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Inflation volatility: an Asian perspective

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For the quarterly data of 10 Asian economies, ranging from the first quarter of 1991 to last quarter of 2012, we model inflation volatility as a time varying process through different symmetric and asymmetric GARCH specifications. We also propose to model inflation volatility on the basis of cyclic component of inflation obtained from an Hodrick Prescott (HP) filter instead of actual inflation when the latter does not fulfil the criterion of stationarity. Through news impact curves (NICs) we tried to highlight the behaviour of inflation volatility in response to lagged inflation shocks under different GARCH specifications. In our results the leverage parameter shows the expected sign and is significant for almost all countries suggesting strong asymmetry in inflation volatility. The hyperbolic sign integral shape of NICs based on Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) highlights the importance of inflation stabilisation programmes particularly because of the subsequent evidence obtained in favour of bidirectional causality running between inflation and inflation volatility. There is also evidence in favour of the argument that a cyclic component of inflation obtained through an HP filter could be used as a suitable proxy of inflation for volatility estimation.

Keywords: inflation volatility; uncertainty; Glosten-Jagannathan-Runkle GARCH (GJR-GARCH); exponential GARCH (EGARCH); asymmetry; Asia

JEL classification: C14, C22, E31, E37

1. Introduction

Inflation is undoubtedly one of the most largely observed and tested economic variables both theoretically and empirically. Its causes, impacts on other economic variables and cost to the overall economy are well known and understood. There could be arguments for having, or not, moderate inflation in the economy and its pros and cons, nonetheless, if the debate focuses on inflation uncertainty or inflation volatility instead of inflation level, economists have almost consensus about its negative impact over some of the most important economic variables, like output and growth rate via different channels.[1]

The primary purpose of this article is to investigate and analyse the behaviour of inflation volatility in different Asian economies. There is a consensus about the negative consequences of inflation volatility on different financial and economic variables which eventually deteriorate the economic growth and welfare. Abundant literature is available on different channels through which inflation volatility distorts decision-making regarding future savings and investments, the efficiency of resource allocation and the level of real output. (Fischer, 1981; Golob, 1993; Holland, 1993).

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However there are two issues which are still debatable and there exist significantly different thoughts about them in economic literature. The first issue is about the causality running between inflation and inflation volatility. Friedman (1977), Ball and Cacchetti (1990), Cukierman and Wachtel (1979), Evans (1991), and Grier and Perry (1998), among other things, provide evidence in support of a positive impact of average rate of inflation on inflation volatility, which is more commonly known as the 'Friedman-Ball Hypothesis'. On the other hand Cukierman and Meltzer (1986), Holland (1995) and Baillie, Chung, and Tieslau (1996) for UK, Argentina, Brazil and Israel and Grier and Perry (1998) for Japan and France provide some evidences, contrary to the above and in support of causality running from inflation volatility to inflation, which is more commonly known as the 'Cukierman-Meltzer Hypothesis'.

The second issue is about the suitable proxy for inflation volatility or uncertainty. Although there could be several ways to estimate inflation volatility from the survey-based methods to empirical models. However, the most common is to estimate inflation volatility by applying the Univariate autoregressive conditional heteroskedasticity (ARCH) or generalized autoregressive conditional heteroskedasticity (GARCH) models proposed by Engle (1983), Bollerslev (1986) and Taylor (1986). Besides Bollerslev (1986) there are several studies which modelled inflation volatility through GARCH frameworks, such as Brunner and Hess (1993) for US consumer price index (CPI) data, Joyce (1995) and Kontonikas (2004) for UK, Della Mea and Peña (1996) for Uruguay, Caporale and McKiernan (1997) for the annualized US inflation rate, Grier and Perry (1998) and Fountas, Karanasos, and Karanassou (2000) for G7 countries, Grier and Grier (1998) for Mexican Inflation and Magendzo (1998) for Inflation in Chile. All these studies modelled inflation volatility through the GARCH model in one way or other.

The major drawback of typical ARCH or GARCH models is that they assume symmetric response of conditional variance (volatility) to positive and negative shocks. However, it has been argued that the behaviour of inflation volatility is asymmetric rather than symmetric. Brunner and Hess (1993), Joyce (1995), Fountas, Karanasos, and Karanassou (2000), Fountas, Karanasos, and Kim (2006) and Baunto, Bordes, Maveyraud-Tricoire, and Rous (2007) are of the view that positive inflation shocks have a significantly greater impact on volatility compared to the negatives inflation shocks. Beyond that there is some evidence from Pakistani data that having not only a lesser impact on inflation volatility, negative inflation shocks can even contribute to reducing inflation volatility (Rizvi & Naqvi, 2010). If this is correct, the symmetric ARCH and GARCH models may provide misleading estimates of inflation uncertainty (Crowford & Kasumovich, 1996).

In this article we model inflation uncertainty as time varying conditional variance through the GARCH framework. By following Fountas and Karanasos (2007) and Bordes and Maveyraud (2008), we also extract inflation volatility using GJR-GARCH (TGARCH) of Glosten, Jagannathan, and Runkle (1993) and Zakoian (1994) and exponential GARCH (EGARCH) model of Nelson (1991) to analyse and capture its asymmetric behaviour (leverage effects) if it exists at all. For those countries where inflation series is found to be non-stationary, we model cyclic component of inflation, obtained through the Hodrick–Prescott filter (1981), in addition to the actual inflation series to extract inflation volatility from it. We also present 'News Impact Curves' (NIC) proposed by Pagan and Schwert (1990) for different GARCH models to identify the degree of asymmetry of volatility to positive and negative shocks of previous periods. And finally, we test Friedman-Ball and Cukierman-Meltzer inflation uncertainty hypotheses through bivariate Granger-Causality test.

A few results are important. The hyperbolic sign integral shape of NICs based on GJR-GARCH is consistent with the results of our previous study based on Pakistani data (Rizvi & Naqvi, 2010) and highlights the importance of inflation stabilisation programmes particularly because of the subsequent evidence obtained in favour of bidirectional causality running between inflation and inflation volatility. There is also evidence in favour of the argument that the cyclic component of inflation could be used as a suitable proxy of inflation for volatility estimation.

The article is organised as follows: description of data and preliminary stationarity analysis of time series is provided in Section 2; Section 3 presents the empirical framework; Section 4 provides estimation and results. Section 5 discusses policy implications and Section 6 concludes.

2. Description and preliminary analysis of data

2.1. Core vs headline inflation

The choice between core vs headline inflation as a suitable proxy of inflation is crucial while modelling inflation volatility. It is generally believed that headline inflation is more volatile than core inflation due to the large commodity representation including oil and food. It is argued by Mishkin (2007) that albeit core inflation may not represent a true picture of the inflation, monetary authorities should respond to and target core inflation as it would be more appropriate than responding to headline inflation due to its inherently highly volatile and less persistent structure.

The above argument has certain shortcomings; many economists raised the question that if the core inflation does not truly represent the inflation in economy do we really need to follow or even control it? The second argument is the persistent increase in oil prices during recent decades, which is definitely reflecting a changing global demand structure for oil and thus the control of which is undoubtedly the part of the medium-term and the long-term policies of monetary authorities.

The myth about core inflation being a better predictor of persistent inflation and thus being the key measure to watch, came under serious threat after the release of a research conducted by Federal Reserve Bank of Philadelphia in May 2008 saying that:

> We find that food and energy prices are *not* the most volatile components of inflation and that, depending on which inflation measure is used, core inflation is not necessarily the best predictor of total inflation. (Novak, Crone, Mester, & Khettry, 2008)

They also strongly suggest considering both core and headline inflation as opposed to only core inflation because both measures provide independent information and the dual focus can significantly improve the accuracy of inflation forecasting model.

In light of the above arguments and keeping in view the fact that our data-set is primarily composed of emerging or less developed countries where the oil price is the major determinant of other products' prices, the overall prices are downward sticky and the percentage of disposable personal income on food consumption is more than 50% as opposed to developed countries where this percentage is between 9% and 15%, it is very difficult for monetary authorities to ignore oil and food prices while modelling and coping with inflation. Therefore, we decide to model inflation volatility on the basis of quarterly series of CPI Inflation.

2.2. Data-set

Our data-set is composed of quarterly estimates of inflation for 10 Asian economies; China, Hong Kong, India, Indonesia, Malaysia, Pakistan, Philippines, Singapore, South Korea and Thailand. All data is taken from International Financial Statistics Database (IFS) of the International Monetary Fund (IMF) and covers the time period from 1991 first quarter to 2012 fourth quarter.

We used quarterly data because of its additional relevance and usability in the context of inflation in less developed countries as observed by Ryan and Milne (1994) and calculated quarterly growth rates on a year-on-year basis by taking fourth lagged difference of natural logarithms of the CPI Series. The descriptive statistics of inflation for sample countries are provided in Table 1.

2.3. Stationarity of variables

To check the order of integration, we conduct the panel unit root tests for inflation in this section. Table 2 reports the summary statistics of five different panel unit root tests each with two classifications, first with constant term only and the second with both constant and trend term. Two out of five tests assume common unit root process in all cross sections where as the rest of three assume individual unit root processes for each cross section, which is more realistic assumption. Only the Levin-Lin-Chu (LLC) test does not reject the null hypothesis of common unit root in both specifications, rest of the tests clearly reject the null hypothesis of common or individual unit root and are highly significant.

The rejection of null in Im-Pesaran-Shin (IPS), Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test is a little vague in the sense that it leads us to accept the alternative of 'some cross sections without unit root'. To have a deep insight about each cross section we report the Im, Pesaran and Shin W-statistics for individual cross sections in Table 3, considering only the intercept term and automatic lag selection based on Schwarz information criterion (SIC). The reason for dropping the linear trend term is that in our opinion economic theory does not provide enough evidence in support of assumptions about the presence of any long-term linear trend in inflation rate.

From Table 3 it is clear that at least in three countries, Hong Kong, India and Pakistan, the t-statistic falls within the acceptance region of null of unit root, thus indicating that inflation is non-stationary there. Some other tests[2] force us to believe the same thing for Singapore and South Korea.

3. Empirical framework

3.1. Construction of mean equation

There are certain economic and financial variables that are widely believed to be important determinants of inflation, however, we choose to model inflation dynamically through an autoregressive process (Equation 1) in which inflation in one period is a function of its lagged values.

$$\pi_t = \lambda + \sum_{i=1}^{k} \delta_i \pi_{t-i} + u_t \tag{1}$$

Table 1. Descriptive statistics of inflation in Asian economies (1991–2012).

	China	Hong Kong	India	Indonesia	Malaysia	Pakistan	Philippines	Singapore	SKorea	Thailand
Mean	6.472663	4.112253	7.496943	11.48022	2.900090	8.015435	7.395483	1.558834	4.611135	3.946988
Median	3.703700	5.174015	7.170915	8.793350	2.795090	8.392045	7.261205	1.501500	4.434340	3.978555
Maximum	27.62790	11.93870	17.86040	78.38900	7.934510	19.34580	19.78290	6.625120	10.98050	10.36330
Minimum	−2.05430	−5.86727	0.461538	−0.572565	0.262055	1.780680	−1.465110	−1.455890	0.594059	−0.92783
Std. dev.	7.813791	5.072901	3.412916	12.80605	1.471188	3.535190	4.024894	1.350859	2.311062	2.239606
Skewness	1.329162	−0.25320	0.573607	3.955498	0.818512	0.262860	0.627741	0.503718	0.535520	0.204393
Kurtosis	3.804831	1.717406	3.027992	19.03415	4.087578	2.780538	4.348371	4.195422	2.799835	2.738530
Jarque-Bera	27.96483	6.972164	4.828574	1172.152	14.16314	1.162950	12.44591	8.655699	4.204641	0.863397
Probability	0.000001	0.030621	0.089431	0.000000	0.000840	0.559073	0.001983	0.013196	0.122173	0.649405
Observations	87	88	88	88	88	86	88	85	85	88

Source: Author’s calculations.

Table 2. Panel unit root tests.

	Individual effects		Individual effects, individual linear trends			
Exogenous variables	Statistic	Prob.**	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)						
Levin, Lin and Chu t*	0.66668	0.7475	2.84705	0.9978	10	826
Breitung t-stat			−2.01232	0.0221	10	816
Null: Unit root (assumes individual unit root process)						
Im, Pesaran and Shin W-stat	−3.69279	0.0001	−2.78323	0.0027	10	826
(ADF) - Fisher Chi-square	61.4599	0.0000	54.8758	0.0000	10	826
(PP) - Fisher Chi-square	45.8235	0.0009	38.2066	0.0084	10	861

Source: Author's calculations.

The reason for the inclusion of autoregressive term $\delta_i \pi_{t-i}$ is straightforward, as inflation, like many other economic variables, has shown strong inertia in various studies. Cecchetti Chu and Steindel (2000) for US data verified that none of the single indicators, out of 19 which are generally believed to be important determinants of inflation, are able to improve the forecasts of autoregressive model clearly and consistently. Binner et al. (2009) also did not find significant support for the usefulness of monetary aggregates in the process of forecasting inflation and they declared non-linear autoregressive model based on kernel methods as best for the job.

The decision about the number of lags to be included in each cross section is based on Akaike information criterion (AIC) and Bayesian information criterion (BIC). To check the presence of serial correlation in the residuals of Autoregressive (AR) model, we applied the Breusch-Godfrey test and Ljung-Box Q statistics and then introduced appropriate AR or Moving Average (MA) terms for errors, as have been indicated by the correlogram to eliminate serial correlation (Equation 2).

$$u_t = \sum_{i=1}^{p} \rho_i u_{t-i} + \sum_{i=1}^{q} \theta_i u_{t-i} + \varepsilon_t \tag{2}$$

Table 3. Im, Pesaran and Shin unit root test statistics for individual cross section.

Cross section	t-Stat	E(t)	E(Var)	Lag	Max Lag	Obs
China	−2.7397	−1.477	0.802	5	11	81
Hong Kong	−0.9262*	−1.481	0.788	4	11	83
India	−1.4050*	−1.427	0.855	8	11	79
Indonesia	−6.4052	−1.526	0.749	1	11	86
Malaysia	−2.7681	−1.526	0.749	1	11	86
Pakistan	−0.9892*	−1.476	0.803	5	11	80
Philippines	−2.4992	−1.478	0.801	5	11	82
Singapore	−2.0354	−1.525	0.750	1	11	83
SKorea	−1.6866	−1.478	0.791	4	11	80
Thailand	−3.8036	−1.526	0.749	1	11	86

*Fails to reject the null of unit root.
Source: Author's calculations.

There are many approaches to estimate models with AR or MA error specifications like Cochrane–Orcutt, Paris–Winsten, Hatanaka, and Hildreth–Lu procedures but they all are bound to operate in the horizon of standard linear regression. Therefore the results obtained from these approaches are not reliable when model contains lagged dependent variable as regressor, as we have in our mean equation (Davidson & MacKinnon, 1993, pp. 329–341; Greene, 1997, pp. 600–607). To overcome this problem we applied non-linear estimation which is applicable even when the model contains endogenous right hand side variables and whose estimates are asymptotically equivalent to maximum likely hood estimates and are asymptotically efficient (Fair, 1984, pp. 210–214; Davidson & MacKinnon, 1993, pp. 331–341).

3.2. *Modelling of non-stationary inflation*

One can argue that the results obtained from the above model could possibly be questionable for those countries where the inflation series is found to be non-stationary. To cope with this problem we proposed to model cyclical component of inflation, obtained from the Hodrick–Prescott (HP) filter, instead of inflation to capture conditional variance or inflation volatility through different GARCH specifications. The use of HP filter as a tool for detrending is popular among researchers and its advantage, compared to traditional differencing method, is that it removes only the slowly moving stochastic long-term trend from the original series thus keeping the persistence of data preserved in the cyclic component. There is also evidence that first difference detrending removes not only the trend but also some other useful information from the original series (Fiorito, 2008) which also makes HP filtering better than simple first difference detrending. While there are certain limitations of HP filter pointed out by Harvey and Jaeger (1993) such as potential spurious cyclical structure and spurious correlations when the series is I(0), yet its usability in detrending cannot be ruled out completely (Ahumada & Garegnani, 1999). Thus, in compatibility to the above methodology, we model πC (Cyclic component of inflation) as well as π (inflation) for Hong Kong, India, Pakistan, Singapore and South Korea where we do not have enough evidence to reject the null of unit root in Inflation series. The structure of Equation 1 will become as Equation (3) and rest of the structures related to residuals and conditional variance will remain the same.

$$\pi C_t = \lambda + \sum_{i=1}^{k} \delta_i \pi C_{t-i} + u_t \tag{3}$$

3.3. *Volatility estimates*

We chose the GARCH specification to model inflation volatility as there is much evidence available which suggest that the GARCH specification is better than ARCH. In an study about the performance of different volatility models, Lunde and Hansen (2001) find that while comparing the competing models on the basis of their out of sample predictive abilities, they do not have enough evidence to reject the hypothesis that 'none of other volatility models are better than GARCH (1,1)'.

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{4}$$

where

$$\omega > 0 \quad \alpha_i \geq 0 \text{ and } \quad i = 1, 2, \ldots\ldots, q$$

$$\beta_j \geq 0 \text{ and } \quad j = 1, 2, \ldots\ldots, p$$

GARCH is more parsimonious compared to ARCH as it captures the effect of infinite number of past squared residuals on current volatility with only three parameters and is less likely to breach non-negativity constraints artificially imposed on ARCH, (Bollerslev, 1986). But the primary restriction of GARCH model is that it enforces a symmetric response of volatility to positive and negative shocks. According to Brunner and Hess (1993) and Joyce (1995), a positive inflation shock is more likely to increase inflation volatility via monetary policy mechanism, as compared to negative inflation shock of equal size. If this is true then we cannot rely on the estimates of symmetric ARCH and GARCH models and will have to go for asymmetric GARCH models. To capture those asymmetric responses of inflation volatility we used two asymmetric formulations of GARCH which are GJR or Threshold GARCH (TGARCH) models of Glosten, Jagannathan, and Runkle (1993) and Zakoian (1994); and the exponential GARCH (EGARCH) model proposed by Nelson (1991).

GJR-GARCH is simply an extension of GARCH(p,q) with an additional term to capture the possible asymmetries (leverage effects). The conditional variance is now:

$$h_t = \omega + \alpha_i \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 I_{t-i} + \beta_j h_{t-j} \tag{5}$$

where $I_{t-1} = 1$, if $\varepsilon_{t-1} < 0$, otherwise $I_{t-1} = 0$. If the asymmetry parameter γ is negative then negative inflationary shocks result in the reduction of inflation volatility (Baunto, Bordes, Maveyraud-Tricoire, & Rous, 2007).

Conditional volatility is positive when $\omega > 0, \alpha_i \geq 0,\ (\alpha_i + \gamma_i)/2 \geq 0$ for $i = 1$ to q, and $\beta_j \geq 0$, for $j = 1$ to p. The process is covariance stationary if and only if $[\sum_{i=1}^{q}(\alpha_i + \gamma_i)/2 + \sum_{j=1}^{p} \beta_j < 1]$ (Forte & Manera, 2006).

The exponential GARCH model was proposed by Nelson (1991). There are various ways to express the conditional variance equation. One possible specification is mentioned in Equation 6 below:

$$log h_t = \omega + \sum_{j=1}^{p} \beta_j \log h_{t-j} + \sum_{i=1}^{q} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} \tag{6}$$

Both of these asymmetric GARCH models have several advantages over the traditional ARCH and GARCH specifications. First, variance specification represented in Equation 5 and Equation 6 makes it possible to capture the asymmetric effects of good news and bad news on one period ahead conditional variance, which is preferable in the context of modelling inflation and inflation volatility. Additionally in EGARCH specification, since the conditional variance is modelled in its logarithmic form, then even in the presence of negative parameters, h_t will be positive thus relieving the non-negativity constraints artificially imposed on GARCH parameters.

3.4. Impact of news on volatility (policy effectiveness)

For further investigation of asymmetric behaviour of inflation volatility, we analysed the effects of news on volatility or inflation uncertainty with the help of the NIC. The idea

Table 4. News impact curves for different GARCH processes.

Model	News impact curve representation
GARCH(1,1)	$h_t = A + \alpha_1 \varepsilon_{t-1}^2$ where $A = \omega + \beta_1 \bar{\sigma}^2$ and $\bar{\sigma}^2 = \omega / [1 - \alpha_1 - \beta_1]$
GJR-GARCH(1,1) Or TGARCH(1,1)	$h_t = A + (\alpha_1 + \gamma_1 I_{t-1}) \varepsilon_{t-1}^2$ where $A = \omega + \beta_1 \bar{\sigma}^2$ and $\bar{\sigma}^2 = \omega / [1 - \alpha_1 - \beta_1 - (\frac{\gamma_1}{2})]$
EGARCH(1,1)	$h_t = A \exp\left\{\frac{\alpha_1 (\lvert \varepsilon_{t-1} \rvert + \gamma_1 \varepsilon_{t-1})}{\bar{\sigma}}\right\}$ where $A = \bar{\sigma}^{2\beta_1} \exp\{\omega\}$ $\bar{\sigma}^2 = \exp\left\{\frac{\omega + \alpha_1 \sqrt{2/\pi}}{1 - \beta_1}\right\}$

Source: Engle and Ng (1993) and Eric Zevot (2008).

was primarily proposed by Pagan and Schwert (1990) and Engle and Ng (1993) to relate how news impact stock volatility. By keeping constant all the information at t-2 and earlier, we can examine the implied relation between ε_{t-1} and h_t which is called the NIC. The primary purpose of the NIC is to graphically represent the impact of past shocks of inflation (news) on current volatility. It is a pictorial representation of the degree of asymmetry of volatility to positive and negative shocks and it plots next period volatility h_t that would arise from various positive and negative values (news) of past inflation shocks (ε_{t-1}) (Pagan & Schwert, 1990), which will effectively help in determining the usefulness of inflation stabilisation programmes and inflation targeting policies. For the standard GARCH model, NIC is a quadratic function centred at $\varepsilon_{t-1} = 0$. The equations of NIC for the GARCH, GJR-GARCH and EGARCH models are provided in Table 4.

Where h_t is the conditional variance at time t, ε_{t-1} is inflation shock at time t−1, $\bar{\sigma}$ is the unconditional standard deviation of inflation shocks, ω is constant term and α_1 and β_1 are the parameters corresponding to ε_{t-1}^2 and h_{t-1} in GARHC, GJR-GARCH and EGARCH specifications.

The shape of NIC depends upon the slope values for positive and negative shocks. For GARCH specifications slope values are same for all shocks thus generating symmetric NIC. However in GJR-GARCH model, for bad news when $\varepsilon_{t-1} > 0$, the slope of NIC is equal to α_1 only and equals to $(\alpha_1 + \gamma_1)$ when $\varepsilon_{t-1} < 0$ which is a case of good news; whereas γ_1 is the asymmetry parameter or leverage parameter in GJR-GARCH and EGARCH specifications.

4. Results and findings

4.1. GARCH specification

We checked the stability condition of three GARCH specifications for all countries in Table 5 and found some violations.

Under symmetric GARCH specification, for South Korean inflation and its cyclic component the ARCH coefficient (α) is negative, for Malaysia and Indonesia the GARCH coefficient (β) is negative; in addition to that there is also a violation of second order stationarity condition in case of China and Indonesia where $(\alpha + \beta) > 1$ due

Table 5. Coefficients restrictions on volatility models.

	GARCH (Mean Reverting Level)	GARCH (Stability)	GJR-GARCH (Covariance Stationarity)	GJR –GARCH (Non Negativity)	EGARCH $\alpha_i - \gamma_i$	EGARCH $\alpha_i + \gamma_i$
CHINA	**−8.2851**	**1.020863**	0.456016	0.098152	0.201157	0.843743
HONG KONG	0.817041	0.727299	0.395387	0.438464	1.247568	1.531182
HONG KONG (Cyclic)	0.937769	0.860247	0.657212	0.07826	0.366703	0.688071
INDIA	4.417416	0.946739	0.542511	**−0.09041**	−0.6009	0.908148
INDIA (cyclic)	1.610521	0.849445	0.625568	0.292448	0.820412	1.112438
INDONESIA	**−4.37187**	**1.854417**	0.269814	**−0.23007**	−2.33769	0.30183
MALAYSIA	0.419635	0.101467	−0.08363	0.160531	0.924166	0.925238
PAKISTAN	2.066967	0.65295	0.564163	**−0.07614**	−0.40042	0.426501
PAKISTAN (Cyclic)	7.629162	0.970386	0.306752	**−0.0505**	−0.15674	0.830713
PHILIPPINES	5.358836	0.918545	0.15968	0.044748	0.144877	0.996703
SINGAPORE	0.249842	0.534586	0.148038	0.015517	0.099954	0.505912
Singapore (Cyclic)	0.346369	0.980668	0.810881	0.092052	−0.08109	0.074869
SOUTH KOREA	1.137714	0.533554	0.659215	0.410593	1.15812	1.172058
SOUTH KOREA (Cyclic)	0.871926	0.47909	0.548528	0.299523	0.709121	1.246789
THAILAND	1.179098	0.605412	0.831552	**−0.0863**	−0.28006	0.427316

*Bold Values represent violations.
Source: Author's calculations.

to which, for these two countries, the long run mean reverting level of volatility is negative (detailed results are provided in Appendix Table 1.A.1).

4.2. GJR-GARCH specification

The results of GJR GARCH are very promising. For almost all instances, except for the cyclic component of inflation in Singapore, the leverage or asymmetry parameter (γ) is negative (significant at 5% or below for Pakistan, China, Indonesia, Thailand and India) which is expected and indicates the fact that negative inflation shocks (good news) in one period reduce the next period volatility. The condition for volatility to be covariance stationary i.e.; $[\sum_{i=1}^{q}(\alpha_i+\gamma_i)/2+\sum_{j=1}^{p}\beta_j<1]$ (column 4 of Table 5) is also fulfilled for all cases. However the non negativity constraint $[(\alpha_i+\gamma_i)/2\geq 0]$ (Column 5 of Table 5) is not fulfilled in case of Pakistan, Indonesia, Thailand and India, the obvious reason for which is that the asymmetry parameter is much larger as well as highly significant than ARCH coefficient for these countries $(\gamma_i>\alpha_i)$ (detailed results are provided n Appendix Table 1.A.2).

4.3. EGARCH specification

EGARCH specification provides us with the relationship between lagged shocks of inflation and the logarithm of the conditional volatility. Because of this logarithmic specification, EGARCH is convenient to handle compared to other GARCH specifications as there are no restrictions on its parameters. In EGARCH specification, past negative shocks have an impact $\alpha_i - \gamma_i$ on the log of the conditional variance, while it is $\alpha_i + \gamma_i$ for positive shocks. Generally it is observed that impact is greater in case of negative shocks $[(\alpha_i - \gamma_i) > (\alpha_i + \gamma_i)]$ because γ_i is expected to be negative or less than zero, but that assumption is valid only if we are modelling returns. For inflation, the converse is true; here we must expect that γ_i is positive so that $[(\alpha_i - \gamma_i) < (\alpha_i + \gamma_i)$ and the impact is lesser on conditional volatility in case of negative inflation shocks (good news) compared to the situation of positive inflation shocks (bad news) (reported in the last two columns of Table 5). It can also be viewed in Appendix Table 1.A.3, that asymmetry parameter γ_i is positive as per expectation in all 15 instances and is significant at 5% or below in eight out of 15 instances.

4.4. News impact curves

NICs obtained by using the equations of Table 4 are reported in Appendix Figure 1.B.1. We would like to specifically highlight the cases of India, Indonesia, Pakistan and Thailand where the NIC is based on GJR-GARCH is quite different from its widely believed parabolic shape as mentioned in Figure 1.

This hyperbolic sign integral shape of GJR-NIC is extremely important for monetary authorities and highlights the importance of inflation stabilisation programmes or inflation targeting policies, which reduces the next period volatility (Johnson, 2002). The results are also consistent with our previous study (Rizvi & Naqvi, 2010) where the

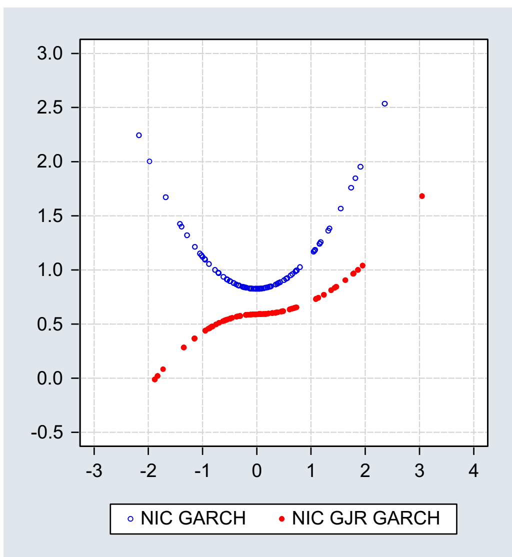

Figure 1. Hyperbolic shape of GJR-GARCH news impact curve (Thailand).
Source: Author's calculations.

Table 6. Test of equality of mean and variance between cyclic and total inflation volatility.

	Pakistan		Hong Kong		South Korea		Singapore		India	
	Test	Prob	Test	Prob	Test	Prob	Test	Prob	Test	Prob
GARCH										
t-test	3.50453	**0.0006**	0.83103	0.4072	13.8952	**0.0000**	25.3493	**0.0000**	2.89231	**0.0043**
Satterthwaite-Welch t-test*	3.50450	**0.0006**	0.83102	0.4074	13.8952	**0.0000**	25.3493	**0.0000**	2.89231	**0.0044**
Anova F-test	12.2815	**0.0006**	0.69060	0.4072	193.077	**0.0000**	642.578	**0.0000**	8.36569	**0.0043**
Welch F-test*	12.2815	**0.0006**	0.69060	0.4074	193.077	**0.0000**	642.578	**0.0000**	8.36569	**0.0044**
EGARCH										
t-test	1.03138	0.3039	1.48288	0.1401	2.11250	**0.0361**	5.18588	**0.0000**	2.13393	**0.0343**
Satterthwaite-Welch t-test*	1.03138	0.3039	1.48288	0.1408	2.11250	**0.0365**	5.18588	**0.0000**	2.13393	**0.0343**
Anova F-test	1.06375	0.3039	2.19895	0.1401	4.46269	**0.0361**	26.8934	**0.0000**	4.55367	**0.0343**
Welch F-test*	1.06375	0.3039	2.19895	0.1408	4.46269	**0.0365**	26.8934	**0.0000**	4.55367	**0.0343**
GJR-GARCH										
t-test	0.40664	0.6848	1.50935	0.1333	0.85746	0.3924	4.00591	**0.0001**	0.55848	0.5772
Satterthwaite-Welch t-test*	0.40664	0.6849	1.50935	0.1343	0.85746	0.3924	4.00591	**0.0001**	0.55848	0.5773
Anova F-test	0.16536	0.6848	2.27814	0.1333	0.73524	0.3924	16.0473	**0.0001**	0.31190	0.5772
Welch F-test*	0.16536	0.6849	2.27814	0.1343	0.73524	0.3924	16.0473	**0.0001**	0.31190	0.5773

*Tests allow for Unequal variances.
Bold values represent a rejection of null of Equality of mean and variance at a significance level of 5% or below
Source: Author's calculations.

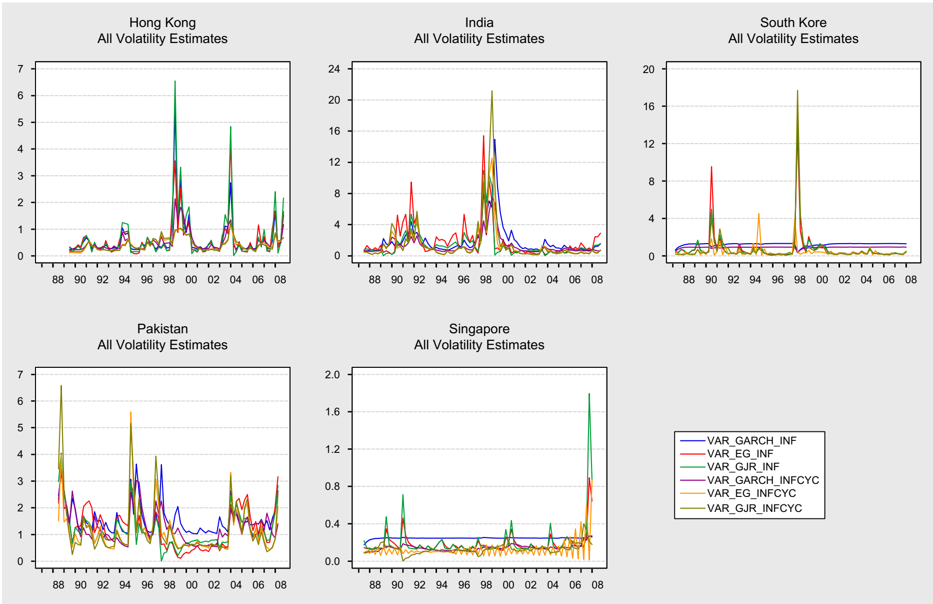

Figure 2. Volatility estimates from total and cyclic components of inflation.
Source: Author's calculations.

same hyperbolic sign integral shape of GJR-NIC was found for Pakistani inflation with a data-set consists of relatively larger time period.

4.5. Modelling cyclic component of inflation to capture inflation volatility

We have mentioned above that for the countries where we found inflation to be non-stationary (Pakistan, Hong Kong, Korea, Singapore and India) we ran additional regressions of cyclic component of inflation and modelled inflation volatility based on the residuals of cyclic inflation. We then compare the volatility based on inflation and the volatility based on cyclic component of inflation for these countries to check how much reliable this procedure is in the volatility estimation when the original series is non-stationary.

Table 6 reports the results of tests of equality of mean and variance between the two volatility estimates based on inflation and on its cyclic component. Graphical representation of all volatility estimates are presented in Figure 2. T-test and Anova F-test assume the equal mean and variance for volatility estimates obtained from total inflation and cyclic component of inflation. Whereas Satterthwaite-Welch t-test and Welch F-test assume equal mean but allow for unequal variances. According to these results we cannot reject the null of equal mean and variance of volatility estimates derived from total and cyclic component of inflation, in four out of five countries under GJR-GARCH specification. Put it in another way, it doesn't matter whether we model inflation volatility from total inflation or its cyclic component because there is evidence that the volatility estimates obtained from both variables are close enough as long as we apply GJR-GARCH specification.

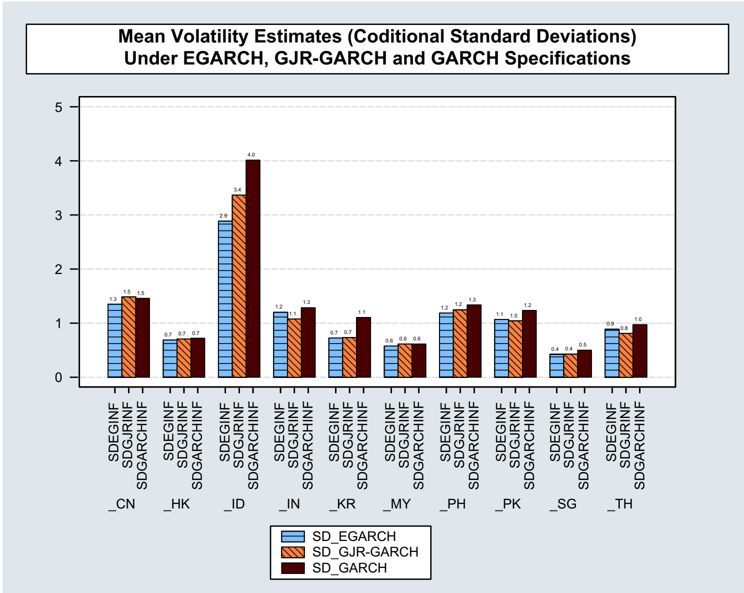

Figure 3. Mean volatility estimates (conditional standard deviations).
Source: Author’s calculations.

4.6. Ranking on the basis of conditional standard deviation

Figure 3 provides relative positions of countries on the basis of mean conditional standard deviations obtained from three different GARCH specifications. There are minor differences in means across three specifications; however the relative position or rank of country is same for all. Indonesia, China, India, Philippines and Pakistan have the most volatile inflation whereas Singapore, Malaysia, Korea and Hong Kong have relatively stable (less volatile) inflation.

As far as the relationship between inflation level and inflation volatility is concerned, there is a strong positive relationship between the two no matter which GARCH specification is used (reported in Appendix Table 1.A.4). However the following graph provides the scatter plot with regression lines during three different time periods and indicates that at least for Hong Kong, Korea, Malaysia and Philippines this relationship is not stable. The change of sign in the slope[3] for these four countries could be an indication of ‘stabilisation hypothesis’ which says that high inflationary and uncertain environment could have a negative impact on succeeding period inflation rate and which one can rationally expect to hold after the Asian financial crisis of 1997, when most central banks started reforming their financial sectors and implemented stabilisation programmes.

4.7. Causality between inflation and inflation volatility

Table 7 reports the categorised summary based on the quantitative results of Granger causality test[4]. It is clear that GARCH specification is not much successful in capturing the causality running between inflation and inflation volatility as for most of the countries we do not find enough evidence to reject either null hypothesis.

Table 7. Categorised results of Granger Causality Test between inflation and inflation volatility.

	GARCH		EGARCH		GJR GARCH	
	Friedman–Ball Hypothesis	Cukierman–Meltzer Hypothesis	Friedman–Ball Hypothesis	Cukierman–Meltzer Hypothesis	Friedman–Ball Hypothesis	Cukierman–Meltzer Hypothesis
Null Hypothesis	π *does not cause* h_t	h_t *does not cause* π	π *does not cause* h_t	h_t *does not cause* π	π *does not cause* h_t	h_t *does not cause* π
CHINA	Strong Rejection	Moderate Rejection	Strong Rejection	Strong Rejection	Strong Rejection	Strong Rejection
HONG KONG	Moderate Rejection	No Rejection	No Rejection	No Rejection	No Rejection	No Rejection
HONG KONG (Cyclic)	Strong Rejection	No Rejection	No Rejection	No Rejection	No Rejection	No Rejection
INDIA	Strong Rejection	Moderate Rejection	Strong Rejection	Strong Rejection	Strong Rejection	Strong Rejection
INDIA (cyclic)	Strong Rejection	No Rejection	Strong Rejection	No Rejection	Strong Rejection	No Rejection
INDONESIA	Strong Rejection	No Rejection	Strong Rejection	Strong Rejection	Strong Rejection	No Rejection
MALAYSIA	Strong Rejection	No Rejection	Moderate Rejection	No Rejection	Strong Rejection	No Rejection
PAKISTAN	No Rejection	No Rejection	Strong Rejection	No Rejection	Strong Rejection	No Rejection
PAKISTAN (Cyclic)	No Rejection	No Rejection	Strong Rejection	Moderate Rejection	Strong Rejection	Moderate Rejection
PHILIPPINES	No Rejection	No Rejection	Strong Rejection	No Rejection	Strong Rejection	No Rejection
SINGAPORE	No Rejection	No Rejection	Strong Rejection	Strong Rejection	Strong Rejection	Strong Rejection
SINGAPORE (Cyclic)	No Rejection	No Rejection	Strong Rejection	Moderate Rejection	Strong Rejection	Strong Rejection
S KOREA	Strong Rejection	No Rejection	Strong Rejection	Moderate Rejection	Strong Rejection	Moderate Rejection
S KOREA (Cyclic)	Strong Rejection	No Rejection	No Rejection	No Rejection	Strong Rejection	No Rejection
THAILAND	No Rejection	No Rejection	Strong Rejection	Moderate Rejection	Strong Rejection	Moderate Rejection

Note: These results are based on the frequency of occurrence of significant wald statistics at less than 1% level. We categorise the results according to the following criteria:
Strong Rejection of Null = More than 70% times wald statistic is significant at less than 1%, from 1 to 10 lags.
Moderate Rejection of Null = 50% to 70% times wald statistic is significant at less than 1%, from 1 to 10 lags.
No Rejection of Null = Less than 50% times wald statistic is significant at less than 1%, from 1 to 10 lags.
Source: Author's calculations.

Overall results are cumbersome but if we focus on asymmetric models (EGARCH and GJR-GARCH), both strongly favour the presence of Friedman-ball hypothesis and reject the presence of Cuckierman-meltzer hypothesis for Indonesia, Malaysia, Pakistan and Phillipines. The results for other countries are although biased in favour of Friedman ball hypothesis but in general they are mixed and support significantly the presence of both hypotheses leading us to infer the presence of bidirectional causality running between inflation and inflation volatility. Hong Kong is a special case for which both asymmetric models strongly reject the presence of any causality between inflation and volatility no matter whether we base our analysis on total inflation or on the cyclic component of inflation.

5. Policy implications

Several important dimensions pertaining to inflation and its volatility have been explored in the above analysis and warrant the special attention of policymakers. First and foremost is the detection and estimation of asymmetry in inflation volatility that has been done by using GJR-GARCH and EGARCH models and further supplemented by NICs to have its graphical view (Appendix Figure 1.B.1). Unless policymakers are aware about those possible asymmetries, they wouldn't be able to truly understand the importance of inflation stabilisation programmes or the inflation targeting policies. These asymmetries are strongly suggestive of the fact that if in one period policymakers are successful in reducing inflation due to inflation stabilisation programmes, it would help them in reducing the next time period's volatility (Johnson, 2002). We would like to draw attention to another fact which is that the two asymmetric specifications, i.e. GJR-GARCH and EGARCH that we used in this study also strongly support the presence of causality running from inflation to inflation volatility commonly known as the Friedman–Ball hypothesis. Although this causality makes the task of policy-makers more difficult because if they miss containing the inflation up the level of target inflation in one period, it would automatically enhance the volatility of inflation in next

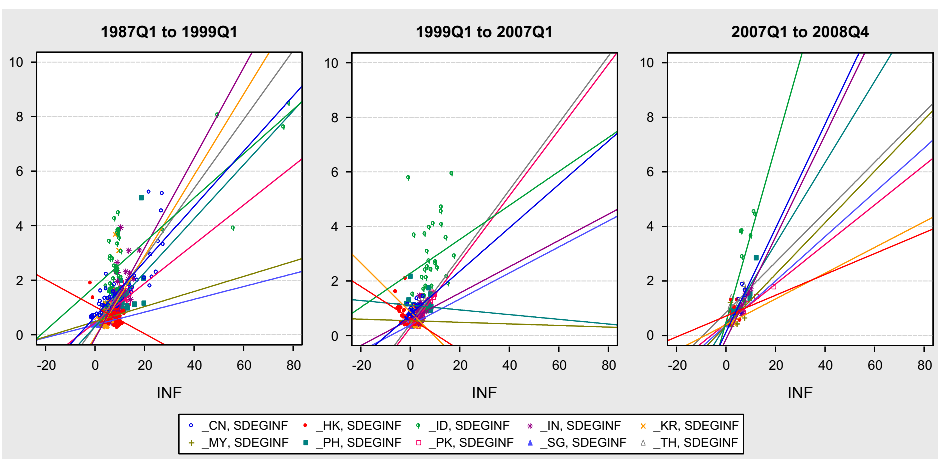

Figure 4. Inflation volatility and inflation across countries and time.
Source: Author's calculations.

period. This increased volatility could be severely damaging for the economy and could wipe out the real economics growth through different channels. Yet on the other hand policymakers could capitalise this causality in their own favour. If they successfully implement the inflation stabilisation programme in one time period, because of the simultaneous presence of asymmetries and causality from inflation to inflation volatility, it would surely reduce the volatility of next period and save the economy from potential losses.

It is also interesting to note that for those four countries (Hong Kong, Korea, Malaysia and Philippines) where we have observed a shift in relationship between inflation volatility and inflation from positive to negative during the period of 1999 to 2007 (Figure 4) granger causality tests strongly ruled out the presence of Cukierman–Meltzer hypothesis. This fact implicitly rejects the existence of so called 'Stabilising Hypothesis' by Holland (1995) which says that high inflation uncertainty can have a negative causal impact on succeeding average inflation rates because the natural stance of policymakers, in the presence of high inflation and high uncertainty, would be to contract the growth of money supply which could reduce average inflation rates in the upcoming periods. Given the low probability of having stabilising hypotheses, the negative relationship between inflation and inflation volatility points out the lack of credibility of inflation stabilisation programmes. However, for China, India, Indonesia and Singapore we have strong evidence of holding both the Friedman–Ball and Cuckierman–Meltzer hypotheses which further increase the importance and need of inflation stabilisation programmes that are already essential for them given the asymmetric responses of volatility to inflation.

6. Conclusion

This study contributes the following in the existing body of knowledge. First of all it can be argued that the asymmetric GJR-GARCH and EGARCH models performed better than symmetric GARCH in capturing inflation volatility for selected Asian economies. The hyperbolic sign integral shape of NIC based on GJR-GARCH for India, Indonesia, Pakistan and Thailand is not only consistent with the results of our previous study based on Pakistani data (Rizvi & Naqvi, 2010), but also highlight the importance of inflation stabilisation programmes and inflation targeting policies where negative inflation shocks reduces one period ahead volatility which could subsequently reduces inflation in further periods and so on. Evidence of bidirectional causality between inflation and inflation volatility also strengthens the idea of having such type of chain reaction. It can also be claimed that volatility estimates obtained from total inflation and cyclic component of inflation exhibit the equal mean and variance properties under GJR-GARCH specification, thus making the cyclic component of inflation obtained from HP filter a suitable proxy of inflation in volatility modelling for those countries where inflation is non-stationary.

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Notes

1. We use the terms inflation uncertainty or inflation volatility interchangeably.
2. We used ADF and PP test individually for all economies instead of conducting a panel unit root test.
3. Change of Sign in slope is robust to change in dependent variable as well as to the lagged values of regressor for these four economies.
4. Detailed results are not reported but can be obtained from authors upon request.

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Appendix 1.A. Results and tables

Table 1.A.1. Estimates based on GARCH Specification.

Country	CHN	HKN[1]	HKN(Cyc) [1]	IND	IND(Cyc)	NDS	MLY	PAK	PAK(Cyc)	PHL	SNG	SNG(Cyc)	SKOR	SKOR(Cyc)	TLN
λ	0.045954	0.018922	−0.001049	0.058756	−0.005063	1.484208***	0.281897*	0.181303	−0.057884	0.134991	0.015423	−0.000792	−0.018147	−0.001391	0.097857
δ_1	1.603851***	1.535378***	1.230251***	1.249537***	0.936348***	1.093169***	1.304491***	1.484289***	1.271754***	1.500361***	1.523460***	1.073894***	0.986233***	0.753511***	1.348317***
δ_2	−0.635760***	−0.548384***	−0.384900**	−0.263443	−0.258466	−0.308437***	−0.404359***	−0.511078***	−0.466799***	−0.526718***	−0.535463***	−0.318257**			−0.375148**
ρ_1		−0.522387***	−0.488810**												
ρ_4		−0.365908***	−0.408268***			−0.266862***	−0.327085***	−0.624402***	−0.548687***						
θ_1															
θ_4	−0.640871***			−0.915237***	−0.960053***					−0.926633***	−0.873307***	−0.898275***	−0.959262***	−0.971121***	−0.759718***
ω	0.172852	0.222808***	0.131056	0.235276	0.242472	3.735401***	0.377056***	0.717341	0.225930	0.436504*	0.116280	0.006696	0.530682***	0.454195**	0.465258
α	0.419361*	0.670459**	0.446452	0.376525**	0.331923**	1.884675***	0.546886*	0.355595**	0.432361**	0.385109**	0.008386	0.087615*	−0.067087	−0.040918***	0.304677
β	0.601502***	0.056840	0.413795	0.570214***	0.517522***	−0.030258	−0.445419	0.297355	0.538025***	0.533436***	0.526200	0.893053***	0.600641***	0.520008**	0.300735
Adj R^2	0.962878	0.977696	0.773874	0.852128	0.776289	0.847551	0.769835	0.877253	0.705477	0.896286	0.884522	0.805243	0.892215	0.775941	0.804962
AIC	3.439067	2.149183	2.064715	3.241209	2.834162	5.101463	1.867303	3.268057	3.091147	3.338663	1.363933	0.984167	2.626359	2.351225	2.756383
SIC	3.640226	2.390896	2.306428	3.440982	3.033935	5.306914	2.072755	3.476485	3.299574	3.538436	1.567932	1.188166	2.799988	2.524855	2.956156
F-Stat	364.1335***	483.1825***	38.64545***	82.63722***	50.15907***	76.05417***	46.15348***	95.09971***	32.53841***	123.4270	105.6825***	57.50610***	138.4101***	58.48779***	59.46863***

[1]For Hong Kong and its cyclic component consider ρ_1 and ρ_4 as ρ_4 and ρ_8 respectively
Note: ***,**,* respectively indicate rejection of the null at 1, 5 and 10% significance levels.

Table 1.A.2. Estimates based on GJR-GARCH or TGARCH specification.

Country	CHN	HKN[1]	HKN(Cyc) [1]	IND	IND(Cyc)	NDS	MLY	PAK	PAK(Cyc)	PHL	SNG	SNG(Cyc)	SKOR	SKOR(Cyc)	TLN
λ	0.075365	0.050665	0.003795	0.146628*	−0.014457	1.754165***	0.268897	0.219229	0.016632	0.148204	0.004074	0.004243	0.082058	−0.004631	−0.056919
δ_1	1.538845***	1.615259***	1.202471***	1.379822***	0.711794***	1.485867***	1.188609***	1.493402***	1.222602***	1.496904***	1.398911***	1.196454***	0.964142***	0.744053***	1.274895***
δ_2	−0.580911***	−0.629885***	−0.379042***	−0.403882***	−0.080039	−0.636588***	−0.281512*	−0.517517***	−0.380957***	−0.526335***	−0.413944***	−0.521752***			−0.269251***
ρ_1		−0.525595***	−0.496227***												
ρ_4		−0.384515***	−0.389596***			−0.426080***	−0.369747***	−0.603399***	−0.557872***						
θ_1															
θ_4	−0.576702***			−0.916417***	−0.943847***					−0.932085***	−0.904857***	−0.892173***	−0.970195***	−0.947597***	−0.892648***
ω	0.179292*	0.157279**	0.064695	0.292477***	0.108094*	5.576977	0.264034***	0.301625	0.382819**	0.683623***	0.111098*	0.032199	0.090362*	0.078963**	0.062652*
α	1.154837***	1.275976*	0.537534	0.526391**	0.845174	0.257231	0.988899**	0.394843**	1.031866**	1.305053*	0.622322*	−0.141545***	0.976033***	1.189094***	0.116599
γ	−0.958532**	−0.399049	−0.381014	−0.707217***	−0.260279	−0.717372**	−0.667837	−0.547115***	−1.132863***	−1.215558	−0.591289	0.325648	−0.154847	−0.590048	−0.289203**
β	0.357863***	−0.043077	0.578952**	0.632924***	0.333120	0.499884	−0.244165	0.640299***	0.357250	0.114932	0.132521	0.718829***	0.248622***	0.249005**	0.917854***
Adj R^2	0.959473	0.977339	0.769251	0.844983	0.759167	0.905427	0.767075	0.877706	0.696557	0.893621	0.877090	0.811574	0.890053	0.770677	0.799030
AIC	3.335648	2.100246	2.056323	3.066536	2.736736	5.200215	1.867619	3.114269	2.955616	3.297456	1.249534	0.871409	2.132409	1.895128	2.626257
SIC	3.565545	2.372174	2.328251	3.294847	2.965047	5.435017	2.102421	3.352472	3.193818	3.525768	1.482675	1.104550	2.334977	2.097696	2.854568
F-Stat	285.0969***	416.1121***	33.08692***	67.18970***	39.27740***	111.7826***	39.10741***	81.99744***	26.90655***	103.0048***	84.59353***	51.45484***	112.9851***	47.48904***	49.27834***

Table 1.A.3. Estimates based on EGARCH specification.

Country	CHN	HKN[1]	HKN(Cyc) [1]	IND	IND(Cyc)	NDS	MLY	PAK	PAK(Cyc)	PHL	SNG	SNG(Cyc)	SKOR	SKOR(Cyc)	TLN
λ	0.083643	0.041972	0.009608	0.116437	−0.012479	1.849843***	0.282653**	0.115142	0.029709	0.148201	0.004435	−0.003575	0.071171	0.000822	0.010679
δ_1	1.612123***	1.570863***	1.235424***	1.354564***	0.715817***	1.426739***	1.225077***	1.450011***	1.241523***	1.404193***	1.431692***	1.308494***	0.966372***	0.835296***	1.301882***
δ_2	−0.645129***	−0.587913***	−0.388306***	−0.372991***	−0.077254	−0.581560***	−0.321904***	−0.464967***	−0.422968***	−0.433432***	−0.444566***	−0.548329***			−0.312298**
ρ_1		−0.520582***	−0.518639***												
ρ_4		−0.376575***	−0.411553***			−0.383506***	−0.442754***	−0.599388***	−0.582201***						
θ_1															
θ_4	−0.600860***			−0.903622***	−0.953488***					−0.927227***	−0.901537***	−0.888155***	−0.967053***	−0.958201***	−0.837196***
ω	−0.394045*	−1.588311***	−0.562562*	−0.027716	−0.805952***	1.917839***	−2.311859***	−0.022040	−0.257020	−0.231147	−0.811989	−4.794491***	−1.145580***	−2.554814***	−0.117975
α	0.522450*	1.389375***	0.527387*	0.153622	0.966425***	−1.017929***	0.924702**	0.013040	0.336986*	0.570790*	0.302933	−0.003112	1.165089***	0.977955***	0.073628
γ	0.321293**	0.141807	0.160684	0.754526***	0.146013	1.319759***	0.000536	0.413461**	0.493727***	0.425913*	0.202979	0.077981	0.006969	0.268834***	0.353688**
β	0.840639***	0.515620***	0.815985***	0.620963***	0.777922***	0.388253***	−0.327627	0.798333***	0.529532**	0.275480	0.656998*	−1.084575***	0.725478***	−0.444877**	0.862470***
Adj R^2	0.962513	0.977339	0.771343	0.844104	0.761322	0.902204	0.766317	0.875221	0.704361	0.896388	0.879387	0.809996	0.890203	0.769486	0.802894
AIC	3.321456	2.117697	2.030690	3.130520	2.746561	4.916108	1.820280	3.128454	2.982521	3.252806	1.266261	0.747647	2.087935	1.766475	2.637711
SIC	3.551352	2.389625	2.302618	3.358832	2.974872	5.150910	2.055082	3.366656	3.220723	3.481117	1.499403	0.980788	2.290503	1.969043	2.866023
F-Stat	309.1099***	416.1112***	33.46856***	66.74782***	39.73254***	107.7504***	38.94613***	80.15983***	27.88827***	106.0521***	86.40846***	50.93841***	113.1567***	47.17755***	50.46294***

Table 1.A.4. Covariance (correlation) analysis.

Correlation Probability	Inflation	Conditional SD EGARCH	Conditional SD GJR-GARCH	Conditional SD GARCH
Inflation	1.000000			
Conditional SD EGARCH	0.665294	1.000000		
Conditional SD GJR-GARCH	0.721565	0.916133	1.000000	
Conditional SD GARCH	0.724494	0.696242	0.738196	1.000000
	0.0000	0.0000	0.0000	———

Appendix 1.B. Figures and graphs

Figure 1.B.1. News impact curves – an overall view