.5: Estimated inflation uncertainty from GJR model and lagged RPI inflation

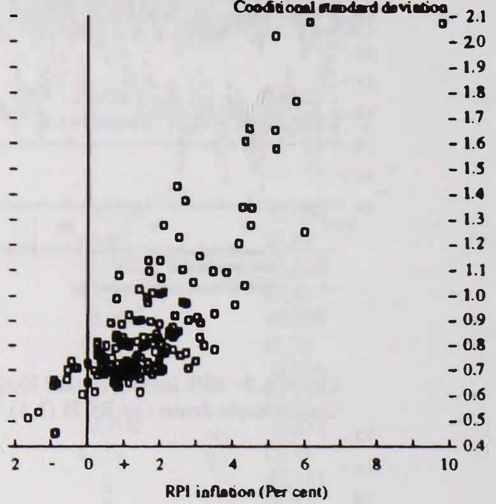


Chart 6.6: Estimated inflation uncertainty from GARCH (1,1) model and lagged RPI inflation

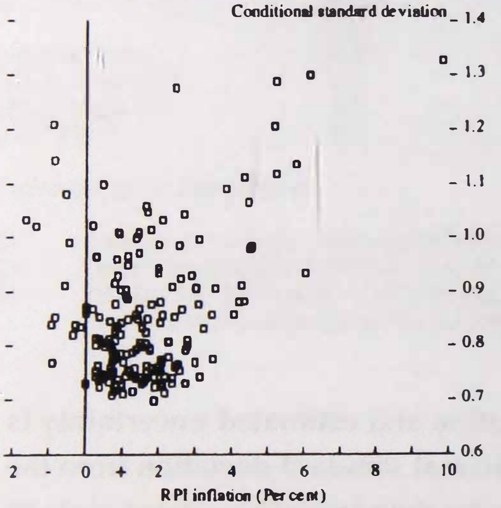


TABLE 6.5: CORRELATION BETWEEN LAGGED QUARTERLY INFLATION AND THE CONDITIONAL STANDARD DEVIATION FROM GARCH, AGARCH, EGARCH AND GJR MODELS

Model	RPI Unadjusted	RPI Adjusted	RPIX Unadjusted	RPIX Adjusted
GARCH	0.543	0.362	0.583	0.414
AGARCH	0.773	0.797	0.719	0.670
EGARCH	0.792	0.801	0.771	0.742
GJR	0.810	0.806	0.792	0.753

7 Conclusions

In this paper, we used a variety of ARCH-related volatility models to estimate UK quarterly inflation uncertainty over the post-war period, conditional on a univariate, fixed parameter specification of mean inflation.

Our results clearly reject the symmetry restriction imposed in standard ARCH and GARCH models, suggesting that measured inflation uncertainty is much more sensitive to 'bad news' than 'good news'. In fact, uncertainty appears almost unaffected when inflation outturns are lower than expected. A comparison of the implied 'news impact curves' of the volatility models investigated with a partially non-parametric model [as recently proposed by Engle and Ng (1993)] suggested that the EGARCH and GJR models offer the best, parsimonious representations of the asymmetries in the data.

We went on to show that our preferred estimates of inflation uncertainty are closely correlated with the level of UK inflation over the postwar period. This finding - which mirrors recent work in the United States by Brunner and Hess (1993) - does not of course establish a causal link. Indeed, the inclusion of lagged inflation terms in the conditional variance specification yielded slightly mixed results. Nevertheless, it is consistent with one of the most important stylised facts of the costs of inflation literature.

References

Ball, L (1992), "Why Does High Inflation Raise Inflation Uncertainty?", *Journal of Monetary Economics*, 29, pp 371-88.

Beaton, R and Fisher, P (1995), "The Construction of RPIY", *Bank of England Working Paper No 28*.

Berndt, E K, Hall, B H, Hall R E and Hausman, J A (1974), "Estimation and Inference in Non-linear Structural Models", *Annals of Economic and Social Measurement*, No 4, pages 653-65.

Bollerslev, T (1986), "Generalized Autoregressive Conditional Heteroscedasticity", *Journal of Econometrics*, 31, pages 307-27.

Brunner, A D and Hess, G D (1993), "Are Higher Levels of Inflation Less Predictable? A State-Dependent Conditional Heteroscedasticity Approach", *Journal of Business and Economic Statistics*, Vol 11, No 2, pages 187-97.

Cosimano, T F and Jansen, D W (1988), "Estimates of the Variance of US Inflation Based on the ARCH Model", *Journal of Money, Credit and Banking*, Vol 20, No 3, pages 409-21.

Cukierman, A and Meltzer, A H (1986), "A Theory of Ambiguity, Credibility, and Inflation Under Discretion and Asymmetric Information", *Econometrica*, Vol 54, No 5, pages 1,099-28.

Devereux, M (1989), "A Positive Theory of Inflation and Inflation Variance", *Economic Enquiry*, Vol XXVII, pages 105-16.

Driffill, J, Mizon, G E and Ulph, A (1990), "Costs of Inflation", in Friedman, B M and Hahn, F H, *The Handbook of Monetary Economics*, Volume II, North Holland.

Engle, R F (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", *Econometrica*, 50, pages 987-1,007.

Engle, R F (1983), "Estimates of the Variance of US Inflation Based Upon the ARCH Model", *Journal of Money, Credit and Banking*, Vol 15, pages 286-301.

Engle, R F (1990), "Discussion: Stock Volatility and the Crash of 87", Review of Financial Studies, Volume 3, Number 1, pages 103-6.

Engle, R F and Kraft (1983), "Multiperiod Forecast Error Variances of Inflation Estimated from ARCH Models" in *Applied Time Series Analysis of Economic Data* (A Zellner, Ed), Bureau of the Census, pages 293-302.

Engle, R F and Ng, V K (1993), "Measuring and Testing the Impact of News on Volatility", *The Journal of Finance*, Vol XLVIII, No 5, pages 1,749-78.

Fischer, S (1981), "Towards an Understanding of the Costs of Inflation: II" *Carnegie Rochester Conference Series on Public Policy*, 15, pages 5-42.

Friedman, M (1977), "Nobel Lecture: Inflation and Unemployment", *Journal of Political Economy*, 85, pages 451-72.

Glosten, L, Jagannathan R and Runkle, D (1989), "Relationship Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks", J L Kellog Graduate School, Northwestern University, unpublished *mimeo*.

Nelson, D (1990), "Conditional Heteroscedasticity in Asset Returns': A New Approach", *Econometrica*, Vol 59, pages 347-70.

Okun (1971), "The Mirage of Steady Inflation", Brookings Papers on Economic Activity, 2, pages 485-98.

Taylor, J B (1981), "On the Relation Between the Variability of Inflation and the Average Inflation Rate", *Carnegie Rochester Conference Series on Public Policy*, 15, pages 57-86.

Tsiddon, D (1993), "The (Mis)Behaviour of the Aggregate Price Level", *Review of Economic Studies*, Vol 60, pages 889-902

White, H (1980), "A Heteroscedasticity - Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity", *Econometrica*, Vol 48, pages 817-38.

Working, H (1960), "Note on the Correlation of First Differences of Averages in a Random Chain", *Econometrica*, Vol 28, 4, pages 916-18.

Zakoian, J (1990), "Threshold Heteroskedasticity Model", INSEE, unpublished *mimeo*.

Annex 1: Data Sources

RPI - Retail price index (1987=100), derived from splicing together series for 1947=100, 1956=100, 1974=100 and 1987=100. Source: 'Retail Prices 1914 - 1990' (1991), *Central Statistical Office*, and CSO code CHAW for more recent data.

RPIX - Retail price index excluding mortgage interest payments (1987=100). Source: CSO code CHMK, sample Jan.1974 - Mar.1994

RPIY - Retail price index excluding mortgage interest payments and indirect tax changes. Source: 'The Construction of RPIY' (1995), R Beaton and P Fisher, Bank of England Working Paper No 28.

Annex 2: Sign and Size Bias Tests

The test results reported in Table 5.5 were derived as follows [for further details see Engle and Ng (1993)].

For the GARCH model, the adjusted scaled residuals were derived from the following least squares regression

$$v_t^2 = \rho_0 + \rho_1 h_{t-1} + \rho_2 \epsilon_{t-1}^2 + v^{*2}_t$$

The $z^{*\prime}$ vector in this case was equal to

$$\{ h_t^{-1} , \epsilon_{t-1}^2 h_t^{-1} , h_{t-1} h_t^{-1} \}$$

For the AGARCH model, the adjusted scaled residuals were derived from the following regression

$$v_t^2 = \rho_0 + \rho_1 [(\gamma_2 + \epsilon_{t-1})^2] + \rho_2 h_{t-1} + \rho_3 [2\gamma_1 (\gamma_2 + \epsilon_{t-1})] + v^{*2}_t$$

The $z^{*\prime}$ vector in this case was equal to

$$\{ h_t^{-1} , (\epsilon_{t-1} + \gamma_2)^2 / h_t , h_{t-1} h_t^{-1} , 2\gamma_1 (\epsilon_{t-1} + \gamma_t) h_t^{-1} \}$$

For the EGARCH model, the adjusted scaled residuals were derived from the following regression

$$v_t^2 = \rho_0 + \rho_1 h_t + \rho_2 [\epsilon_{t-1} h_t / \sqrt{h_{t-1}}] + \rho_3 [h_t \log h_{t-1}]$$

$$+ \rho_4 [h_t (|\epsilon_{t-1}| / \sqrt{h_{t-1}}) - \sqrt{(2/\Pi)}] + v_t^{*2}$$

The $z^{*\prime}$ vector in this case was equal to

$$\{\epsilon_{t-1} / \sqrt{h_{t-1}},\ \log h_{t-1},\ (|\epsilon_{t-1}| / \sqrt{h_{t-1}} - \sqrt{(2/\Pi)})\}$$

For the GJR, the adjusted scaled residuals were derived from the following regression

$$v_t^2 = \rho_0 + \rho_1 h_{t-1} + \rho_2 \epsilon_{t-1}^2 + \rho_3 D_{t-1}^+ \epsilon_{t-1}^2 + v_t^{*2}$$

The $z^{*\prime}$ vector in this case was equal to

$$\{h_t^{-1},\ \epsilon_{t-1}^2 / h_t,\ h_{t-1} / h_t,\ D_{t-1}^+ \epsilon_{t-1}^2 / h_t\}$$

Bank of England Working Paper Series

Publication date in italics

1	Real interest parity, dynamic convergence and the European Monetary System *(June 1992)*	Andrew G Haldane Mahmood Pradhan
2	Testing real interest parity in the European Monetary System *(July 1992)*	Andrew G Haldane Mahmood Pradhan
3	Output, productivity and externalities—the case of banking *(August 1992)*	R J Colwell E P Davis
4	Testing for short-termism in the UK stock market *(October 1992)*	David Miles
5	Financial deregulation and household saving *(October 1992)*	Tamim Bayoumi
6	An investigation of the effect of funding on the slope of the yield curve *(January 1993)*	D M Egginton S G Hall
7	A simple model of money, credit and aggregate demand *(April 1993)*	Spencer Dale Andrew G Haldane
8	Bank credit risk *(April 1993)*	E P Davis
9	Divisia indices for money: an appraisal of theory and practice *(April 1993)*	Paul Fisher Suzanne Hudson Mahmood Pradhan
10	The effect of official interest rate changes on market rates since 1987 *(April 1993)*	Spencer Dale
11	Tax specific term structures of interest rates in the UK government bond market *(April 1993)*	Andrew J Derry Mahmood Pradhan
12	Regional trading blocs, mobile capital and exchange rate co-ordination *(April 1993)*	Tamim Bayoumi Gabriel Sterne
13	Temporary cycles or volatile trends? Economic fluctuations in 21 OECD countries *(May 1993)*	Gabriel Sterne Tamim Bayoumi
14	House prices, arrears and possessions: A three equation model for the UK *(June 1993)*	F J Breedon M A S Joyce
15	Tradable and non-tradable prices in the UK and EC: measurement and explanation *(June 1993)*	C L Melliss

16	The statistical distribution of short-term libor rates under two monetary regimes *(September 1993)*	Bahram Pesaran Gary Robinson
17	Interest rate control in a model of monetary policy *(September 1993)*	Spencer Dale Andrew G Haldane
18	Interest rates and the channels of monetary transmission: some sectoral estimates *(September 1993)*	Spencer Dale Andrew G Haldane
19	The effect of futures trading on cash market volatility: evidence from the London stock exchange *(December 1993)*	Gary Robinson
20	M0: causes and consequences *(December 1993)*	F J Breedon P G Fisher
21	An empirical analysis of M4 in the United Kingdom *(December 1993)*	P G Fisher J L Vega
22	A model of building society interest rate setting *(June 1994)*	Joanna Paisley
23	Deriving estimates of inflation expectations from the prices of UK government bonds *(July 1994)*	Mark Deacon Andrew Derry
24	Estimating the term structure of interest rates *(July 1994)*	Mark Deacon Andrew Derry
25	Potential credit exposure on interest rate swaps *(August 1994)*	Ian Bond Gareth Murphy Gary Robinson
26	New currencies in the Former Soviet Union: a recipe for hyperinflation or the path to price stability? *(September 1994)*	C L Melliss M Cornelius
27	Inflation, inflation risks and asset returns *(November 1994)*	Jo Corkish David Miles
28	The construction of RPIY *(February 1995)*	R Beaton P G Fisher
29	Pricing deposit insurance in the United Kingdom *(March 1995)*	David Maude William Perraudin
30	Modelling UK inflation uncertainty: the impact of news and the relationship with inflation *(April 1995)*	M A S Joyce