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Modeling the Impact of News on volatility: The Case of Iran

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Abstract

In this paper various ARCH models and relevant news impact curves including a partially nonparametric (PNP) one are compared and estimated with daily Iran stock return data. Diagnostic tests imply the asymmetry of the volatility response to news. The EGARCH model, which passes all the tests and appears relatively matching with the asymmetry in the data, seems to be the most adequate characterization of the underlying data generating process. The PNP model successfully reveals the shape of the news impact curve and is a useful approach to modeling conditional heteroskedasticity.

Keywords: news impact curve; Volatility; Stock Market

I- Introduction

Empirical research over the past two decades has provided much evidence that volatility is time-varying, and that changes in volatility are predictable, to some extent, in many asset markets. Numerous approaches of forecasting volatility have been proposed in the literature; most of them are linked to the autoregressive conditional heteroskedasticity (ARCH) models originally introduced by Engle (1982) and generalized (GARCH) by Bollerslev (1986).

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Generally the ARCH–GARCH-type approaches of conditional heteroskedasticity can be interpreted as models of news effects on volatility. A unified treatment of a variety of symmetric and asymmetric GARCH models is discussed in Hentschel (1995).

There appears to be widespread agreement on Asymmetric effects of good news (unexpected increase in price) and bad news (unexpected drop in price), suggesting a negative shock to stock returns will generate more volatility than a positive shock of equal magnitude, (see, for example, French et al., 1987; Nelson, 1991; Pagan and Schwert, 1990; Sentena, 1992; Campbell and Hertschel, 1992; Engle, 1993; Henry, 1998; and Friedmann and Sanddorf-Köhle, 2002). Some researchers suggest that as stock prices fall, the weight attached to debt in the capital structure increases. This increase in leverage will cause equity holders, who bear the residual risk of the firm, to anticipate higher expected future returns volatility (see Black, 1976 Christie, 1982, and Schwert, 1989) .Others have argued that the asymmetry could arise from the feedback from volatility to stock price when changes in volatility induce changes in risk premiums (see Pindyck, 1984, French et al., 1987, Campbell and Hentschel, 1992, and Wu, 2001).

Engle and Ng (1993) compare asymmetric volatility models, which allow good and bad news to have different effects on future volatility. They recommend the concept of a news impact curve as a standard measure of how news effects predicted volatility. Fitting a variety of asymmetric volatility models to daily Japanese stock returns, they initially conclude that the asymmetric model proposed by Glosten, Jagannathan, and Runkle (1993) and the EGARCH model introduced by Nelson (1991) are superior. They provide further evidence that the EGARCH model produces conditional variances which are much larger than those predicted by the other models. As a consequence, the standard deviation of the EGARCH estimated conditional variance in Engle and Ng's (1993) study is even higher than that of the squared residual itself. This contradicts the basic theoretical decomposition of the variance of the squared residual. Engle and Ng find that the best model is the one proposed by Glosten, Jagannathan, and Runkle (GJR).

In this paper we compare and estimate various ARCH models including a partially nonparametric one with daily Iran stock return data and use the news impact curve analysis of Engle and Ng (1993) in order to examine the relationship between return shocks and conditional volatility. In Section II, several volatility models that allow for asymmetry in the impact of news on volatility are compared. Section III provides data descriptions. Section IV discusses the estimation and testing procedure and presents initial empirical results. Section V presents the partially non-parametric model of stock return volatility and estimates of the news impact curves. The section VI concludes the paper.

II- Models of Asymmetric Volatility

It is a well-known empirical fact in finance research that asset returns are not normally and independently distributed. Engle (1982) presents the ARCH model which specifies the conditional variance of innovations ε_t, $\sigma_t^2 = \mathrm{Var}(\varepsilon_t | \varepsilon_{t-1}, \varepsilon_{t-2}, ...)$ as a distributed lag over past squared innovations ε_{t-i}^2 as shown by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \quad (1)$$

Where $\omega > 0, \alpha_1, ..., \alpha_p \geq 0$ are constant parameters. The effect of a return shock i periods ago ($i < p$) on current volatility is shown by the parameter α_i. Normally, we would expect that $a_i < a_j$ for $i > j$. That is, the older news, the less effect it has on current volatility. In an ARCH(p) model, old news which arrived at the market more than p periods ago has no effect at all on current volatility.

Bollerslev (1986) presented the Generalized ARCH or GARCH model

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (2)$$

Where $\omega > 0, \alpha_1, ..., \alpha_p \geq 0$, $\beta_1, ..., \beta_p \geq 0$ are constant parameters. The GARCH model corresponds to an infinite order ARCH model. A common parameterization for the GARCH model that has been adopted is the

GARCH(1,1) specification under which the effect of a shock to volatility declines geometrically over time.

The ARCH(p) and GARCH(p, q) models impose symmetry on the conditional variance structure which may not be appropriate for modeling and forecasting stock return volatility. One method proposed to capture such asymmetric effects is Nelson's (1991) exponential GARCH or EGARCH model

$$\log(\sigma_t^2) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{\frac{2}{\pi}}\right] + \beta\log\sigma_t^2 + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \tag{3}$$

where w, α, β and δ are constant parameters. The EGARCH model has two distinct advantages over the GARCH model. First, the logarithmic construction of Equation 3 ensures that the estimated conditional variance is strictly positive, thus the non-negativity constraints used in the estimation of the ARCH and GARCH models are not necessary. Secondly, since the parameter δ typically enters Equation 3 with a negative sign, bad news, $\varepsilon_t < 0$, generates more volatility than good news.

The generalized quadratic ARCH or GQARCH(1, 1) model of Sentena (1992) takes the form

$$\sigma_t^2 = \omega + \alpha(\varepsilon_{t-1} + \delta)^2 + \beta\sigma_{t-1}^2 \tag{4}$$

where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ are constant parameters. The estimated value of the parameter δ is usually negative, thus Equation 4 responds asymmetrically to positive and negative shocks of equal magnitude.

Another approach to asymmetry is to distinguish the sign of the shock as in the GJR(Glosten, Jaganathan and Runklel 1993) model

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta N_{t-1}\varepsilon_{t-1}^2 \tag{5}$$

where N_{t-1} is a dummy variable that takes the value of unity if $\varepsilon_{t-1} < 0$ and zero otherwise. The GJR model is closely related to the threshold ARCH, or TARCH model of Rabemananjara and Zakoian (1993) and Zakoian (1994). Provided that $\delta > 0$, the GJR model generates higher values for σ_t^2 given

$\varepsilon_{t-1} < 0$ than for a positive shock of equal magnitude. As with the ARCH and GARCH models the parameters of the conditional variance, Equation 5, are subject to non-negativity constraints.

Suppose information is held constant at time $t-2$ and before, Engle and Ng(1993) describe the relationship between ε_{t-1} and σ_t^2 as the news impact curve. The news impact curves of the GARCH(1, 1) and GQARCH models are symmetric and centered at $\varepsilon_{t-1} = 0$ and $\varepsilon_{t-1} = -\delta$, respectively. The news impact curves of the EGARCH(1, 1) and GJR models are centered at $\varepsilon_{t-1} = 0$. The EGARCH(1, 1) has a steeper slope for $\varepsilon_{t-1} < 0$, provided that $\delta < 0$ in Equation 3, while the GJR has different slopes for its positive and negative sides. Table 1 presents the relevant news impact curves, evaluating the lagged conditional variance σ_t^2, at its unconditional level σ^2.

Table 1: News Impact curves

Model	News Impact curve
GARCH(1, 1)	$\sigma_t^2 = A + \alpha\varepsilon_{t-1}^2$ where $A = w + \beta\sigma^2$
EGARCH(1, 1)	$\sigma_t^2 = A\exp[\frac{\delta+\alpha}{\sigma}\varepsilon_{t-1}]$, for $\varepsilon_{t-1} > 0$ $\sigma_t^2 = A\exp[\frac{\delta-\alpha}{\sigma}\varepsilon_{t-1}]$, for $\varepsilon_{t-1} < 0$ where $A = \sigma^{2\beta}\exp(w - \alpha\sqrt{\frac{2}{\pi}})$
GQARCH	$\sigma_t^2 = A + \alpha(\varepsilon_{t-1} + \delta)^2$ where $A = w + \beta\sigma^2$
GJR	$\sigma_t^2 = A + \alpha\varepsilon_{t-1}^2$, for $\varepsilon_{t-1} > 0$ $\sigma_t^2 = A + (\alpha+\delta)\varepsilon_{t-1}^2$, for $\varepsilon_{t-1} < 0$ where $A = w + \beta\sigma^2$

III- Data Description

The data consist of 1327 observations of the closing value of the Tehran Exchange Price Index (TEPIX), from the Iran stock market, sampled daily from 3/30/1998 to 5/05/2003. The data are transformed to continuously compounded returns, calculated as $R_t = \log(\frac{p_t}{p_{t-1}})(100)$, where R_t represents the value of the index at time t. The mean function is specified as regression of R_t on a constant and $R_{t-1}, R_{t-2}, R_{t-7}$. The day-of-week effects are not significant in mean function. The residuals from the mean regression, r_t, are the unpredictable stock return data. Table 2 presents summary statistics for r_t.

Table 2: Summary Statistics for r_t

$\bar{r}_t$	$var(r_t)$	Sk	Ku	B-J	Q(10)	Q2(10)	A(10)	R(2)
0.000	0.1848	-0.397	49.4157	118797.5	20.605	207.03	148.402	88.545
		(0.000)	(0.000)	(0.000)	(0.024)	(0.000)	(0.000)	(0.000)

Notes: Marginal significant levels displayed as(.). Sk and Ku are tests for zero skewness and excess kurtosis. B-J is the Bera-Jarque test for normality, distributed as $\chi^2(2)$. Q (10) and $Q^2(10)$ are Ljung-box tests for serial correlation in the returns and squared returns data respectively, distributed as $\chi^2(10)$. A(10) is Engle's(1982) test for tenth order ARCH, distributed as $\chi^2(10)$. R(2) is Ramsey's(1969) RESET test for non-linear dependence in the conditional mean of r_t distributed as $\chi^2(1)$.

The unconditional mean of r_t is zero, by construction. The unconditional variance is 0.1848, but visual inspection of the time series plot of the data (Fig. 1) suggests that the volatility of the absolute value of r_t displays the clustering phenomenon associated with GARCH processes. Large shocks of either sign tend to be followed by large shocks, and small shocks of either sign tend to follow small shocks.

There is significant evidence of ARCH in the data, as shown by the test for tenth order ARCH and the Ljung-Box Q statistic on the squared return data. There is also some evidence of serial correlation in the mean as shown by the Ljung-Box Q statistic for the prefiltered return data. Furthermore, the null hypothesis of no higher order non-linear dependence in r_t, i.e. dependence between R_t and R_t^2 was rejected using Ramsey's (1969) RESET test. The estimated unconditional density function for r_t is clearly skewed to the left and markedly leptokurtic. The Bera-Jarque test for normality is significant at any reasonable level of confidence.

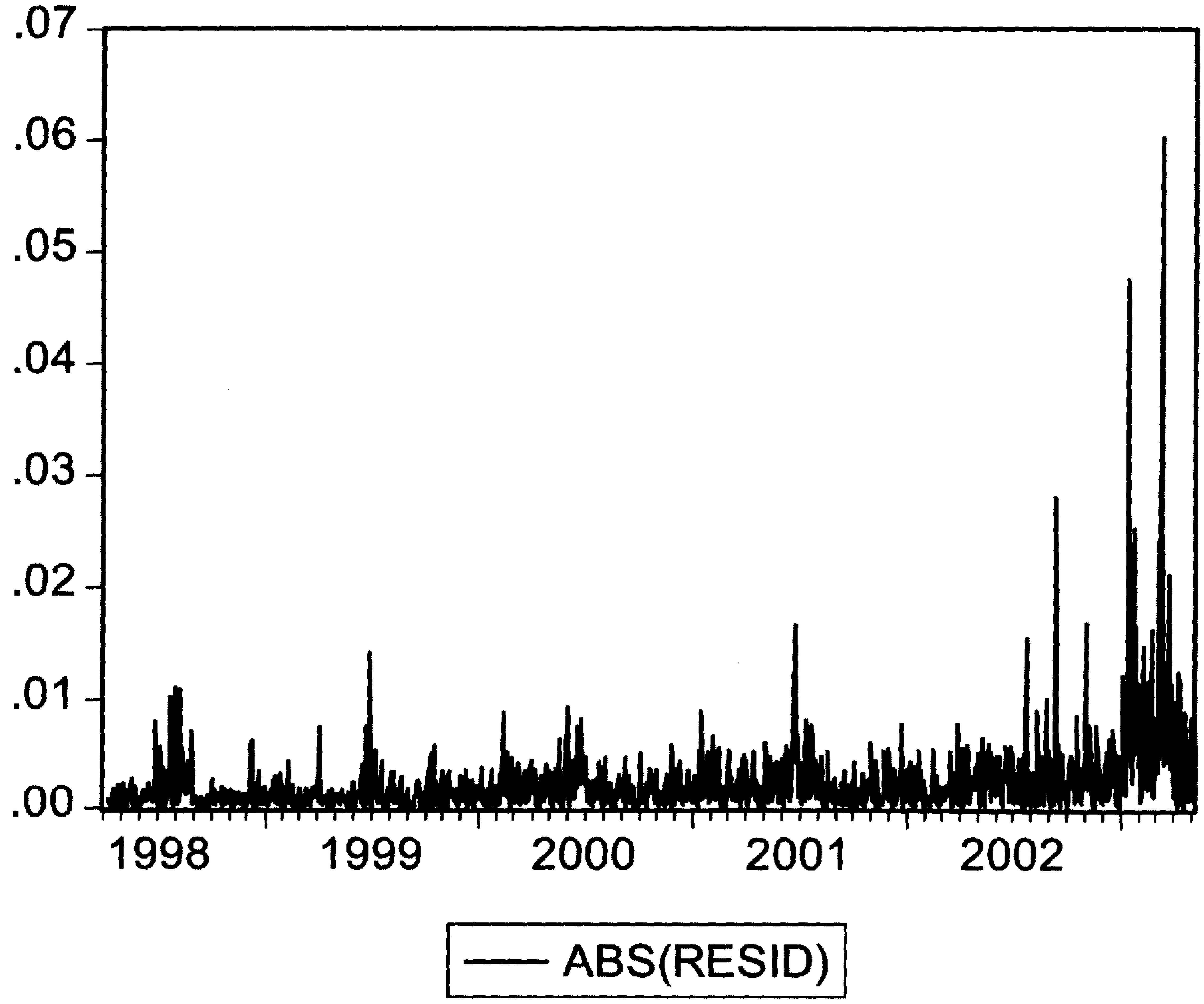

Fig 1: Time Series Plot of $|r_t|$

IV- Empirical Estimation and Results

Engle and Ng(1993) describe three tests which examine whether it is possible to predict the squared normalized residual $z_t^2 = \varepsilon_t^2 / \sigma_t^2$ using some variables observed in the past which are not included in the regression model. Define N_{t-1} as in Equation 5, and let $P_{t-1} = 1 - N_{t-1}$. In the sign bias test z_t^2 is regressed on a constant and N_{t-1}. If the coefficient on N_{t-1} is significant then positive and negative innovations affect future volatility differently. The negative size bias test examines whether the magnitude of negative innovations causes the bias to predicted volatility. The test examines the significance of $N_{t-1}\varepsilon_{t-1}$ in the regression of z_t^2 on a constant and $N_{t-1}\varepsilon_{t-1}$. The positive size bias test examines the significance of $P_{t-1}\varepsilon_{t-1}$ in the regression of z_t^2 on a constant and $P_{t-1}\varepsilon_{t-1}$. Engle and Ng (1993) show that a joint test for size and sign bias, based on the Lagrange Multiplier principal, may be obtained by $T.R^2$ from the regression

$$z_t^2 = \phi_0 + \phi_1 N_{t-1} + \phi_2 N_{t-1}\varepsilon_{t-1} + \phi_3 P_{t-1}\varepsilon_{t-1} + \eta_t$$

The estimation and test results for the models defined in Equations 2-5, are displayed in Table 3. In this paper variance equation is extended to allow for the inclusion of a dummy variable, SAT, for Saturday which is meant to capture weekend non-trading. The Bera-Jarque test for normality is significant for all models. When the assumption of conditional normality does not hold, the ARCH parameter estimates will still be consistent, provided the mean and variance functions are correctly specified. So we used quasi-maximum likelihood (QML) covariance and standard errors using the methods described by Bollerslev and Woldridy (1992).

The Ljung-Box test statistics for tenth order serial correlation in the normalized residuals are significant at five percent level for all the models but the EGARCH. The tests for sign and negative size bias, as well as the joint tests, are significant for GARCH (1, 1) with GQARCH being only marginally rejected by the joint test, suggesting a sign or asymmetric effect, as well as a size effect, that differs for negative and positive ε's. The Ljung-Box test on z_t^2, which is commonly used as a specification check for volatility models, does not have much power in detecting misspecifications related to the leverage or asymmetric effects. The parameter δ in the GJR model is not significant, suggesting that the GJR model can not capture the asymmetry inherent in the data. Overall the exponential GARCH conditional variance equation seems to outperform the alternative models in capturing the dynamic behavior of the Iran stock returns.

Table 3: Estimated of the parametric volatility models

	GARCH	EGARCH	GIR	GQARCH
w	1.96e-7 (1.692)	-0.624 (-2.713)	2.05e-07 (3.022)	2.19e.5 (0.718)
α	0.203 (3.562)	0.3867 (4.713)	0.3861 (4.712)	0.146 (3.063)
β	0.817 (16.666)	0.969 (62.567)	0.813 (22.140)	0.887 (3.0896)
δ	-	-0.169 (6.877)	0.0707 (0.860)	-0.3653 (-2.453)
log likelihood Sk	5873.829 0.3867 [0.000]	5879.08 0.4222 [0.000]	5875.67 0.4128 [0.000]	5880.969 0.367 [0.000]
Ku	10.744 [0.000]	10.782 [0.000]	10.513 [0.000]	10.554 [0.000]
Q(10)	19.622 [0.033]	12.199 [0.134]	26.925 [0.003]	27.651 [0.004]
$Q^2(10)$	3.4725 [0.968]	3.385 [0.971]	3.730 [0.959]	287.5 [0.995]
IGARCH	0.5362	-	0.0608	0.02974
Wald	[0.464]	-	[0.805]	[0.863]
$H_0:\rho=1$	-6.3549	-8.5633	-4.6736	-7.4666
J-B	3338.276 [0.000]	3378.261 [0.000]	3149.554 [0.000]	3175.215 [0.000]
Sign bias	3.3127	0.9271	0.9671	1.416
Negative size bias	-4.2149	-0.6711	-0.5719	-1.607
Positive size bias	1.3144	-0.3221	0.8778	0.5862
Joint test	8.3227 [0.000]	1.3587 [0.715]	2.3916 [0.511]	7.6371 [0.0735]

Notes: Asymptotic t-ratios are displayed as (.). Marginal significant levels displayed as [.]. IGARCH is a robust Wald test of the null H_0: $\alpha+\beta=1$.

If $\sum_{i=1}^{p}\alpha_i + \sum_{j=1}^{q}\beta_j = 1$ in Equation 2 then, using the terminology of Engle and Bollerslev(1986), the model is said to be integrated in variance. The null hypothesis of variance non-stationarity in models (2)-(5) is tested using the QML estimator. Lumsdaine (1991) and Lee and Hansen(1994)indicate that Providing certain assumptions hold, even in the case of IGARCH, QML estimation will be asymptotically normal. Deb(1995) provides evidence that the QML estimator of the EGARCH(1, 1) has poor finite sample properties when the data generating process has conditional excess kurtosis. Pagan (1995) argues that the estimation problem for the EGARCH model may not be well defined under the null of integration in variance. Moreover an integrated EGARCH process is neither strictly stationary nor covariance stationary. Psaradakis and Tzavalis(1995) suggest a regression-based test for integration in variance for the exponential family of ARCH models. They argue that such tests have well defined limiting distributions under the null hypothesis, which may not be the case for the Wald test based on the (quasi) maximum likelihood estimator. Psaradakis and Tzavalis base their inference on the logarithmic GARCH(1,1) process, written as:

$$\ln\sigma_t^2 = w + \alpha\ln\varepsilon_{t-1}^2 + \beta\ln\sigma_{t-1}^2 \tag{6}$$

Based upon the ARMA form of Equation 6 an autoregression such as

$$\ln\varepsilon_t^2 = \theta + \gamma T + \rho\ln\varepsilon_{t-1}^2 + u_t \tag{7}$$

where $\rho = \alpha + \beta$ provides an alternative test, since if $\rho = 1$, the process in Equation 7 is integrated. Such a test may be based on the Phillips-Perron (1988) non-parametric unit root test, (PP), or indeed the augmented Dickey-Fuller unit root test (ADF), (Dickey and Fuller, 1981). Note that in Equation 7 θ, γ and ρ are constant parameters and T is a time trend. Psaradakis and Tzavalis provide Monte Carlo evidence demonstrating that tests based on autoregressive approximations of the ARMA representation have minimal size distortion, and appeared robust to model misspecification. Their procedure extends to the EGARCH(1, 1) case since, following Pantula (1986), Equation 3 may be rearranged to yield

$$\ln\varepsilon_t^2 = w + \rho\ln\varepsilon_{t-1}^2 + \delta\ z_{t-1} + \alpha[|z_{t-1}| - E|z_{t-1}|] + \xi - \rho\xi_{t-1} \tag{8}$$

where $\xi_t = \ln(z_t^2)$. If $\rho = 1$ then the process in (8) is integrated. Since the noise function in Equation 8 can be shown to have a MA(1) representation, Psaradakis and Tzavalis argue that regression-based criteria provide appropriate statistics for testing the hypothesis of integration in conditional variance.

Given that returns are the product of two stationary processes $\varepsilon_t = z_t \sigma_t$, the GARCH model represents a strictly stationary process. However, under IGARCH the variance of returns does not exist, thus the process is not covariance stationary; see Nelson (1990) and Pagan (1995) for further details. Nelson (1990) demonstrates that even under the null of integration in variance the series ε_t^2 is stationary. Thus, using the ARMA form of Equations 2, 4 or 5, the null hypothesis $H_0 : \rho = 1$ may be tested using standard distribution theory as suggested by Tzavalis and Wickens (1993).

The Wald tests for infinite persistence in the GARCH (1, 1), GJR and GQARCH models support the null hypothesis of variance non-stationarity, while the regression based tests indicate a GARCH process that is covariance stationary. The QML-based Wald test may be less robust to misspecification of the conditional variance equation than the regression-based tests, which in line with the conclusion of Psaradakis and Tzavalis (1995).

As a further diagnostic check for the adequacy of the various parameterizations of the conditional variance equations the moment type specification test suggested by Pagan and Sabau (1992) was computed from the regression

$$\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 \hat{\sigma}_t^2 + \eta_t \tag{9}$$

where $\hat{\varepsilon}_t^2$ and $\hat{\sigma}_t^2$ are the squared innovations and the estimated conditional variances, respectively, from the models reported in Table 3. Under the null hypothesis of correct specification, the moment condition $E(\varepsilon_t^2 | I_{t-1}) = \sigma_t^2$ implies that $\phi_0 = 0$, $\phi_1 = 1$. The results of the ordinary least squares estimation of (9) presented in Table 4 suggest that just the EGARCH variance model pass moment specification test, Once again implying the GJR and GQARCH are a poor characterization of the underlying data generating process.

Table 4: Moment Specification Test for the Estimated Conditional Variance Model

	GARCH	EGARCH	GJR	GQARCH
ϕ_0	0.5678	-0.1569	0.6842	0.2712
	(1.4509)	(-0.3278)	(0.8934)	(1.8709)
ϕ_1	0.6598	1.1054	0.8034	1.3769
	(6.6209)	(4.6791)	(5.9545)	(7.6860)

Notes: Heteroscedasticity consistent t-ratios, calculated using the White(1980) estimator are reported as(.)

V- News Impact Curves

Engle and Ng(1993) propose a partially non-parametric(PNP) model to estimating the news impact curve which allows the data to reveal the curve directly. This will allow consistent estimation of news impact curve under a range of conditions. It is labeled partially nonparametric because the long memory in variance equation is given by a parametric component. The PNP model is specified as

$$\sigma_t^2 = w + \beta\sigma_{t-1}^2 + \sum_{i=0}^{m^+}\theta_i P_{it-1}(\varepsilon_{t-1} - i\sigma) + \sum_{i=0}^{m^-}\delta_i N_{it-1}(\varepsilon_{t-1} + i\sigma) \qquad (10)$$

where w, β, θ_i, $(i = 0,\dots,m^+)$, and δ_i $(i = 0,\dots,m^-)$ are constant parameters and

$P_{it} = 1$ if $\varepsilon_t > i\sigma$

$= 0$ otherwise

$N_{it} = 1$ if $\varepsilon_t < -i\sigma$

$= 0$ otherwise

This functional form, which is really a linear spline with knots at the $i\sigma$, is guaranteed to be continuous. Between 0 and σ the slop is θ_0 while between σ and 2σ it is $\theta_0 + \theta_1$, and so forth. Above $m^+\sigma$, the slope is the sum of all the θ's.

In this study the PNP model is estimated for $m^+ = m^- = 4$, with the kinks at ε_{t-1} equal to 0, $\pm\sigma$, $\pm 2\sigma$, $\pm 3\sigma$ and $\pm 4\sigma$, yielding ten coefficients of the news impact curve. The results are displayed in Table 5. If we compare the value of the coefficients corresponding to $P_{it-1}(\varepsilon_{t-1} - i\sigma)$ to their counterparts $N_{it-1}(\varepsilon_{t-1} + i\sigma)$ we can see that negative ε_{t-1}'s cause more volatility than positive ε_{t-1}'s of equal absolute size. The estimated parameter values for the terms $P_{3t-1}(\varepsilon_{t-1} - 3\sigma)$ and $N_{4t-1}(\varepsilon_{t-1} - 4\sigma)$ have unexpected signs and magnitudes. Since these terms are for the extreme ε_t's, they might be driven by only a few outliers. Moreover they are not significant using the Bollerslev-Wooldridge robust standard errors. The findings suggest that the news impact curve for the Iran market is asymmetric.

Table 5: Estimates of the PNP Model of the News Impact curve

w	0.0969711		
	(4.890910)		
β	0.78648		
	(8.78655)		
θ_0	0.27678	δ_0	-0.24564
	(5.53658)		(-4.63264)
θ_1	0.57345	δ_1	-1.09776
	(0.42309)		(-0.98756)
θ_2	1.57450	δ_2	-3.72567
	(4.79045)		(-6.76567)
θ_3	-2.91070	δ_3	-7.89685
	(-0.78965)		(-5.21567)
θ_4	3.54769	δ_4	5.21567
	(2.49718)		(0.90417)

Notes: robust t-ratios displayed as (.)

To compare the impact curve of the nonparametric model with those implied by the various volatility models, we compute the implied volatility level for each model at several prespecified values for ε_{t-1}, assuming that $\sigma^2 = 0.1848$. The results are summarized in Table 6.

Table 6: Estimated News impact Curves

ε_{t-1}	GARCH	GJR	EGARCH	GQANCH	PNP
-10	20.4832	24.4703	0.9015	27.6171	0.9076
-9	16.6251	20.0398	0.8983	24.9914	0.8771
-8	13.1690	15.0869	0.7862	20.6171	0.8695
-7	10.1152	12.1858	0.7348	15.9914	0.7956
-6	7.4740	8.0899	0.6825	12.968	0.7452
-5	5.2487	6.7829	0.6116	9.2095	0.7218
-4	3.0041	4.7008	0.5478	7.1058	0.6991
-3	1.7098	2.7836	0.4996	3.6824	0.6532
-2	0.9679	1.7814	0.4935	2.4870	0.6011
-1	0.3577	0.3997	0.4879	1.3467	0.5852
0	0.1381	0.1545	0.4795	0.0308	0.2811
1	0.3577	0.3284	0.4814	0.2424	0.3521
2	0.9679	0.8534	0.4828	0.9913	0.3500
3	1.7098	1.7377	0.4847	2.0924	0.4815
4	3.0041	2.9095	0.4868	3.2399	0.4959
5	5.2487	4.6052	0.4886	6.9823	0.5010
6	7.4740	6.6844	0.4893	8.7998	0.5861
7	10.1152	8.3572	0.4916	12.5403	0.5015
8	13.1690	11.6734	0.4932	15.8497	0.4831
9	16.6251	14.1231	0.4946	20.5722	0.3011
10	20.4832	17.5463	0.4963	24.9634	0.2194

Of all four parametric models, the EGARCH have news impact curves closest to the one suggested by the nonparametric estimation. If we consider the very extreme values for ε_{t-1}, we see the GQARCH and GJR returns unreasonably large estimates of σ_t^2. For example, the GJR model produces a ridiculously high σ_t^2 of 24.4703 for an ε_{t-1} equal to -10 which is about 132 times the value of the unconditional variance. The news impact curve estimates suggest that the GJR, GQARCH, and GARCH models are too extreme in the tails, and thus an inadequate characterization of the conditional variance of the Iran stock market. The EGARCH model appears to be the most adequate representation of the underlying data generating mechanism.

VI- Summary and Conclusions

In this paper we conducted a close examination of the relationship between return shocks and conditional volatility, applying the news impact curve as a standard measure of how news is incorporated into volatility estimates. In order to better estimate and match news impact curves to the data, several new candidates for modeling time-varying volatility are introduced and contrasted. These models allow several types of asymmetry in the impact of news on volatility. Furthermore, some diagnostic tests are used to determine whether the volatility estimates adequately represent the data. Finally a partially nonparametric model is suggested which allows the data to determine the news impact curve directly.

These models are fitted to daily Iran stock market from 3/30/1998 to 5/05/2003. The findings indicate that negative shocks introduce more volatility than positive shocks. Moreover the partially nonparametric (PNP) ARCH model, when fitted to the data, confirm this behavior. The diagnostic tests and the behavior of news impact curves imply that the best model is the EGARCH process. Other models seem to have some problem in capturing the correct impact of news on volatility.

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