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INFLATION AND INFLATION UNCERTAINTY IN LATVIA

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WORKING PAPER

CONTENT

ABBREVIATIONS

ADF – Augmented Dickey–Fuller Test
AIC – Akaike information criterion
ARCH – Autoregressive Conditional Heteroskedasticity
ARMA – Autoregressive Moving Average
CPI – Consumer Price Index
CSB – Central Statistical Bureau of Latvia
EMU – Economic and Monetary Union
EU – European Union
GARCH – Generalised Autoregressive Conditional Heteroskedasticity
GARCH–M – Generalised Autoregressive Conditional Heteroskedasticity in mean
HQ – Hannan–Quinn information criterion
IGARCH – Integrated Generalised Autoregressive Conditional Heteroskedasticity
LM test – Lagrange Multiplier Test
QML – Quasi-Maximum Likelihood
SC – Schwartz Information Criterion
UK – United Kingdom
US – United States of America

ABSTRACT

The paper considers interrelation between inflation and inflation uncertainty in Latvia. The monthly growth in CPI in the period from January 1994 to June 2007 has been used as an inflation measure. The application of the GARCH–M model with lagged inflation in GARCH equation proves that a positive relationship between inflation and inflation uncertainty does exist. It suggests that increased inflation uncertainty raises inflation, and, vice versa, increased inflation is a cause for higher uncertainty about inflation in the future.

Key words: *inflation, inflation uncertainty, GARCH–M*

JEL classification codes: *C22, E31, E37*

INTRODUCTION

In order to enter the euro area, Latvia, like any other new EU Member State, is required to meet the Maastricht convergence criteria. One of the criteria is price stability according to which inflation shall be no more than 1.5 percentage points above the average rate of the three countries with the lowest inflation rates. Between December 2005 and June 2007, the highest permissible inflation rate under the Maastricht price stability criterion was 3.3%. Recently, inflation rate in Latvia has soared above the level of the Maastricht criterion. It is a serious obstacle on Latvia's road to joining the euro area in the near future; hence, identifying and perceiving the driving forces behind inflation is an extremely pressing problem to deal with.

The results of a great number of empirical and theoretical research prove that inflation causes higher costs for both the economy and the community overall. Among the most important costs of inflation mention should be made of uncertainty about future inflation rates. Inflation uncertainty means price uncertainty in the future. Inflation uncertainty affects the decision-making process of both businesses and consumers, as they do reckon with the future inflation rate. Increasing long-term inflation rates is one of the channels through which inflation uncertainty affects the economy. If inflation uncertainty increases, the risk inherent in long-term investment interest rate instruments will become stronger because of increasing uncertainty about real profits. That is why investors are likely to impose much higher long-term interest rates. Inflation uncertainty may also be looked upon as a cause for uncertainty about contractual payments in the future. For instance, due to inflation uncertainty both the employers and employees will be insecure about the real future value of wages. Inflation uncertainty also has an effect on uncertainty about future real value of rent. Uncertainty about future interest rates and other economic variables may have a negative effect on the economic activity.

Can inflation uncertainty raise inflation? M. Friedman (12) was the first to pose the question in his address at the Nobel Prize Award Ceremony. L. Ball (2) proposed a model in which he formalised M. Friedman's arguments within the framework of asymmetric information game between economic agents and policymakers.

Why can inflation uncertainty increase (decrease) along with inflation rate? When inflation is low, policymakers attempt to maintain it low and do not engage in any policy adjustments. When inflation is high, inflation reducing policy is likely to be launched. The latter will lead to raised inflation uncertainty. The effects of monetary policy on inflation are ambiguous, and it will take some time for monetary policy to affect inflation. First, monetary policy affects the banking system; then, through the banking system, the effect will spill over to the real sector, and, finally, a pass-through to inflation will be observed. The timing and the extent to which monetary policy affects inflation depend on the economic circumstances and are difficult to predict.

A. Cukierman and A. H. Meltzer (6) dealt with the converse causality relationship or the effects of inflation uncertainty on inflation. They proved that increased uncertainty about money supply and inflation raises the optimal inflation rate set by policymakers.

Modelling inflation uncertainty via GARCH models, the author has arrived at two basic assumptions. First, inflation uncertainty in Latvia displays variability over time. Second, inflation and inflation uncertainty are interdependent.

Section 1 presents the definition of inflation uncertainty and the model used in the empirical part of the research. Section 2 provides the overview of empirical works on inflation uncertainty. Section 3 deals with the data used in modelling inflation uncertainty. Section 4 sums up the results of preliminary unit root test for inflation time series, estimates GARCH(p, q) models, presents conclusions regarding evolvement of inflation uncertainty over time, and discusses GARCH(p, q)–M models with lagged inflation in variance equation. Conclusions are presented in the final section of the paper.

1 ESTIMATING INFLATION UNCERTAINTY

Since inflation uncertainty is unobservable, its estimation is quite problematic. R. F. Engle (8) and T. Bollerslev (3) introduced a model known as the GARCH model where the conditional variance of one-step-ahead forecast error is used as a measure of inflation uncertainty. The GARCH(q, p) model is defined as follows:

$$\pi_t = bX_t + \varepsilon_t \qquad\qquad [1],$$

$$\varepsilon_t \sim N(0, h_t) \qquad\qquad [2],$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \qquad\qquad [3],$$

where X_t is the vector of explanatory variables, including time lags of inflation (π_t), ε_t is the forecast error, h_t is the conditional variance of forecast error.

Equation [3] demonstrates that conditional variance of forecast error depends on squared error lags and on the lags of conditional variance itself. That is why conditional variance of inflation increases in periods of significant model forecast error clustering. Therefore, if the absolute value of the forecast error rises along with inflation, inflation and inflation uncertainty are positively interrelated. Earlier research by A. M. Okun (16) and S. Fischer (11) uses standard deviation of inflation time series or variance as inflation uncertainty measure. This inflation uncertainty measure has a drawback: instead of measuring future uncertainty of variable values it measures the variability of the time series. An increase in inflation variance may be caused by anticipated changes in inflation; hence it does not always imply an increase in uncertainty.

2 SURVEY OF INFLATION AND INFLATION UNCERTAINTY STUDIES. GARCH MODEL APPLICATION

Such studies primarily focus on inflation and inflation uncertainty in G7 countries. On the basis of the US and UK data, R. F. Engle (8; 9) and T. Bollerslev (3) observed a substantial variability of inflation uncertainty over time; however, interrelation between inflation and inflation uncertainty was not detected.

R. Baillie, Chung Ching-Fan and M. A. Tieslau tested the causality direction of inflation and inflation uncertainty by including lagged inflation in conditional variance equation and standard deviation in inflation equation.(1) The authors proved that there was an interrelation between inflation and inflation uncertainty in the US and some other countries with high inflation rates (Argentina, Brazil and Israel).

T. Caporale and B. McKiernan (5) applied the GARCH model to the US monthly inflation data. The authors established that there was a significant positive relationship between inflation rate and conditional variance (uncertainty) of inflation. They maintained that the results were also robust for alternative inflation models, and, at the same time, unlikely to depend on whether the data of US high inflation observed in the 1970s were included in or excluded from estimations.

K. B. Grier and M. J. Perry (13) used conditional variance estimated with the GARCH model and the Granger causality test to determine the causality direction of inflation and inflation uncertainty. The authors found that inflation had a positive substantial impact on inflation uncertainty (hypothesis by Friedman–Ball) in all G7 countries; this impact, however, was not unambiguous. In three countries, including the US, increased inflation uncertainty lowered inflation, which contradicts the Cukierman–Meltzer theory. At the same time, with inflation uncertainty growing, inflation rose in Japan and France.

3 DATA USED IN THE RESEARCH

In this research, month-on-month percentage changes in Latvia's CPI from January 1994 to June 2007 have been used as an inflation measure (a total of 160 observations). The time series is given in Chart 1.
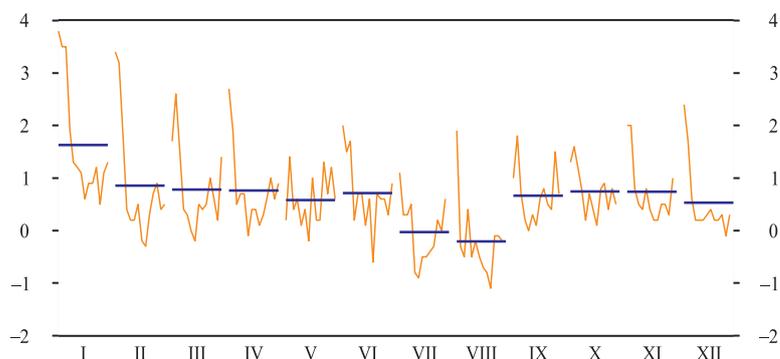
Chart 1
Month-on-month CPI changes
(%)
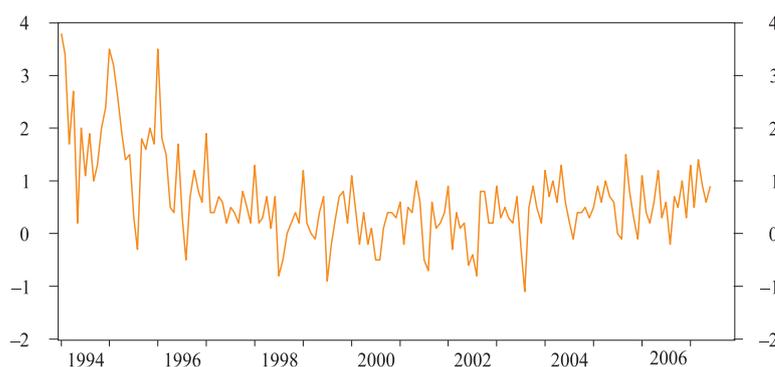
Sources: CSB and Bank of Latvia calculations.

Chart 1 shows the cyclical nature of the series. The monthly breakdown of the serial dynamics (Chart 2) testifies that the average inflation rate in January was higher than in other months but in July and August it was considerably lower.

Chart 2
Average changes in CPI by month
(%)

4 EMPIRICAL MODELS AND RESULTS

4.1 Unit Root Tests

The ADF test has been used for stationarity testing of preliminary seasonally adjusted inflation time series, which means that raw data were regressed to seasonal dummies s_1, s_2, ..., s_{12}. Theoretical justification of such an approach is given by D. A. Dickey, W. R. Bell and R. B. Miller.(7)

The number of lags for the ADF test has been chosen by minimising SC. The following model specifications have been used in the test: without a constant and trend, with a constant, and with both a constant and a trend. Test results are showed in Table 1 of the Appendix. They confirm stationarity of inflation time series.

4.2 GARCH(p, q) Models

The selection of the GARCH(p, q) model was based on the general-to-specific approach, minimisation of AIC, SC and HQ, to achieve non-autocorrelated residuals and their squares, as well as on the condition that the variance process is non-negative and stationary. G@RCH 2.3 (15), *PcGive* and *Eviews* 5.1 software have been used in the estimation. As a result, the following ARMA(1,1)–GARCH(1,1) model has been obtained:

$$\pi_t - c = \gamma_1 s_1 + \gamma_7 s_7 + \gamma_8 s_8 + \varphi_1\left(\pi_{t-1} - c\right) + \theta_1 \varepsilon_{t-1} + \varepsilon_t,$$

$$\varepsilon_t \sim N(0, h_t),$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}.$$

An auto regression specification admitting the modelling of time series persistence property is generally used in research papers (13; 14). However, the author opted for the ARMA(1,1) specification, for it ensures much lower AIC, SC and HQ values. More important, however, is the fact that autoregression specifications do not permit getting rid of autocorrelation in residuals and squared residuals in GARCH models. In order to arrive at consistent estimates of the coefficient error covariance matrix in the case of residual non-normality, QML method has been used. The research carried out by T. Bollerslev and J. M. Wooldridge (4) provides the essence of the method.

6

Table 2 of the Appendix presents an overview of the parameter estimation of three most appropriate models.

Model 1. ARMA(1,1)–GARCH(1,1) with a constant in a conditional variance equation.

Model 2. ARMA(1,1)–GARCH(1,1) without a constant in a conditional variance equation.

Model 3. ARMA(1,1)–IGARCH(1,1).

The model specification includes only significant seasonal dummies s_1, s_7 and s_8 that correspond to January, July and August respectively. The Wald test suggested that the coefficients of dummy variables corresponding to the remaining months differ insignificantly; hence the model supports the data in Chart 2. Upon changing model specifications, coefficient changes are insignificant and testify to model robustness[1]. It should be noted that GARCH equation of Model 2 is not stationary, and the fourth moment and unconditional variance do not exist. For these reasons, Model 3 ARMA(1,1)–IGARCH(1,1) (10) has been estimated. The significance of GARCH coefficients suggests that inflation uncertainty changes over time.

Table 3 of the Appendix provides the results of model residual diagnostic tests. The results of all three models vary insignificantly. *P*-values of skewness and kurtosis as well as the Jarque–Bera test cannot reject the hypothesis on standardised residual normality at the 1% significance level for all models.

For all models, Box–Pierce statistic demonstrates no autocorrelation in standardised residuals and standardised squared residuals for 5, 10, 20 and 30 lags. In order to test the presence of ARCH effect, LM test has been applied to residuals. In this test (proposed by R. F. Engle (8)), square residuals ε_t were regressed to their time lags and the constant.

$$\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_p \varepsilon_{t-p}^2 \,.$$

The null hypothesis (constant variance) is defined as $H_0 : \alpha_1 = \alpha_2 = ... = \alpha_p = 0$.

The rejection of this hypothesis implies that the ARCH effect exists in residuals. T. Bollerslev proved that the p-order ARCH LM test is equivalent to the GARCH(i, j) test where $i + j = p$. In this test, statistic $N*R^2$ is asymptotically distributed as $\chi^2(p)$ where N is the number of observations. The LM test cannot reject the ARCH effect non-existence hypothesis in residuals for 1–2 and 1–5 lag structures at the 10% significance level (see ARCH 1–2 and ARCH 1–5 in Table 3 of the Appendix). The test results suggest that model specification is correct.

Judging by all information criteria, the ARMA(1,1)–IGARCH(1,1) model is the most appropriate. Chart 3 shows model's residuals, squared residuals and conditional variance of the process. In addition, the conditional variance at the beginning considerably exceeded that of the other periods.

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[1] Upon changing model estimation time interval samples, coefficients remain robust.

Chart 3
**ARMA(1,1)–IGARCH(1,1) model
residuals, squared residuals and
conditional variance**
(%)

Model residuals (E)

Squared residuals

Conditional variance (H)
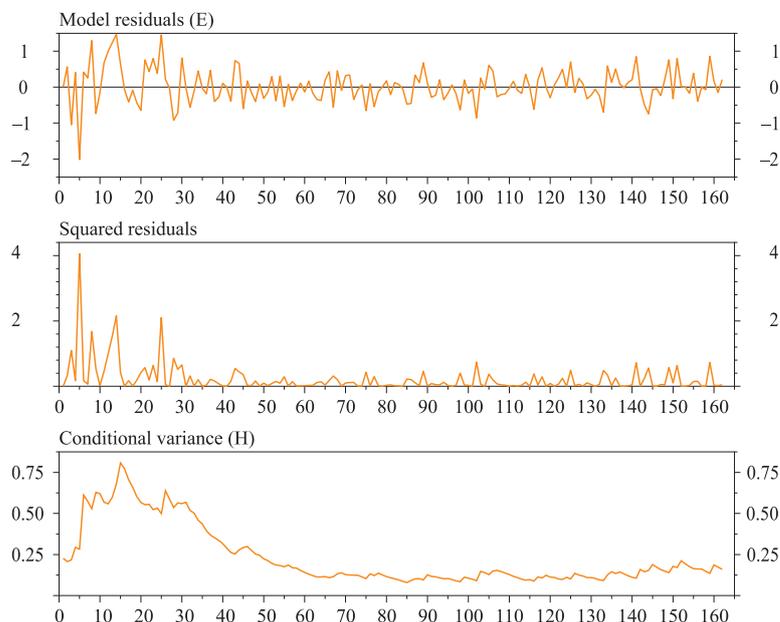
4.3 GARCH–M with Lagged Inflation in Variance Equation

A model that admits a simultaneous testing of two theories – those of Friedman–Ball and Cukierman–Meltzer, i.e. testing of the relationship between inflation and inflation uncertainty, could be the GARCH–M model with lagged inflation values in a conditional variance equation:

$$\pi_t - c = \gamma_1 s_1 + \gamma_7 s_7 + \gamma_8 s_8 + \varphi_1\left(\pi_{t-1} - c\right) + \delta h_t + \theta_1 \varepsilon_{t-1} + \varepsilon_t \qquad [4],$$

$$\varepsilon_t \sim N(0, h_t) \qquad [5],$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda\left|\pi_{t-1}\right| \qquad [6].$$

However, this specification leads either to non-converging coefficient computation procedure or such coefficient values that admit a negative variance. Duly accounting for such problems and using the general-to-specific approach, as well as considering AIC, SC un HQ minimisation, the following AR(1)–GARCH(1,1)–M model is obtained:

$$\pi_t = \gamma_1 s_1 + \gamma_7 s_7 + \gamma_8 s_8 + \varphi_1 \pi_{t-1} + \delta h_t + \varepsilon_t \qquad [7],$$

$$\varepsilon_t \sim N(0, h_t) \qquad [8],$$

$$h_t = \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \lambda\left|\pi_{t-1}\right| \qquad [9].$$

The model estimation results are provided in Table 4 of the Appendix. On the one hand, the estimation of the system of equations [7]–[9] points to a positive influence from the absolute inflation value of the past month on the current conditional inflation variance (coefficient λ). On the other hand, there exists an explicit positive

influence on inflation from variance, or the GARCH–M effect (coefficient δ). Consequently, the model outcomes enabled the author to assert that a relationship between inflation and inflation uncertainty does exist in Latvia.

Table 5 of the Appendix shows the results of model residual tests. *P*-values of skewness and kurtosis as well as the Jarque–Bera test cannot reject the hypothesis about standardised residual normality at the 10% significance level. Box–Pierce statistic demonstrates no autocorrelation in standardised residuals for 5, 10, 20 and 30 lags at 5% significance level. LM test cannot reject the hypothesis about the absence of ARCH effect in residuals for structures with 1–2 and 1–5 time lags (see ARCH 1–2 and ARCH 1–5 in Table 5 of the Appendix).

The information criteria values are considerably lower than for models dealt with above in Section 4.2. This suggests that the GARCH–M model has an advantage over the other models.

CONCLUSIONS

The paper considers causality between inflation and inflation uncertainty in Latvia. CPI monthly growth from January 1994 to June 2007 has been used as inflation measure. Conditional variance of ARMA model's forecast error has been employed to measure inflation uncertainty. Conditional variance has been calculated on the basis of GARCH model's various specifications.

After determination of stationarity of Latvia's seasonally adjusted inflation time series, time-varying inflation uncertainty in the reviewed period was detected.

The significance of ARMA(1,1)–GARCH(1,1) and ARMA(1,1)–IGARCH(1,1) model coefficients suggests that inflation uncertainty evolves over time.

The application of the GARCH–M model with lagged inflation in GARCH equation proves that a positive relationship between inflation and inflation uncertainty does exist. It means that increased inflation uncertainty raises inflation, and, vice versa, increased inflation is a cause for higher uncertainty about inflation in the future. The results obtained suggest that Latvia's data are in support of the Friedman–Ball and Cukierman–Meltzer theories.

After minimisation of AIC, SC and HQ, AR(1)–GARCH(1,1)–M with lagged inflation in GARCH equation may be considered the best forecasting model.

APPENDICES

Table 1
Unit root tests. Inflation in Latvia (January 1994–June 2007)

	Without constant and trend	With constant	With constant and trend
p-value of ADF test	−4.640 (0.0000)	−4.639 (0.0002)	−4.736 (0.0009)
Critical value at the 1% level	−2.579	−3.471	−4.016
Critical value at the 5% level	−1.943	−2.879	−3.438
Critical value at the 10% level	−1.615	−2.576	−3.143

Notes.
The null hypothesis: inflation time series has unit root, i.e. it is not stationary.
Provided are *t*-statistic values of unit root test.
MacKinnon one-sided *p*-values are given in parentheses.

Table 2
Inflation GARCH model estimation

	Model 1	Model 2	Model 3
Mean equation			
c	0.459*** (0.0001)	0.470*** (0.0002)	0.472*** (0.0002)
γ_1	0.723*** (0.000)	0.721*** (0.000)	0.720*** (0.000)
γ_7	−0.722*** (0.000)	−0.732*** (0.000)	−0.730*** (0.000)
γ_8	−0.899*** (0.0000)	−0.922*** (0.000)	−0.923*** (0.000)
φ_1	0.911*** (0.000)	0.906*** (0.000)	0.906*** (0.000)
θ_1	−0.700*** (0.000)	−0.673*** (0.000)	−0.673*** (0.000)
Variance equation			
α_0	0.008 (0.155)	−	−
α_1	0.072* (0.074)	0.092** (0.031)	0.087*** (0.003)
β_1	0.880*** (0.000)	0.910*** (0.000)	0.913*** (0.000)

Notes.
P-values of estimated coefficients are given in parentheses.
*, **, *** denote 10%, 5% and 1% significance levels respectively.

Table 3
Diagnostic statistics for Model 1, 2 and 3

	Model 1	Model 2	Model 3
Normality test			
Skewness	−0.209	−0.253	−0.248
	(0.272)	(0.184)	(0.192)
Kurtosis	0.861	0.786	0.787
	(0.023)	(0.038)	(0.038)
Jarque–Bera test	6.193	5.896	5.865
	(0.045)	(0.052)	(0.053)
Standardised residual Q-statistic			
Q(5)	5.416	5.201	5.241
	(0.144)	(0.158)	(0.155)
Q(10)	8.847	8.241	8.299
	(0.355)	(0.410)	(0.405)
Q(20)	23.157	22.922	22.992
	(0.185)	(0.194)	(0.191)
Q(30)	27.136	27.009	27.057
	(0.511)	(0.518)	(0.515)
Standardised squared residual Q-statistic			
$Q^2(5)$	3.106	3.121	3.103
	(0.375)	(0.373)	(0.376)
$Q^2(10)$	9.977	10.817	10.859
	(0.267)	(0.212)	(0.210)
$Q^2(20)$	19.784	18.896	18.969
	(0.345)	(0.398)	(0.394)
$Q^2(30)$	25.085	26.529	26.519
	(0.623)	(0.544)	(0.544)
ARCH 1–2	0.861	0.965	0.962
	(0.425)	(0.383)	(0.384)
ARCH 1–5	0.640	0.739	0.736
	(0.669)	(0.595)	(0.598)
Information criterion			
AIC	1.310	1.327	1.314
SC	1.482	1.480	1.448
HQ	1.380	1.389	1.369

Notes.
P-values are given in parentheses.
Normality test null hypothesis: residual normality.
ARCH 1–2 and ARCH 1–5: LM tests for 1–2 and 1–5 lag structures.

Table 4
Estimation of GARCH–M model with lagged inflation in GARCH equation

	Coefficient	Standard error	*t*-values	*t*-probability
Mean equation				
γ_1	0.729	0.110	6.616	0.000
γ_7	−0.735	0.116	−6.326	0.000
γ_8	−0.906	0.111	−8.129	0.000
φ_1	0.153	0.071	2.148	0.033
δ	3.331	0.389	8.572	0.000
Variance equation				
α_1	0.004	0.032	0.141	0.888
β_1	0.870	0.032	26.93	0.000
λ	0.030	0.0093	2.991	0.0013

Table 5
Diagnostic statistics for GARCH–M model

	GARCH–M
	Normality test
Skewness	0.100 (0.600)
Kurtosis	0.305 (0.421)
Jarque–Bera test	0.898 (0.638)
Standardised residual Q-statistic	
Q(5)	3.859 (0.425)
Q(10)	7.032 (0.634)
Q(20)	20.931 (0.341)
Q(30)	27.099 (0.566)
Standardised squared residual Q-statistic	
$Q^2(5)$	5.575 (0.134)
$Q^2(10)$	15.108 (0.057)
$Q^2(20)$	24.576 (0.137)
$Q^2(30)$	35.811 (0.147)
ARCH 1–2	2.039 (0.134)
ARCH 1–5	1.165 (0.329)
Information criterion	
AIC	1.181
SC	1.334
HQ	1.243

Notes.
P-values are given in parentheses.
Normality test null hypothesis: residual normality.
ARCH 1–2 and ARCH 1–5: LM tests for 1–2 and 1–5 time lag structures.

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