Is the relationship between inflation and its uncertainty linear?

M. KARANASOS[a] and S. SCHURER[b]
[a] *Brunel University, Middlesex, UK*
[b] *Ruhr Graduate School in Economics, Essen, Germany*

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Abstract

We use parametric power ARCH models of the conditional variance of inflation and monthly data in Germany, the Netherlands and Sweden for the period 1962-2004 to examine the relationship between inflation and inflation uncertainty. In two out of the three countries inflation significantly raises inflation uncertainty as predicted by Friedman. Increased nominal uncertainty affects inflation in all countries but not in the same manner. The results for Germany and the Netherlands support the Cukierman-Meltzer hypothesis. In Sweden uncertainty about the future inflation appears to have a negative impact on inflation.

Keywords: GARCH-in-mean, Inflation, Level effect, Nominal uncertainty, Power transformation.
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Address for correspondence: RWI Essen, Hohenzollernstrasse 1-3, D-45128 Essen, Germany; Email: schurer@rwi-essen.de, Tel: +49 (0)201 8149 508; Fax: +49 (0) 201 8149 500.

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 front. Friedman (1977) argues that a rise in the average rate of inflation leads to more uncertainty about the future rate of inflation. The opposite type of causation between inflation and its uncertainty has also been analyzed in the theoretical literature. Cukierman and Meltzer (1986) argue that central banks tend to create inflation surprises in the presence of more inflation 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 inflation uncertainty, one can conclude that greater uncertainty-which many have found to be negatively correlated to economic activity-is part of the costs of inflation. Thus, if we attempt to provide a satisfactory answer to the questions 'what actions should the central bankers take?', and 'what is the optimal strategy for monetary authorities to follow?', we must first develop some clear view about the temporal ordering of inflation and nominal uncertainty.

The GARCH time series studies that examine the link between inflation rates and inflation uncertainty use various sample periods, frequency data sets and empirical methodologies. For example, Baillie et al. (1996) employ an ARFIMA-GARCH-in-mean model, Grier and Perry (1998) and Fountas and Karanasos (2005) estimate univariate component GARCH specifications, Conrad and Karanasos (2005a,b) utilize the ARFIMA-FIGARCH model, and Fountas et al. (2005) use a bivariate constant correlation GARCH formulation. Despite using different GARCH specifications all these studies focus exclusively on the standard Bollerslev type of model.

There seems to be no obvious reason why one should assume that the conditional variance is a linear function of lagged squared errors. 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 which 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 one. This result appears to argue against Bollerslev's type of GARCH model.

In this paper, the above issues are analyzed empirically for Germany, the Netherlands and Sweden with the use of a parametric power ARCH model (PARCH). The PARCH model may also be viewed as a standard GARCH model for observations that have been transformed by a sign-preserving power transformation implied by a (modified) PARCH parameterization. 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 inflation uncertainty and inflation 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 of model is augmented by the 'heteroscedasticity parameter' (the 'power' term), the estimates of the ARCH and GARCH parameters almost certainly change. More importantly, we find that the inflation-uncertainty relation 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.

This article is organized as follows: Section 2 considers the hypotheses about the causality between inflation and inflation uncertainty in more detail. In Section 3, we describe the time series model for inflation and uncertainty about inflation and discuss its merits. The empirical results are reported in Section 4. Section 5 contains summary remarks and conclusions.

2 The link between inflation and its uncertainty

2.1 Theory

In this Section, we discuss the economic theory concerning the link between inflation uncertainty and macroeconomic performance. Since Friedman (1977) stressed the harmful effects of nominal uncertainty on employment and production much research has been carried out investigating the relationship between inflation and uncertainty about inflation. The effect of inflation on its unpredictability is theoretically ambiguous. Several researchers contend that since a reduction in inflation causes an increase in the rate of unemployment, a high rate of inflation produces greater uncertainty about the future direction of government policy and the future rates of inflation. Ball's (1992) model formalizes this idea in the context of a repeated game between the monetary authority and the public. Ball (1992) extends a Barro-Gordon model of a repeated game by introducing exogenous shocks and two Central Bank policy-makers, one Conservative and one Liberal, who have different preferences over how to react in times of high inflation. In these times the public is confused because it does not know which policy maker is in charge, which in turn increases their uncertainty about future inflation. According to the Friedman hypothesis we test for a positive effect of inflation on its uncertainty. 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 inflation, thus reducing nominal uncertainty. However, this effect might only be present in periods of high inflation. This means that the effect 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 inflation uncertainty will raise average inflation due to the behavior of the Central Bank in an uncertain environment. Their model is embedded in a Barro-Gordon setting in which there exists no commitment mechanism for the Central Bank. Therefore, the Central Bank can pursue two objectives: keeping inflation low and stimulating the economy by surprise inflation. Since the objective function of the Central Bank and the money supply process are modelled as random variables, the public has difficulties to infer what caused higher inflation. It could be either that the Central Bank finds it more important to stimulate the economy or that a random money supply shock occurred. Due to this information asymmetry the Central Bank has an incentive to create inflation surprises in the presence of higher nominal uncertainty.

Finally, Holland (1995) predicts the opposite effect of inflation uncertainty on average inflation. He assumes the Central Bank to be following a stabilisation motive. If the Central Bank analysts observe increasing inflation uncertainty due to an increasing inflation rate, the Central Bank will contract the money supply. This measure is justified by reducing the potential of severe negative welfare effects. According to the Holland hypothesis, we test for a negative effect of uncertainty on inflation.

2.2 Empirical Evidence

In this Section, we discuss previous empirical testing of the inflation-uncertainty hypothesis. The relationship between inflation and its uncertainty has been analyzed extensively in the empirical literature. Recent time series studies have focused on the GARCH conditional variance of inflation as a statistical measure of its uncertainty. 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 two-step approach, estimates of the conditional variance are obtained from the estimation of the standard GARCH model and then these estimates are used in running Granger-causality tests to examine the causality between the two variables. In particular, Grier and Perry (1998) find that in all G7 countries inflation significantly raises its uncertainty. They also find evidence in favor of the Cukierman-Meltzer hypothesis for some countries and in favor of the Holland hypothesis for other countries. Fountas et al. (2004), using quarterly data and employing the EGARCH model, find that in five European countries inflation significantly raises nominal uncertainty. Their results regarding the direction of the impact of a change in inflation uncertainty on inflation were generally consistent with the existing rankings of Central Bank independence. Conrad and Karanasos (2005b) analyze the inflation dynamics of several countries belonging to the European Monetary Union and of the UK. They provide strong evidence that increased inflation raises its uncertainty. However, they find that uncertainty surrounding future inflation has a mixed impact on inflation.

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 US inflation and its uncertainty. 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 UK, and Karanasos et al. (2004) for the US, find strong evidence in favor of a positive bidirectional relationship in accordance with the predictions of economic theory.

There are only two studies using European data that are based on GARCH measures of inflation uncertainty. They are Fountas et al. (2004) and Conrad and Karanasos (2005b). This study aims to fill the gaps arising from the lack of interest in the European case where the results would have interesting implications for the successful implementation of common European monetary policy and from the methodological shortcomings of the previous studies.

3 PARCH Model

Since its introduction by Ding et al. (1993), the properties of the PARCH model have been frequently examined. Laurent (2004) derives analytical expressions for the score of the asymmetric PARCH (APARCH) specification while Karanasos and Kim (2005) study its autocorrelation function. The use of the PARCH model is now widespread in the literature (see, for example, Conrad and Karanasos, 2004 and Conrad et al., 2004).

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. In addition, $\{e_t\}$ are independent, identically distributed random variables with $E(e_t) = E(e_t^2 - 1) = 0$. h_t is positive with probability one and is a measurable function of Σ_{t-1}, which in turn is the sigma-algebra generated by $\{\pi_{t-1}, \pi_{t-2}, \ldots\}$. That is h_t denotes the conditional variance of the inflation $\{\pi_t\}$, $(\pi_t|\Sigma_{t-1}) \sim (0, h_t)$.

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'. That is, we use $g(h_t) = h_t$, $g(h_t) = \sqrt{h_t}$, or $g(h_t) = \ln(h_t)$.

Moreover, h_t is specified as an APARCH(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 ($\delta > 0$) is the 'heteroscedasticity' parameter, α and β are the ARCH and GARCH coefficients respectively, and ς ($|\varsigma| < 1$) is the leverage term. Within the APARCH model, by specifying permissible values for α, β, γ_l, ς and δ in (2), it is possible to nest a number of the more standard ARCH and GARCH specifications (see Ding et al*.*, 1993).

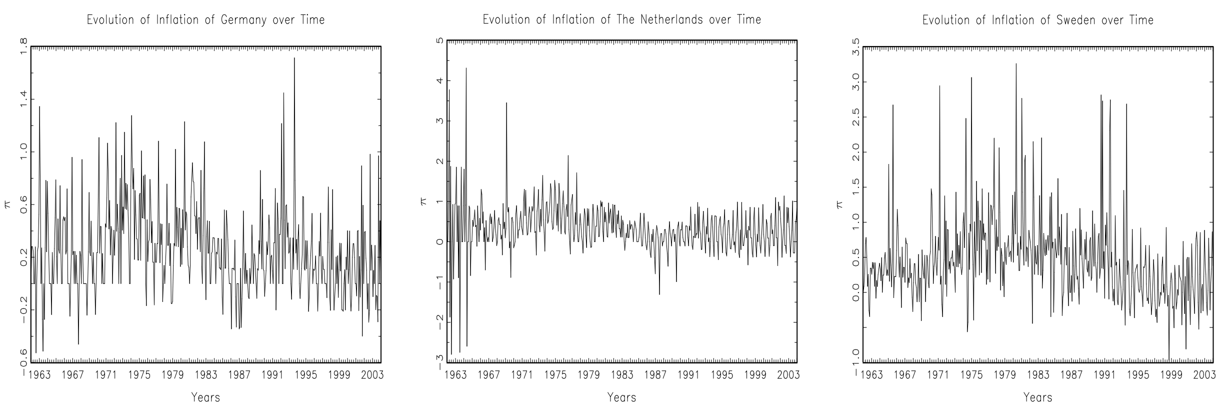
In order to distinguish the general model in (1) from a version in which $k = \gamma_l = \varsigma = \beta = 0$, we will hereafter refer to the former as APGARCH-in-mean-level (APGARCH-ML) and the latter as PARCH.

4 Empirical Analysis

4.1 The data

We use monthly data on the CPI (Consumer Price Index) as proxies for the price level.[1] The data range from 1962:01 to 2004:01 and cover three European countries, namely, Germany, the Netherlands, and Sweden. Inflation is measured by the monthly difference of the log CPI [$\pi_t = 100{\cdot}\log(\mathrm{CPI}_t/\mathrm{CPI}_{t-1})$]. Allowing for differencing leaves 504 usable observations. The inflation rates of the three countries are plotted in figure 1. The results of the Phillips-Perron unit root tests (not reported) imply that we can treat the three inflation rates as stationary processes. The summary statistics (not reported) indicate that the distribution of the three inflation series is skewed to the right and has fat tails. The large values of the Jarque-Bera statistic imply a deviation from normality.

Figure 1. Evolution of inflation over time.

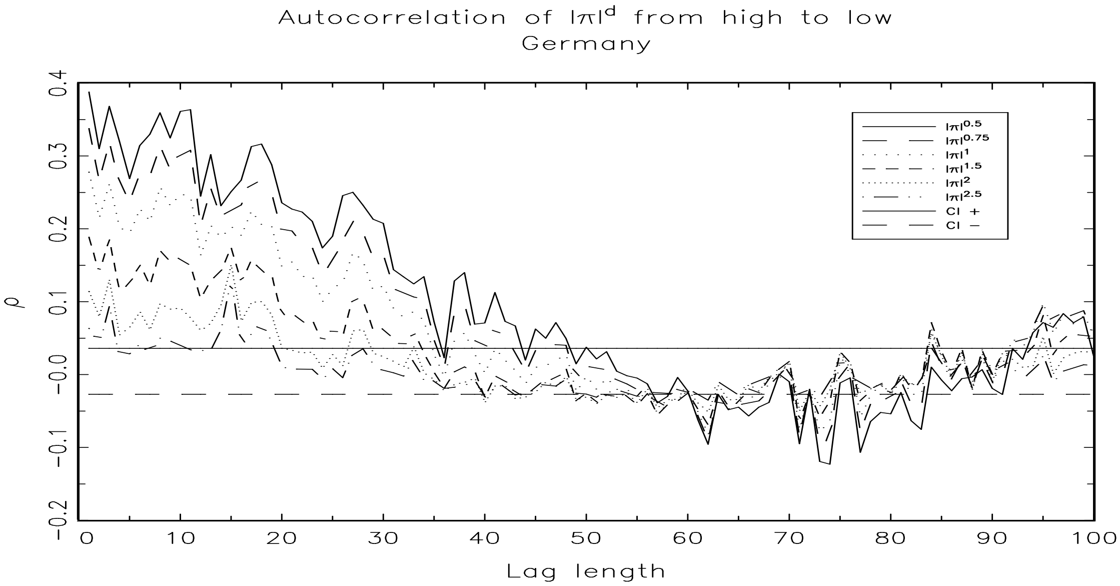


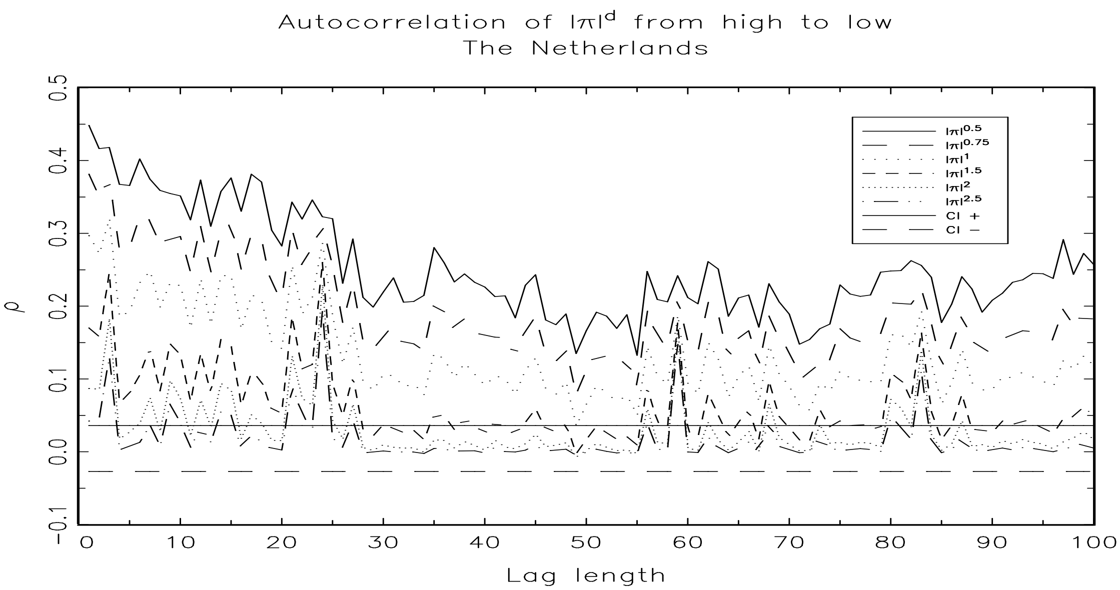
Next, we examine the sample autocorrelations of the power transformed absolute inflation $|\pi_t|^d$ for various positive d. Figure 2 shows the autocorrelogram of $|\pi_t|^d$ from lag 1 to 100 for $d = 0.5$, 0.75, 1, 1.5, 2, 2.5. The horizontal lines show the $\pm 1.96/\sqrt{T}$ which is the confidence interval for the estimated sample autocorrelations if the process π_t is independently and identically distributed (i.i.d). In our case $T = 505$, so $1.96/\sqrt{T} = 0.0872$.

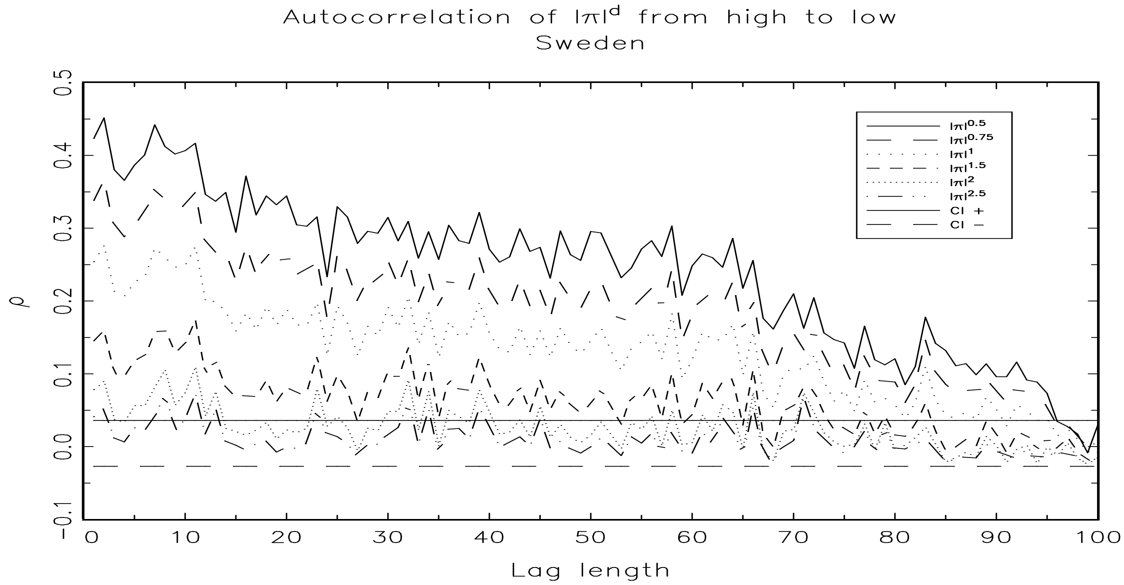
The sample autocorrelations for $\sqrt{|\pi_t|}$ are greater than the sample autocorrelations for $|\pi_t|^d$ ($d = 0.5$, 0.75, 1, 1.5, 2, 2.5) at every lag up to at least 100 lags for the Netherlands and Sweden, and up to at least 50 lags for Germany. In other words, the most interesting finding from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

[1] Since most of the studies use CPI based inflation measures (i.e., Conrad and Karanasos, 2005a,b) we construct our inflation and inflation uncertainty measures from the Consumer Price Index. Alternatively, one can use either the Producer Price Index (PPI) or the GNP deflator. Brunner and Hess (1993) use all three measures of inflation but they discuss only the results using CPI inflation. Grier and Perry (2000) and Fountas and Karanasos (2005) use both (CPI and PPI) indices and find that the CPI and PPI results are virtually identical.

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

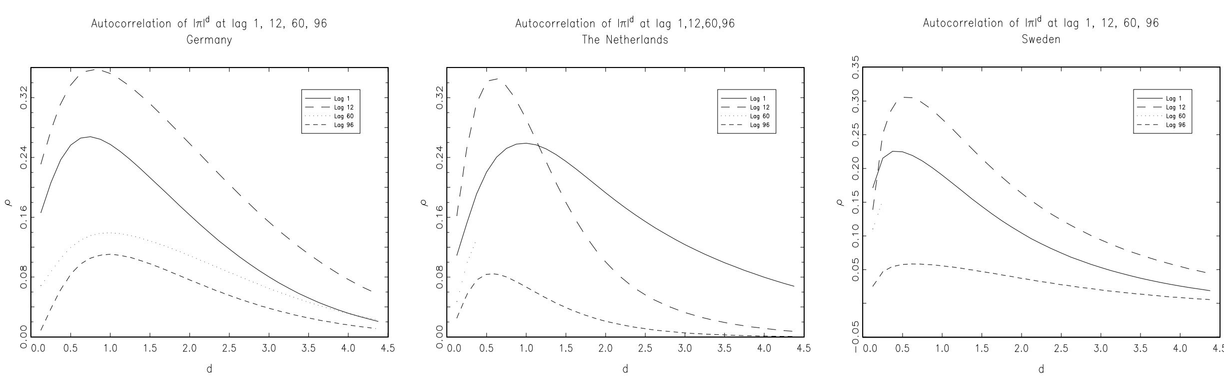






To illustrate this more clearly, we calculate the sample autocorrelations $\rho_\tau(d)$ as a function of d, $d > 0$, for lags $\tau = 1, 12, 60, 96$ and taking $d = 0.125, 0.25, \ldots, 1.75, 1.875, 2, \ldots, 4.5$. Figure 3 gives the plots of calculated $\rho_\tau(d)$ at $\tau = 1, 12, 60, 96$. For example, for lag 12, there is a unique point d^* around 0.5, 0.6 and 0.8 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 $d \neq d^*$.

Figure 3. Autocorrelations of $|\pi_t|^d$ at lags 1, 12, 60 and 96.



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 results for the period 1962-2004.[2]

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

[2] Due to space limitations, we have not reported the estimated equations for the conditional means. They are available upon request from the authors.

distributions. As reported by Palm (1996), the use of a student-t distribution is widespread in the literature. In accordance with this, we estimate all the models using two alternative distributions: the normal and the student-t.

The $\widehat{\alpha}$ parameter is significant for all countries but Sweden (when the innovations e_t are student-t distributed), while $\hat{\beta}$ is highly significant for all countries. For all countries we find the leverage term ς to be insignificant and therefore we re-estimate the model excluding this parameter. In only one out of the six cases was the estimated power term statistically significant. This case is Sweden when the distribution of the errors is student-t. 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 the Akaike Information Criterion (AIC) choose (P)GARCH models with power term parameters (δ) between 1 and 1.5. In Germany the values of the power coefficients for the two preferred specifications are below 1. For Sweden, when the errors ε_t are conditionally normal, the chosen value of the power coefficient (0.40) is markedly lower than the estimated power term with t-distributed errors (1.71).

Table 1. PGARCH Models.

	Germany	Netherlands	Sweden
Panel A: Student-t distribution			
$\widehat{\alpha}$	0.08 (0.04)	0.03 (0.02)	0.06 (0.05)
$\widehat{\beta}$	0.79 (0.11)	0.94 (0.02)	0.93 (0.03)
$\widehat{\delta}$	0.50 –	1.30 –	1.71 (1.06)
$\widehat{r}$	5.24 (1.39)	3.49 (0.53)	2.66 (0.39)
Panel B: Normal distribution			
$\widehat{\alpha}$	0.12 (0.04)	0.18 (0.12)	0.12 (0.04)
$\widehat{\beta}$	0.73 (0.10)	0.81 (0.11)	0.79 (0.09)
$\widehat{\delta}$	0.80 –	1.10 –	0.40 –

For each of the three European countries, Table 1 reports estimates of the parameters for the PGARCH model. r are the degrees of freedom of the student-t distribution. The numbers in parentheses are standard errors.

Next, we report the estimation results of an AR-PGARCH-M model of inflation for the three European countries. Table 2a reports only the estimated parameters of interest. In all countries the estimates for the 'in-mean' parameter ($\widehat{k}$) are statistically significant. In Germany and the Netherlands there is evidence in favor of the Cukierman-Meltzer hypothesis since the value of the 'in-mean' coefficient is positive. Evidence in favor of the Holland hypothesis applies in Sweden. Hence, overall, the evidence on the effect of inflation uncertainty on inflation is mixed.

Table 2a. PGARCH-M Models.

	Germany	Netherlands	Sweden
Panel A: Student-t distribution			
$\widehat{k}$	0.97 (0.60)	$0.08^{\star}$ (0.03)	-0.06^{*} (0.03)
$\widehat{\delta}$	0.50 –	0.8 –	1.63 (0.89)
$\widehat{r}$	5.30 (1.42)	3.50 (0.53)	2.41 (0.07)
Panel B: Normal distribution			
$\widehat{k}$	0.97 (0.60)	0.34^{*} (0.16)	-0.33 (0.13)
$\widehat{\delta}$	0.80 –	1.00 –	0.40 –

For each of the three European countries, Table 2a reports estimates of the parameters (of interest) for the PGARCH-M model. The numbers in parentheses are standard errors. * $g(h_t) = \sqrt{h_t}$. * $g(h_t) = \ln(h_t)$.

Table 2b reports, for Germany, estimates of the k parameters of the (P)GARCH-M model with $g(h_t) = h_t$, for various positive δ. The estimated values of the 'in mean' effect are sensitive to changes in the 'power' term. Note that, when the student-t distribution is used, the $\widehat{k}$ parameter is significant only when $\delta = 0.5$. When the errors are conditionally normal, the significance of the 'risk premium' decreases monotonically when δ exceeds 0.80. It is important to mention that the AIC is minimized when $\delta = 0.5$. The most interesting finding is that the autocorrelation function of $|\pi_t|^d$ reaches its maximum, approximately, at this point.

Table 2b. (P)GARCH-M Models (Germany).

δ	0.50	0.70	0.80	1.00	1.20	1.30	1.50	1.70	1.80	2.00
Student-t distribution										
k	0.968 [0.108]	0.764 [0.184]	0.772 [0.186]	0.707 [0.236]	0.635 [0.281]	0.614 [0.297]	0.577 [0.329]	NC*	NC	NC
AIC	**0.1254**	0.1258	0.1261	0.1269	0.1280	0.1286	0.1300	-	-	-
ML	-20.90	-21.01	-21.08	-21.28	-21.55	-21.71	-22.03	-	-	-
Normal distribution										
k	0.859 [0.1075]	0.947 [0.1487]	0.966 [0.1099]	0.964 [0.1149]	0.884 [0.1434]	0.845 [0.1594]	0.773 [0.194]	NC	NC	NC
AIC	**0.1717**	0.1726	0.1728	0.1744	0.1763	0.1773	0.1794	-	-	-
ML	-33.32	-33.55	-33.61	-34.00	-34.46	-34.71	-35.22	-	-	-

Table 2b 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.
* No convergence. The bold numbers indicate the minimum value of the AIC.

In what follows we report the estimation results of an AR-PGARCH-L model of inflation in three countries with lagged inflation included in the conditional variance (the 'level' effect). In the expressions for the conditional variances reported in Table 3, 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 for all countries. In Germany and Sweden there is strong evidence that inflation affects its uncertainty positively as predicted by Friedman (1977) and Ball (1992). In sharp contrast, inflation may cause lower nominal uncertainty in the Netherlands, thus supporting the Ungar-Zilberfarb argument.

Table 3. PGARCH-L Models.

	Germany	Netherlands	Sweden
	Panel A: Student-t distribution		
$\widehat{\gamma}_i$	0.05 (0.02)	-0.08 (0.02)	0.21 (0.08)
$\widehat{\gamma}_j$	–	0.05 (0.02)	0.12 (0.07)
$\widehat{\delta}$	1.60 –	1.58 (0.24)	1.45 (0.80)
$\widehat{r}$	5.77 (1.62)	13.09 (1.76)	2.68 (0.45)
	Panel B: Normal distribution		
$\widehat{\gamma}_i$	0.04 (0.03)	-0.18 (0.04)	0.11 (0.04)
$\widehat{\gamma}_j$	–	0.17 (0.04)	–
$\widehat{\delta}$	1.77 (0.61)	0.81 (0.26)	1.37 (0.54)

For each of the three European countries, Table 3 reports estimates of the parameters (of interest) for the PGARCH-L model. The numbers in parentheses are standard errors. $i = 10, 2,$ and 4 for Germany, the Netherlands and Sweden respectively. $j = 3,$ and 7 for the Netherlands and Sweden respectively.

Finally, we report the estimation results of an AR-PGARCH-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 twelfth lag of average inflation to influence the conditional variance. Table 4 reports only the estimated parameters of interest. As with the simple 'level' model, we find again support of the Friedman's hypothesis for Germany and Sweden whereas for the Netherlands we find that the effect of inflation on its uncertainty is negative as predicted by Ungar and Zilberfarb (1993). 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 favor of the Cukierman-Meltzer hypothesis for Germany and the Netherlands and in favor of the Holland hypothesis for Sweden.

Table 4. PGARCH-ML Models.

	Germany	Netherlands	Sweden
	Student-t distribution		
$\widehat{k}$	0.55^* (0.32)	0.19 (0.13)	-0.48 (0.26)
$\widehat{\gamma}_i$	0.05 (0.02)	-0.09 (0.02)	0.12 (0.04)
$\widehat{\gamma}_j$	–	0.08 (0.02)	–
$\widehat{\delta}$	0.40 –	1.5 –	1.57 (0.89)
	Normal distribution		
$\widehat{k}$	1.26 (0.68)	0.33 (0.10)	$-0.19^\star$ (0.07)
$\widehat{\gamma}_i$	0.05 (0.02)	-0.16 (0.03)	0.20 (0.06)
$\widehat{\gamma}_j$	–	0.15 (0.03)	0.12 (0.03)
$\widehat{\delta}$	0.50 –	0.61 (0.24)	1.59 (0.32)

For each of the three European countries, Table 4 reports estimates of the parameters (of interest) for the PGARCH-ML model. The numbers in parentheses are standard errors. * $g\left(h_t\right)=\sqrt{h_t}$. * $g(h_t)=\ln(h_t)$. $i=10,2,$ and 4 for Germany, the Netherlands and Sweden respectively.

5 Conclusions

We have used monthly data on inflation in Germany, the Netherlands and Sweden to examine the possible relationship between inflation and its uncertainty, and hence test a number of economic theories. The results in this paper highlight the importance of using the PGARCH specification in order to model the power transformation of the conditional variance of inflation. The PGARCH 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.

The application of the PGARCH approach allows us to derive two important conclusions. First, the Friedman hypothesis that inflation leads to more nominal uncertainty applies in two out of the three European countries. Similarly, mixed evidence is found regarding the direction of the impact of a change in uncertainty on inflation. We found that uncertainty about inflation causes negative nominal effects in Sweden. This evidence favors the 'stabilization hypothesis' put forward by Holland (1995). In Germany and the Netherlands we found strong evidence in favor of the Cukierman-Meltzer hypothesis. According to Devereux (1989) inflation uncertainty can have a positive impact on inflation via the real uncertainty channel. If the variability of real shocks is the predominant cause of nominal uncertainty, then inflation uncertainty and inflation are positively correlated. As real shocks become more variable the optimal degree of indexation declines. The inflation rate rises only after the degree of indexation falls. Assuming that changes in the degree of indexation take time to occur, greater inflation uncertainty precedes higher inflation.

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