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Modeling Inflation Volatility: Evidence from Two post-Soviet Economies

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Abstract

This paper examines inflation volatility estimating a variety of GARCH models with the consideration of the heavy-tailed conditional densities for two post-Soviet transition economies, namely Belarus and Kazakhstan. An EGARCH type model combined with dummies detected from Iterative Cumulative Sum of Squares (ICSS) algorithm, called ICSS-EGARCH, is found to be useful for modeling the inflation volatility. The main finding is that the standard GARCH models perform poorly in terms of parameter inequality restrictions. In addition, the ignorance of structural changes in volatility appears to lead to overestimation of persistence parameters of EGARCH models. Moreover, asymmetry in volatility is also evident when analyzing the inflation rates data. Finally, relying on several model selection criteria, we have discovered that ICSS-EGARCH type models fit better than other models considered in this study.

Keywords and Phrases: GARCH, EGARCH, ICSS-EGARCH, Heavy-tailedness, Inflation.

AMS Classification: 62P20, 62M10, 91B84.

1 Introduction

The analysis of inflation volatility has been an important issue in transition countries in recent years. The governments in these countries are concerned about inflation volatility because it might have an effect on macroeconomic variables by increasing risk and uncertainty. Financial volatility literature documents a wide variety of volatility modeling techniques ranging from structural models to time series equations such as GARCH family models. The GARCH models have been successful in capturing several stylized facts of financial time series, such as time-varying volatility, persistence and clustering of volatility, and asymmetric reactions to positive and negative shocks of equal magnitude (Morimune, 2007). Apart from that, as Daly (2008) notes, the numerous applications of (G)ARCH models have been documented in the literature since their introduction by Engle (1982) and Bollerslev (1986).

Here, it is worth mentioning the argument by Lastrapes (1989) and Lamoureux and Lastrapes (1990) which state that the GARCH family models might overestimate the volatility persistence in case the financial returns exhibit regime shifts. One should note that the countries under investigation experienced sudden economic declines during the initial unfavorable transition period that led to the periods of extremely high inflation volatility followed by successive stabilizations (see Figure 1 and 2). In addition, relatively high fluctuations in inflation rates occurred during the Russian financial crisis in 1998. Hence, sudden variance changes or regime shifts which characterize most of transition economies' inflation rates must be taken into account in GARCH estimations. A strand of research has documented the existence of severe excess kurtosis in the estimated standardized residuals. We are in the opinion that the excess kurtosis seems to be originated from aberrant observations such as structural changes and outliers. Here, it is worth noting the study by Franses and Ghijsels (1999) that proposed a methodology to detect and correct additive outliers (AO) in GARCH estimations. Apart from that, Charles and Darné (2005) extended the Franses-Ghijsels (1999) methodology accounting for the innovative outliers (IO). Another strand of literature employed Iterative Cumulative Sum of Squares (ICSS) algorithm advocated by Inclan and Tiao (1994) to detect sudden shifts in unconditional variance and accounted for these shifts in variance equations using dummy variables (see Wison *et al.*, 1996; Malik, 2003; Law, 2007; Hammoudeh and Li, 2008; Kanga, 2009; Kasman, 2009; and more recently Malik, 2011, among many others). Unlike many earlier studies, this paper exploits ICSS-EGARCH specification to model inflation volatility.

The main objective of this paper is to examine the behavior of inflation volatility using the data of Belarus and Kazakhstan. To this end, this study models the inflation volatility utilizing the various GARCH family models ranging from standard to asymmetric models such as GARCH, GARCH-M, EGARCH, EGARCH-M, ICSS-EGARCH, and ICSS-EGARCH-M. Relying on the diagnostic checks and the several selection criteria, the paper seeks the most favored GARCH family model for the countries under study. In addition, heavy-tailedness and non-normality facts in inflation data are taken into account considering heavy-tailed conditional densities such as Students-t or generalized error distributions (GED). The estimation results reveal that the EGARCH model combined with dummies for regime changes outperform standard GARCH and EGARCH models in the sense of several selection criteria and diagnostics for both countries under study. This finding is consistent with many earlier studies which arrive at a conclusion that ICSS-GARCH model outperforms the standard GARCH models (see, for example, Malik and Hassan, 2004; Kang *et al.*, 2009).

The rest of the paper is organized as follows. Section 2 briefly describes the data characteristics used in this study. Section 3 provides a brief exposition of a methodology and models employed in this paper. Section 4 reports the empirical results and assesses model adequacy. Finally, section 5 provides some concluding remarks.

2 Data characteristics

This study used monthly consumer price index (CPI) data for Belarus and Kazakhstan spanning from January 1993 to October 2007 to model the inflation volatility process. The inflation series are constructed as $\ln(CPI_t/CPI_{t-1})$, where CPI_t is the consumer price index at time t. Data has been collected from the International Financial Statistics database of International Monetary Fund.

Table 1: Descriptive statistics for the CPI inflation series

	Belarus	Kazakhstan
No. of observations	178	178
Mean	0.0695	0.0410
Median	0.0314	0.0080
Maximum	0.4220	0.4413
Minimum	-0.0068	-0.0095
Std.dev	0.0921	0.0845
Skewness	1.8414	2.6780
Kurtosis	5.6139	9.4349
Jarque-Bera	151.26 [0.000]	519.87 [0.000]

Figures in square bracket denote p-values.

The Table 1 reports summary statistics for the inflation series. The results reveal that sample means for the inflation series are positive and they are smaller than the standard deviation. Obviously, one can see from Table 1 that the kurtosis coefficients and Jarque-Bera tests indicate that the inflation series of the countries seems to follow heavy-tailed distributions. This is signal for departure from normality. In addition, to test for unit root, we utilized the standard augmented Dickey-Fuller (ADF) unit root tests to the inflation series. As presented in Table 2, the inflation rate follows a stationary process, regardless whether a trend variable is included or excluded in the model. This allows us to provide confirmatory evidence of stationarity in the two ex-Soviet countries. In this study, we treat inflation series as I(0) process.

Table 2: Unit root test results for the CPI inflation series

	Belarus	Kazakhstan
No intercept and no trend	-2.5426 [0.011]	-6.4043 [0.000]
Intercept	-2.8722 [0.050]	-6.3973 [0.000]
Intercept and trend	-3.6769 [0.026]	-5.6819 [0.000]

Figures in square bracket denote p-values.

Finally, before modeling, we perform the standard Engle's ARCH Lagrange multiplier (LM) test. According to the LM statistic results provided in Table 3, inflation series in two countries under study show strong evidence of ARCH effects. The ARCH-LM test statistics for the lags 1 and 3 are significant at the conventional significance levels for both countries under study.

Table 3: ARCH LM diagnostic test for the residuals of AR(1) process

	Belarus	Kazakhstan
ARCH(1)	22.946 [0.000]	81.343 [0.000]
ARCH(3)	11.227 [0.000]	52.091 [0.000]

Figures in square bracket denote p-values. ARCH test at lag 1 and 3 is based on F statistic.

3 Methodology

In this section, we discuss the methodology used in this study.

3.1 The sudden changes in variance

In this study, we employ the ICSS algorithm developed by Inclan and Tiao (1994) to detect sudden changes in unconditional variance. The ICSS algorithm focuses on identifying an unconditional variance change due to a sudden shift that changes the variance until the the data experiences next shock. This approach has been shown to be an effective tool in detecting sudden changes when the series suffer from structural changes even there is 'masking effect' in the data.

Let r_t be the inflation series and with unconditional variance σ^2. The variances within each interval are given by $\tau_j^2,\ j = 0,\ 1,\ \ldots,\ N_T$. Here, N_T is the total number of variance changes in T observations and $1 < k_1 < k_2 < \cdots < k_{NT} < T$ are the change points.

$$\begin{aligned}
\sigma_t^2 &= \tau_0^2 \quad \text{for} \quad 1 < t < k_1 \\
\sigma_t^2 &= \tau_1^2 \quad \text{for} \quad k_1 < t < k_2 \\
&\vdots \\
\sigma_t^2 &= \tau_{NT}^2 \quad \text{for} \quad k_{NT} < t < k_T
\end{aligned}$$

To detect the variance changes, the iterative cumulative sum of squares are computed using $C_k = \sum_{t=1}^{k} r_t^2$ for $k = 1, \ldots, T$. Then D_k series are generated as $D_k = (C_k/C_T) - (k/T)\ k = 1, .., T$ with $D_0 = D_T = 0$. In case, there is no change in variance, D_k oscillates around zero when plotted against k. If the change is detected in variance, D_k series considerably moves up and down from zero. In the latter case, sudden changes in variance are detected using the critical values tabulated in Table 1 in the study by Inclan and Tiao (1994).

The significant changes are detected using the critical values obtained from the distribution of $\sqrt{T/2}\,|D_k|$ where $\sqrt{T/2}$ is multiplied by D_k to standardize the distribution. To identify significant changes we do not consider D_k series. Rather, we examine $\sqrt{T/2}\,|D_k|$ series. The null hypothesis of homogeneous variance can be rejected if the maximum of $\sqrt{T/2}\,|D_k|$ exceeds the critical value. Let k^* denote the value at which maxk $\sqrt{T/2}\,|D_k|$ reached. If maxk $\sqrt{T/2}\,|D_k|$ falls outside the predetermined boundary, then k^* is taken as point in unconditional variance change.

Usually, D_k series is not enough to detect the multiple variance changes because of the 'masking effect'. The masking effect' means that moderate variance changes may not be detected because of the large variance changes. To resolve this issue, Inclan and Tiao (1994) developed an algorithm that is capable of detecting the multiple changes in the series. The D_k statistic allows to identify only one break point at a time. After finding one break point the sample is segmented into parts and will be checked for other break points. Inclan and Tiao's (1994) algorithm for detection of multiple change points is as follows.

Step 1

In the first step, $D_k\left(a\left[t_1 : T\right]\right)$ series are constructed. Let k^* be a point which $D_k\left(a\left[t_1 : T\right]\right)$ achieves its maximum value. In addition, we define

$$M\left(t_1 : T\right) = \max_{t_1 \leq k \leq T} \sqrt{T/2}\left|D_k\left(a\left[t_1 : T\right]\right)\right|$$

If $M\left(t_1 : T\right) > D^*$, then it is considered that there is a break point at $k^*\left\{D_k\left(a\left[t_1 : T\right]\right)\right\}$ and proceed to the next step. On the other hand, if $M\left(t_1 : T\right) < D^*$, then series do not contain any significant variance changes and algorithm stops here.

Step 2a

In this step, $t_2 = k^*\left(a\left[t_1 : T\right]\right)$ is defined and $D_k\left(a\left[t_1 : t_2\right]\right)$ is computed. In case, $M\left(t_1 : t_2\right) > D^*$ then there is another change point within the interval $\left(t_1 : t_2\right)$. Here, the algorithm continues until $M\left(t_1 : t_2\right) < D^*$ and If $M\left(t_1 : t_2\right) < D^*$ is found then there is no any further significant change point in this interval. The change point can be expressed as k_{first}.

Step 2b

Now similar search is performed from the first change point found in step 1, all the way to the end of the series. Define a new value for t_1: $t_1{=}k^*\left(a\left[t_1 : T\right]\right) + 1$ and evaluate $D_k\left(a\left[t_1 : T\right]\right)$. This step is also repeated until $M\left(t_1 : T\right) < D^*$. Here, the change point can be expressed as k_{last}.

Step 2c

If $k_{first} = k_{last}$, there appears to be one change point. The algorithm stops here. However, $k_{first} < k_{last}$, then we keep both points as change point and repeat step 1 and 2 from the middle part of the series.

Step 3

If there are two or more potential change points, it is important that these change points must be in ascending order. Let *cp* the vector of all detected change points in using the steps shown above. Two extreme values are defined $cp_0 = 0$ and $cp_{NT+1} = T$. One should check each possible change point by computing $D_k\left(a\left[cp_{j-1} + 1 : cp_{j+1}\right]\right)$, $j = 1, \ldots, N_T$. If $M\left[cp_{j-1} + 1 : cp_{j+1}\right]{>}D^*$, then the change point is kept, otherwise dropped.

3.2 The GARCH models

We begin the description of GARCH models used in this study by outlining some of the usual stylized facts in the financial returns. As Morimune (2007) notes, the success of GARCH family models can be attributed largely to their ability to capture several stylized facts of financial time series, such as time-varying volatility, volatility clustering, persistence, and asymmetric reactions to positive and negative shocks of equal magnitude. Considering these stylized facts, we analyze the inflation volatility process in the countries under study by estimating the GARCH, GARCH-M, EGARCH, EGARCH-M, ICSS-EGARCH, and ICSS-EGARCH-M. The GARCH-M, EGARCH-M, and ICSS-EGARCH-M models are estimated including standard deviation of conditional variance, $h_t^{1/2}$, in conditional mean equations. Here, the ICSS-EGARCH model is an extension of the Nelson's (1991) exponential GARCH model with an autoregressive form of mean equation and variance equation augmented with dummies for the sudden unconditional variance shifts in inflation series. As mentioned earlier, to detect the multiple discrete changes in variance of inflation data, we employ the ICSS algorithm developed by Inclan and Tiao (1994).

The mean equations can be specified using an appropriate ARMA (*p, q*) process. We consider following general GARCH (*p, q*) (Bollerslev, 1986) specification to capture symmetric conditional volatility in this paper. The mean and variance equations for GARCH process are given as,

$$r_t = \pi_0 + \sum_{i=1}^{p} \pi_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{1}$$

$$\varepsilon_t|\Psi_{t-1} \sim N(0, h_t), \text{ and } t(0, h_t, \nu)$$

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

The mean equation for GARCH-M can be specified as,

$$r_t = \pi_0 + \sum_{i=1}^{p} \pi_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varphi\sqrt{h_t} \tag{3}$$

$$\varepsilon_t|\Psi_{t-1} \sim N(0, h_t), \text{ and } t(0, h_t, \nu)$$

and, conditional variance of GARCH-M takes the following form,

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

and following inequality restrictions are imposed to ensure the strict positivity of conditional variances

$$\alpha_0 > 0 \tag{5}$$
$$\alpha_i \geq 0, \quad \text{for} \quad i = 1, \ldots, q \tag{6}$$
$$\beta_i \geq 0, \quad \text{for} \quad i = 1, \ldots, p \tag{7}$$

Inequality restrictions for the case p=q=1 are α_0>0, α_1>0, $\beta_1 \geq 0$. These are sufficient conditions to ensure that the conditional variance are strictly positive $h_t > 0$.

As mentioned above, the problem with a standard GARCH model is that all estimated coefficients must be positive. To resolve this problem, Nelson (1991) introduced the exponential GARCH model that does not require all variance equation parameters to be positive. Nelson's (1991) exponential GARCH model with ARMA-based mean equation can be expressed as follows. Innovations are assumed to follow generalized error distribution (GED). The mean equation for EGARCH can be written as,

$$r_t = \pi_0 + \sum_{i=1}^{p} \pi_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{8}$$

where $\varepsilon_t|\Psi_{t-1} \sim$ GED $(0, h_t, \upsilon)$ while the conditional variance equation is given as,

$$\log(h_t) = \omega + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{h_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}} + \sum_{j=1}^{q} \beta_j \log(h_{t-j}), |\beta_j| < 1 \tag{9}$$

Similarly, the mean equation for EGARCH-M models can be written as

$$r_t = \pi_0 + \sum_{i=1}^{p} \pi_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varphi\sqrt{h_t} \tag{10}$$

where $\varepsilon_t|\Psi_{t-1} \sim$ GED $(0, h_t, \upsilon)$ and, the conditional variance is the same as outlined in equation (9).

It is apparent from the visual evidences and the appropriate statistics (excess kurtosis, and highly significant Jarque-Bera statistics) that all inflation series seem to follow a heavy tailed conditional density. The heavy tailed process seems to be caused by structural breaks in the inflation series. Obviously, from the plot of the series it is impossible to detect all breaks in the data because of the 'masking effect'. As we mentioned earlier, to detect the multiple discrete changes in variance of inflation series, we use ICSS algorithm developed by Inclan and Tiao (1994). Hence, the mean equation for ICSS-EGARCH is given as,

$$r_t = \pi_0 + \sum_{i=1}^{p} \pi_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}, \tag{11}$$

where $\varepsilon_t|\Psi_{t-1} \sim$ GED $(0, h_t, \upsilon)$ while the variance equation can be specified as,

$$\log(h_t) = \omega + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{h_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}} + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) + d_1 D_1 + \cdots + d_n D_n \tag{12}$$

For the ICSS-EGARCH-M models, the mean equation is as follows,

$$r_t = \pi_0 + \sum_{i=1}^{p} \pi_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varphi\sqrt{h_t}, \tag{13}$$

where $\varepsilon_t|\Psi_{t-1} \sim$ GED $(0, h_t, \upsilon)$, while the variance equation can be specified similar to (12).

Following the numerous studies (see Wilson *et al.* (1996); Law (2007); and Marcelo *et al.* 2008; among others), we constructed dummy variables, D_1, ..., D_n, which take a value of one from each point of sudden change of variance onwards and zero otherwise.

4 Empirical results

We begin the analysis by first estimating the standard GARCH and EGARCH models. Then, we have modeled the ICSS-EGARCH to take into account the sudden changes in the inflation series for comparison. In this study, we estimate the AR (p,q)-GARCH(1,1) and AR (p,q)-EGARCH(1,1) models using maximum likelihood technique. Here, we assume that the errors follow normal as well as Student's-t distributions for standard GARCH models while in EGARCH models stochastic errors are assumed to follow the GED. Following the suggestion by Bollerslev and Mikkelsen (1996), we use AIC and SC information criteria in a model selection. In addition, we use the robust standard errors suggested by Bollerslev and Wooldridge (1992) for statistical inference on estimated parameters. The Tables 4 and 5 report the estimated GARCH and GARCH-M models while Table 6 presents the estimation results for EGARCH and EGARCH-M volatility models along with the diagnostic tests of the residuals. We first look at whether the standard GARCH models satisfy the several inequality restrictions imposed on the parameters of variance equation. As mentioned earlier, in standard GARCH models, all coefficients in the second moment equation must carry the positive values to ensure the strict positivity of conditional variances. In all cases, the parameters of conditional variance equations are found to be positive. Thus, these models appear to satisfy a positivity restriction. Another restriction is the sum of ARCH and GARCH effects must have the values of less than one, that is,

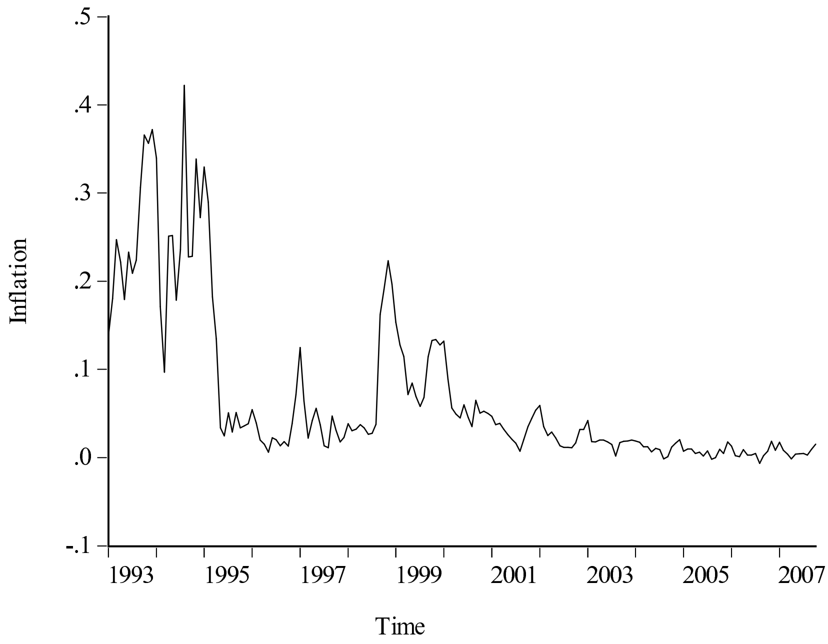

Figure 1: Monthly CPI inflation rates of Belarus

$\hat{\alpha} + \hat{\beta} < 1$. Here, we should note that the persistence[1] of the shocks in the conditional variance for both GARCH and GARCH-M models is more than one across the results assuming different distribution hypotheses. Obviously, none of the GARCH and GARCH-M models satisfy this constraint.

Table 6 reports estimated EGARCH and EGARCH-M models assuming GED conditional density. In our preliminary analysis, we have also estimated the EGARCH and EGARCH-M volatility models assuming a normal distribution. The results of using normal distribution not shown here for space consideration, and they are found to be unsatisfactory in terms of diagnostic checks. Here, it is worth noting several advantages of this specification. First, there is no positivity constraint on the parameters in the second moment equations. Hence, the coefficients can take the negative values as well. Next important advantage of the EGARCH models is it can capture the asymmetric effect which is the common phenomenon in the financial time series by the statistical significance of the parameter, $\hat{\gamma}$. In addition, the volatility persistence can be captured by the estimated parameter, $\hat{\beta}$. Similar to standard GARCH models, in EGARCH models, the estimated residuals should not be serially correlated and

[1]In the standard GARCH models, the sum of α and β measures the persistence of volatility for a given shock and would have a value of one for an integrated GARCH (IGARCH) process (see, for example, Malik, 2003).

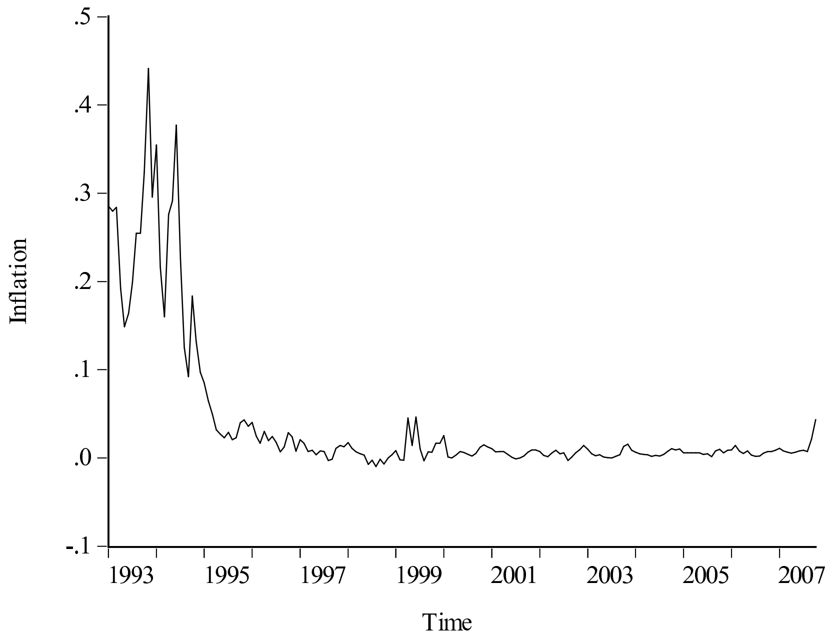

Figure 2: Monthly CPI inflation rates of Kazakhstan

should not display any remaining ARCH effect. We can test to ensure that our model has captured these properties by computing Ljung-Box-Q statistics for standardized residuals and squared standardized residuals. To test any remaining ARCH effects, we report ARCH LM test in Table 6. The Ljung-Box-Q statistic for both standardized residuals and squared standardized residuals reveals that the conditional mean and variance equations are specified properly except for the Kazakhstan's EGARCH-M. In this model, the Q statistics for standardized residuals show the significant value at 1%. Moreover, the signs of heteroscedasticity are removed in two countries' models except Kazakhstan's EGARCH-M. These statistics show that mainly the mean and variance equations are specified properly. However, Kazakhstan's EGARCH-M performs poorly in terms of diagnostics. Next, one needs to look at the βs and they must be statistically significant and $|\hat{\beta}| < 1$. As shown in Table 6, the persistence parameter is statistically highly significant and the absolute value is less than one for both countries. Here, several important features of these models are worth noting. First, the persistence of the shocks in the conditional variance for all EGARCH and EGARCH-M models is close to one except Kazakhstan's EGARCH-M. Between the two countries, Belarus exhibits a larger persistence of volatility than Kazakhstan. All in all, EGARCH models generally provide better fit than the standard GARCH models.

Table 4: Estimates for GARCH models

	Belarus		Kazakhstan	
	Student's-t	Normal	Student's-t	Normal
Mean equation				
$\hat{\pi}_0$	0.0114 [0.028]	-	0.0054 [0.000]	0.0098 [0.001]
$\hat{\pi}_1$	0.8565 [0.000]	0.8568 [0.000]	0.7865 [0.000]	0.8182 [0.000]
Variance equation				
$\hat{\omega}$	1.9E-5 [0.096]	2.1E-5 [0.066]	4.1E-6 [0.060]	5.7E-6 [0.045]
$\hat{\alpha}_1$	0.5588 [0.021]	1.6407 [0.215]	0.7382 [0.046]	0.6754 [0.024]
$\hat{\beta}_1$	0.5740 [0.000]	0.2808 [0.198]	0.5180 [0.000]	0.4733 [0.000]
AIC	-5.1809	-4.7994	-6.7491	-6.4758
SC	-5.0733	-4.7276	-6.6414	-6.3862
LogL	464.51	428.75	603.29	578.11
$\hat{Q}(10)$	4.4944 [0.876]	8.2702 [0.507]	9.5125 [0.391]	10.035 [0.348]
$\hat{Q}^2(10)$	4.4944 [1.000]	8.2702 [0.998]	9.5125 [0.785]	10.035 [0.415]
ARCH LM test	0.1028 [0.998]	0.1209 [0.998]	0.5339 [0.861]	0.8221 [0.601]

Figures in square bracket denote p-values; AIC, SC, and LogL denote Akaike information criterion, Schwarz criterion and log-likelihood value respectively; $\hat{Q}(10)$ and $\hat{Q}^2(10)$ are the Ljung-Box Q statistics for residuals and squared standardized residuals at lag 10 respectively; ARCH LM test at lag 10 is based on F-statistic.

Next we turn to the estimates of ICSS-EGARCH and ICSS-EGARCH-M models. As mentioned earlier, the ICSS-EGARCH models are estimated accounting for the regime shifts in inflation series. The regime shifts in inflation series are detected employing ICSS algorithm advocated by Inclan and Tiao (1994). The major economic and political events that coincide with the regime shifts are provided in Table 7. When sudden shifts in variance are identified in observation k^*, then the dummies $D_1, \ldots, D_n$ are incorporated into the variance equation which take the value of one starting from k^* onward and zero otherwise. Also, in this specification, there is no positivity restriction on parameters of conditional variance equation. The estimates of ICSS-EGARCH and ICSS-EGARCH-M models are reported in Table 8. We have estimated ICSS-EGARCH models assuming GED including all dummies detected by

Table 5: Estimates for GARCH-M models

	Belarus		Kazakhstan	
	Student's-t	Normal	Student's-t	Normal
Mean equation				
$\hat{\varphi}$	-0.3159 [0.134]	-0.0991 [0.612]	-0.4322 [0.011]	-0.7498 [0.024]
$\hat{\pi}_1$	0.8495 [0.000]	0.8384 [0.000]	0.7719 [0.000]	0.7672 [0.000]
Variance equation				
$\hat{\omega}$	1.9E-5 [0.091]	2.3E-5 [0.052]	4.1E-6 [0.051]	6.6E-6 [0.024]
$\hat{\alpha}_1$	0.4986 [0.031]	1.6161 [0.021]	0.6964 [0.041]	0.7124 [0.016]
$\hat{\beta}_1$	0.5963 [0.000]	0.2761 [0.204]	0.5180 [0.000]	0.4292 [0.000]
AIC	-5.1829	-4.7846	-6.7563	-6.4825
SC	-5.0753	-4.6949	-6.6486	-6.3927
LogL	464.69	428.44	603.93	578.70
$\hat{Q}(10)$	5.3742 [0.801]	6.9456 [0.643]	14.776 [0.097]	16.883 [0.051]
$\hat{Q}^2(10)$	0.4913 [1.000]	1.2239 [0.999]	3.2834 [0.952]	2.8711 [0.969]
ARCH LM test	0.0426 [0.990]	0.1098 [0.990]	0.2922 [0.980]	0.2473 [0.990]

Figures in square bracket denote p-values; AIC, SC, and LogL denote Akaike information criterion, Schwarz criterion and log-likelihood value respectively; $\hat{Q}(10)$ and $\hat{Q}^2(10)$ are the Ljung-Box Q statistics for residuals and squared standardized residuals at lag 10 respectively; ARCH LM test at lag 10 is based on F-statistic.

the ICSS methodology in the second moment equations. The log-likelihood function convergence has been achieved in all ICSS-EGARCH models. The selection criteria and diagnostics for ICSS-EGARCH models are reported in Table 8. The results show that these tests no longer reject serial correlation and homoskedasticity in the standardized residuals. Hence, these diagnostic tests support the modeling approach adopted in the current study. However, as Ljung-Box-Q and ARCH LM test statistics reveal, Kazakhstan's ICSS-EGARCH-M model suffers from serial correlation as well as heteroskedasticity. Hence, due to the poor performance, we do not consider this model in later discussions. All persistence parameters are statistically highly significant. Here, it is worth noting that there is a considerable reduction in the persistence coefficient of volatility when sudden shifts in variance are taken into account. This

Table 6: Estimates for EGARCH and EGARCH-M models assuming GED

	Belarus		Kazakhstan	
	EGARCH	EGARCH-M	EGARCH	EGARCH-M
Mean equation				
$\hat{\varphi}$	-	2.4365 [0.000]	-	0.1118 [0.000]
$\hat{\pi}_0$	0.0111 [0.032]	-	0.0061 [0.000]	-
$\hat{\pi}_1$	0.8852 [0.000]	0.0694 [0.000]	0.7256 [0.000]	0.5353 [0.000]
Variance equation				
$\hat{\omega}$	-0.4587 [0.017]	-0.6053 [0.000]	-1.0135 [0.000]	-3.1325 [0.000]
$\hat{\alpha}_1$	0.1317 [0.300]	0.0748 [0.161]	0.6439 [0.000]	-1.4522 [0.008]
$\hat{\gamma}_1$	0.2637 [0.028]	0.4987 [0.000]	0.0420 [0.738]	3.6966 [0.000]
$\hat{\beta}_1$	0.9627 [0.000]	0.9414 [0.000]	0.9411 [0.000]	0.4632 [0.000]
$\hat{\upsilon}$ Tail parameter	0.9338 [0.000]	0.9699 [0.000]	0.8488 [0.000]	0.2540 [0.000]
AIC	-5.1294	-5.1148	-6.7138	-6.0416
SC	-5.0037	-4.9892	-6.5882	-5.9160
LogL	460.95	459.66	601.17	541.68
$\hat{Q}(10)$	3.938 [0.915]	4.3723 [0.885]	7.3177 [0.604]	111.80 [0.000]
$\hat{Q}^2(10)$	0.703 [1.000]	3.9090 [0.917]	1.8046 [0.994]	15.606 [0.076]
ARCH LM test	0.065 [0.990]	0.3196 [0.970]	0.2180 [0.990]	3.8367 [0.000]

Figures in square bracket denote p-values; AIC, SC, and LogL denote Akaike information criterion, Schwarz criterion and log-likelihood value respectively; $\hat{Q}(10)$ and $\hat{Q}^2(10)$ are the Ljung-Box Q statistics for residuals and squared standardized residuals at lag 10 respectively; ARCH LM test at lag 10 is based on F-statistic.

finding is consistent with many other findings in literature as GARCH specification might overestimate the persistence if the sudden changes in unconditional variance are ignored. Among others, these include Wilson *et al.*, (1996), Malik *et al.* (2005), Law (2007), Mansur *et al.* (2007), and more recently Marcelo *et al.* (2008).

Furthermore, we find that the asymmetric coefficient, γ, is positive and statistically significant at the conventional levels in all cases except Kazakhstan's EGARCH and Belarus's ICSS-EGARCH models. Obviously, the current analysis reveals that the

Table 7: Break points and economic events

Change points	Economic and political events
Belarus	
1995 M4	Associated with the poor performance due to unfavorable initial conditions during the earlier period of transition
1998 M8	The effects of Russian financial default
2000 M3	Government constructed the stabilization programs
2002 M4	Low inflation volatility period due to the outcome of economic reforms
Kazakhstan	
1994 M12	From the beginning of 1992, the most prices were liberalized. Consequently, more intensive financial reforms began in 1993
1996 M11	Low volatility period is characterized by outcome of financial sector reforms together with general economic liberalization and favorable export prices
1999 M3	The impacts of Russian financial crisis
2000 M1	Low volatility period with general economic liberalization
2007 M8	A parliamentary election was held in Kazakhstan on 18 August 2007

The break points in inflation data are detected using an ICSS algorithm

GARCH model that carries the symmetry restrictions and without taking into account the regime shifts is not well suited in the present context to model the inflation fluctuations.

Finally, the dummies that account for the tranquil period after the initial unfavorable transition period, Russian financial crisis, and further two stabilization periods are incorporated in the variance equations. In Belarus, these four dummies carry the significant right signs in all cases. The only insignificant parameter is d_4. In other words, the first stabilization period after the initial volatile period and Russian crisis contribute to inflation volatility negatively and positively respectively in Belarus. In Kazakhstan, we included five dummies in the second moment equation detected by ICSS algorithm. They are the relatively tranquil period after the initial high volatile period, and the stabilized period due to the government's stabilization policies, Russian financial default period, and the final stabilized periods after 2001, and final volatile period. The parameters on all five dummy variables are statistically significant at conventional levels. The exceptions are dummy for stabilized period due to the government's stabilization policies and final volatile period. However, despite the statistical insignificance of several dummies for both countries at conventional levels, we did not exclude these dummies from variance equations because omissions of these dummies have tremendous effects on other parameters. In sum, the coefficients on regime dummies carry the expected signs in all cases for both countries.

Table 8: Estimates for ICSS-EGARCH and ICSS-EGARCH-M assuming GED

	Belarus		Kazakhstan	
	ICSS-EGARCH	ICSS-EGARCH-M	ICSS-EGARCH	ICSS-EGARCH-M
Mean equation				
$\hat{\varphi}$	-	2.9437 [0.000]	-	2.5482 [0.000]
$\hat{\pi}_0$	0.0119 [0.017]	-	0.0078 [0.000]	-
$\hat{\pi}_1$	0.8601 [0.000]	0.0475 [0.000]	0.7916 [0.000]	0.0421 [0.000]
Variance equation				
$\hat{\omega}$	-2.4915 [0.002]	-2.2908 [0.000]	-2.1698 [0.000]	-2.3289 [0.000]
$\hat{\alpha}_1$	0.1729 [0.482]	0.1235 [0.162]	-0.4356 [0.014]	0.1106 [0.221]
$\hat{\gamma}_1$	0.1643 [0.289]	0.2663 [0.000]	0.3758 [0.014]	0.4131 [0.000]
$\hat{\beta}_1$	0.4987 [0.003]	0.5465 [0.000]	0.5247 [0.000]	0.5232 [0.000]
$\hat{\upsilon}$ Tail parameter	1.2796 [0.000]	1.6557 [0.000]	2.2186 [0.000]	1.1699 [0.000]
$\hat{d}_1$	-1.5614 [0.007]	-1.6991 [0.000]	-2.0593 [0.000]	-1.9818 [0.000]
$\hat{d}_2$	0.5621 [0.078]	1.0191 [0.000]	-0.2004 [0.251]	-0.7736 [0.000]
$\hat{d}_3$	-1.1497 [0.002]	-0.9940 [0.000]	1.4553 [0.000]	1.0440 [0.000]
$\hat{d}_4$	-0.4869 [0.149]	-0.6801 [0.000]	-2.1789 [0.000]	-1.2624 [0.000]
$\hat{d}_5$	-	-	1.7083 [0.188]	1.4411 [0.004]
AIC	-5.2478	-5.3688	-6.9797	-6.7578
SC	-5.0505	-5.1714	-6.7644	-6.5425
LogL	475.44	486.14	629.71	610.07
$\hat{Q}(10)$	5.2360 [0.813]	46.639 [0.000]	12.031 [0.212]	36.309 [0.000]
$\hat{Q}^2(10)$	5.9241 [0.747]	46.430 [0.000]	5.4528 [0.793]	86.809 [0.000]
ARCH LM test	0.7904 [0.638]	2.2677 [0.016]	0.5019 [0.880]	9.5443 [0.000]

Figures in square bracket denote p-values; AIC, SC, and LogL denote Akaike information criterion, Schwarz criterion and log-likelihood value respectively; $\hat{Q}(10)$ and $\hat{Q}^2(10)$ are the Ljung-Box Q statistics for residuals and squared standardized residuals at lag 10 respectively; ARCH LM test at lag 10 is based on F-statistic.

5 Concluding remarks

The paper estimates and examines various GARCH family volatility models for the inflation rates of two ex-Soviet transition economies. The initial empirical finding presented in this study is that the standard GARCH and GARCH-M models perform poorly in terms of coefficient restrictions. In addition, one should note that the countries under study experienced sudden economic declines during the initial unfavorable transition period that led to the periods of relatively high inflation volatility followed by successive stabilizations. Moreover, a high volatility in inflation rates occurred during the Russian financial default in 1998. Hence, unexpected variance changes (regime shifts) are found to be evident in the inflation rates. The regime shifts detected by ICSS algorithm have been taken into account in the second moment equations of EGARCH models. Furthermore, this paper has examined whether or not the sudden changes in variance have an impact on the persistence of inflation volatility. The estimation results reveal that accounting for sudden changes in the second moment equations significantly reduces the volatility persistence. Apart from that, we find that the asymmetric coefficient, γ, is positive and statistically significant at the conventional levels in all cases except Kazakhstan's EGARCH and Belarus's ICSS-EGARCH models. Finally, relying on several model selection criteria, we have discovered that ICSS-EGARCH type models fit better than other models considered in this study.

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