Analyzing US Inflation by a GARCH Model with Simultaneous Feedback

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Abstract: - We examine the relationship between inflation and inflation uncertainty in the US using a GARCH model that allows for simultaneous feedback between the conditional mean and variance of inflation. We also compare the properties of the observed time series with the theoretical properties of GARCH models to illustrate how theoretical results on the correlation structure can facilitate model identification. In agreement with the predictions of economic theory, we find strong evidence for a positive bidirectional relationship between inflation and inflation uncertainty.

Key-words: - Inflation, inflation uncertainty, GARCH-in-mean-level.

1 Introduction

The relationship between the inflation rate and inflation uncertainty has been the subject of considerable research in theoretical and empirical macroeconomics since the publication of Milton Friedman's (1977) Nobel lecture. Friedman (1977) and Ball (1992) argue that higher inflation rates lead to higher levels of inflation uncertainty. As Friedman (1977, p. 466) wrote: "A burst of inflation produces strong pressure to counter it. Policy goes from one direction to another, encouraging wide variation in the actual and anticipated rate of inflation...".[1] The theoretical macroeconomics literature has also analyzed the opposite direction of causality, running from inflation uncertainty to the rate of inflation. Cukierman and Meltzer (1986) show that an increase in uncertainty about money growth and inflation will increase the optimal average inflation rate because it provides an incentive to the policymaker to create an inflation surprise in order to stimulate output growth.

Despite the considerable volume of research on the relationship between inflation and inflation uncertainty, there is little evidence in the empirical literature in support of the bidirectional causality between the two variables. The well known autoregressive conditional heteroskedasticity (ARCH) family of stochastic processes has been widely used in the literature to proxy uncertainty by the conditional variance of unpredictable shocks to the inflation rate.[2] Using US data, Brunner and Hess (1993) and Grier and Perry (1998) find that inflation has a significant and positive effect on inflation uncertainty, while Baillie et al. (1996) reject the Friedman-Ball hypothesis. Regarding the opposite direction of feedback, Baillie et al. (1996) find that inflation uncertainty has no significant effect on inflation. In sharp contrast to the predictions of the Cukierman-Meltzer theory, Grier and Perry (1998) find that an increase in inflation uncertainty lowers inflation in the US.

The contribution of this paper is twofold. First, we test the Friedman-Ball and Cukierman-Meltzer

[1] Friedman's intuitive result has also been subsequently derived formally by Ball (1992) in an asymmetric information game where the public faces uncertainty about the type of the policymaker.

[2] Two measures of uncertainty that have also been used in empirical studies are the dispersion of survey-based individual forecasts and the standard deviation of inflation. The major disadvantage of these measures is their inability to distinguish between variability and uncertainty. This is because they include both predictable and unpredictable variability, even though the former does not imply any uncertainty.

theories for the US by estimating a dynamic model of inflation with simultaneous feedback between its conditional mean and variance and find that both hypotheses fit the data well. We refer to this model as the GARCH-in-mean-level (GARCH-M-L) model. Second, we derive the theoretical moments and autocorrelation structure of the estimated model and compare them with the properties of the observed data to facilitate model identification.

The paper is organized as follows. Section 2 presents the empirical approach. Section 3 provides a number of theoretical results on the covariance structure of the inflation rate and inflation uncertainty of the estimated model and uses them as diagnostic tools. Section 4 concludes.

2 Empirical Model

We use seasonally adjusted time series on the US Consumer's Price Index (CPI)-OECD, Main Economic Indicators-and construct the inflation rate (y_t) series as the first difference of the log of CPI . Our sample includes 470 monthly observations covering the period 1/1960 - 2/1999. The inflation rate possesses significant autocorrelations and has a non-normal distribution that is leptokurtic and skewed to the right. In addition, the significant autocorrelations of the squared deviations of inflation from its sample mean indicate the existence of ARCH effects. Furthermore, application of standard unit root tests shows that the US inflation rate is generated by a stationary stochastic process. The aforementioned tests are not reported to conserve space.

We proceed with the estimation of models from the AR-GARCH-M-L family so that we take into account the serial correlation and the ARCH effects observed in our time series data, and capture the possible simultaneous feedback between inflation and inflation uncertainty. Following a general to specific approach we estimated the following AR(24)-GARCH(1,1)-M(0)-L(1) model:

$$\begin{aligned} y_t &= \underset{[0.00]}{0.7\,(10)^{-3}} + \underset{[0.00]}{0.31 y_{t-1}} - \underset{[0.53]}{0.03 y_{t-12}} \\ &\quad - \underset{[0.28]}{0.04 y_{t-24}} + \underset{[0.00]}{460\widehat{h}_t} - \widehat{\varepsilon}_t, \qquad (1) \\ \widehat{h}_t &= - \underset{[0.99]}{0.9\,(10)^{-7}} + \underset{[0.00]}{0.04\widehat{\varepsilon}_{t-1}^2} + \underset{[0.00]}{0.84\widehat{h}_{t-1}} \\ &\quad + \underset{[0.00]}{0.2\,(10)^{-3}\, y_{t-1}}\,, \qquad (2) \end{aligned}$$

where p-values are given in brackets. Note also that ε_t is conditionally normal with mean zero and variance h_t. In other words, $\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$, where Ω_{t-1} is the information set up to time $t-1$. Table 1 presents some of our estimations. The above model (or Model 1 in Table 1) was chosen on the basis of diagnostic tests and the Akaike Information (AIC) and Schwarz (SC) model selection criteria. Note that the exclusion of the "in-mean" and "level" effects from our inflation model means that its performance deteriorates (see Models 2 and 4 in Table 1).

To make our inference robust to possible non normality, equations (1)-(2) were jointly estimated under quasi maximum likelihood. The Ljung-Box Q_{12} and Q_{12}^2 statistics for the autocorrelations of the level and squares of the standardized residuals, respectively, are statistically insignificant at the (at least) 1% size of the test (see Table 1), and the Shapiro-Wilk test indicates that the standardized residuals are normally distributed.[3] Therefore, residual diagnostics yield no evidence of misspecification for the above estimated model.

According to the estimates in eq. (1)-(2), the "in-mean" effect is stronger than the "level" effect: a one unit increase in the inflation rate will increase the next period's inflation uncertainty by 0.2 units, while a unit increase in inflation uncertainty will increase the inflation rate by 0.46 units.[4] The positive relationship between inflation and inflation uncertainty is depicted in Figure 1, which plots the inflation rate and its corresponding conditional standard deviation.

[3] The drawback of the tests based on skewness and kurtosis, like the Jarque-Bera test, is that their behaviour may be erratic in small samples. In this case the Shapiro-Wilk (SW) test could be seen as a better alternative. The SW test for Model 1 in Table 1 is 0.99 [p-value=0.52].

[4] The unit of measurement of our monthly inflation rate series is 0.1 % , i.e. 0.001. Consequently, the unit of measurement of its variance is $(0.1\%)^2$, i.e. 0.000001. So the estimated "in-mean" and "level" effects are given by 460(0.000001)=0.46(0.001) and $(0.2\times10^{-3})(0.001)$=0.2(0.000001), respectively.

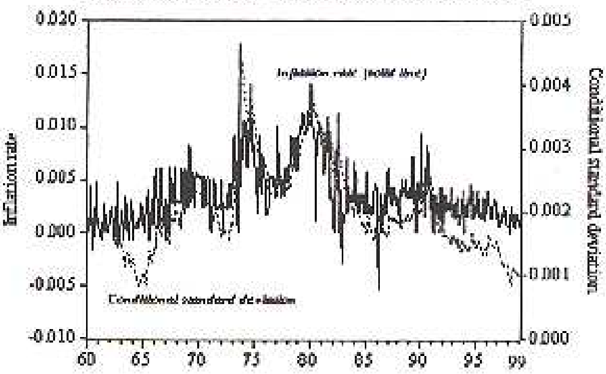
Table 1: AR-GARCH-M-L

Model	1	2	3	4	5
Mean effect	459.9 [0.00]		0.35 [0.10]		210.1 [0.05]
Level effect	.0002 [0.00]	.0002 [0.07]	.00006 [0.38]		.0005 [0.05]
SC	-4249	-4218	-4215	-4198	-4284
AIC	-4285	-4251	-4252	-4226	-4325
Q_{12}	17.5 [0.13]	53.0 [0.00]	46.8 [0.00]	63.8 [0.00]	11.8 [0.46]
Q_{12}^2	25.7 [0.012]	8.88 [0.71]	10.8 [0.55]	8.60 [0.74]	26.3 [0.009]
[p-values in brackets]					

Table 2: AR-EGARCH-M-L

Model	6	7	8
Cond. dist.	gaussian	generalized error	
Mean effect	340.7 [0.02]	638.8 [0.00]	2.06 [0.00]
Level effect	170.1 [0.00]	52.21 [0.00]	68.61 [0.00]
SC	-4082	-4239	-4179
AIC	-4123	-4284	-4224
Q_{12}	48.7 [0.00]	26.3 [0.01]	24.8 [0.02]
Q_{12}^2	6.31 [0.90]	19.1 [0.09]	15.3 [0.23]
[p-values in brackets]			

Figure 1
Inflation Rate and its Conditional Standard Deviation
AR(2 4) - GARCH(1,1) - M(0) - L(1) Model, 2/1962-2/1999



We checked the robustness of our results to (i) the distributional assumption by estimating eq. (1)-(2) with a conditional t distribution (see Model 5 in Table 1);[5] (ii) the functional form of the in-mean effect by having as a regressor in eq. (1) the conditional standard deviation instead of the variance (Model 3 in Table 1);[6] and (iii) the functional form of the conditional variance by using an exponential GARCH (EGARCH) specification with errors drawn from either the normal or the generalized error distributions (Table 2). In all cases the in-mean and level effects remained both positive and statistically different from zero at conventional significance levels.

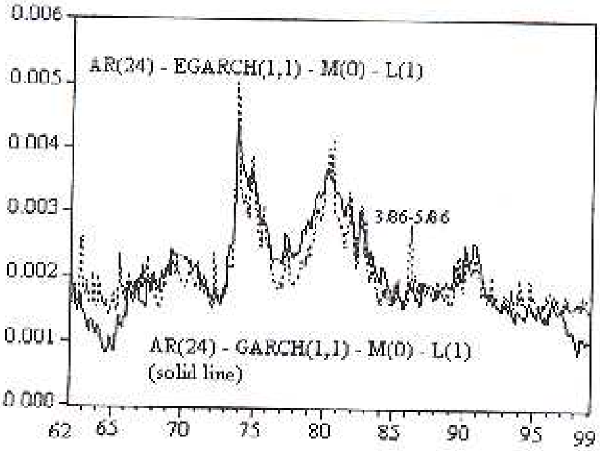
Figure 1 also provides evidence that higher levels of inflation are less predictable. According to our estimates, the conditional standard deviation averages about 2% (annual rate) in the low inflation years of the 1960's and it reaches a maximum of 5% and 4.5% (annual rate) in the mid 1970's and 1980, respectively. These estimates of the conditional standard deviation are very similar to the ones obtained by Brunner and Hess (1993). It is worth noting that, while Brunner and Hess (p.195) argue that it is the relaxation of the symmetry restriction in conditional volatility models which enables them to find that higher levels of inflation are less predictable, we reach the same conclusion by using a symmetric model with mutual feedback. We compare our results to theirs by using the EGARCH process of Model 6 (see Table 2).[7] Figure 2 shows that the conditional standard deviations of the AR-GARCH-M-L and AR-EGARCH-M-L models are quite similar, and both models support a positive relationship between inflation and inflation uncertainty. Our preference for the AR-GARCH-M-L model over the AR-EGARCH-M-L specification is justified by the model selection criteria, diagnostic tests, and the unreasonably high inflation volatility of the latter model during the 3/86-5/86 disinflation period.

[5] Note that the Shapiro-Wilk test is 0.97 [p-value=0.002], thus indicating that the model with the t distribution is not well specified.

[6] Baillie et al. (1996) use the conditional standard deviation to capture the "in-mean" effect in their model.

[7] Brunner and Hess (1993), using US CPI data from 1947-1992, selected an ARIMA(1,0,1) model for the conditional mean and a state-dependent model (SDM) for the conditional variance of the inflation rate. They argue that EGARCH estimates of the conditional standard deviation were nearly identical to those obtained by the SDM.

Figure 2
Conditional Standard Deviations of GARCH and EGARCH Models



Next, we examine the stability conditions and the autocorrelation structure of the estimated AR-GARCH-M-L model given by eq. (1)-(2).[8]

3 Theoretical Properties

3.1 Stability conditions of the estimated model

Let us express the above AR(24)-GARCH(1,1)-M(0)-L(1) model in terms of its theoretical parameters:

$$\left(1-\phi_1 L-\phi_{12}L^{12}-\phi_{24}L^{24}\right) y_t = b+\varepsilon_t+\delta h_t, \quad (3)$$

$$\left(1-\beta^* L\right) h_t = \omega+\alpha L v_t+\gamma L y_t, \quad (4)$$

where $\beta^* \equiv \alpha+\beta$, and $v_t \equiv \varepsilon_t^2 - h_t$. The univariate ARMA representation of the inflation rate (y_t) is

$$A(L)\, y_t = b^* + B_{y\varepsilon}(L)\,\varepsilon_t + B_{yv}(L)\, v_t, \quad (5)$$

where

$$\begin{aligned} A(L) \;&\equiv\; 1-(\phi_1+\beta^*+\delta\gamma)L+\phi_1\beta^* L^2 \\ &-\phi_{12}L^{12}+\beta^*\phi_{12}L^{13}-\phi_{24}L^{24}+\beta^*\phi_{24}L^{25} \\ &\equiv\; \Pi_{i=1}^{25}\left(1-\lambda_i L\right), \end{aligned} \quad (6)$$

and

$$\begin{aligned} B_{y\varepsilon}(L) &\equiv 1-\beta^* L, \quad B_{yv}(L) \equiv \delta\alpha L \\ b^* &\equiv (1-\beta^*)\, b+\delta\omega. \end{aligned} \quad (7)$$

The univariate ARMA representation of the conditional variance is

$$A(L)\, h_t = \omega^* + B_{h\varepsilon}(L)\,\varepsilon_t + B_{hv}(L)\, v_t, \quad (8)$$

where

$$\begin{aligned} B_{h\varepsilon}(L) &= \gamma L, \\ B_{hv}(L) &= \alpha\left(L-\phi_1 L^2-\phi_{12}L^{13}-\phi_{24}L^{25}\right), \\ \omega^* &\equiv \omega(1-\phi)+\gamma b, \quad \phi \equiv \phi_1+\phi_{12}+\phi_{24}. \end{aligned} \quad (9)$$

We use eq. (6) to check the stability of our estimated model (1)-(2). Note that the λ's in (6) denote the reciprocals of the roots of the $A(L)$ polynomial. Using the estimated parameters we find that all roots have modulus less than one,[9] and thus our selected model is dynamically stable.

3.2 Autocorrelation structure of the estimated model

The autocorrelation function of the inflation rate (ρ_{ym}) is

$$\rho_{ym} = \frac{\gamma_{ym}}{\gamma_{y0}} \quad (m \in \mathbb{N}), \quad (10)$$

where

$$\gamma_{ym} \equiv \gamma_{ym}^{\varepsilon} E(h_t) + \gamma_{ym}^{v} E\left(h_t^2\right), \quad (11)$$

with

$$\gamma_{y0}^{\varepsilon} = \sum_{i=1}^{25} \frac{\lambda_i^{24}\left[1+(\beta^*)^2-2\beta^*\lambda_i\right]}{\prod_{\substack{k=1\\k\neq i}}^{25}(\lambda_i-\lambda_k)\prod_{k=1}^{25}(1-\lambda_i\lambda_k)}, \quad (12)$$

$$\underset{m\geq 1}{\gamma_{ym}^{\varepsilon}} = \sum_{i=1}^{25} \frac{\lambda_i^{24+m}\left[1+(\beta^*)^2-\beta^*(\lambda_i+\lambda_i^{-1})\right]}{\prod_{\substack{k=1\\k\neq i}}^{25}(\lambda_i-\lambda_k)\prod_{k=1}^{25}(1-\lambda_i\lambda_k)}, \quad (13)$$

$$\gamma_{ym}^{v} = \sum_{i=1}^{25} \frac{\lambda_i^{24+m}}{\prod_{\substack{k=1\\k\neq i}}^{25}(\lambda_i-\lambda_k)\prod_{k=1}^{25}(1-\lambda_i\lambda_k)} 2\delta^2\alpha^2. \quad (14)$$

The first and second moments of the conditional variance h_t, $E(h_t)$ and $E\left(h_t^2\right)$, and the kurtosis coefficient (k) of the errors are

$$E(h_t) = \frac{(1-\phi)\omega+\gamma b}{1-(\phi_1+\beta^*+\delta\gamma)+\phi_1\beta^*-\phi_{12}+\beta^*\phi_{12}-\phi_{24}+\beta^*\phi_{24}}, \quad (15)$$

[8] To derive the properties of the AR(24)-GARCH(1,1)-M(0)-L(1) process we use the theoretical results given by Karanasos (2001, 2004).

[9] In particular, we find one real root and twelve pairs of conjugate complex roots with modulus ranging from 0.862 to 0.979.

$$E\left(h_t^2\right) = \frac{[E(h_t) + \gamma^{\xi}_{h0}]\,E(h_t)}{1 - \gamma^{v}_{h0}}, \tag{16}$$

$$k = \frac{E(\varepsilon_t^4)}{[E(\varepsilon_t^2)]^2} = \frac{3E(h_t^2)}{[E(h_t)]^2}, \tag{17}$$

where γ^{ξ}_{h0} and γ^{v}_{h0} are given below by eq. (20) and (22), respectively.

The autocorrelation function of the conditional variance ρ_{hm}, for $m \geq 24$, is given by

$$\rho_{hm} = \frac{\gamma_{hm}}{\gamma_{h0}}, \tag{18}$$

where

$$\gamma_{hm} = \gamma^{\xi}_{hm} E(h_t) + \gamma^{v}_{hm} E(h_t^2), \tag{19}$$

with

$$\gamma^{\xi}_{\substack{hm\\ m\geq 0}} = \sum_{i=1}^{25} \frac{\lambda_i^{24+m}}{\prod\limits_{\substack{k=1\\ k\neq i}}^{25}(\lambda_i - \lambda_k)\prod\limits_{k=1}^{25}(1-\lambda_i\lambda_k)}\gamma^2, \tag{20}$$

$$\begin{aligned}\gamma^{v}_{\substack{hm\\ m\geq 24}} = \textstyle\sum_{i=1}^{25} & \frac{\lambda_i^{24+m}}{\prod\limits_{\substack{k=1\\ k\neq i}}^{25}(\lambda_i - \lambda_k)\prod\limits_{k=1}^{25}(1-\lambda_i\lambda_k)} 2\alpha^2[1+\phi_1^2 \\ & +\phi_{12}^2 + \phi_{24}^2 - \phi_1(\lambda_i + \lambda_i^{-1}) + \phi_1\phi_{12}(\lambda_i^{11} + \lambda_i^{-11}) \\ & +(\phi_{12}\phi_{24} - \phi_{12})(\lambda_i^{12} + \lambda_i^{-12}) \\ & +\phi_1\phi_{24}(\lambda_i^{23} + \lambda_i^{-23}) - \phi_{24}(\lambda_i^{24} + \lambda_i^{-24})],\end{aligned} \tag{21}$$

$$\begin{aligned}\gamma^{v}_{h0} = \textstyle\sum_{i=1}^{25} & \frac{\lambda_i^{24}}{\prod\limits_{\substack{k=1\\ k\neq i}}^{25}(\lambda_i - \lambda_k)\prod\limits_{k=1}^{25}(1-\lambda_i\lambda_k)} 2\alpha^2[1+\phi_1^2 \\ & +\phi_{12}^2 + \phi_{24}^2 - 2\phi_1\lambda_i + 2\phi_1\phi_{12}\lambda_i^{11} + \\ & 2(\phi_{12}\phi_{24} - \phi_{12})\lambda_i^{12} + 2\phi_1\phi_{24}\lambda_i^{23} - 2\phi_{24}\lambda_i^{24}].\end{aligned} \tag{22}$$

The condition for the existence of the second moment of the conditional variance is that the denominator of eq. (16) is positive, i.e. $1 > \gamma^{v}_{h0}$. Inserting our estimated parameters in eq. (22) we get $\gamma^{v}_{h0} = 0.125$, which satisfies the above condition. Next, we use eq. (15)-(16) to compute the theoretical variance of h_t : $var(h_t) = 1.2\,(10)^{-11}$; note that the sample variance of the estimated conditional variance h_t is $1.1\,(10)^{-11}$. To compute the theoretical variance of the inflation rate (γ_{y0}) we use eq. (10), (12), and (14), for $m = 0$, and obtain $\gamma_{y0} = 9.82\,(10)^{-6}$. This value is very close to $9.27\,(10)^{-6}$, the sample variance of the inflation rate for the estimation period.

Next, we use eq. (10)-(14) to compute the first 84 autocorrelations of the inflation ratem, which are presented in Figure 3a. We then use eq. (18)-(21) to compute the autocorrelations (of order 24 to 84) of h_t, plotted in Figure 3b. Observe the high correlations that characterize the uncertainty of the inflation rate process.

Furthermore, for the computation of the mth cross correlation between the inflation rate and its conditional variance, $\rho_{hy,m} \equiv \mathrm{Corr}(h_t, y_{t-m})$, $m \in \mathbb{Z}$, we use the following results:

$$\rho_{hy,m} = \frac{\gamma_{hy,m}}{\sqrt{\gamma_{y0}\gamma_{h0}}}, \tag{23}$$

where

$$\gamma_{hy,m} = \gamma^{\xi}_{hy,m} E(h_t) + \gamma^{v}_{hy,m} E(h_t^2), \tag{24}$$

with

$$\gamma^{v}_{\substack{hy,m\\ m>0}} = \sum_{i=1}^{25} \frac{\lambda_i^{24-m}2\delta\alpha^2[1-\phi_1\lambda_i^{-1}-\phi_{12}\lambda_i^{-12}-\phi_{24}\lambda_i^{-24}]}{\prod\limits_{\substack{k=1\\ k\neq i}}^{25}(\lambda_i-\lambda_k)\prod\limits_{k=1}^{25}(1-\lambda_i\lambda_k)}, \tag{25}$$

$$\gamma^{v}_{\substack{hy,m\\ m\leq 0}} = \sum_{i=1}^{25} \frac{\lambda_i^{24-|m|}2\delta\alpha^2[1-\phi_1\lambda_i-\phi_{12}\lambda_i^{12}-\phi_{24}\lambda_i^{24}]}{\prod\limits_{\substack{k=1\\ k\neq i}}^{25}(\lambda_i-\lambda_k)\prod\limits_{k=1}^{25}(1-\lambda_i\lambda_k)}, \tag{26}$$

$$\gamma^{\xi}_{\substack{hy,m\\ m>0}} = \sum_{i=1}^{25} \frac{\lambda_i^{24-m}[-\beta^*\gamma+\gamma\lambda_i^{-1}]}{\prod\limits_{\substack{k=1\\ k\neq i}}^{25}(\lambda_i-\lambda_k)\prod\limits_{k=1}^{25}(1-\lambda_i\lambda_k)}, \tag{27}$$

$$\gamma^{\xi}_{\substack{hy,m\\ m\leq 0}} = \sum_{i=1}^{25} \frac{\lambda_i^{24+|m|}[-\beta^*\gamma+\gamma\lambda_i]}{\prod\limits_{\substack{k=1\\ k\neq i}}^{25}(\lambda_i-\lambda_k)\prod\limits_{k=1}^{25}(1-\lambda_i\lambda_k)}. \tag{28}$$

When $m = 0$, eq. (23)-(28) give the theoretical instantaneous cross correlation between inflation and its conditional variance: $\rho_{hy,0} = 0.703$. This is very close to the corresponding sample value of 0.682. Figures 3c-3d present the theoretical cross correlation functions between inflation and its conditional variance. Observe the slowly decaying pattern which characterizes the correlation structure in Figures 3a-3d.

Finally, it is important to note that the theoretical autocorrelations of inflation move quite closely with its sample autocorrelations (see Figure 3a). Similarly, Figure 3c shows that the theoretical cross correlations between inflation and the lags of its conditional variance follow the pattern of the sample cross correlations. Since the true conditional variance of inflation is unobservable, Figure 3c uses two alternative measures as a proxy: the estimated conditional variance of our model and the squared values of the inflation series. The plots in Figures 3a-3d show that the AR-GARCH-M-L model can approximate reality quite well, and demonstrate how theoretical results on the correlation structure of the model can be used as model identification criteria.

Figure 3a
Autocorrelations of inflation

Figure 3b
Autocorrelations of conditional variance

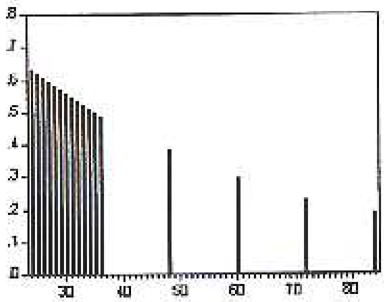
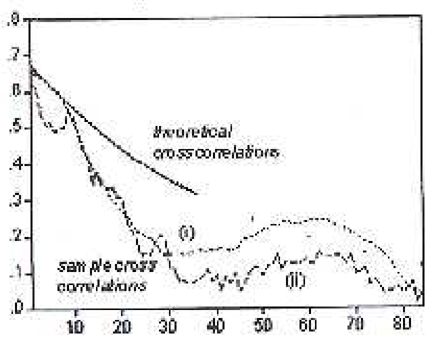
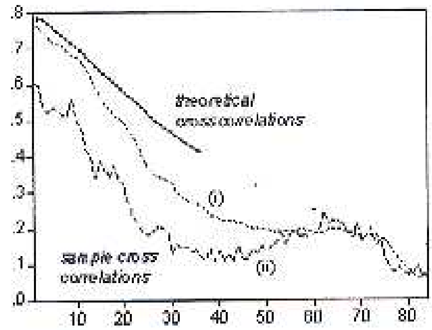


Figure 3c
Cross correlations between inflation
and the lags of its conditional variance



Sample cross correlations between (i) inflation and the lags of the estimated conditional variance, and (ii) inflation and the lags of its squared values.

Figure 3d
Cross correlations between the lags of inflation
and its conditional variance



Sample cross correlations between (i) the lags of inflation and the estimated conditional variance, and (ii) the lags of inflation and its squared values.

4 Conclusions

We examined the relationship between inflation and inflation uncertainty in the US using a GARCH model that allows for simultaneous feedback between the conditional mean and variance of inflation. In sharp contrast with existing empirical evidence, we showed that there is a strong positive bidirectional relationship between inflation and inflation uncertainty. Our findings are in agreement with the predictions of economic theory expressed by the Friedman-Ball and Cukierman-Meltzer hypotheses. We also illustrated how theoretical results on the correlation structure of GARCH models can be used to facilitate model identification in applied work.

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