Modelling Inflation Uncertainty Using EGARCH: An Application to Turkey

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Abstract

This paper uses a EGARCH method to model inflation uncertainty in Turkey. Unlike ARCH and GARCH methods, the EGARCH method both hampers the effect of outlying shocks in the estimation of inflation uncertainty and enables the separate treatment of the negative and positive shocks to inflation. As inflation uncertainty itself may follow a seasonal pattern, the series is subjected to monthly seasonal adjustment. The inflation measure we use in this paper is the monthly CPI inflation and covers the period from 1986:1 to 2000:12. The evidence in the paper shows that monthly seasonality has a significant effect on inflation uncertainty. Moreover, once seasonal effects are accounted for, lagged inflation no longer appears to affect inflation uncertainty.

JEL Classifications: E31; E37 and E30
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I. Introduction

Studying inflation uncertainty is not only highly important but also highly feasible in Turkey where high and variable inflation rates over more than two decades provides a laboratory environment. Friedman (1977) argues that inflation uncertainty is costly since it distorts relative prices and increases risk in nominal contracts. Therefore, as inflation becomes highly unpredictable, investment and growth slows down. In Turkey, although the average growth of real GDP has been more than four percent per annum since 1970s, growth has nevertheless been highly volatile, calling into question the role of inflation uncertainty, among other factors.

This paper analyses the dynamics of inflation uncertainty in Turkey. Various studies in the literature provide empirical evidence on the positive relationship between inflation and inflation uncertainty.[1] Using an autoregressive conditional heteroskedasticity (ARCH) model, Neyapti (2000) shows that inflation significantly raised the uncertainty of wholesale price inflation in Turkey between 1982 to 1999. Evidence in Nas and Perry (2000) supports this finding, while the evidence on the effect of inflation uncertainty on the level of inflation is mixed and depends on the time period analysed.

In this paper, we model inflation and inflation uncertainty using the exponential generalized ARCH (EGARCH) model. This method is superior to the class of ARCH models in various respects and has not yet been used in the literature to model inflation uncertainty.

[1] See Holland (1984) for a review of such empirical studies. Ball and Cecchetti (1990), Brunner and Hess (1993), Caporale and McKiernan (1997) all provide evidence for the positive association between the mean and the variance of inflation, both across countries and over time for the US.

The data used in the current study is monthly CPI inflation from 1986 to 2000. Given that the conditional variance of inflation might have a seasonal pattern[2], we use monthly dummies to estimate the model. The organisation of the rest of the paper is as follows. Section II outlines the model, Section III reports the evidence and, finally, Section IV concludes.

II. The Model

The class of ARCH models allows us to estimate time varying conditional variance. Generalised ARCH (GARCH) models include lags of the conditional variance to estimate the conditional variance of the model. Nelson (1991) proposes an extended version of such models: EGARCH. EGARCH method is more advantageous than both ARCH and GARCH methods to model inflation uncertainty for the following reasons. First, it allows for the asymmetry in the responsiveness of inflation uncertainty to the sign of shocks to inflation. Second, unlike GARCH specification, the EGARCH model, specified in logarithms, does not impose the non-negativity constraints on parameters. Finally, modelling inflation and its uncertainty in logarithms hampers the effects of outliers on the estimation results.

The EGARCH model has been commonly used to examine the interest rates, interest rate futures markets, to model foreign exchange rates and to analyse stock returns (see, for example, Brunner and Simon [1996]; Hu, Jiang and Tsoukalas [1997]; Koutmos and Booth [1995]; and Tse and Booth [1996]). Although the literature on the EGARCH models is quite extensive, to our knowledge, no paper has yet examined the inflation uncertainty using this method. This paper fills that gap in

[2] Stochastic seasonality is tested using Franses (1990). Evidence suggests that there are seasonal unit roots in the log of CPI, but since all roots are not equal to zero, it is not appropriate to apply the Ä12 filter. However, CPI contains a nonseasonal unit root, and therefore it can be modelled in first differences and using seasonal dummies.

the literature. This paper has a further contribution to the literature due to the the inclusion of seasonal terms in the conditional variance equation.

Following Berument and Guner (1997) and Berument and Malatyali (2001) we model inflation by using lagged inflation and monthly seasonal dummies to account for seasonality:

$$\pi_t = \sum_{i=1}^{n} \alpha_i \pi_{t-i} + \sum_{i=1}^{12} \delta_i m_{it} + \lambda D94_t + \varepsilon_t \text{...}(1)$$

where π_t represents inflation; m_{it} stands for the monthly dummies (i=1,2....,12) that account for monthly seasonal effects; $D94_t$ is the dummy variable that takes the value of 1 for the 4^{th} month of 1994 to account for the 1994 financial crisis, and takes the value of zero otherwise. ε_t is the error term at time *t*. Due to Nelson (1991), we assume that ε_t has General Error Distribution with mean zero and the variance h^2_t , ie. $\varepsilon_t \sim (0,\ h^2_t)$.[3] *n* is the lag order of the autoregressive process. To avoid the dummy variable trap, constant term is not included in the equation of conditional mean inflation [equation (1)].

$$Log h_t^2 = \beta_0 + \beta_1 |\varepsilon_{t-1}| / h_{t-1} + \beta_2 \varepsilon_{t-1} / h_{t-1} + \beta_3 Log h_{t-1}^2 + \lambda_1 D94_t + \lambda_2 D94_{t-1} \text{.................}(2)$$

Equation (2) is the EGARCH representation of the conditional variance of inflation at time *t*. $|\varepsilon_{t-1}|/h_{t-1}$, $\varepsilon_{t-1}/h_{t-1}$ and the log of the lagged value of the conditional variance (h^2_t) are used to explain the behaviour of the conditional variance [equation (2)]. We also include a dummy for 1994:3 ($D94_{t-1}$), since the presence of the $D94_t$ dummy alone makes the residual term in Equation (1) zero for 1999:4. In Equation (2), several economically meaningful restrictions could be tested. Here, the incorporation

[3] Quasi-robust standard errors are used (see Bollerslev and Woolridge, 1992).

of the restrictions $(\hat{a}_1+\hat{a}_2+\hat{a}_3)<1$ and $|\beta_3|<1$ implies that inflation volatility never explodes. If $\hat{a}_2>0$, then volatility increases when the innovation is positive and decreases when the innovation is negative.

Equation (2) can be modified by adding monthly dummies in order to explore the seasonal dynamics of the conditional variance equation. We report below the results of the estimation of two models. The first model (Model 1) is based on Equation (1) and Equation (2) reported above; and the second model (Model 2) is based on Equation (1) and a version of Equation (2) modified with the inclusion of seasonal dummies.

III. Empirical Results

The inflation measure used in this analysis is the first difference of the logarithm of the seasonally unadjusted CPI over the period 1986:1 to 2000:12. In what follows, we report the estimation results of both Model 1 and Model 2.

III.1. Model 1

The optimal lag length (n) of the inflation rate in equation (1) is selected as 7 based on the Final prediction Error criteria (FPE). The FPE allows us to select the optimum lag order such that the errors of the regression are no longer autocorrelated. If the error terms are autocorrelated, the ARCH-LM test of Engle (1982) incorrectly suggests that the ARCH effect is present (see, Cosimano and Jansen, 1988). The following are the joint estimates of equations (1) and (2) whose test statistics are reported in the Appendix.

	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	m11	m12
π_t:	42.75	18.11	11.92	26.46	-0.42	-7.69	9.30	18.65	38.83	30.59	16.42	8.63
	(7.53)	(3.25)	(1.93)	(4.55)	(-0.08)	(-1.28)	(1.59)	(4.63)	(7.20)	(5.58)	(2.80)	(1.27)

D94	π_{t-1}	π_{t-2}	π_{t-3}	π_{t-4}	π_{t-5}	π_{t-6}	π_{t-7}
160.09	0.44	0.02	-0.02	-0.09	0.13	0.05	0.07
(44.04)	(6.32)	(0.16)	(-0.34)	(-1.95)	(2.60)	(1.28)	(1.81)

	Constant	$\vert\varepsilon_{t-1}\vert/h_{t-1}$	$\varepsilon_{t-1}/h_{t-1}$	Log h_{t-12}	$D94_t$	$D94_{t-1}$
Log h^2_t	1.40	0.34	0.22	0.66	-13.39	10.57
	(2.28)	(2.01)	(1.75)	(5.34)	(-13.06)	(3.56)

Note: Reported under each variable are the estimated parameters and the t-statistics (in parentheses).

The Ljung-Box Q-statistics cannot reject the null hypothesis that there is no autocorrelation for both the estimated and the standardised residuals (ε_t/h_t) of equation (1). Moreover, the ARCH-LM statistics can not reject the null hypothesis that there is no ARCH effect for the standardised residuals up to the 24th lag.

By using the standardised lagged residual ($\varepsilon_{t-1}/h_{t-1}$) in the variance equation (Equation 2), we allow for the possibility of the leverage effect. The estimated coefficient of the standardised lagged residual is positive and statistically significant at 10% level. This suggests when there is an unanticipated increase in inflation, inflation uncertainty increases more than when there is unanticipated decrease in inflation. Next, we estimate the same model by including the monthly dummies in the conditional variance equation.

III.2. Model 2

The estimation results of Model 2 are reported below to test the significance of seasonal effects on the conditional variance of inflation:

	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	m11	m12
π_t	46.28	23.30	18.89	31.95	9.81	-2.92	12.05	21.30	41.24	36.15	24.73	14.87
	(8.21)	(5.40)	(3.87)	(6.02)	(2.57)	(-0.53)	(1.97)	(5.98)	(7.62)	(10.07)	(5.40)	(2.71)

D94	π_{t-1}	π_{t-2}	π_{t-3}	π_{t-4}	π_{t-5}	π_{t-6}	π_{t-7}
161.19	0.35	0.00	-0.01	-0.08	0.09	0.08	0.04
(46.53)	(21.83)	(-0.04)	(-0.20)	(-2.79)	(2.00)	(2.47)	(1.04)

	$\lvert\varepsilon_{t-1}\rvert/h_{t-1}$	$\varepsilon_{t-1}/h_{t-1}$	$\text{Log } h_{t-12}$	$D94_t$	$D94_{t-1}$	m1	m2	m3	m4	m5	m6
$\text{Log } h^2_t$	0.55	0.09	0.05	-6.45	-7.64	5.20	4.19	3.58	4.09	3.64	4.58
	(3.19)	(0.78)	(0.20)	(-5.90)	(-4.42)	(4.09)	(2.59)	(2.56)	(2.52)	(2.89)	(3.79)

	m7	m8	m9	m10	m11	m12
$\text{Log } h^2_t$	4.80	3.67	4.62	3.84	3.49	4.14
	(3.05)	(2.35)	(3.96)	(2.63)	(2.82)	(3.34)

Note: Reported under each variable are the estimated parameters and the t-statistics (in parentheses).

This models yields different results than Model 1 in various respects. First, the leverage effect in the conditional variance is not statistically significant. Among the seasonal dummies added to the model, while all have positive and statistically significant effects, the first, sixth, seventh and the ninth months have the highest contribution to the conditional variability of inflation. This finding makes sense since in January, both the government launches its economic program and the private sector sets its prices for the year ahead. During the months of June and July, agricultural sector prices start to be formed; susceptibility of the agricultural sector to weather conditions may influence inflation volatility dynamics. In September, agricultural support prices are announced and education spending increases. Likelihood ratio tests reject the null hypotheses that the months of January, June, July and September do not differ from the rest of the months in the conditional variance equation. This clearly suggests a yearly pattern in the level of inflation uncertainty.

We also tried a specification where the conditional variance is estimated with a lagged inflation term. However, the effect of lagged inflation in the estimation is statistically insignificant and also has a negligible magnitude.

IV. Conclusion

The main findings of the paper are as follows. Firstly, the evidence shows that, in Turkey, the effect on inflation uncertainty of positive shocks to inflation are greater than that of negative shocks to inflation. Secondly, when monthly dummies are used in modelling both inflation and inflation uncertainty, the effect of lagged inflation on inflation uncertainty disappears. It is, therefore, possible to conclude that there is no significant lagged effect of inflation on inflation uncertainty. Lastly, the evidence presented in this paper of the significant seasonal effects of inflation on conditional variability cautions against a further difficulty in inflation forecasting.

REFERENCES:

Ball, L. and S. Cecchetti (1990), " Inflation and Inflation Uncertainty at Short and *Brookings Papers on Economic Activity*, 215-54.

Berument H and N. Guner, 1997, "Inflation, Inflation Risk and Interest Rates: A Case Study For Turkey", Middle East Technical University Studies in Development 24(3), 319-27.

Berument H., and K. Malatyali (2001), "Determinants of Interest Rates in Turkey", *Russian and East European Finance and Trade,* forthcoming.

Bollerslev, T., and J.M. Wooldridge, (1992), "Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances", Econometric Reviews, 11, 143-172.

Brunner, A.D. and D.P. Simon, (1996), "Excess Returns and Risk at the long End of The Treasury Market: an EGARCH-M Approach", *The Journal of Financial Research*, 14, 1, 443-457.

Caporale, T and B. McKiernan, 1997, "High and Variable Inflation: Further Evidence on the Friedman Hypothesis", *Economic Letters* 54, 65-68.

Cosimano, T. and J. Dennis, (1988), "Estimation of the Variance of US Inflation Based upon the ARCH Model", *Journal of Money, Credit, and Banking,* 20(3) 409-423.

Engle, R., (1982) "Autoregressive Conditional Heteroscedasticity with Estimates of United Kingdom Inflation" *Econometrica*, 987-1007.

Franses, P.H.., (1990), "Testing For Seasonal Unit Roots in Monthly Data", Econometric Institute Report, No.9032A, Erasmus University, Rotterdam.

Friedman, M., (1977), Nobel Lecture: Inflation and Unemployment, *Journal of Political Economy,* Vol. 85, 451-472.

Holland, A. S., 1984, " Does Higher Inflation Lead to More Uncertain Inflation?"

Federal Reserve Bank of St. Louis Review 66, 15-26.

Hu, M.Y., C.X. Jiang, and C. Tsoukalas, (1997), "The European Exchange Rates Before and After the Establishment of the European Monetary System", *Journal of International Financial Markets, Institutions and Money*, 7, 235-253.

Koutmos, G., and G.G. Booth, (1995), "Asymmetric Volatility Transmission in International Stock Markets", *Journal of International Money and Finance*, 14, 747-762.

Nas, T. F. and M.J. Perry, (2000), " Inflation, Inflation Uncertainty and Monetary *Contemporary Economic Policy*, 18, 170-180.

Nelson, D.B., (1991), "Conditional Heteroskedasticity in Asset Returns: A New Approach", *Econometrica*, 59, 347-370.

Neyapti, B., (2000), " Inflation and Inflation Uncertainty in Turkey: Evidence from the Past Two Decades", mimeo.

Tse, Y., and G.G. Booth, (1996), "Common Volatility and Volatility Spillovers Between U.S. and Eurodollar Interest Rates: Evidence from The Features Market", *Journal of Economics and Business*, 48, 299-312.

APPENDIX

Table 1: Test statistics for Model (1):

	Test Statistic for residual (ε_t)	Level of Significance:	Test Statistic the for standardised residual ($\varepsilon_{t-1}/h_{t-1}$)	Level of Significance:
Skewness	0.65		0.106	
Kurtosis	8.2		3.7	
Jarque-Bera	191.95		3.7	
Ljung Box Q(6)	4.85	0.56	3.03	0.80
Ljung Box Q(18)	8.48	0.97	10.96	0.90
Log-Likelihood			-608.65	
LM ARCH (6)			2.85	0.83
LM ARCH (12)			7.18	0.85
LM ARCH (18)			11.89	0.87
LM ARCH (24)			15.78	0.90

Table 2: Test statistics for Model (2):

	Test Statistic for residual (ε_t)	Level of Significance:	Test Statistic the for standardised residual ($\varepsilon_{t-1}/h_{t-1}$)	Level of Significance:
Skewness	1.013		0.17	
Kurtosis	9.24		2.88	
Jarque-Bera	285.16		0.85	0.65
Ljung Box Q(6)	5.51	0.48	6.88	0.33
Ljung Box Q(18)	8.52	0.97	13.46	0.76
Log-Likelihood			-602.3	
LM ARCH (6)			7.7	0.81
LM ARCH (12)			14.27	0.71
LM ARCH (18)			20.57	0.67
LM ARCH (24)			15.78	0.90