Inflation targeting and the inflation-inflation uncertainty relationship in Sweden: evidence from GARCH Modeling

Jui Sen

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Abstract

This paper investigates the relationship between inflation and inflation uncertainty as well as the role of the adoption of inflation targeting in the context of Sweden economy. The study utilizes 566 monthly data of Sweden inflation over the period 1971M02-2018M03. We employ symmetric, asymmetric and component GARCH-M model for our investigation. The result indicates high inflation increases inflation uncertainty and inflation uncertainty increases average inflation rate. We also find that adoption of inflation targeting erases inflation persistence and reduces inflation uncertainty in the long-run.

1. Introduction

Inflation uncertainty induces significant economics cost as it clouds the both intertemporal and intratemporal resource allocation decision made by individuals and firms. Most previous studies have found that there is positive correlation between inflation and inflation uncertainty and higher inflation reduces the effectiveness of relative price and lowers the growth of output.

In the 1990's a number of industrialized countries adopted inflation targeting to stabilize the inflation so that it can encourage the investment, reduce capital fight, protect the economy from the erosion of saving and ensure the growth of output. Here, the central bank assume and declare an explicit inflation rate target and attempt to drive the actual inflation toward that target by raising or lowering the main short-term monetary instrument i.e. interest rate. Sweden adopted the inflation targeting in January 1993 and their target inflation rate is two percent.

In this paper, we look at the relationship between inflation-inflation uncertainty and the impact of inflation targeting using the Swedish data over the period 1971M02-2018M03. Most previous studies show that GARCH techniques are popular for the investigation of inflation-uncertainty relationship, where we can assume that the estimated conditional volatility can suffice as a representative for uncertainty. Here we apply several GARCH related models to explain time varying inflation volatility.

The paper proceeds as follows. In section 2, we approach review of literature and economic theory and then develop questions to address in this paper. In section 3, we provide the description of our econometric models. In section 4, we give an overview of Swedish inflation data and discuss the stationarity test of this data. Section 5 and 6 represent empirical results and conclusion respectively.

2. Review of Literature and Economic Theory

Seven countries – New Zealand, Canada, United Kingdom, Australia, Sweden, Czech Republic and Israel adopted inflation targeting with in the period 1990-1997. A number of emerging economies adopted inflation targeting after the 1997 crisis, which compelled them to give up the fixed exchange rate peg. Cecchetti and Ehrmann (2000) argue that after the 1990 most of the central banks of major economies showed the tendency to reduce inflation variability irrespective of whether they adopted inflation targeting or not. However, the variability of inflation fell more for the targeters compare to non-targeters.

Friedman (1977) argues that high inflation lead to the erratic policy responses made by monetary authority, which in turn create inflation uncertainty in the future. This inflation uncertainty hampers both the intertemporal and intratemporal allocation of resources and leads to the cost of unanticipated inflation. Ball (1992) represents Friedman's argument in the form of asymmetric information game where the public faces uncertainty regarding the decisions of policy-makers. High Inflation creates more uncertainty about future inflation in the mind of public as they are not certain about how the policymaker will response to this high inflation rate. This kind of uncertainty usually does not arise in the presence of low inflation rate. Meltzer (1986) and Chukierman (1992) suggest the reverse causation link of Friedman & Ball view, that is, higher inflation uncertainty raises the optimal inflation rate.

For the investigation of inflation-uncertainty relationship Johnson (2002) measures uncertainty as the standard deviation of individual forecast and shows a positive correlation between inflation and uncertainty. Kontonikas (2004) shows a positive relationship between past inflation and current uncertainty, where the uncertainty is proxied using the conditional volatility from symmetric, asymmetric and component GARCH-M model of inflation. The result also shows that the adoption of inflation targeting reduces inflation variability and long-run uncertainty.

In this paper, we address three questions. First, does high past inflation rate increase current inflation uncertainty? Second, does High inflation uncertainty raise optimal inflation rate? Finally, does inflation uncertainty fall with the adoption of inflation targeting? Here, initially we develop an equation of conditional mean of series and perform the diagnostic test. Then we do the sensitivity analysis to estimate the structural change in the inflation dynamic. We check the inflation uncertainty link pre-target and after-target period before estimating the conditional variance of inflation. We employ symmetric GARCH-M, threshold GARCH-M and component GARCH-M to investigate the inflation-uncertainty relationship and impact of inflation targeting where the estimated conditional volatility plays the role for uncertainty.

3. Description of Econometric Models

To estimate the series of time varying conditional volatility first we need to develop an conditional mean equation. Here, we have used the autoregressive model for inflation where our data set is monthly data. We have used 1month, 3month, 6month and 12month lagged inflation; that means the maximum lag length of one year.

$$\text{Monthly(M)} \quad \Pi_t = \alpha_0 + \alpha_1 \Pi_{t-1} + \alpha_2 \Pi_{t-3} + \alpha_3 \Pi_{t-6} + \alpha_4 \Pi_{t-12} + \mu_t \qquad \text{(i)}$$

We later introduce a multiplicative dummy variable D_t via lag 1 and lag 12 inflation so that we can observe the change in slope of average inflation after targeting. Here, D_t is a dummy variable which is equal to zero during the period before the adoption of inflation target and one during inflation target.

$$\text{Monthly(M)} \quad \Pi_t = \alpha_0 + (\alpha_1 + \alpha_5 D_t)\Pi_{t-1} + \alpha_2 \Pi_{t-3} + \alpha_3 \Pi_{t-6} + (\alpha_4 + \alpha_6 D_t)\Pi_{t-12} + e_t \qquad \text{(ii)}$$

To examine the time varying volatility of inflation during pre-target and after target period we regress squared OLS residual on a constant and on their lagged values. We apply LM test to check the ARCH effect.

$$e_t^2 = \beta_0 + \sum\beta_i\, e_{t-i}^2 + \theta_t \qquad \text{(iii)}$$

We do a pre-test of inflation-uncertainty link by regressing OLS squared residual on a constant and a variable, which reflect the effect of past inflation. Here, we consider three alternative lagged inflation variables. Π_{t-1}, $|\triangle\Pi_{t-1}|$ and $\Pi_{t-1}{}^2$ represent level of inflation (asymmetric measure), absolute change in inflation and squared inflation (symmetric measure) respectively.

$$e_t^2 = \beta_0 + \sum\beta_i\, \Pi_{t-I} + \theta_{1t} \qquad \text{(iv-a)}$$

$$e_t^2 = \beta_0 + \sum\beta_i |\triangle\Pi_{t-i}| + \theta_{2t} \qquad \text{(iv-b)}$$

$$e_t^2 = \beta_0 + \sum\beta_i\, \Pi_{t-i}{}^2 + \theta_{3t} \qquad \text{(iv-c)}$$

We formally examine the relationship between past inflation and current conditional volatility and the impact of inflation targeting by employing GARCH-M model. For this purpose, we modify our equation (ii) so that we can allow the feedback affect between conditional mean and conditional variance, where h_t denotes the conditional variance of inflation.

Monthly(M) $\Pi_t = \alpha_0 + (\alpha_1 + \alpha_5 D_t)\Pi_{t-1} + \alpha_2\Pi_{t-3} + \alpha_3\, \Pi_{t-6} + (\alpha_4 + \alpha_6 D_t)\, \Pi_{t-12} + \delta\, \sqrt{h_t} + v_t$ (v)

$$h_t = c + \sum \alpha_1\, e_{t-i}^2 + \sum \beta_j\, h_{t-j} + \lambda z_t \qquad \text{(vi)}$$

Here, Z_t represents the vector of exogenous variance regressors.

We employ T-GARCH to examine the impact of asymmetric news on inflation uncertainty, where $w_t = 1$ if $e_t < 0$ and 0 otherwise.

$$h_t = c + \sum \alpha_1 e_{t-i}^2 + \sum \beta_j h_{t-j} + \gamma w_{t-1} e^2_{t-1} + \lambda z_t \quad \text{(vii)}$$

Finally, we employ C-GARCH to decompose inflation uncertainty into short-run and long run component. It allows the transitory deviation of conditional volatility around a time-varying trend, C_t.

$$h_t = C_t + \alpha_1 (e_{t-i}^2 - C_{t-1}) + \beta_1 (h_{t-1} - C_{t-1}) \quad \text{(viii)}$$

$$C_t = C + \rho C_{t-1} + \mu(e_{t-i}^2 - h_{t-1}) + \lambda z_t \quad \text{(ix)}$$

4. Overview of Sweden Inflation Data

In our studies, we use 578 monthly Sweden data of Consumer price index (CPI) over the period 1970M01-2018M03. The data are obtained from the Federal Reserve Economic Data. We converted not seasonally adjusted data into seasonally adjusted data. Then, we estimate the inflation data as the first difference of log consumer price index.

$$\text{Inflation, } \Pi_t = 100*(\ln CPI_t - \ln CPI_{t-1})$$

Figure 1 plots the monthly average data of Sweden inflation. From the pattern of plot, we can assume the inflation data is stationary. From the correlogram (Table 1), we can see some highs and lows in the ACF. The data have seasonality. However, we use the Augmented Dickey Fuller test (ADF) and Philips Perron (PP) model to examine the stationarity of the data. Table 2 represents the ADF and PP t-statistics of Unit Root test. Both results suggest that the data set can be treated as integrated of order zero, I(0), variable. As we found the dataset is stationary then we can make a start with the autoregressive model.

5. Empirical Results

5.1 Benchmark autoregressive conditional mean model

In our first conditional mean equation (1) we estimate the ordinary least square parameters for the full sample period. For the full sample, all lagged coefficients are significant at 5% level. We perform a set of diagnostic tests to check whether the residuals are serially correlated. Breusch-Godfrey Serial (LM) test shows there is serial correlation for full sample period. Ljung-box serial correlation test are insignificant for all lags except for lag-12. Hence, we cannot confirm that the benchmark autoregressive model performs adequately. [Table 3 about here]

5.2 Sensitivity Analysis

We do sensitivity analysis as we expect a structural break around January 1993, when Sweden adopted inflation targeting. We re-estimate Equation (i) for both pre-target and after-target period. The result dictates significant change in the behavior pattern of inflation. 12-month lagged coefficient (α_4) was significant before inflation targeting, but it becomes insignificant during inflation targeting period. Therefore, there is no significant coefficient of lagged inflation during the inflation-targeting period.

We also formally check the stability using the Chow break-point test. We set break-point date on 1993M01 to check the stability. We find chow breakpoint F test is strongly significant and firmly rejected the null hypothesis that there is no break at specified breakpoint. The Wald-X^2 test also firmly rejects the null of no structural change. It indicates the residual volatility is not same for both pre-targeting and inflation-targeting period.

The results of sensitivity analysis suggest our autoregressive model misspecified. We now modify our first equation by including multiplicative dummy variable $D_{t.}$ on lagged-1 and lagged-

12 inflation. That means we now use equation (ii). It would help us to remove the instability by changing the slope of average inflation for the adoption of IT. [Table 3 about here]

5.3 Dummy variable model and the dynamic of inflation

The estimated least square parameters using equation (ii) shows significant improvement on statistical performance. Here, all inflation lag (except lag 2 inflation) and dummy coefficients are significant. The adjusted R^2 improves from 0.228297 to 0.246329 and residuals volatility declines from 126.829 to 123.379. The negative sum of dummy coefficients ($\alpha_5 + \alpha_6 = -0.406656$) indicates the inflation tenacity has declined after the adoption of inflation targeting. The Wald test statistics for the joint significance of α_5 & α_6 equals 15.42231, which firmly reject the null hypothesis ($\alpha_5 = \alpha_6 = 0$). Comparing the outcomes of equation (i) and (ii) we find equation (ii) better fits and it also helps to examine the negative effect of inflation targeting on the Sweden inflation persistence. [Table 3 about here]

5.4 Time varying inflation volatility and pre-test of the inflation-uncertainty link

To examine time-varying volatility we employ equation (iii) on equation (i) and (ii), i.e regressing the squared OLS residual on a constant and its lagged values. On equation (ii) we see that the F and TR^2 test statistics rejects the null that there is no ARCH effect. We also find Ljung-Box statistics of the squared residuals (Q^2) are firmly significant for all lags. On equation (i) for the pre-targeting period, it rejects the null hypothesis of no ARCH effect for some lags. But during the inflation targeting period the F and TR^2 test statistics fail to reject that there is no ARCH effect, which indicates the inflation targeting period is more stable. The squared residuals (Q^2) Ljung box statistics are also insignificant for all lags during inflation targeting period. [Table 4 about here]

We perform a pre-test of inflation-uncertainty link using equation iv-(a), iv-(b) and iv-(c). When we regress squared residual on past inflation. Here, we see the relationship between past inflation (both asymmetric and symmetric) and inflation uncertainty is positive and significant during the pre-targeting period. However, we see a relationship breakdown during the inflation-targeting period. It indicates inflation targeting may reduce inflation uncertainty. [Table 5 about here]

5.5 GARCH model of Inflation Uncertainty

We formally examine the relationship between inflation & inflation uncertainty and the role of inflation targeting by employing different GARCH model. Using equation (v) and (vi) we employ GARCH-M model. To examine the effect of price level change on inflation variability we restrict lagged inflation in a way so that it contain only past level of inflation, where we employ both asymmetric and symmetric measure of lagged inflation. The equation (v) and (vi) show there is strong relationship between past inflation and current conditional volatility of inflation. As the coefficient (λ) of one period lagged inflation (z_t) is significant and positive, it is consistent with the idea of Friedman-Ball link, which means high past inflation creates more uncertainty about future inflation. We also find that the co-efficient (δ) of conditional variance of inflation is statistically significant and positive. It satisfies Cukierman-Meltzer prediction, which imply high inflation uncertainty has impact on average inflation. The Ljung Statistics of standardized and squared standardized residuals are insignificant for almost all lags and LM test significant for all lags. It implies the model is adequately performing. [Table 6 about here]

To examine the impact of asymmetric news on inflation-uncertainty, we employ T-GARCH model using equation (v) and (vii). We find LM test statistics and Ljung statistics of residuals and squared residuals are significant for some lags. We also find the asymmetric parameter (γ) is also insignificant. Therefore, we can say that the T-GARCH model is not performing adequately for our monthly inflation data. [Table 6 about here]

We employ symmetric GARCH (p,q)-M models augmented by lagged inflation and targeting dummy. First, we consider IT dummy as the conditional variance regressor. Nevertheless, we control the standard relationship between inflation and inflation uncertainty, the coefficient (λ_1) of dummy remains negative (-0.282752) and significant at the 5% level. Later we consider both Lagged-1 inflation and IT dummy as the conditional variance regressors & we find the coefficient (λ_1) of dummy increases from (-0.282752) to (-0.087028). As it is still negative and significant at the 5% level, we can understand that the impact of short run IT is little but still significant. As the results of Ljung-Box statistics and LM test are insignificant for all lags, it ensures the model is perfectly fit. [Table 7 about here]

Finally, we employ C-GARCH-M model to decompose the inflation uncertainty into short run and long run component. It shows the coefficient (λ_1) of dummy is negative and significant (-0.057415). Hence, we can say that in the long run inflation targeting reduces inflation uncertainty. On the other side, the coefficient of past inflation (λ_2) reflects the relationship between past inflation and future uncertainty. As λ_2 is positive and significant (0.061386), it supports the argument for controlling the inflation to reduce inflation uncertainty. The estimation of persistence (ρ) is 0.739348. It is lower than unit value (1), which indicates the long-run mean recurrence of inflation's conditional variance does not happen in a very slow process. The diagnostic test using Ljung-box test and LM test ensures there is no serial correlation and ARCH effect on this model. [Table 7 about here]

6. Conclusion

In this paper, we inspect the pattern of relationship between inflation and inflation uncertainty and the influence of inflation targeting to reduce the inflation uncertainty in the context of Sweden economy. The literature review part shows the significant economic cost of the inflation uncertainty. Here, we formally employed asymmetric, asymmetric, threshold and component GARCH-M model for the investigation. The limitation is in our monthly data the threshold GARCH-M has not performed adequately that is why we fail to understand the impact of asymmetric news on inflation-uncertainty relationship.

The results of asymmetric and symmetric GARCH-M model augmented my lagged inflation show high past inflation increases current inflation uncertainty (Friedman-Ball view) and high inflation uncertainty raises average inflation rate (Meltzer-Cukierman view). The output of Symmetric GARCH-M model augmented by past inflation and inflation targeting dummy shows that in the short run the impact of inflation targeting to reduce uncertainty is little but still significant. From the results of component GARCH-M model, we see high inflation increases inflation uncertainty in the long run and we also see adoption of inflation targeting reduces inflation uncertainty in the long run. Briefly, we can say that, the economy with high inflation variability should admit the benefit of inflation targeting to reduce economic cost.

References

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Figures & Tables

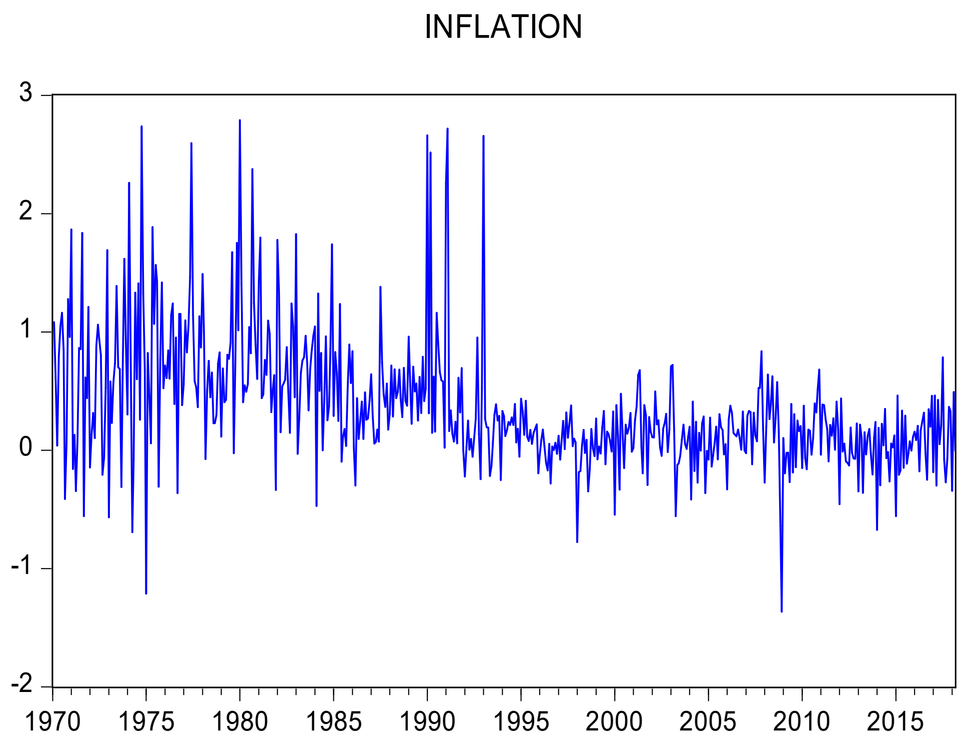

Figure1: Average Monthly Inflation, Sweden 1970M01-2018M03

Table:1 Correlogram of Inflation Data												
AC	0.32	0.27	0.24	0.25	0.29	0.32	0.33	0.33	0.30	0.24	0.31	0.40
PAC	0.32	0.19	0.12	0.13	0.17	0.17	0.15	0.15	0.10	0.02	0.12	0.21
Q-stat	58.34	101.26	133.70	170.32	220.42	280.60	342.47	406.70	459.37	493.09	549.57	642.90
Prob	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 2: Unit Root Test, Sweden Inflation Rate, 1970M01-2018M03		
Test Critical Values	Constant, Linear trend	
1% level -3.974039	ADF t-statitics	-21.18783
5% level -3.417627	PP t-statistics	-21.73717
10% level -3.131240		

Table 3: OLS estimates of inflation conditional mean equation (i) & (ii)				
	02/71-03/18		02/71-12/92	01/93-03/18
	Equation(i)	Equation(ii)	Equation(i)	
Coefficients			Pre-target	After-target
α_0	0.111161*	0.141628*	0.408348*	0.082187*
α_1	0.155673*	0.170648*	0.06771	0.08554
α_2	0.078624*	0.049546	-0.026687	0.034713
α_3	0.158573*	0.130917*	0.080856	0.03187
α_4	0.277297*	0.311847*	0.228577*	0.075776
α_5		-0.203328*		
α_6		-0.285324*		
Diagostic Statistics				
Adjusted R^2	0.228297	0.246329	0.057112	0.003286
Sum Squared Resid	126.7829	123.379	91.15626	26.80431
Q(1)	1.2954	0.7494	0.0332	0.5651
Q(4)	6.2898	4.6566	1.6397	1.7812
Q(12)	45.213*	36.914*	19.567	4.7357
T*R^2 (4)	10.22094*	8.070564	3.261332	33.48797
T*R^2 (12)	62.71221*	51.89886*	25.77649*	39.99424*
Testing for breakpoint at 01/1993: Chow-break point F-test: 8.316682*.				
Wald X^2 test for structural change: 41.58341*				
Wald X^2 test for joint significance of Dummy Coefficient 15.42231*				

* indicates Statistical significance at 5% level

Table 4: Testing for time-varying residual variance in the conditional mean			
Equation (ii) 02/71- 03/18 Full Sample			
q	F-statistic	TR^2	Q^2
4	3.054666*	12.06371*	13.997*
8	2.778945*	21.71661*	26.794*
12	3.808838*	43.15816*	56.769*
Equation (i) 02/71- 12/92 Pre-Target			
q	F-statistic	TR^2	Q^2
4	0.68972*	2.782963*	2.7328
8	0.878072	7.079422	7.0433
12	1.305551	15.50192	15.387
Equation (i) 01/93-03/18 After-Target			
q	F-statistic	TR^2	Q^2
4	2.318686	9.144014	0.1151
8	1.306915	10.40399	0.1483
12	0.94681	11.42605	0.212

* indicates statistical significance at the 5% level

Table 5: Inflation Uncertainty and Lagged Inflation Variable			
	Equation (ii)	Equation (i)	
Lagged Inflation Variable	Full Sample	Pre-target	After-target
Π_{t-1}	0.199421*	0.159193*	0.066438
$\lvert \triangle\Pi_{t-1} \rvert$	0.251056*	0.180846*	0.199696*
Π_{t-1}^{2}	0.094224*	0.074062*	0.026782

* indicates statistical significancs at 5% level

Table 6: Symmetric and Threshold GARCH(p,q)-M Models augmented by lagged inflation variables			
Conditional Mean	Asymmetric GARCH-M Equation (v)	Symmetric GARCH-M Equation (v)	Threshold GARCH-M Equation (vii)
α_0	0.065799*	0.079356*	0.160558*
α_1	0.144896*	0.49777*	0.172959*
α_2	0.035206	0.023802	0.047426
α_3	0.074002	0.184276*	0.11618*
α_4	0.277142*	0.175841*	0.28511*
α_5	-0.288368*	-0.639559*	-0.174409
α_6	-0.245491*	-0.126005*	-0.236654
δ	0.557662*	0.183536*	-0.053337
Conditional variance	(p,q) =(1,1) $Z_t = \Pi_{t-1}$	(p,q) =(0,1) $Z_t = \lvert\Pi_{t-1}\rvert$	(p,q) =(1,1) $Z_t = \Pi_{t-1}$
c	0.003668*	0.023037*	0.175878*
α_1	0.073468*	0.59059*	-0.037138
β_1	0.788943*		0.548437*
λ	0.076621*	0.277671*	0.01438
γ			-0.07679
Duagnostic Statistics			
LL	-264.6748	-297.6933	-401.9359
Q(1)	0.0705	4.7707*	0.4971
Q(4)	1.4616	4.9792	7.2426
Q(12)	7.599	13.175	41.505*
Q^2 (4)	0.7798	2.0302	23.214*
TR^2(8)	2.221205	3.794993	25.10452*

* indicates statistical significance at the 5% level

Table 7: Symmetric and Componen GARCH(p,q)-M Models augmented by past inflation and targeting dummy			
Conditional Mean	Symmetric GARCH-M Equation (v) & (VI)	Symmetric GARCH-M Equation (v) & (vi)	Component GARCH-M Equation (v) (viii), (ix)
α_0	0.010393	0.051947**	0.035635
α_1	0.081064	0.09668	0.059273
α_2	0.017522	0.020318	0.004345
α_3	0.064635	0.069051	0.054666
α_4	0.1818**	0.22996**	0.188084**
α_5	-0.077285*	-0.195195*	-0.192548*
α_6	-0.062386*	-0.126955*	-0.097506
δ	1.045934**	0.728726**	
Conditional variance	(p,q) =(1,1) $Z_t = D_t$	(p,q) =(1,1) $Z_t = [D_t \Pi_{t-1}]$	(p,q) =(1,1) $Z_t = [D_t \Pi_{t-1}]$
c	0.337065**	0.100663**	0.257807**
α_1	0.088246**	0.112011**	0.090483**
β_1	0.046934	0.543579**	0.002093
λ_1	-0.282752**	-0.087028**	-0.057415**
λ_2		0.072242**	0.061386**
ρ			0.739348**
μ			0.028267
Duagnostic Statistics			
LL	-258.4306	-253.5303	-249.9411
Q(1)	0.0082	0.0048	6.00E-05
Q(4)	2.856	1.6487	1.8956
Q(12)	0.412	9.4696	7.3329
Q^2 (4)	12.425	2.0261	2.027
TR^2(8)	5.291332	2.271692	2.468278

** indicates statistical significance at the 5% level

*indicates statistical significance at the 10% level