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INFLATION, INFLATION UNCERTAINTY, AND A COMMON EUROPEAN MONETARY POLICY

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Abstract

The relationship between in‡ation and in‡ation uncertainty is investigated in six European Union countries for the period 1960 to 1999. EGARCH models are used to generate a measure of in‡ation uncertainty and then Granger methods are employed to test for causality between average in‡ation and in‡ation uncertainty. In all the European countries, except Germany, in‡ation signi…cantly raises in‡ation uncertainty as predicted by Friedman. However, in all countries except the UK, in‡ation uncertainty does not cause negative output e¤ects, implying that a common European monetary policy applied by the ECB might not lead to asymmetric real e¤ects via the in‡ation uncertainty channel. Less robust evidence is found regarding the direction of the impact of a change in in‡ation uncertainty on in‡ation. In Germany and the Netherlands, increased in‡ation uncertainty lowers in‡ation, while in Italy, Spain, and to a lesser extent France, increased in‡ation uncertainty raises in‡ation. These results are generally consistent with the existing rankings of Central Bank Independence.

Keywords: EMU, Exponential GARCH, In‡ation, In‡ation Uncertainty.
JEL Classi…cation: C22, C32, E31, E58.

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1 INTRODUCTION

The importance of in‡ation uncertainty as a distinct channel in explaining the real e¤ects of in‡ation has recently been given considerable empirical support (Grier and Tullock, 1989, Grier and Perry, 2000, Judson and Orphanides, 2000). This channel was …rst highlighted in Friedman's (1977) Nobel lecture. Friedman supplied an informal argument that an increase in the average in‡ation rate would lead to more in‡ation uncertainty, thus creating distortions in the workings of the price mechanism in allocating resources e¢ciently. Subsequent theoretical research focused on the opposite type of causation, which runs from in‡ation uncertainty to in‡ation. For example, Cukierman and Meltzer (1986) employ the Barro-Gordon set up and show that an increase in uncertainty about money growth and in‡ation will increase the optimal average in‡ation rate because it provides an incentive to the policymaker to create an in‡ation surprise in order to stimulate output growth. Holland (1995) argues that more in‡ation uncertainty can lead to a lower average in‡ation rate if the Central Bank tries to minimise the welfare losses arising from more in‡ation uncertainty. In addition, the evidence on the direction of the e¤ect of in‡ation uncertainty on in‡ation can be compared with the existing measures of Central Bank Independence (Grier and Perry, 1998). These authors do …nd that the most independent Central Banks are in countries where in‡ation declines as in‡ation uncertainty rises, thus contradicting the Cukierman-Meltzer hypothesis.

The issue of the relationship between in‡ation, in‡ation uncertainty, and output growth acquires great importance for the member countries of the Euro zone. First, evidence that higher in‡ation causes more in‡ation uncertainty and, therefore, possible negative output e¤ects would strengthen the case for the choice of price stability by the European Central Bank (ECB) as one of the primary objectives of monetary policy. Second, if the e¤ects of in‡ation on output that take place via changes in in‡ation uncertainty di¤er across the Euro zone, it is possible that a common monetary policy that results in similar in‡ation rates across countries will have asymmetric real e¤ects. In other words, a reduction in in‡ation arising from a contractionary monetary policy applied by the ECB could reduce output in some countries but increase output in others, depending on the combination of two e¤ects: (a) The Friedman hypothesis, i.e., the e¤ect of in‡ation on in‡ation uncertainty and (b) the e¤ect of in‡ation uncertainty on output growth. Therefore, lack of uniform evidence supporting the e¤ect of in‡ation on output via the in‡ation uncertainty channel across the Euro-zone countries would have important policy implications as it would make a common monetary policy a less e¤ective stabilization policy tool in dealing with national disparities.

Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) techniques represent a commonly-used approach to proxy uncertainty using the conditional variance of unpredictable shocks to the in‡ation rate[1]. These techniques have recently been employed by Grier and Perry (1998) to investigate the direction of causality in the in‡ation-in‡ation uncertainty relationship for the G7[2]. Similarly, Grier and Perry

[1] Alternative measures of uncertainty include survey-based forecasts and a moving standard deviation of in‡ation.

[2] We di¤er from this study in several respects: the GARCH model employed, the sample period, the data frequency, the country group, and the consideration of output growth and its relationship with

(2000) aim to examine the in‡ation-output uncertainty nexus in the US. The empirical evidence to date on the Friedman and the Cukierman-Meltzer hypotheses provided by Grier and Perry (1998) and a few other recent studies summarised below is rather mixed. Grier and Perry (1998)[3] use a GARCH model to estimate in‡ation uncertainty and run Granger causality tests. We employ an exponential GARCH (EGARCH) model for two reasons: First, we …nd evidence for asymmetries in the in‡ation uncertainty-in‡ation relationship and, second, we follow Brunner and Hess (1993) in testing Friedman's hypothesis.

Our paper contributes to the empirical relationship between in‡ation and in‡ation uncertainty in several ways: First, we use an EGARCH model instead of a GARCH model, as discussed above. Second, we examine the relationship between in‡ation and in‡ation uncertainty for several EU countries in order to examine whether a case could be made against a common monetary policy, along the lines discussed above. Third, we examine whether in‡ation is costly, a much-debated issue in monetary economics. Our approach allows us to distinguish between the direct costs of in‡ation, and those that arise via the in‡ation uncertainty channel, as predicted by Friedman (1977). The rest of the paper is structured as follows: In section 2 our theoretical econometric model is presented. In section 3 we summarise our empirical results. In section 4 we interpret these results and relate them to the predictions of economic theory and other recent empirical studies. Finally, section 5 concludes.

2 THE EGARCH MODEL

2.1 THE AR(p)-EGARCH(1,1) PROCESS

One of the principal empirical tools used to model in‡ation uncertainty has been the ARCH class of models. Following Engle's (1982) pathbreaking idea, several formulations of conditionally heteroscedastic models (e.g. GARCH, Fractional Integrated GARCH, Switching GARCH, Component GARCH) have been introduced in the literature, forming an immense ARCH family. However, as Brunner and Hess (1993, p. 187) argue, "The GARCH model places a symmetric restriction on the conditional variance. Since the variance is a function of squared residuals, agents become more uncertain about future in‡ation whether in‡ation unexpectedly falls or unexpectedly rises. The essence of Friedman's hypothesis is inconsistent with such a symmetry restriction, since new information suggesting that in‡ation is lower should reduce, rather than raise, uncertainty about future in‡ation".

Many of the proposed GARCH models include a term that can capture correlation between the in‡ation rate and in‡ation uncertainty. Models with this feature are often termed asymmetric or leverage volatility models. One of the earliest asymmetric GARCH models is the EGARCH model of Nelson (1991). In contrast to the conventional GARCH speci…cation which requires nonnegative coe¢cients, the EGARCH model, by modeling

in‡ation uncertainty.

[3] The authors estimate both asymmetric and symmetric GARCH models. However, they cannot reject the null hypothesis of symmetry. They, therefore, proceed to perform the Granger-causality tests using the estimated conditional variance from the GARCH model of each country.

the logarithm of the conditional variance, does not impose the nonnegativity constraints on the parameter space. Of the many di¤erent functional forms, the EGARCH model has become perhaps the most common. In particular, various cases of the EGARCH model have been applied by many researchers. For example, Brunner and Hess (1993), using EGARCH models, …nd that estimates of the conditional variance of U.S. in‡ation are very similar to those obtained using state-dependent models.

We model the conditional mean of in‡ation as

$$\phi(L)y_t = \phi + \varepsilon_t, \tag{1a}$$

with

$$\phi(L) = \prod_{l=1}^{p}(1 - \phi_l L), \tag{1b}$$

where y_t denotes the rate of in‡ation. Equation (1) is simply an AR(p) process.

In addition, we model the time-varying residual variance as an EGARCH(1,1) process. This can be written as

$$\varepsilon_t = e_t h_t^{\frac{1}{2}}, \tag{2a}$$

$$(1 - \beta L)\ln(h_t) = \omega + d\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + c\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right), \tag{2b}$$

where $\{e_t\}$ is a sequence of independent, normally distributed random variables with mean zero and variance 1. In the empirical work reported below, we estimate AR(p)-EGARCH(1,1) models for in‡ation and then use the conditional variance h_t as a measure of in‡ation uncertainty.

3 EMPIRICAL ANALYSIS

3.1 METHODOLOGICAL ISSUES

The relationship between in‡ation and in‡ation uncertainty could be estimated in a simultaneous approach as in a GARCH-in-mean (GARCH-M) model that includes a function of the lagged in‡ation rate in the conditional variance equation or a two-step approach where an estimate of the conditional variance is …rst obtained from a GARCH-type model and then causality tests are run to test for bidirectional e¤ects. Examples of the former approach include Brunner and Hess (1993), Grier and Perry (1998), Baillie et al (1996) and Fountas et al (2000)[4]. The latter approach was followed in Grier and Perry (1998).

[4]Grier and Perry (1998) use a Component GARCH-M model of US in‡ation that includes lagged in‡ation in the conditional variance, whereas Brunner and Hess (1993) use a state-dependent model

The simultaneous approach su¤ers from the disadvantage that it does not allow the testing of a lagged e¤ect of in‡ation uncertainty on in‡ation, which would be expected in a study that employs monthly or quarterly data. As Grier and Perry (1998) mention, the impact of a change in in‡ation uncertainty on average in‡ation, via a change in the stabilization policy of the monetary authority, takes time to materialize and cannot be fairly tested in a model that restricts the e¤ect to being contemporaneous.

3.2 The EMPIRICAL EVIDENCE TO DATE

The in‡ation-in‡ation uncertainty relationship has been analysed extensively in the empirical literature. Holland (1993) and Davis and Kanago (2000) survey this literature. In‡ation uncertainty is measured either using survey-based forecasts of in‡ation or the GARCH approach. In the recent literature that employs the GARCH approach, the U.S. evidence in favour of the Friedman hypothesis is mixed. Brunner and Hess (1993), Grier and Perry (1998, 2000) and Fountas et al (2000) …nd evidence in favour, whereas Baillie et al (1996) …nd evidence against it. The US evidence on the Cukierman-Meltzer hypothesis is rather negative. Only Fountas et al (2000) …nd evidence in favour of the hypothesis. There are a limited number of studies using international data that employ the GARCH approach. They are Baillie et al (1996) and Grier and Perry (1998). Grier and Perry (1998) …nd evidence supporting the Friedman hypothesis in the rest of the G7 countries but Baillie et al (1996) …nd mixed evidence. Grier and Perry (1998) …nd evidence supporting the Cukierman-Meltzer hypothesis in Japan and France and Baillie et al (1996) in the UK and three high-in‡ation economies, Argentina, Brazil and Israel.

This study aims to …ll the gaps arising from the methodological shortcomings of the previous studies and the lack of interest in the European case, where the results would have interesting implications for the successful implementation of common European monetary policy.

3.3 UK RESULTS

3.3.1 DESCRIPTION OF THE UK DATA AND ESTIMATION RESULTS

We …rst test for the relationship between in‡ation and in‡ation uncertainty using UK data. Even though the UK is not presently a member of the Euro zone, it is likely that it will participate in the European monetary union (EMU) in the future. In our empirical application we use non-seasonally adjusted time series data on Consumer Price Index obtained from the OECD Main Economic Indicators Database. Our sample includes quarterly data from 1960:Q1 through 1999:Q2. Figure 1 plots the in‡ation rate (π_t) series constructed as the …rst di¤erence of the log of CPI. To establish that the in‡ation data series is stationary we use both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests presented in Table 1(a) below. Using the second lagged di¤erence terms in

where the standard deviation of in‡ation is included in the mean equation and the lagged value of the squared deviation of in‡ation from a parameter is included in the variance equation. Baillie et al (1996) model in‡ation as a fractionally-integrated process and include lagged in‡ation in the conditional variance equation and the standard deviation in the mean equation. Fountas et al (2000) use a GARCH-M model that includes the lagged in‡ation rate in the variance equation.

the ADF test and setting the truncation lag at four in the PP test, we …nd that both tests reject the null hypothesis of a unit root at 0.01 signi…cance level. Hence, we have evidence in this sample that the UK in‡ation rate is stationary. We choose an AR(6) plus 2 seasonal dummy variables[5] model for the mean in‡ation rate and an EGARCH(1,1) model for the variance equation, according to the minimum Akaike Information Criterion (AIC) and Schwarz criterion (SC).

Table 1(b) presents the estimates of an AR(6)-EGARCH(1,1) model for the UK in‡ation rate with two seasonal dummies. The model was estimated under quasi-maximum likelihood estimation using the consistent variance-covariance estimator of Bollerslev and Wooldridge (1992). Residual diagnostics for this model are also reported in Table 1(b), and include Ljung-Box (Q) tests for residual correlation, and Ljung-Box diagnostics for serial dependence in the squared residuals. As reported, the Ljung-Box tests for serial correlation in the levels and squares of the standardized residuals do not reject the hypothesis of no autocorrelation. Thus, the Ljung-Box tests indicate that the estimated model …ts the data very well. The persistence of volatility implied by the EGARCH equation is measured by the size of β, which is highly signi…cant. Asymmetry in in‡ation uncertainty is conveniently quanti…ed by examining the sign of d. In the present case, the positive and signi…cant value of the coe¢cient implies that periods of positive in‡ation shocks are accompanied by high in‡ation uncertainty and periods of negative in‡ation shocks are accompanied by lower uncertainty about in‡ation. In summary, the AR(6)-EGARCH(1,1) model seems to …t both the mean and variance of the UK in‡ation rate quite well.

3.3.2 GRANGER-CAUSALITY TESTS

Next we employ Granger methods to test for bidirectional causality between in‡ation and in‡ation uncertainty. In particular, we test the null hypotheses that in‡ation does not Granger-cause in‡ation uncertainty, and that in‡ation uncertainty does not Granger-cause in‡ation using two, four, six, and eight lags[6]. The F statistics are reported in Table 2. These statistics have been obtained following correction for serial correlation and/or heteroskedasticity in the unrestricted regression in each case. The …rst null hypothesis is rejected at 0.01 level for all lags, while the second is also rejected at 0.10 or better. The sum of the coe¢cients on lagged uncertainty in the in‡ation equation (at lags 2 and 6) and on lagged in‡ation in the in‡ation uncertainty equation are positive. We thus provide strong empirical con…rmation of Friedman's hypothesis. We also …nd some evidence that increased in‡ation uncertainty increases in‡ation, con…rming the theoretical predictions made by Cukierman and Meltzer (1986).

In‡ation uncertainty has real e¤ects only if it leads to output losses. To test for such e¤ects we have used the index of industrial production to construct the growth rate of output. Our Granger-causality results in Table 2 (fourth column) indicate that higher in‡ation uncertainty causes a negative output growth e¤ect, thus supporting the argument

[5] The seasonal dummy variables are included to seasonally adjust the in‡ation series. We …nd that 2 of these dummies are jointly statistically signi…cant.

[6] It is possible to test for the relationship between in‡ation and its uncertainty simultaneously, as argued in Appendix A.

that higher in‡ation uncertainty is part of the welfare costs of in‡ation[7]. Finally, in the last column of Table 2, we report the F statistics on the causal e¤ect of in‡ation uncertainty on output growth, where the regression includes in addition lagged in‡ation rates. The rationale for this choice is to control for possible e¤ects of in‡ation uncertainty on output that take place via changes in in‡ation [8]. The reported results indicate that in‡ation uncertainty still a¤ects output negatively, even though the e¤ect is perhaps somewhat weaker (i.e., it applies for two and four lags only).

3.3.3 PREDICTABILITY OF HIGHER LEVELS OF UK INFLATION

Several researchers, such as Engle (1983) and Cosimano and Jansen (1988), have failed to …nd strong evidence that higher rates of in‡ation are less predictable. Using the EGARCH model, we compare our results with theirs. The in‡ation and in‡ation uncertainty series for the AR(6)-EGARCH(1,1) model are shown in Figure 2, which plots the in‡ation rate and its corresponding conditional standard deviation in dual scale.

In contrast to the conclusion of the above-mentioned studies, Figure 2 provides evidence that higher levels of in‡ation are less predictable. According to our estimates, the conditional standard deviation average (annual rate) in the low-in‡ation 1960s is about 2.4%. In the high-in‡ation 1970s, the conditional standard deviation average (annual rate) is about 4.3%. Finally, in the low-in‡ation environment of the 1990s, the average of the conditional standard deviation is only 2.4%. Brunner and Hess (1993) argue that it is the relaxation of the symmetry restriction in conditional volatility models which enables them to …nd that higher levels of in‡ation are less predictable. We reach the same conclusion by using an EGARCH model. To compare our results to theirs we also use an asymmetric GARCH process. The AIC and SC were -6.979647 and -6.759845 respectively, much worse than those of the EGARCH model. The estimates of the conditional standard deviation were quite unsatisfactory as well. Figure 3 shows that the volatility of in‡ation for the GARCH model is unreasonably high during the relatively low and stable in‡ation years of the late 1980s and 1990s.

3.4 EVIDENCE FOR THE EURO-ZONE COUNTRIES

3.4.1 DESCRIPTION OF THE DATA AND ESTIMATION RESULTS

We apply the above empirical approach to …ve European countries (France, Germany, Italy, the Netherlands, and Spain) that are presently members of the Euro zone. Our group of countries includes the largest four EMU countries. We use quarterly non-seasonally adjusted time series on CPI obtained from the OECD main economic indicators database from 1960:Q1 to 1999:Q3[9]. To adjust the time series for seasonality, we use 3 seasonal dummy variables in each country, provided they are jointly signi…cant[10].

[7] This result is identical if we use GDP to measure real output.

[8] We are grateful to an anonymous referee for this point.

[9] The time series for France ends in 1999:Q2, for Germany in 1999:Q2, for Italy in 1999:Q3, for the Netherlands in 1999:Q2, and for Spain in 1999:Q2.

[10] The seasonal dummy variables are jointly signi…cant in all the examined countries except for the Netherlands and Spain.

Table 3 presents ADF and PP tests of the unit root hypothesis for each country. The PP tests reject the null hypothesis of a unit root for all six countries at 0.01 (0.05 for France) signi…cance level. The ADF tests for France, Germany, and Italy fail to reject the null hypothesis of a unit root, but we will consider their in‡ation series stationary in our analysis, taking into consideration the Phillips-Perron results.

The best …tted model is chosen according to the minimum values of the AIC and SC. We choose an EGARCH(1,1) speci…cation for the conditional variance and an AR(3) model for France, an AR(7) for Germany, an AR(4) for Italy, and an AR(8) for the Netherlands and Spain. Table 4 shows the estimated results for each country for the models speci…ed above. In all countries, except Germany, the estimated coe¢cient d is statistically signi…cant and positive, indicating evidence of asymmetry in the conditional variance. This implies that negative and positive shocks to the in‡ation process have a di¤erent impact on in‡ation uncertainty. More speci…cally, positive (negative) in‡ation surprises lead to more (less) in‡ation uncertainty. For Germany, the estimated coef-…cient of asymmetry is negative, implying that a positive in‡ation shock leads to less uncertainty about in‡ation. This …nding can be attributed to the strong commitment of the German monetary authority towards anti-in‡ationary policies. We also perform the same speci…cation tests for the adequacy of the models as we did for the UK above. For all the estimated models, residuals diagnostics (not reported) yield no evidence of mis-speci…cation.

3.4.2 GRANGER-CAUSALITY TESTS

Table 5 reports the Granger-causality test results for the above …ve countries. The null hypothesis that in‡ation does not Granger-cause in‡ation uncertainty is rejected for all the examined countries at the 0.05 level and for each lag length, except Germany. These results are similar to those of the UK, supporting the Friedman hypothesis. The null hypothesis that in‡ation uncertainty does not Granger-cause in‡ation is rejected in all countries. However, only in the case of Italy, France (2 lags) and Spain (6 and 8 lags) is the e¤ect positive, supporting the Cukierman - Meltzer hypothesis. For Germany and the Netherlands, where the e¤ect is negative, we …nd evidence in favour of Holland's (1995) stabilisation hypothesis discussed below.

Finally, the fourth column of Table 5 indicates that in‡ation uncertainty does not Granger cause output growth in all countries, except perhaps Italy, where we …nd a signi…cant and negative impact on real output growth at the 10% level and the Netherlands and Spain, where the e¤ect is positive. Somewhat similar results apply in the last column of Table 5, which adds the in‡ation rate in the right-hand side of the regression. The only di¤erences are the insigni…cance of in‡ation uncertainty in Italy and the slight evidence for a positive impact in France. These results are discussed further below[11].

[11] The choice of the industrial production index in measuring real output is dictated by the unavailability of quarterly national acccounts (and hence GDP) for the full sample period for several countries in our sample.

3.4.3 PREDICTABILITY OF INFLATION

As in the case of UK in‡ation, there is evidence that higher rates of in‡ation are less predictable for each of the other European countries. This conclusion is derived from an examination of the plots (not reported) of the in‡ation rate and its corresponding conditional standard deviation for each country. This result is in agreement with the conclusion of Brunner and Hess (1993) for the US. According to our estimated model for France, the average of the conditional standard deviation (annual rate) in the high-in‡ation 1970s is 2% and in the low-in‡ation environment of the 1990s only 0.9%. Similarly, according to our estimated model for Spain, the average value of the conditional standard deviation (annual rate) in the 1970s is 4% whereas in the stable in‡ationary environment of the 1990s the average …gure is 1.6%. Similar results apply for the rest of the countries in our sample.

3.5 ROBUSTNESS

Our sample period 1960-99 includes various exchange rate and monetary policy regimes. For example, the UK operated under a managed ‡oat regime, following the collapse of the Bretton Woods system, for most of our sample, except for the brief period of ERM participation. In addition, from 1979 to 1990, Thatcher's government emphasised a strong anti-in‡ation objective. Hence, we repeat the above analysis for the UK for two periods: 1973-99 (the managed ‡oat regime) and 1979-90 (the Thatcher years). The results are presented in Table 6. Overall, these results are in broad agreement with those reported in Table 2. It is interesting to note that during the Thatcher years in‡ation uncertainty had no impact on output growth, a result that is very robust to the presence or absence of lagged in‡ation in the regression equation. Moreover, there is some evidence, in both periods under consideration, that in‡ation uncertainty lowers in‡ation, in agreement with the stabilisation hypothesis.

For the rest of our sample, countries that were ERM members for most of our original sample period 1960-99, we repeat the above analysis for the period 1983-99[12]. The choice of this period is based on the widely accepted notion that the ERM entered a calmer phase in 1983 following the turbulent early years (Gros and Thygesen, 1992). Following the estimation of GARCH models for each country (results not reported), we perform Granger-causality tests as previously and report the results in Table 7. These results support those reported for the full sample period (see Table 5) in many respects. First, we …nd strong support for the Friedman hypothesis regarding the positive impact of in‡ation on in‡ation uncertainty in most countries (see column 2). Second, as was the case in the analysis of the full period, we …nd that in‡ation uncertainty does not seem to lead to lower output, with a single exception (last two columns of Table 7). Finally, signi…cant di¤erence obtains between the full sample and the post-1983 period on the signi…cance of the causal e¤ect of in‡ation uncertainty on in‡ation. We …nd (column 3) that in most countries, there is no causal e¤ect. This result squares with the loss of

[12] For all 6 countries, we have re-estimated the GARCH model using the new sample periods and obtained new values for the conditional variances. These values have then been used in performing the Granger-causality tests.

monetary policy independence in the ERM period, as monetary policy was constrained by the exchange-rate peg objective.

4 DISCUSSION

Our full sample period includes considerable in‡ation diversity both across countries and across time. The high-in‡ation 1970s was followed by the low-in‡ation 1980s and 1990s. This was the case for two reasons: First, the global reduction in in‡ationary pressures. Second, some European countries, France, Italy, and Spain in our sample, joined the European Monetary System (EMS) in 1979 in order to borrow Germany's anti-in‡ation reputation. This is less so for the Netherlands, which has traditionally aligned its monetary policy stance to Germany's. The reduction in in‡ation for France, Italy, and Spain was more prevalent during the last stage of the EMS, starting in 1987. During most of the 1990s, in‡ation remained low and relatively stable. The signi…cant variability in the level of in‡ation and the uncertainty about it during our sample period provides the testing ground to examine the bidirectional relationship between in‡ation and in‡ation uncertainty.

We discuss …rst the Granger-causality results on the e¤ect of in‡ation on in‡ation uncertainty. Our results indicate strong evidence in support of the Friedman hypothesis for all countries, except Germany[13]. The lack of evidence for Germany is not surprising, as it is consistent with Ball's (1992) theory, which formalised Friedman's prediction[14]. Using Ball's (1992) argument, an increase in German in‡ation would not lead to more in‡ation uncertainty as the Bundesbank had a strong anti-in‡ation reputation, and, therefore, was willing to bear the costs of disin‡ation. Our result on the Friedman hypothesis for France, Italy, and the UK is consistent with the Grier and Perry (1998) study of the G7. However, in contrast to our study, Grier and Perry (1998), using a di¤erent methodology (GARCH model), sample size (1948-93), and data frequency (monthly, as opposed to quarterly) …nd support for Friedman's hypothesis for Germany. Our …nding of a non causal e¤ect of in‡ation on in‡ation uncertainty for this country indicates that in‡ation uncertainty in Germany is not caused by rising in‡ation rates.

Regarding the causality from in‡ation uncertainty to output growth, our Granger-causality tests indicate that only in the UK does in‡ation uncertainty have a negative e¤ect on output growth (when the full period is used). In the EMU countries during the more relevant 1983-1999 period such an e¤ect does not apply. This is according to the last column of Table 7 which allows us to separate the e¤ects of in‡ation uncertainty on output. Hence, we conclude that the welfare costs of in‡ation do not seem to be signi…cant, with the exception of the UK[15]. This …nding has important implications for the ECB's policymaking strategy. In particular, it supports those claiming that the objective

[13] No evidence in favour of the Friedman hypothesis applies for the Netherlands and Spain when the 1983-99 period is used.

[14] Ball (1992) uses an asymmetric information game where two policymakers with di¤erent preferences towards in‡ation alternate stochastically in o¢ce. Therefore, a higher current in‡ation rate raises in‡ation uncertainty as it is not known which policymaker will be in o¢ce in the next period.

[15] For the UK, the welfare cost of in‡ation was contained by the adoption of in‡ation targeting in 1992, following the country's brief participation in the EMS.

of price stability has been overemphasised by the ECB. The second implication of these output growth Granger-causality results concerns the application of a common monetary policy by the ECB following the launch of the Euro zone in 1999. As we saw earlier, in‡ation uncertainty does not seem to cause negative real e¤ects across all countries in our sample, except in the UK. Hence, a common European monetary policy would have relatively symmetrical real e¤ects (=zero), which work through the in‡ation uncertainty channel, across the EMU countries[16].

Our evidence on the Cukierman-Meltzer hypothesis is rather mixed. For Germany and the Netherlands, we …nd evidence against this hypothesis. This evidence partially favours the "stabilization hypothesis" put forward by Holland (1995). He claims that for countries where in‡ation leads to in‡ation uncertainty and real costs, we would expect the Central Bank to stabilize in‡ation, hence a negative e¤ect of in‡ation uncertainty on in‡ation. Our evidence is in part[17] consistent with this argument for Germany and the Netherlands. In contrast, for Italy, France (2 lags) and Spain (not robust across the various lags considered) we …nd evidence in favour of the Cukierman-Meltzer hypothesis. Hence, these countries would be expected to gain signi…cantly from EMU as the surrender of their monetary policy to the ECB would eliminate the policymakers' incentive to create in‡ation surprises. Finally, our evidence for the UK is rather mixed. At 2 and 6 lags, we …nd evidence supporting the Cukierman-Meltzer hypothesis and at 4 and 8 lags evidence against the hypothesis. Our evidence for France (lag 2) and the UK (2 and 6 lags) squares with the …ndings of Grier and Perry (1998) and Baillie et al (1996), respectively.

More independent Central Banks would have stronger anti-in‡ation preferences than the government and hence lead to a lower optimal in‡ation rate (Rogo¤, 1985). Moreover, if in‡ation uncertainty is costly, i.e., it implies real output e¤ects, and in‡ation can a¤ect in‡ation uncertainty (the Friedman hypothesis), an independent Central Bank will have a greater incentive (and freedom) to reduce in‡ation in response to more uncertainty. This is because in doing so (and hence keeping in‡ation uncertainty lower), the Central Bank can attain both lower in‡ation and higher output, i.e., a higher welfare level. The predictions of this analysis are borne out by the empirical evidence. Alesina and Summers (1993) show that more independent Central Banks are indeed associated with both lower in‡ation and in‡ation uncertainty.

Our results for the impact of in‡ation uncertainty on in‡ation are generally consistent with the existing literature on the rankings of Central Bank Independence (see Alesina and Summers, 1993). Countries like France, Italy and Spain have less independent Central Banks than Germany and the Netherlands, at least using the measures of Central Bank Independence that refer to the pre-1990 period, which is more in line with our sample period. Hence, we would expect that less independent Central Banks would be more likely to cause in‡ation surprises in response to higher in‡ation uncertainty, a result consistent

[16] For the Netherlands, Spain, and possibly France, we …nd evidence that in‡ation uncertainty raises output growth, in particular when the full sample period 1960-99 is used. This, seemingly, surprising result may arise under the assumption of risk averse agents and a precautionary motive for savings, as Dotsey and Sarte (2000) have shown in their theoretical model. According to their argument, when in‡ation uncertainty rises, savings increase and this boosts investment and growth.

[17] Our partial support arises from a lack of evidence for a negative impact of in‡ation uncertainty on output growth for these two countries and a lack of evidence for the Friedman hypothesis for Germany.

with the Cukierman-Meltzer hypothesis. Our empirical analysis generally supports this prediction. Our conclusion on France and Germany also agrees with Grier and Perry (1998).

5 CONCLUSIONS

The relationship between in‡ation and in‡ation uncertainty has been investigated in six European Union countries for the period 1960 to 1999. EGARCH models were used to generate a measure of in‡ation uncertainty and then Granger methods were employed to test for causality between average in‡ation and in‡ation uncertainty. In all the European countries of our sample, except Germany, in‡ation signi…cantly raises in‡ation uncertainty, as predicted by Friedman. However, in all countries, except the UK, in‡ation uncertainty does not cause negative output e¤ects, implying that a common European monetary policy applied by the ECB might not lead to asymmetric real e¤ects via the in‡ation uncertainty channel.

Less robust evidence is found regarding the direction of the impact of a change in in‡ation uncertainty on in‡ation. In Germany and the Netherlands, increased in‡ation uncertainty lowers in‡ation, while in Italy, Spain, and to a lesser extent France, increased in‡ation uncertainty raises in‡ation. These results are generally consistent with the existing rankings of Central Bank Independence.

The reported di¤erences in the results between this study and related studies, such as Grier and Perry (1998), can be attributed to the di¤erent methodologies, sample periods, and data frequency. These di¤erences highlight the need for further empirical work in search of more robust evidence on the relationship between in‡ation, in‡ation uncertainty and output growth. This work will provide an additional testing ground for the empirical relevance of economic theories and at the same time will be rather informative for the authorities in charge of monetary policymaking.

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APPENDIX A

This appendix reports the estimation results of an Exponential GARCH-in-mean model of in‡ation in six countries with lagged in‡ation included in the conditional variance. As in the text, the estimation period is 1960-1999 and the data frequency quarterly. We simultaneously estimate a system of equations that allows only the current value of either the conditional variance or standard deviation of in‡ation[18] to a¤ect average in‡ation and also allows up to the twelfth lag of average in‡ation to in‡uence the conditional variance. The model includes the in‡ation equation which adds the in‡ation variance to the equation reported in the text

$$\pi_t = \mathbf{e}_{t\,|\,1} + \delta h_t + \varepsilon_t,$$

with

$$\varepsilon_t = e_t h_t^{\frac{1}{2}},$$

and the conditional variance equation:

$$(1 - \beta L)\ln(h_t) = \omega + c\,|e_{t\,|\,1}| + de_{t\,|\,1} + k_i \pi_{t\,|\,i}$$

In the mean equation, $\mathbf{e}_{t\,|\,1}$ stands for the part of the regression that includes the intercept and lagged in‡ation rates. In the variance equation, various lags of in‡ation (from 1 to 12) were considered with the best model chosen on the basis of the minimum value of the Akaike information criterion.

The Table below reports only the estimated parameters of interest:

	EGARCH Level	EGARCH In-Mean	EGARCH Level In-Mean	
	k_i	δ	k_i	δ
UK	k_4 = 23.67 (0.03)	17.28 (0.32)	k_4 = 25.20 (0.03)	7.92 (0.72)
FRANCE	k_6 = 6.26 (0.00)	177.18 (0.00)	k_4 = 15.82 (0.05)	80.39 (0.00)
GERMANY	k_4 = 18.63 (0.16)	¡ 46.85 (0.74)	k_2 = 8.05 (0.36)	¡ 46.21 (0.65)
ITALY	k_4 = 8.42 (0.06)	¡ 15.28 (0.40)	k_6 = 3.40 (0.08)	¡ 12.94 (0.44)
NETH/NDS	k_6 = 3.21 (0.76)	2.50 (0.79)	k_{12} = 0.37 (0.97)	¡ 3.20 (0.81)
SPAIN	k_6 = 20.74 (0.04)	13.87 (0.60)	k_6 = 20.92 (0.03)	¡ 3.99 (0.60)

Notes: (1) Probability values are given in parentheses.

(2) k_i indicates the estimated coe¢cient that corresponds to the ith lag in the in‡ation rate.

Note that when we estimate the model for the UK without the in-mean e¤ect (δ = 0), the coe¢cient for the e¤ect of the 4th lag of in‡ation is 23.67 and is statistically signi…cant.

[18] According to the information criteria, the models with the variance of in‡ation were preferred to those with the standard deviation.

When we estimate the model without the level effect ($k_i = 0$), the in-mean coefficient is insignificant (the probability value is 0.32). When we estimate the model with the simultaneous feedback between the conditional variance and the conditional mean (last two columns in the Table), the above results imply a positive association between lagged inflation and uncertainty similar to that found using the two-step method in the text. We do not find a significant effect of uncertainty on average inflation. However, as we emphasize in the text, such a result is plausible, as any relationship where uncertainty influences average inflation takes time to materialize and cannot be fairly tested in a model that restricts the effect to being contemporaneous.

A comparison of the results of the simultaneous estimation (last two columns in Table) with the Granger causality results reported in the text for the rest of the countries indicates that, in general, there is consistency between the two approaches. In particular, as far as the Friedman hypothesis (significance of k_i) is concerned, we find the two approaches to be in agreement, except in the case of the Netherlands. However, a comparison of the significance of the causal effect of inflation uncertainty on the inflation rate is not valid due to the contemporaneous nature of the effect under the simultaneous approach. As expected, the simultaneous approach does not detect such an effect in the majority of countries considered.

Table 1:
(a) In‡ation unit root tests

Country	ADF t-statistic	Phillips-Perron t-statistic
UK	-2.620***	-8.040***

Notes: (1) In the ADF tests, we use two lagged di¤erenced terms. In the Phillips-Perron tests, the truncation lag is set at four.

(2) *** indicates rejection of the unit root null at the 0.01 level.

(b) The estimated AR(6)-EGARCH(1,1) Model for the UK in‡ation rate

$$\pi_t = \underset{(0.00)}{0.003} + \underset{(0.00)}{0.566}\pi_{t-1} + \underset{(0.00)}{0.178}\pi_{t-4} - \underset{(0.01)}{0.169}\pi_{t-5} + \underset{(0.00)}{0.188}\pi_{t-6} + \underset{(0.00)}{0.009}d_{2t} - \underset{(0.00)}{0.007}d_{3t} + \varepsilon_t$$

$$\ln(h_t) = \underset{(0.01)}{-3.196} + \underset{(0.00)}{0.697}\ln(h_{t-1}) + \underset{(0.18)}{0.242}|e_{t-1}| + \underset{(0.02)}{0.437}e_{t-1}$$

$Q(12) = 8.789[0.721]$, $Q(24) = 24.810[0.416]$, $Q(36) = 38.650[0.351]$
$Q^2(12) = 12.957[0.372]$, $Q^2(24) = 22.579[0.545]$, $Q^2(36) = 26.794[0.867]$

Notes: (1) The …rst equation represents the estimated conditional mean of the autoregressive model. d_{2t} and d_{3t} are seasonal dummies. The …gures in parentheses under the coe¢cients and inside the square brackets show the probability values.

Table 2: Granger-Causality tests: UK (1960-1999)

	H_0: $\pi_t \not\to h_{\pi t}$	H_0: $h_{\pi t} \not\to \pi_t$	H_0: $h_{\pi t} \not\to y_t$	H_0^a: $h_{\pi t} \not\to y_t$
Two Lags	4.741¤¤¤(+)	3.070¤¤¤(+)	8.775¤¤(-)	6.770¤¤¤(-)
Four Lags	4.721¤¤¤(+)	8.343¤¤(-)	6.410¤¤¤(-)	3.589¤¤¤(-)
Six Lags	9.202¤¤¤(+)	6.864¤(+)	5.410¤¤¤(-)	1.610
Eight Lags	5.294¤¤¤(+)	5.568¤(-)	3.345¤(-)	0.966

Notes: (1) The …gures are F statistics. (2) $\pi_t \not\to h_{\pi t}$: In‡ation does not Granger-cause in‡ation uncertainty; $h_{\pi t} \not\to \pi_t$: In‡ation uncertainty does not Granger-cause in‡ation; $h_{\pi t} \not\to y_t$: In‡ation uncertainty does not Granger-cause output growth. (3) superscript (a) means that lagged in‡ation has been added to the regression. (4) the positive or negative sign in parentheses indicates the sign of the sum of the lagged coe¢cients in the respective equation. (5) ***, ** and * indicate rejection of the null hypothesis at the 0.01, 0.05 and 0.10 levels of signi…cance, respectively.

Table 3: In‡ation unit root tests

Country	ADF t-statistic	Phillips-Perron t-statistic
France	-1.910	-3.110**
Germany	-2.150	-5.420***
Italy	-2.340	-3.880***
Netherlands	-4.840***	-11.150***
Spain	-2.720*	-6.550***

Notes: (1) In the ADF tests we use two lagged di¤erenced terms. In the Phillips-Perron tests the truncation lag is set at four, (2) ***, ** and * indicate rejection of the unit root null at the 0.01, 0.05 and 0.10 levels of signi…cance, respectively.

Table 4: The Estimated AR(p)-EGARCH(1,1) Models

	Country				
Parameter	France	Germany	Italy	Neth/nds	Spain
π_{t-1}	0.645[0.000]	0.351[0.000]	0.754[0.000]	0.471[0.000]	0.182[0.006]
π_{t-2}	-0.016[0.837]		0.114[0.240]		0.247[0.001]
π_{t-3}	0.296[0.000]	0.279[0.000]	0.063[0.408]		0.191[0.022]
π_{t-4}		0.361[0.000]	0.039[0.420]	0.337[0.000]	0.232[0.000]
π_{t-5}				-0.195[0.000]	
π_{t-6}				0.115[0.010]	
π_{t-7}		-0.205[0.003]			-0.193[0.003]
π_{t-8}				0.218[0.000]	0.253[0.000]
d	0.223[0.000]	-0.032[0.736]	0.422[0.000]	0.347[0.050]	0.126[0.001]
c	-0.215[0.013]	0.319[0.070]	-0.194[0.000]	0.912[0.000]	-0.163[0.048]
β	0.942[0.000]	0.680[0.011]	0.942[0.000]	0.745[0.000]	0.969[0.000]

Notes: (1) The estimated conditional variance equation has the form:

$\ln(h_t) = \omega + \beta \ln(h_{t-1}) + c\,|e_{t-1}| + d\,e_{t-1}$

(2) A constant term and seasonal dummies were included but not reported.

(3) Probability values are given in square brackets.

Table 5: Granger causality tests for in‡ation and in‡ation uncertainty (1960-1999)

	H_0: π_t ! $h_{\pi t}$	H_0: $h_{\pi t}$! π_t	H_0: $h_{\pi t}$! y_t	H_0^a: $h_{\pi t}$! y_t
(A) France				
Two Lags	46.381¤¤¤(+)	6.319¤¤¤(+)	0.274	1.425
Four Lags	28.570¤¤¤(+)	0.002	0.443	0.657
Six Lags	22.838¤¤¤(+)	0.240	1.128	1.902¤(+)
Eight Lags	17.676¤¤¤(+)	0.918	1.003	1.110
(B) Germany				
Two Lags	1.200	0.946	0.850	0.728
Four Lags	0.669	2.780¤¤(-)	0.517	0.528
Six Lags	0.350	3.235¤¤¤(-)	1.151	0.535
Eight Lags	0.407	3.520¤¤¤(-)	0.803	0.409
(C) Italy				
Two Lags	42.552¤¤¤(+)	0.039	2.540¤(-)	0.023
Four Lags	39.568¤¤¤(+)	4.559¤¤¤(+)	1.277	0.389
Six Lags	34.108¤¤¤(+)	6.458¤¤¤(+)	0.856	0.853
Eight Lags	38.773¤¤¤(+)	4.334¤¤¤(+)	1.754¤(-)	1.016
(D) The Neth/nds				
Two Lags	20.394¤¤¤(+)	5.188¤¤¤(-)	8.106¤¤¤(+)	5.978¤¤¤(+)
Four Lags	9.382¤¤¤(+)	5.256¤¤¤(-)	6.889¤¤¤(+)	3.318¤(+)
Six Lags	10.114¤¤¤(+)	3.526¤¤¤(-)	3.734¤¤¤(+)	1.806¤(+)
Eight Lags	8.280¤¤¤(+)	2.820¤¤¤(-)	7.823¤¤¤(+)	0.606
(E) Spain				
Two Lags	10.021¤¤¤(+)	1.081	3.254¤¤(+)	6.643¤¤¤(+)
Four Lags	8.221¤¤¤(+)	0.454	1.766	3.256¤¤¤(+)
Six Lags	7.142¤¤¤(+)	2.227¤¤(+)	2.113¤¤(+)	4.026¤¤¤(+)
Eight Lags	4.952¤¤¤(+)	2.212¤¤(+)	1.346	3.677¤¤¤(+)

Notes: (1) The …gures are F statistics.

(2) π_t ! $h_{\pi t}$: In‡ation does not Granger-cause in‡ation uncertainty; $h_{\pi t}$! π_t: In‡ation uncertainty does not Granger-cause in‡ation; $h_{\pi t}$! y_t: In‡ation uncertainty does not Granger-cause output growth.

(3) superscript (a) means that lagged in‡ation has been added to the regression.

(4) the positive or negative sign in parentheses indicates the sign of the sum of the lagged coe¢cients in the respective equations.

(5) ***, ** and * indicate rejection of the null at the 0.01, 0.05 and 0.10 levels of signi…cance, respectively.

Table 6: Granger-Causality tests: UK

	H_0: $\pi_t \not\to h_{\pi t}$	H_0: $h_{\pi t} \not\to \pi_t$	H_0: $h_{\pi t} \not\to y_t$	H_0^a: $h_{\pi t} \not\to y_t$
1979-90				
Two Lags	0.350	14.867***(-)	0.873	0.360
Four Lags	3.150***(+)	6.233**(-)	1.375	0.554
Six Lags	2.585**(+)	2.785**(-)	1.030	0.428
Eight Lags	3.495**(-)	2.615**(-)	0.909	0.560
1973-99				
Two Lags	38.047***(+)	0.722	2.514*(-)	1.061
Four Lags	38.830***(+)	2.286*(-)	2.518**(-)	0.815
Six Lags	55.507***(+)	1.050	5.604***(-)	0.896
Eight Lags	39.675***(+)	1.118	3.700***(-)	1.113

Notes: (1) The …gures are F statistics.

(2) $\pi_t \not\to h_{\pi t}$: In‡ation does not Granger-cause in‡ation uncertainty; $h_{\pi t} \not\to \pi_t$: In‡ation uncertainty does not Granger-cause in‡ation; $h_{\pi t} \not\to y_t$: In‡ation uncertainty does not Granger-cause output growth.

(3) superscript (a) means that lagged in‡ation has been added to the regression.

(4) the positive or negative sign in parentheses indicates the sign of the sum of the lagged coe¢cients in the respective equations.

(5) ***, ** and * indicate rejection of the null at the 0.01, 0.05 and 0.10 levels of signi…cance, respectively.

Table 7: Granger causality tests for in‡ation and in‡ation uncertainty (1983-1999)

	H$_0$: π_t ! $h_{\pi t}$	H$_0$: $h_{\pi t}$! π_t	H$_0$: $h_{\pi t}$! y_t	H$_0^a$: $h_{\pi t}$! y_t
(A) France				
Two Lags	4.724¤¤¤(+)	0.001	2.015	2.373¤(+)
Four Lags	3.432¤¤¤(+)	0.169	1.905	1.766
Six Lags	3.031¤¤¤(+)	0.237	0.552	1.018
Eight Lags	3.111¤¤¤(+)	0.396	0.604	1.269
(B) Germany				
Two Lags	2.762¤(+)	0.651	1.566	1.410
Four Lags	4.026¤¤¤(+)	0.943	1.670	1.689
Six Lags	2.927¤¤¤(+)	0.845	2.479¤¤¤(-)	1.643
Eight Lags	2.293¤¤¤(+)	0.691	1.937¤(-)	1.374
(C) Italy				
Two Lags	5.898¤¤¤(+)	3.605¤¤¤(-)	1.127	2.079
Four Lags	5.576¤¤¤(+)	2.038¤(-)	0.780	1.535
Six Lags	3.015¤¤¤(+)	2.933¤¤¤(-)	1.018	1.778
Eight Lags	1.947¤(+)	2.608¤¤¤(-)	1.033	0.844
(D) The Neth/nds				
Two Lags	3.829¤¤¤(-)	4.492¤¤¤(-)	0.546	0.299
Four Lags	8.285¤¤¤(-)	1.442	2.068¤(+)	0.124
Six Lags	14.995¤¤¤(-)	0.971	1.585	0.297
Eight Lags	9.717¤¤¤(-)	1.069	0.539	0.686
(E) Spain				
Two Lags	0.890	1.629	0.081	0.074
Four Lags	1.567	1.659	2.594¤¤¤(+)	2.923¤¤¤(+)
Six Lags	0.754	1.483	2.004¤(+)	1.549
Eight Lags	0.561	1.772	1.626	1.245

Notes: (1) The …gures are F statistics.

(2) π_t ! $h_{\pi t}$: In‡ation does not Granger-cause in‡ation uncertainty; $h_{\pi t}$! π_t: In‡ation uncertainty does not Granger-cause in‡ation; $h_{\pi t}$! y_t: In‡ation uncertainty does not Granger-cause output growth.

(3) superscript (a) means that lagged in‡ation has been added to the regression.

(4) the positive or negative sign in parentheses indicates the sign of the sum of the lagged coe¢cients in the respective equations.

(5) ***, ** and * indicate rejection of the null at the 0.01, 0.05 and 0.10 levels of signi…cance, respectively.

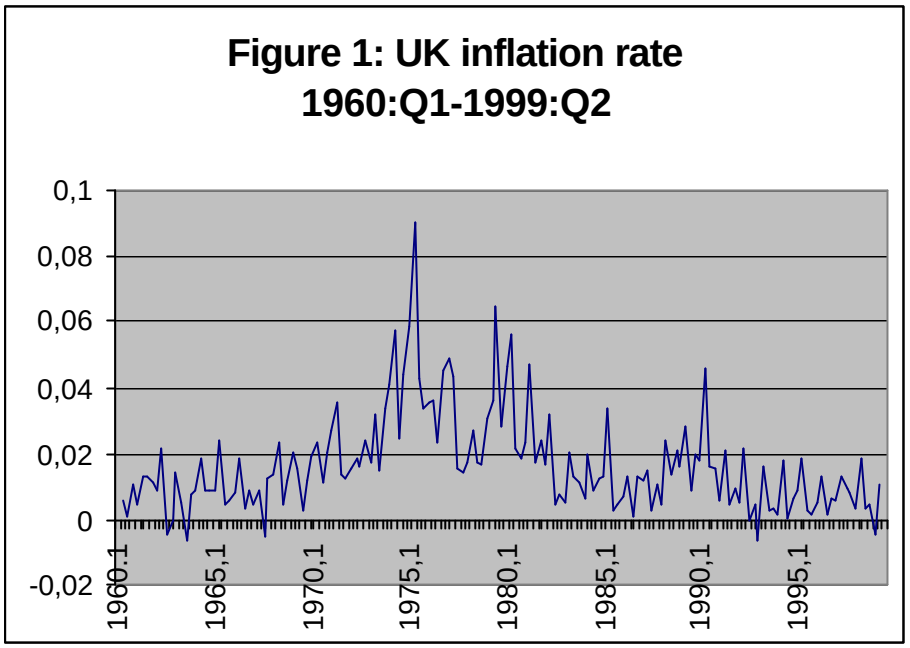
Figure 1: UK inflation rate
1960:Q1-1999:Q2
0,1
0,08
0,06
0,04
0,02
0
-0,02
1960.1
1965.1
1970.1
1975.1
1980.1
1985.1
1990.1
1995.1

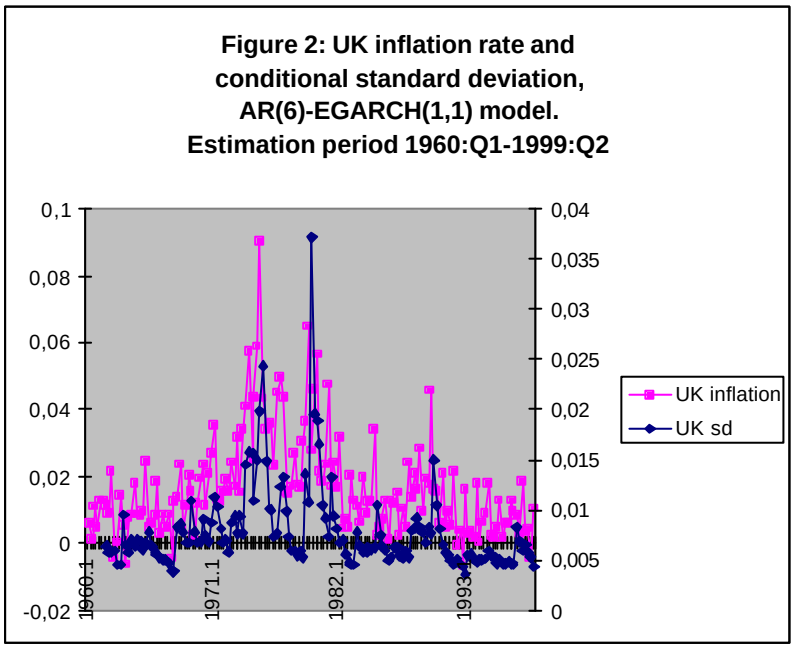
Figure 2: UK inflation rate and
conditional standard deviation,
AR(6)-EGARCH(1,1) model.
Estimation period 1960:Q1-1999:Q2
0,1
0,08
0,06
0,04
0,02
0
-0,02
0,04
0,035
0,03
0,025
0,02
0,015
0,01
0,005
0
1960.1
1971.1
1982.1
1993.1
UK inflation
UK sd
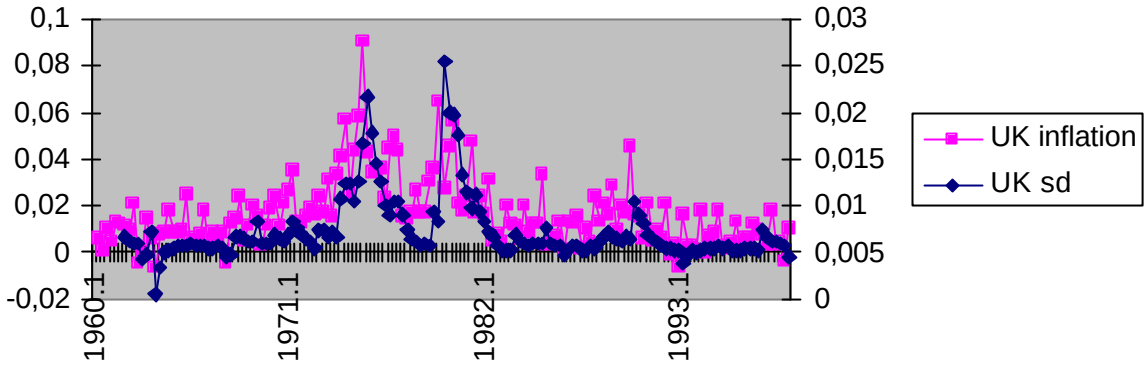
Figure 3: Inflation rate and conditional standard deviation, AR(6)-Asymmetric GARCH(1,1) model. Estimation period 1960:Q1-1999:Q2