German Economic Review 9(3): 265–286

Is the Relationship between Inflation and Its Uncertainty Linear?

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Abstract. *We use parametric power ARCH models of the conditional variance of inflation to model the relationship between inflation and its uncertainty using monthly data for Germany, the Netherlands and Sweden over a period ranging from 1962 to 2004. For all three countries inflation significantly raises inflation uncertainty as predicted by Friedman. Increased uncertainty affects inflation in all countries but not in the same manner. For Sweden we find a negative impact in accordance with the Holland hypothesis, whereas for Germany and the Netherlands we find the opposite in support of the Cukierman–Meltzer hypothesis. In a sensitivity analysis we show that an arbitrary choice of the heteroscedasticity parameter influences this relationship significantly.*

JEL classification: *C*22, *E*31.

Keywords: GARCH-in-mean; inflation; level effect; nominal uncertainty; power transformation.

1. INTRODUCTION

The issue of the welfare costs of inflation has been one of the most researched topics in macroeconomics both on the theoretical and empirical fronts. Friedman (1977) argues that a rise in inflation leads to more nominal uncertainty. The opposite direction of causation has also been analysed in the theoretical literature. Cukierman and Meltzer (1986) argue that central banks (CBs) tend to create inflation surprises in the presence of more nominal uncertainty. Clarida *et al.* (1999) emphasize the fact that since the late 1980s a stream of empirical work has presented evidence that monetary policy may have important effects on real activity. Consequently, there has been a great resurgence of interest in the issue of how to conduct monetary policy. If an increase in the rate of inflation causes an increase in its uncertainty, one can conclude that greater uncertainty – which many have found to be negatively correlated with economic activity – is part of the costs of inflation. Thus, if we attempt to provide a satisfactory answer to the questions 'What actions should central bankers take?' and 'What is the optimal strategy for monetary authorities to follow?', we must first develop a clear view about the temporal ordering of inflation and nominal uncertainty.

Many studies examining the link between inflation and uncertainty use GARCH estimation methods, but they differ in the choice of sample periods, frequency data sets and empirical specifications. For example, Baillie *et al.* (1996) employ an ARFIMA-GARCH-in-mean model, Fountas and Karanasos (2007) and Grier and Perry (1998) estimate univariate component GARCH specifications, Conrad and Karanasos (2005a, 2005b) utilize the ARFIMA-FIGARCH model, and Fountas *et al.* (2006) use a bivariate constant correlation GARCH formulation.

Despite using different GARCH specifications, all these studies focus exclusively on the standard Bollerslev-type model, which assumes that the conditional variance is a linear function of lagged squared errors. There seems to be, however, no economic reason why one should make such a strong assumption. The common use of a squared term in this role is most likely to be a reflection of the normality assumption traditionally invoked working with inflation data. However, if we accept that inflation data are very likely to have a non-normal error distribution, then the superiority of a squared term is lost and other power transformations may be more appropriate. Indeed, for non-normal data, by squaring the inflation rates one effectively imposes a structure on the data that may potentially furnish sub-optimal modelling and forecasting performance relative to other power terms. If π_t represents inflation in period t, this paper considers the temporal properties of the functions of $|\pi_t|^d$ for positive values of d. We find, as an empirical fact, that the autocorrelation function of $|\pi_t|^d$ is a concave function of d and reaches its maximum when d is smaller than 1. This result serves as an argument against a Bollerslev-type model.

In this paper, we illustrate these concerns empirically for Germany, the Netherlands and Sweden using a parametric power ARCH model (PARCH). The PARCH model can be viewed as a standard GARCH model for observations that have been changed by a sign-preserving power transformation implied by a (modified) PARCH parametrization. The PARCH model increases the flexibility of the conditional variance specification by allowing the data to determine the power of inflation for which the predictable structure in the volatility pattern is the strongest. This feature in the volatility processes of inflation has major implications for the inflation–uncertainty hypothesis. To test for the relationship between the two variables we use the simultaneous-estimation approach. Under this approach, we estimate a PARCH-in-mean model with the conditional variance equation incorporating lags of the inflation series (the 'level' effect), thus allowing simultaneous estimation and testing of the bidirectional causality between the inflation series and the associated uncertainty. Moreover, He and Teräsvirta (1999) emphasize that, if the standard Bollerslev-type model is augmented by the 'heteroscedasticity' parameter (the 'power' term), the estimates of the ARCH and GARCH coefficients almost certainly change. More importantly, we find that the inflation–uncertainty relationship is sensitive to changes in the values of the 'heteroscedasticity' parameter. Put differently, the estimated values of the 'in-mean' and the 'level' effects are fragile to changes in the 'power' term.

The article is organized as follows: in Section 2 we consider in more detail the hypotheses about the causality between inflation and its uncertainty. In Section 3, we describe the time-series model for inflation and explain its merits. We report the empirical results in Section 4, and in Section 5 we evaluate the robustness of our findings. Section 6 discusses our results and proposes extensions of the time-series model for inflation. Section 7 outlines our conclusions.

2. THE LINK BETWEEN INFLATION AND ITS UNCERTAINTY

2.1. Theory

The effect of inflation on its uncertainty is theoretically ambiguous. The Friedman (1977) hypothesis stresses the harmful effects of nominal uncertainty on employment and production. On this basis several researchers contend that a high rate of inflation produces greater uncertainty about the future direction of government policy and, thus, about future rates of inflation. Ball (1992) formalizes this idea in the context of a repeated game between the monetary authority and the public. This extension of a Barro–Gordon model introduces exogenous shocks and two CB policy-makers, one Conservative and one Liberal, who have different preferences over how to react in times of high inflation. During these times the public is confused because it does not know which policy-maker is in charge. This incomplete information, in return, increases the public's uncertainty about future inflation. In accordance with the Friedman hypothesis, we test for a positive effect.

In contrast, Ungar and Zilberfarb (1993) propose a mechanism that may weaken, offset, or even reverse the direction of the traditional view concerning the inflation–uncertainty relationship. They argue that, as inflation rises, economic agents invest more resources in forecasting it, thus reducing nominal uncertainty. However, this effect might only be present in periods of extreme inflation, which means that it comes into action only if the inflation rate surpasses a crucial threshold.

On the other hand, Cukierman and Meltzer (1986) predict that an increase in uncertainty will raise inflation due to the behaviour of the CB in an uncertain environment. Their model is embedded in a Barro–Gordon setting in which the CB is not tied to a commitment rule on money supply growth. Therefore, the CB can pursue both objectives of 'keeping inflation low' and 'stimulating the economy by surprise inflation'. Because the objective function of the CB and the money supply process are modelled as random variables, the public has difficulties inferring what caused higher inflation. It could be either that the CB finds it more important to stimulate the economy or that a random money supply shock occurred. Owing to this information asymmetry the CB has an incentive to create inflation surprises in the presence of higher nominal uncertainty. In accordance with the Cukierman and Meltzer hypothesis, we test for a positive effect.

Finally, Holland (1995) predicts the opposite effect of uncertainty on inflation. He assumes the CB to be motivated by a desire for stability. If the CB analysts observe increasing nominal uncertainty due to an increasing inflation rate, the CB will restrict money supply growth. This measure is justified by reducing the potential of severe negative welfare effects of increasing inflation. In accordance with the Holland hypothesis, we test for a negative effect.

2.2. *Empirical evidence*

The relationship between the two variables has been analysed extensively in the empirical literature. Recent time-series studies have focused particularly on the GARCH conditional variance of inflation as a statistical measure of nominal uncertainty (see e.g. Grier and Perry, 2000). To test for the relationship between uncertainty and indicators of macroeconomic performance such as inflation one can use either the two-step or the simultaneous-estimation approach.

Under the former approach, estimates of the conditional variance are obtained from the estimation of a standard GARCH model and these estimates are used in running Granger-causality tests to examine the causality between the two variables. Under the latter approach the model is estimated with the conditional variance (lagged inflation) included as a right-hand-side variable in the mean (variance) equation.

Applying the two-step methodology, Grier and Perry (1998) in the G7 countries, and Conrad and Karanasos (2005b) and Fountas *et al.* (2004) in several European countries, find that inflation significantly raises its uncertainty. They also find evidence in favour of the Cukierman–Meltzer hypothesis for some countries and in favour of the Holland hypothesis for other countries. Their results regarding the impact of uncertainty on inflation were generally consistent with the rankings of CB independence (CBI).

Some studies use GARCH models that include a function of the lagged inflation rate in the conditional variance equation. In particular, Brunner and Hess (1993) allow for asymmetric effects of inflation shocks on nominal uncertainty and find a weak link between the two variables in the United States. Two studies use GARCH-type models with a joint feedback between the conditional mean and variance of inflation. Baillie *et al.* (1996), for three high-inflation countries and the United Kingdom, and Karanasos *et al.* (2004) for the United States, find strong evidence in favour of a positive bidirectional relationship in accordance with the predictions of economic theory.

There is very little research based on GARCH measures of uncertainty that investigates the case of Europe as one economic region, which nevertheless could serve as a basis for successful implementation mechanisms of a common European monetary policy. Conrad and Karanasos (2005b) and Fountas *et al.* (2004) fill in some of the gaps that arise from the lack of interest in the European case and from the methodological shortcomings of the previous studies.

3. THE PARCH MODEL

Since its introduction by Ding *et al.* (1993), the PARCH model has been frequently applied. For example, Hentschel (1995) defined a parametric family of asymmetric GARCH formulations that nests the EGARCH and PARCH models. He and Teräsvirta (1999) considered a family of first-order asymmetric GARCH processes that includes the asymmetric PARCH (A-PARCH) as a special case. Brooks *et al.* (2000) analysed the applicability of the PARCH models to national stock market returns for ten countries.[1] Laurent (2004) derives analytical expressions for the score of the A-PARCH model. The use of the PARCH model is now widespread in the literature (see e.g. Conrad *et al.*, 2006, 2007; Giot and Laurent, 2003; Karanasos and Kim, 2006; Karanasos and Schurer, 2005; Mittnik and Paolella, 2000).

Let π_t follow an autoregressive (AR) process augmented by a 'risk premium' defined in terms of volatility

$$\Phi(L)\pi_t = \phi_0 + kg(h_t) + \varepsilon_t \tag{1}$$

with

$$\varepsilon_t \equiv e_t h_t^{\frac{1}{2}}$$

where by assumption the finite-order polynomial $\Phi(L) \equiv \sum_{i=1}^{p} \phi_i L^i$ has zeros outside the unit circle and the symbol '$\equiv$' is used to indicate equality by definition. In addition, $\{e_t\}$ are independent and identically distributed (i.i.d.) random variables with $E(e_t) = E(e_t^2 - 1) = 0$. The conditional variance of inflation $\{\pi_t\}$, h_t is positive with probability one and is a measurable function of the sigma-algebra Σ_{t-1}, which is generated by $\{\pi_{t-1}, \pi_{t-2}, \ldots\}$.

Furthermore, we need to choose the form in which the time-varying variance enters the specification of the mean to determine the 'risk premium'. This is a matter of empirical evidence. In the empirical results that follow we employ three specifications for the functional form of the 'risk premium' [$g(h_t) = h_t$, $g(h_t) = \sqrt{h_t}$, or $g(h_t) = \ln(h_t)$].

1. It is worth noting that Fornari and Mele (1997) show the usefulness of the PARCH scheme in approximating models developed in continuous time as systems of stochastic differential equations. This feature of GARCH schemes has usually been overshadowed by their well-known role as simple econometric tools providing reliable estimates of unobserved conditional variances (Fornari and Mele, 2001).

Moreover, h_t is specified as an A-PARCH(1,1) process with lagged inflation included in the variance equation

$$h_t^{\frac{\delta}{2}} = \omega + \alpha h_{t-1}^{\frac{\delta}{2}} f(e_{t-1}) + \beta h_{t-1}^{\frac{\delta}{2}} + \gamma_l \pi_{t-l} \tag{2}$$

with

$$f(e_{t-1}) \equiv [|e_{t-1}| - \varsigma e_{t-1}]^{\delta}$$

where δ with $\delta > 0$ is the 'heteroscedasticity' parameter, α and β are the ARCH and GARCH coefficients, respectively, ς with $|\varsigma| < 1$ is the 'leverage' term and γ_l is the 'level' term for the lth lag of inflation. The model imposes a Box–Cox power transformation of the conditional standard deviation process and the asymmetric absolute residuals. The expected value of $f(e_{t-1})$ is given by

$$E[f(e_{t-1})] = \begin{cases} \dfrac{1}{\sqrt{\pi}}\left[(1-\varsigma)^{\delta} + (1+\varsigma)^{\delta}\right] 2^{\left(\frac{\delta}{2}-1\right)} \Gamma\left(\dfrac{\delta+1}{2}\right), & \text{if } e_{t-1} \overset{\text{(i.d.)}}{\sim} N(0,1) \\ \dfrac{(r-2)^{\frac{\delta}{2}} \Gamma\left(\frac{r-\delta}{2}\right) \Gamma\left(\frac{\delta+1}{2}\right)}{\Gamma(r/2) 2\sqrt{\pi}} \left[(1-\varsigma)^{\delta} + (1+\varsigma)^{\delta}\right], & \text{if } e_{t-1} \overset{\text{(i.d.)}}{\sim} t_r(0,1) \end{cases}$$

where N and t denote the Normal and Student's t distributions, respectively, r are the degrees of freedom of Student's t distribution and $\Gamma(\cdot)$ is the gamma function. The δth moment of the conditional variance is a function of the above expression (see Karanasos and Kim, 2006).

Within the A-PARCH model, by specifying permissible values for δ, α, β, ς and γ_l in equation (2), it is possible to nest a number of the more standard ARCH and GARCH specifications (see Brooks *et al.*, 2000; Ding *et al.*, 1993; Hentschel, 1995). For example, in equation (2) let $\delta = 2$ and $\varsigma = \gamma_l = 0$ to get the GARCH model. In order to distinguish the general model in equations (1) and (2) from a version in which $k = \gamma_l = \varsigma = \beta = 0$, we will hereafter refer to the former as A-PGARCH-in-mean-level (A-PGARCH-ML) and the latter as PARCH.

4. EMPIRICAL ANALYSIS

4.1. Power-transformed inflation

We use monthly data on the consumer price index (CPI) as proxies for the price level.[2] The data range from January 1962 to January 2004 and cover three European countries, namely, Germany, the Netherlands and Sweden. We have chosen these three particular countries given their different histories

2. Most studies use CPI-based inflation measures (i.e. Conrad and Karanasos, 2005a, 2005b); therefore, we construct our measures also from the CPI. Alternatively, one can use either the producer price index (PPI) or the GNP deflator. Brunner and Hess (1993) use all three measures but they discuss only the results using CPI inflation. Fountas and Karanasos (2007) and Grier and Perry (2000) use both (CPI and PPI) indices and find that the results are virtually identical.

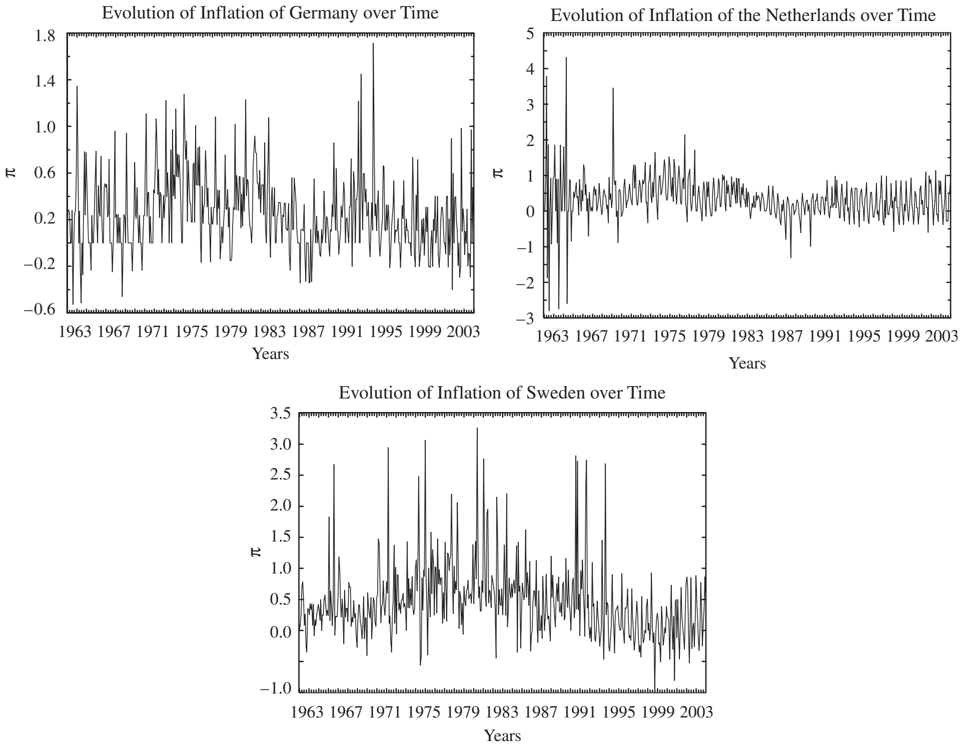

Figure 1 Evolution of inflation over time

in monetary policy pursued by their respective CBs and inflation. This choice allows us to test the various hypotheses of the behaviour of the CBs in response to increasing inflation and/or inflation uncertainty.

Inflation is measured by the difference between two months of the logarithm of CPI, i.e. [$\pi_t = 100 \cdot \ln(\mathrm{CPI}_t/\mathrm{CPI}_{t-1})$], which leaves us with 505 usable observations. The inflation rates of the three countries are plotted in Figure 1. These display the differences in monetary policy. Germany pursued for most of the time period a committed money growth target that explicitly took the Bundesbank's inflation goal into consideration and therefore yields a relatively stable inflation rate. Sweden's rather volatile inflation rate is a result of its CB commitment to fixed exchange rate, at least until the beginning of the 1990s. The Netherlands is an interesting case to investigate, because its inflation rate remained relatively stable over the decades despite, similar to Sweden, its commitment to a fixed exchange rate regime.

The results of the Phillips–Perron unit-root tests (not reported) imply that we can treat the three rates as stationary processes. The summary statistics (not reported) indicate that the distribution of the three series is skewed to the right and has fat tails. The large values of the Jarque–Bera statistic imply a deviation from normality.

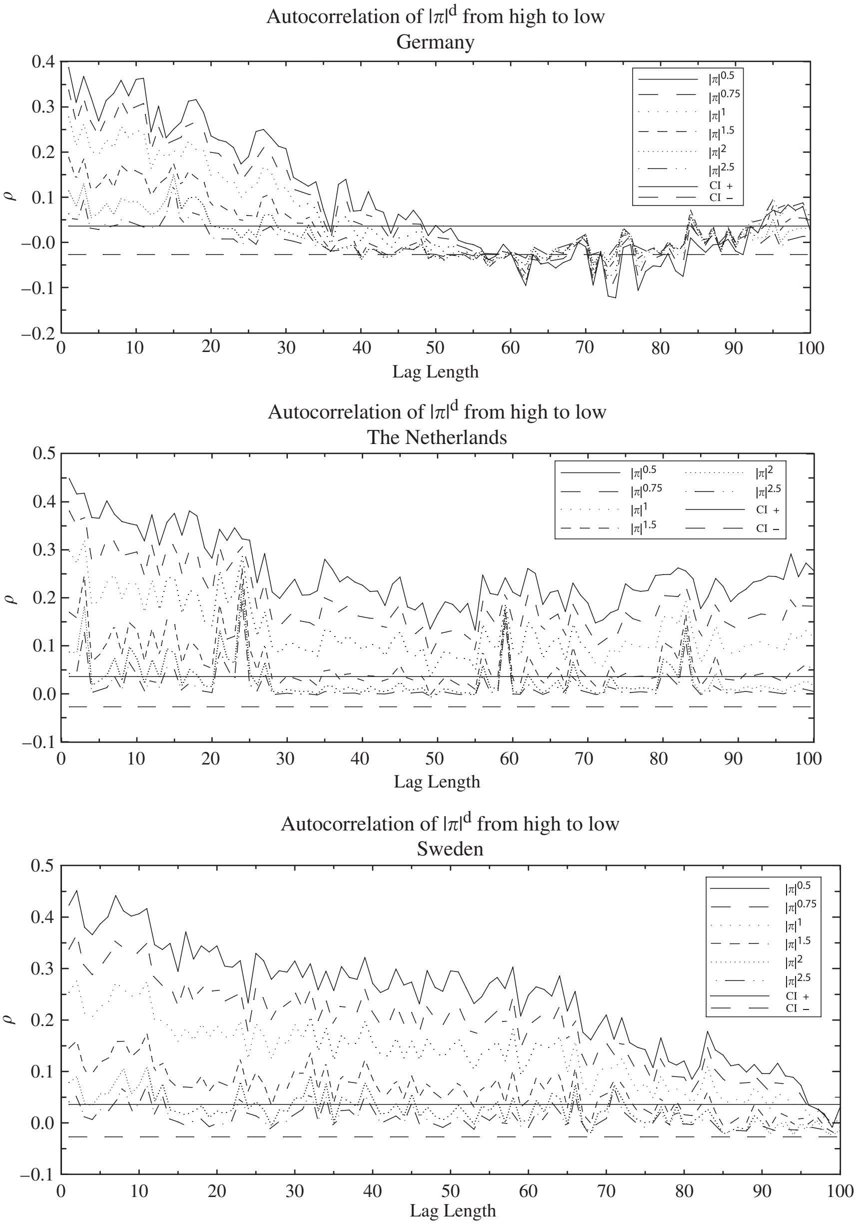

Figure 2 Autocorrelations of $|\pi_t|^d$

Next, we examine the sample autocorrelations of the power transformed absolute inflation $|\pi_t|^d$ for various positive values of d. Figure 2 shows the autocorrelogram of $|\pi_t|^d$ from lag 1 to 100 for $d = 0.5$, 0.75, 1, 1.5, 2 and 2.5. The horizontal lines show the $\pm 1.96/\sqrt{T}$ confidence interval (CI) for the

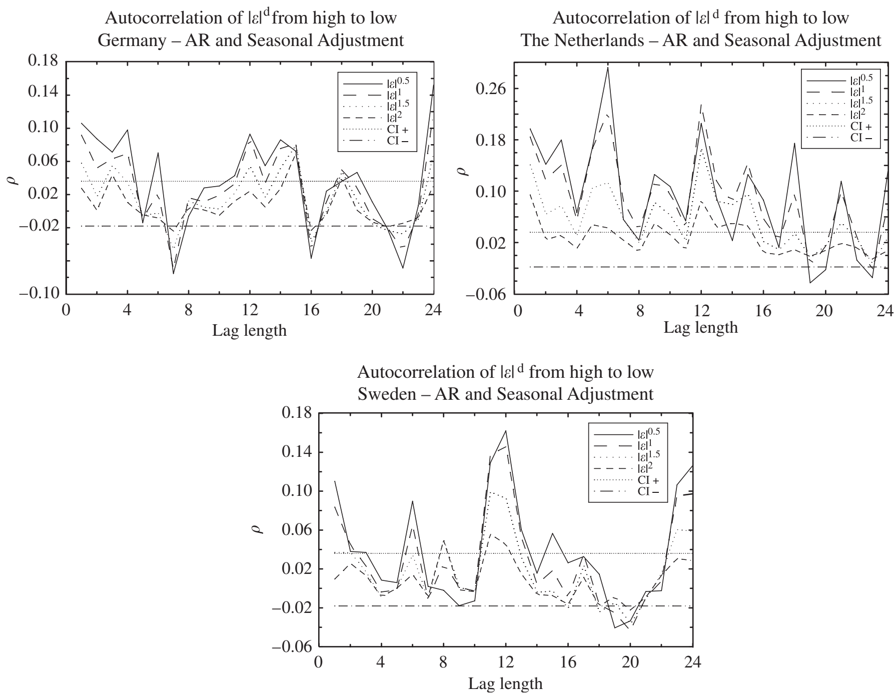

Figure 3 Autocorrelations of $|\varepsilon_t|^d$

estimated sample autocorrelations if the process π_t is i.i.d. In our case $T = 505$, so $\mathrm{CI} = \pm 1.96/\sqrt{T} = \pm 0.0872$.

The sample autocorrelations for $\sqrt{|\pi_t|}$ are greater than the sample autocorrelations of $|\pi_t|^d$ for $d = 0.75$, 1, 1.5, 2 and 2.5 at every lag up to at least 100 lags for the Netherlands and Sweden, and up to at least 50 lags for Germany. In other words, the most interesting finding from the autocorrelogram is that $|\pi_t|^d$ has the strongest and slowest decaying autocorrelation when $d = 0.5$. Furthermore, the power transformations of absolute inflation when d is less than or equal to 1 have significant positive autocorrelations at least up to lag 100, 95 and 35 for the Netherlands, Sweden and Germany, respectively.

Figure 3 shows the autocorrelogram for power transformations of absolute residuals $|\varepsilon_t|^d$ from AR models that incorporate seasonal dummy variables (see next section). We plot the sample autocorrelations from lag 1 to 24 for $d = 0.5$, 1, 1.5 and 2. In general, the most interesting finding from the autocorrelogram is that, at most lags, $|\varepsilon_t|^d$ has the lowest autocorrelation when $d = 2$.

To illustrate this more clearly, we calculate the sample autocorrelations of the absolute value of inflation $\rho_\tau(d)$ as a function of d for lags $\tau = 1$, 12, 60 and 96 and taking $d = 0.125, 0.25, \ldots, 1.75, 1.875, 2, \ldots, 4.5$. Figure 4 provides the plots of the calculated $\rho_\tau(d)$. For example, for lag 12, there is a unique

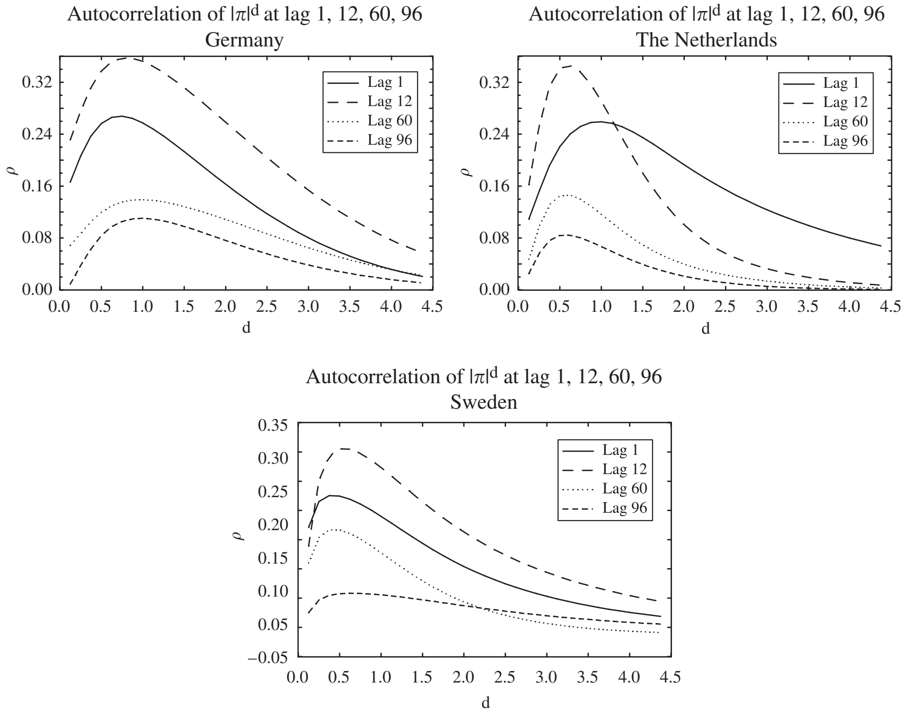

Figure 4 Autocorrelations of $|\pi_t|^d$ at lags 1, 12, 60 and 96

point d^* equal to 0.50, 0.625 and 0.75 for Sweden, the Netherlands and Germany, respectively, such that $\rho_{12}(d)$ reaches its maximum at this point: $\rho_{12}(d^*) > \rho_{12}(d)$ for $d \neq d^*$.

Because for the choice of the econometric model it is important whether the strength of autocorrelation persists in the residuals of the model, we analogously present in Figure 5 the plots of calculated $\rho_\tau(d)$ for $|\varepsilon_t|^d$. For example, $\rho_{24}(d)$ reaches its maximum at 0.5, 0.625 and 0.75 for the Netherlands, Sweden and Germany, respectively. These figures confirm the claim that in our data the autocorrelation structure of inflation is the strongest for values of d smaller than 1.

4.2. Estimated models of inflation

We proceed with the estimation of the AR-PGARCH(1,1) model in equations (1) and (2) in order to take into account the serial correlation observed in the levels and power transformations of our time-series data. Table 1 reports the estimated parameters of interest for the period 1962–2004. These were obtained by quasi-maximum likelihood estimation as implemented in EVIEWS. The best-fitting specification is chosen according to the likelihood

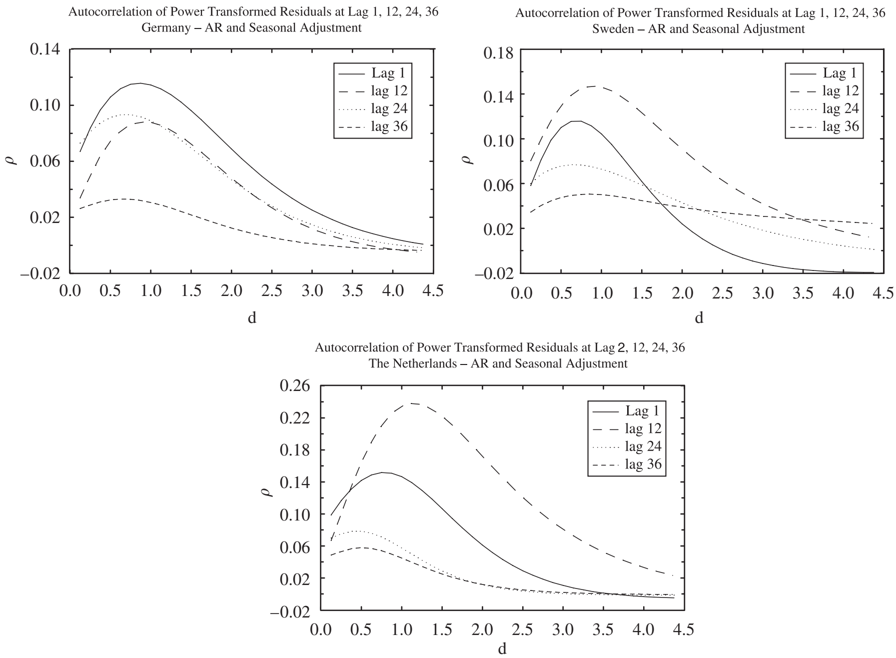

Figure 5 Autocorrelations of $|\varepsilon_t|^d$ at lags 1, 12, 24 and 36

ratio results and the minimum value of the information criteria (IC) (not reported). Once heteroscedasticity in the conditional mean has been accounted for, an AR(12) specification appears to capture the serial correlation in all three inflation series.[3]

The existence of outliers causes the distribution of inflation to exhibit excess kurtosis. To accommodate the presence of such leptokurtosis, one should estimate the PGARCH models using non-normal distributions. As reported by Palm (1996), the use of Student's *t* distribution is widespread in the literature. In accordance with this, we estimate all the models using two alternative distributions: the normal and Student's *t*. Moreover, we allow for the possibility of seasonality in the inflation data. The mean equation is modified to include seasonal dummy variables on the intercept. In other words, the dummy variables (not reported) are included to seasonally adjust the inflation series. We find that four of these dummies are jointly statistically significant for Germany and the Netherlands and five for Sweden.

For all countries, we find the leverage term ς to be insignificant and therefore we re-estimate the model excluding this parameter. The estimated β parameter is highly significant in all cases while α is significant for all countries but the Netherlands and Sweden (when the innovations e_t are

3. Owing to space limitations, we have not reported the estimated equations for the conditional means. These are provided on request.

Table 1 (P)GARCH models

	Normal			Normal (seasonal dummies)			Student's t		
	Germ	Neth	Swed	Germ	Neth	Swed	Germ	Neth	Swed
α	0.12	0.18	0.13	0.14	0.17	0.11	0.08	0.01	0.06
	(0.04)	(0.03)	(0.04)	(0.04)	(0.11)	(0.04)	(0.04)	(0.01)	(0.05)
β	0.73	0.81	0.78	0.68	0.85	0.86	0.06	0.90	0.93
	(0.10)	(0.03)	(0.08)	(0.10)	(0.07)	(0.05)	(0.02)	(0.03)	(0.03)
δ	0.80	1.10	0.40	0.50	0.80	0.80	0.50	3.36	1.71
	–	–	–	–	–	–	–	(0.54)	(1.06)
r	–	–	–	–	–	–	5.24	3.43	2.66
							(1.39)	(0.55)	(0.39)

Notes: For each of the three European countries, this table reports estimates of the parameters (of interest) for the (P)GARCH model. Germ, Neth and Swed denote Germany, the Netherlands and Sweden, respectively. The numbers in parentheses are robust standard errors. r are the degrees of freedom of Student's t distribution.

Student's t distributed). These are the only two (out of the nine) cases where the estimated power term is statistically significant (see Table 1). In order to distinguish the general PGARCH model from a version in which δ is fixed to a specific value we will hereafter refer to the latter as (P)GARCH.

For the Netherlands, when the innovations are Student's t distributed, the IC chooses a PGARCH model with estimated power term parameter of $\delta = 3.36$. The corresponding values for the normal distribution are markedly lower: $\delta = 1.10$ for the model without and $\delta = 0.80$ with seasonal dummies. For Germany, the Akaike IC (AIC) choose (P)GARCH models with 'power' coefficients δ below 1. For Sweden, when the errors ε_t are Student's t distributed, the estimated value of $\delta = 1.71$ is markedly higher than the power terms with innovations that are drawn from the normal distribution: $\delta = 0.40$ for the model without and $\delta = 0.80$ for the model with seasonal dummies.

Next, we report the estimation results of an AR-(P)GARCH-M model of inflation, with $g(h_t) = h_t$, for all three countries. Table 2 reports only the estimated parameters of interest. In all countries the estimates for the 'in-mean' parameter (k) are statistically significant (see the 'Mean' columns of Table 2). The effects are significant at the 10% (Germany), 4% (the Netherlands) and 1% (Sweden) levels. In Germany and the Netherlands there is evidence in favour of the Cukierman–Meltzer hypothesis because the value of the 'in-mean' coefficient is positive: 0.87 and 0.27, respectively. Evidence in favour of the Holland hypothesis applies in Sweden. Hence, overall, the evidence on the effect of nominal uncertainty on inflation is mixed. In all three countries the values of the 'power' coefficients are below 1.

Table 3 reports for Germany estimates of the k parameters of the (P)GARCH-M model with $g(h_t) = h_t$ and errors that are conditionally normal,

Table 2 (P)GARCH-ML models (normal distribution)

	Mean: $g(h_t)=h_t$			Level				Mean-level: $g(h_t)=h_t$			
	Germ	Neth	Swed	Germ	Neth		Swed	Germ	Neth		Swed
k	0.87	0.27	−0.43	–	–		–	1.35	0.27		−0.47
	(0.53)	(0.13)	(0.16)					(0.57)	(0.12)		(0.20)
γ_i	–	–	–	0.06	0.08	−0.07	0.11	0.07	0.08	−0.07	0.16
				(0.03)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.05)
				{11}	{3}	{7}	{4}	{11}	{3}	{7}	{11}
δ	0.50	0.70	0.40	1.38	0.80		1.37	0.80	0.80		0.45
	–	–	–	(0.71)	–		(0.54)	–	–		(0.17)

Notes: For each of the three European countries, this table reports estimates of the parameters of interest for the various (P)GARCH-ML models. In all cases $g(h_t)=h_t$. The numbers in parentheses are robust standard errors. The numbers in { } indicate the lags of the 'level' terms.

Table 3 (P)GARCH-M models for Germany (normal distribution)

δ	0.50	0.70	0.80	1.00	1.20	1.30	1.50	1.70	1.80	2.00
k	0.87	NC[a]	0.97	0.96	0.88	0.84	0.77	NC	NC	NC
	[0.103]		[0.110]	[0.115]	[0.143]	[0.159]	[0.194]			
AIC	**0.172**	–	0.173	0.174	0.176	0.177	0.179	–	–	–
LL	−33.43	–	−33.61	−34.00	−34.46	−34.71	−35.22	–	–	–

Notes: This table reports estimates of the 'in-mean' parameters of the (P)GARCH-M model with $g=h_t$ of various positive δ. The numbers in brackets are p-values. The bold numbers indicate the minimum value of the AIC. LL denotes the maximum log-likelihood value.
[a] No convergence.

for various positive δ. The estimated values of the 'in-mean' effect are sensitive to changes in the 'power' term. Note that the statistical significance of the 'risk premium' decreases monotonically as the value of δ increases (see p-values in square brackets in Table 3). There is no convergence as soon as δ is equal to or higher than 1.70.

In what follows we report the estimation results of an AR-PGARCH-L model of inflation in the three countries with lagged inflation included in the conditional variance as the 'level' effect. In the expressions for the conditional variances reported in Table 2, various lags of inflation (from 1 to 12) were considered with the best model chosen on the basis of the minimum value of the AIC. Statistically significant effects are present (see the 'Level' columns of Table 2). For all countries there is strong evidence that inflation affects its uncertainty positively as predicted by Ball (1992) and Friedman (1977). The estimated (absolute) 'level' coefficient is in the range $0.06<|\gamma_i|<0.11$. The L models for Germany and Sweden generated very similar ‘heteroscedasticity’ parameters: 1.38 and 1.37, respectively. The chosen value of δ for the Netherlands (0.80) is lower than the corresponding values for Germany and Sweden.

Finally, Table 2 also reports the estimation results of an AR-(P)GARCH-ML model. That is, we estimate a system of equations that allows only the current value of the conditional variance to affect average inflation and that also allows up to the 12th lag of the latter to influence the former. All ‘level’ and ‘in-mean’ estimated coefficients are highly significant. As with the L model, we again find support for Friedman’s hypothesis in all three countries (see the ‘Mean-level’ columns of Table 2). The (absolute) ‘level’ parameter is in the range $0.07<|\gamma_i|<0.16$. Moreover, we find mixed evidence regarding the direction of the impact of a change in nominal uncertainty on inflation. That is, we find evidence in favour of the Cukierman–Meltzer hypothesis for Germany and the Netherlands and in favour of Holland’s hypothesis for Sweden. Germany is the country with the highest ‘risk premium’ parameter (1.35). As with the M models in all three countries, the values of the ‘power’ coefficients are below 1. When we include ‘level’ effects the impact of uncertainty on inflation is stronger. On the other hand, the impact of inflation on its uncertainty is robust to the inclusion or exclusion of ‘in-mean’ effects.

5. ROBUSTNESS CHECKS

The obtained results in favour of the Cukierman–Meltzer hypothesis for Germany are surprising given that its CB, the Deutsche Bundesbank, followed a strong and reliable commitment to a money growth target that incorporated a precise inflation goal, over the sample period. For this reason, we test whether they are a statistical construct. First, to check the sensitivity of our results to the form in which the time-varying variance enters the specification of the mean, we also use either the conditional standard deviation or the logarithm of the conditional variance as regressor in the mean equation. The picture is similar to that with the conditional variance (see Table 4), except for that the effect of inflation uncertainty on inflation is now much smaller. That is, we find evidence for supporting the Cukierman–Meltzer theory in Germany and the Netherlands and evidence for the Holland hypothesis in Sweden. The influence of nominal uncertainty on inflation becomes stronger when we account for ‘level’ effects.

Next, to check the sensitivity of our results to the distribution of the innovations we are also using Student’s *t* distribution. In general, the results are very similar to those obtained when the innovations are drawn from the normal distribution (see Table 5). That is, in all three countries inflation has a positive impact on its uncertainty. Regarding the reverse causal effect our evidence is country-specific. In particular, it is positive for Germany and the Netherlands (but insignificant) and negative for Sweden. When we account for ‘level’ effects the evidence for the Cukierman–Meltzer in Germany and for

Table 4 (P)GARCH-ML models (normal distribution)

	Mean			Mean-level		
	Germ	Neth	Swed	Germ	Neth	Swed
$g(h_t) = \sqrt{h_t}$						
k	0.53	0.42	– 0.32	0.64	0.39	– 0.44
	(0.28)	(0.15)	(0.13)	(0.30)	(0.12)	(0.09)
δ	0.55	0.70	0.40	0.80	0.80	0.40
	–	–	–	–	–	–
$g(h_t) = \ln(h_t)$						
k	0.04	0.08	– 0.11	0.06	0.06	– 0.14
	(0.02)	(0.03)	(0.06)	(0.03)	(0.02)	(0.06)
δ	0.52	1.00	0.70	0.80	0.80	0.44
	–	–	–	–	–	(0.15)

Notes: For each of the three European countries, this table reports estimates of the parameters of interest for the various (P)GARCH-ML models when the distribution of the errors is normal. The numbers in parentheses are robust standard errors.

Table 5 (P)GARCH-ML models (Student's t distribution)

	Mean: $g(h_t) = h_t$			Level					Mean-level: $g(h_t) = h_t$			
	Germ	Neth	Swed	Germ	Neth		Swed		Germ	Neth		Swed
k	0.89	0.03	– 0.24	–	–		–		1.07	0.14		– 0.57
	(0.57)	(0.09)	(0.18)						(0.65)	(0.13)		(0.30)
γ_i	–	–	–	0.09	– 0.07	0.08	0.21	0.12	0.07	– 0.08	0.09	0.15
				(0.02)	(0.02)	(0.02)	(0.08)	(0.07)	(0.02)	(0.02)	(0.02)	(0.03)
				{12}	{2}	{3}	{4}	{7}	{10}	{2}	{3}	{11}
δ	0.50	3.20	1.69	1.20	1.60		1.45		1.20	1.50		0.50
	–	–	(0.85)	–	–		(0.79)		–	–		–
r	5.46	3.20	2.43	5.79	3.78		2.68		5.78	3.76		2.91
	(1.48)	(0.01)	(0.33)	(1.55)	(0.60)		(0.45)		(1.63)	(0.59)		(0.45)

Notes: For each of the three European countries, this table reports estimates of the parameters of interest for the various (P)GARCH-ML models and assuming Student's t distribution for the error term. In all cases $g(h_t) = h_t$. The numbers in parentheses are robust standard errors. The numbers in { } indicate the lags of the 'level' terms.

the Holland hypothesis in Sweden becomes stronger. When we exclude the 'level' effects the negative impact of uncertainty on inflation in Sweden disappears.

Furthermore, to check the sensitivity of our results to the possible presence of seasonality in the inflation data we are also using the normal distribution including seasonal dummy variables on the intercept of the mean equation. In general, the results are very similar to those obtained without the use of dummy variables (see Table 6). That is, the strong evidence in support of the Friedman hypothesis in all countries is invariant to the inclusion or exclusion of the 'in-mean' effect. Moreover, the evidence for the Cukierman–Meltzer (Holland) hypothesis in Germany (Sweden) becomes weaker in the absence of 'level' effects. In the Netherlands inflation is independent of changes in its uncertainty.

Finally, Table 7 reports again for Germany for the same reasons as before, estimates of the k parameters of the (P)GARCH-M model, with $g(h_t) = h_t$, for various positive δ. Similar to our sensitivity analysis with seasonally

Table 6 (P)GARCH-ML models (normal distribution, seasonal dummies)

	Mean: $g(h_t) = h_t$			Level				Mean-level: $g(h_t) = h_t$			
	Germ	Neth	Swed	Germ	Neth		Swed	Germ	Neth		Swed
k	1.13	0.03	−0.38	–	–		–	1.33	0.11		−0.27
	(0.56)	(0.13)	(0.21)					(0.58)	(0.12)		(0.07)
γ_i	–	–	–	0.03	0.05	−0.04	0.18	0.06	0.07	−0.05	0.11
				(0.01)	(0.01)	(0.01)	(0.05)	(0.03)	(0.02)	(0.02)	(0.02)
				{11}	{3}	{7}	{4}	{10}	{3}	{7}	{11}
δ	0.70	1.00	0.40	2.40	1.50		1.36	1.49	0.80		0.40
	–	–	–	–	–		(0.26)	(0.57)	–		–

Notes: For each of the three European countries, this table reports estimates of the parameters of interest for the various PGARCH-ML models. In all cases $g(h_t) = h_t$. The numbers in parentheses are robust standard errors. The numbers in { } indicate the lags of the 'level' terms.

Table 7 (P)GARCH-M models for Germany

δ	0.50	0.70	0.80	1.00	1.20	1.30	1.50	1.70	1.80	2.00
Student's t-distribution										
k	0.89	NC[a]	0.77	0.71	0.63	0.61	0.58	NC	NC	NC
	[0.12]		[0.19]	[0.23]	[0.28]	[0.30]	[0.33]			
AIC	**0.125**	–	0.126	0.127	0.128	0.129	0.130	–	–	–
LL	−21.04	–	−21.08	−21.28	−21.55	−21.71	−22.04	–	–	–
Normal distribution (seasonal dummies)										
k	NC	1.13	1.22	1.01	0.97	0.94	0.87	0.81	0.79	0.74
		[0.04]	[0.03]	[0.07]	[0.09]	[0.10]	[0.13]	[0.16]	[0.17]	[0.19]
AIC	–	**0.101**	0.102	0.104	0.107	0.108	0.110	0.113	0.114	0.116
LL	–	−11.99	−12.29	−12.74	−13.34	−13.64	−14.23	−14.83	−15.13	−15.72

Notes: This table reports estimates of the 'in mean' parameters of the (P)GARCH-M model with $g(h_t) = h_t$, for various positive d. The numbers in brackets are p-values. The bold numbers indicate the minimum value of the AIC. LL denotes the maximum log-likelihood value.
[a] No convergence.

unadjusted data, the estimated values of the ‘in-mean’ effect are sensitive to changes in the ‘power’ term. Note that when Student’s t distribution is used the k parameter is significant only when $\delta = 0.5$. It is important to mention that when the errors are conditionally normal and we incorporate seasonal dummies in the model the AIC is minimized when $\delta = 0.7$. In addition, the significance of the ‘risk premium’ decreases monotonically as soon as δ exceeds 0.80. The most interesting finding is that the autocorrelation function of $|\pi_t|^d$ (for lag 12) reaches its maximum, approximately, at this point. Even though the IC and the LL values favour the model setting $\delta = 0.7$, the institutional setting of Germany’s CB would *a priori* justify a hypothesis in which the ‘in-mean’ effect is statistically not different from zero (e.g. $\delta = 2$).

6. DISCUSSION

6.1. Comparison with other work

The results presented above carry noteworthy implications for macroeconomic modelling and policy-making. Our very strong evidence on the Friedman hypothesis is in broad agreement with the findings of the overwhelming majority of empirical studies. The country-specific evidence on the Cukierman–Meltzer hypothesis is anticipated given that national CBs adjust their rate of money growth differently to nominal uncertainty depending on their relative preference towards inflation stabilization. Previous literature reports mixed results that are sensitive to factors such as the measure of uncertainty and the countries examined. In general, when we use the value of the ‘power’ term that is preferred by the IC, we find that the evidence in support of the Cukierman–Meltzer hypothesis for Germany is robust to (i) the functional form in which the time-varying variance enters the specification of the mean, (ii) the distribution of the innovations and (iii) the possible presence of seasonality in the inflation data. We show, however, that the significance of the ‘in-mean’ effect is sensitive to the choice of the ‘heteroscedasticity’ parameter.

The GARCH time-series studies, which examine the inflation–uncertainty link, use various sample periods, frequency data sets and empirical methodologies. Some GARCH studies utilize the simultaneous-estimation approach. For example, Baillie *et al.* (1996) and Fountas *et al.* (2004) find that in Germany inflation is independent of changes in its uncertainty, whereas in Conrad and Karanasos (2005b) the estimation routine does not converge. When we estimate Bollerslev’s model (i.e. the GARCH specification with $\delta = 2$) our results square with the findings of these studies. In particular, when the innovations are drawn either from the normal or from Student’s t distribution the estimation routine does not converge, whereas when we incorporate seasonal dummy variables in the model the ‘in-mean’ coefficient is insignificant. Germany’s Deutsche Bundesbank followed (for the sample period used in our study) a tight money growth target that incorporated an inflation stabilization goal. This policy contradicts the theoretical Central

Banker proposed by the Cukierman–Meltzer hypothesis who exploits uncertainty about inflation to conduct money supply shocks.

Contradictory empirical results, for Germany, are reported by various researchers. Given the theoretical ambiguity, it is not surprising that the statistical evidence is also ambiguous. Conrad and Karanasos (2005b), Fountas and Karanasos (2007), Fountas *et al.* (2004, 2006) and Grier and Perry (1998) use the Granger-causality approach and reach a striking variety of conclusions about the responsiveness of inflation to changes in its uncertainty. For example, Grier and Perry (1998) find that it has a negative impact whereas Fountas and Karanasos (2007) find evidence for a positive effect. In sharp contrast, Fountas *et al.* (2006) find that inflation is independent of changes in its uncertainty.

6.2. CBI

One obvious reason for these differences among countries is that they follow different monetary policies and dispose of different Central Banking institutions. Grier and Perry (1998) look at ratings of CBI to explain differences in the impact of uncertainty on inflation across countries. They note that countries disposing of a low rating of CBI usually are the ones associated with an opportunistic CB response towards growing uncertainty. Conrad and Karanasos (2005b) use the CBI measure designed by Alesina and Summers (1993) to test this claim. The measure rates a CB on a scale from 1 (minimum independence) to 4 (maximum independence). Germany, with a score of 4, is rated as highly independent, whereas the Netherlands is rated as relatively independent with a score of 2.5 and Sweden rated at a medium score of 2. For Sweden our evidence for the Holland hypothesis is in line with their results. Conrad and Karanasos (2005b) obtain mixed evidence for Germany. When considering eight lags for uncertainty, they find a positive impact. However, when considering longer lags (e.g. 12 as the optimal lag length) they find a negative effect. They interpret this as support of Holland's stabilization hypothesis by arguing that monetary policy takes time to materialize.

Moreover, in the case of the Netherlands, they find strong evidence for the Cukierman–Meltzer hypothesis at lag 4 in the two-step approach but they estimate an insignificant 'in-mean' coefficient. They point out that such a result is plausible, because any relationship where uncertainty influences inflation takes time to materialize and cannot be fairly tested in a model that restricts the effect to being contemporaneous.

6.3. Possible extensions

The main goal of this article is to investigate the inflation–uncertainty link and to estimate the optimal 'power' parameter driving the degree of heteroscedasticity, for three European countries. However, one might also ask why it is necessary to allow for 'power' effects in the conditional variance of inflation. To answer this we must query the possible theoretical sources of heteroscedasticity in the inflation shocks. It will be very useful to provide a theoretical rationale for the dynamics of inflation. Here the choice of the PGARCH model is justified solely on empirical grounds.

Possible extensions of this article could go in different directions. Karanasos and Zeng (2007) find that the significance and even the sign of the 'in-mean' effect vary with the choice of the lag. Their analysis suggests that the behaviour of macroeconomic performance depends on its uncertainty, but also that the nature of its dependence varies with time. One could provide an enrichment of the PGARCH model by allowing lagged values of the conditional variance to affect the inflation. Recently Baillie *et al.* (2002) have focused their attention on the topic of long memory and persistence in terms of the first two conditional moments of the inflation process. In the context of our analysis, incorporating long memory either in the AR or in the PGARCH specification or in both could be at work. We look forward to sorting this out in future work.

Finally, Karanasos and Schurer (2005) highlight the importance of using the PGARCH specification in order to model the power transformation of the conditional variance of growth. Using a bivariate AR-PGARCH-ML model, one can test for the empirical relevance of several theories that have been advanced on the relationship between the inflation, output growth and their respective uncertainties. This is undoubtedly a challenging yet worthwhile task. Conrad and Karanasos (2005b) analyse the inflation dynamics of several countries belonging to the European Monetary Union and of the United Kingdom.

Given the scope of this paper, we have not been able to deal with all European countries. We investigate the inflation–uncertainty link in Germany and the Netherlands, which are two countries with highly and relatively independent CBs, respectively. We also examine the aforementioned relationship in Sweden, which is an average country regarding CBI ratings. To highlight the importance of using the PGARCH specification in order to model the inflation dynamics of the other European countries we should have to go into greater detail than space in this paper permits.

7. CONCLUSIONS

We have used monthly data on inflation in three European countries to examine the possible relationship between inflation and its uncertainty, and hence test a number of economic hypotheses. From this empirical investigation we derive two important results.

First, the overall evidence for the economic hypotheses we tested is mixed. We find evidence for the Cukierman–Meltzer hypothesis, which Grier and Perry (1998) label as the 'opportunistic Fed', only in two out of three countries, namely Germany and the Netherlands. Increases in nominal uncertainty raise the optimal average inflation by increasing the incentive for the policy-maker to create inflation surprises. In sharp contrast, evidence for the Holland hypothesis applies in Sweden. This result suggests that the 'stabilizing Fed' notion is plausible. Increased inflation raises uncertainty, which creates real welfare losses and then leads to monetary tightening to lower inflation and thus also uncertainty. Even though mixed across the countries, these effects are robust to changes in the error distribution and in the complexity of the model. For the reverse relationship, the Friedman hypothesis has explanatory power for all three countries.

Second, in this study we draw attention to the peculiarity that even in countries with highly or relatively independent CBs, such as Germany and the Netherlands, the 'in-mean' effect can be positive when the optimal 'heteroscedasticity' parameter is used. We have shown this exemplary with the case of Germany. The statistical significance of the 'in-mean' effect is highly dependent on the choice of the value of the 'heteroscedasticity' parameter. For both error distributions the effect becomes insignificant if the 'power term' surpasses a specific value. This suggests that if we had assumed *a priori* a linear relationship between inflation and its uncertainty, the so-called Bollerslev specification, we would not have detected any significant link between the two variables. Most interestingly, this value coincides with the one chosen by the IC and the one for which the sample autocorrelation of the power-transformed inflation series is maximal. Whether this coincidence is systematic will be the focus of further research.

Thus, our results highlight the importance of using the PGARCH specification to model the power transformation of the conditional variance of inflation. It increases the flexibility of the conditional variance specification by allowing the data to determine the power of inflation, for which the predictable structure in the volatility pattern is the strongest.

ACKNOWLEDGEMENTS

We greatly appreciate two anonymous referees for their valuable comments, which led to a substantial improvement on the previous version of the article. We would also like to thank C. Conrad, C. Hanck and M. Karanassou for their helpful comments and suggestions.

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