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Volatility in the Emerging Stock Markets in Central and Eastern Europe: Evidence on Croatia, Czech Republic, Hungary, Poland, Russia and Slovakia#

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Abstract

This paper investigates the main features of stock market volatility in the emerging markets of European transition economies using daily indexes. Starting with the universe of all stock markets in the transition economies, we use the criterion of data availability to obtain a sample of six stock markets, namely the markets in Croatia, Czech Republic, Hungary, Poland, Russia and Slovakia. We apply ARIMA, the BDSL procedure and symmetric as well as asymmetric GARCH models to test for daily return volatility. The main findings are fourfold. First, in all the six markets, volatility exhibits significant conditional heteroskedasticity and non–linearity. Second, volatility seems to be of a persistent nature; however, no asymmetric volatility effects are found for most of the markets. Third, as measured by a GARCH–in–Mean model, volatility does not explain expected returns for any of the six markets. Although

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GARCH appears to be the most appropriate process in characterising volatility in these markets, the explanation provided by symmetric and asymmetric GARCH models is not significant enough for predicting future volatility. Fourth, while the evidence suggests that the martingale hypothesis can be significantly rejected for all the six markets, none of the markets shows the well–known day–of–the–week anomaly commonly reported in most stock markets.

Key Words: volatility; emerging stock markets; Central and Eastern Europe; non-linearity; GARCH; GARCH-M.

JEL Classification Nos: G1, G14

1. Introduction

The emerging stock markets in the transition economies of Central and Eastern Europe have been trying to revitalise their stock markets through private floatations and privatisation of public enterprises.[1] Consequently, most of these emerging markets have captured the attention of investors in recent years. However, the contagion effects arising from the crisis in South East Asian financial markets in April 1997 underline the importance of a careful examination of the nature of volatility in the emerging markets in European transition economies.[2]

Although volatility has been studied in many contexts, as pointed out by Shiller (1990), the existing literature indicates that, in general, the volatility of equity returns has been mainly investigated with respect to the developed stock markets in industrial countries [see Green, Maggioni and Murinde (2000)]. Most empirical studies use the Autoregressive Conditional Heteroskedasticity (ARCH) models developed by Engle (1982) and later generalised by

[1] [1] This is because during the communist era, these transition economies did not have a market-oriented financial system (Doukas, Murinde and Wihlborg, 1998: p. 2).

[2] [2] The role of the stock market in igniting and fuelling the crisis cannot be underestimated in the sense that the crisis broke out when trading of the shares of finance companies on the Stock Exchange of Thailand was suspended in April 1997.

Bollerslev (1986), as well as extensions of the ARCH [see, for example, Baillie, Bollerslev and Mikkelsen (1996)].[3] For instance, using daily data from the S&P index for 1928 to 1994, French, et al. (1987) find evidence of conditional volatility in returns. Several others have reported intertemporal relationship between volatility and expected returns in the US [see, for example, Pindyck (1984), Chou (1988), and Baillie and DeGennaro (1990)], while other studies have not [for example, Theodossiou and Lee (1995)]. A number of these studies report that the variance of returns in time shows strong correlations with prior innovations [see, for example, Geyer (1994) and Errunza, Hogan, Kini and Padmanabhan (1994)]. In general, recent studies on volatility in developed stock markets generally suggest the presence of conditional volatility (Sakata and White, 1998), non-linearities (de Lima, 1998), day-of-the-week anomalies (Aggarwal and Schatzberg, 1997) and volatility transmission or spillovers (Koutmos & Booth 1995, Booth, Martikainen and Tse, 1997).

There is relatively less empirical research on the volatility of equity returns in emerging stock markets, with even less studies on the markets in the transition economies of Central and Eastern Europe. Among the few studies, Bolt and Milobedzki (1994) analyse the return on shares quoted on the Warsaw Stock Exchange in the period 1991-1993 and find that the distributional asymmetry and truncations of the returns make it difficult to test hypotheses on the price setting mechanism (see also Cutler, 1995). High volatility in all the monthly stock price series on the Warsaw Stock Exchange is found by Flores and Szafarz (1997) in an investigation of the content of the information set used by the agents in the market. The methodology of the study supposes that the innovations in the price series are orthogonal to all variables within or outside a given information set. In addition to confirming high volatility in the

[3] [3] See Bollerslev, Chou and Kroner (1992) for a comprehensive review of the ARCH model and its various extensions.

price series, it is found that macroeconomic fundamentals are still absent from the market. This conclusion is consistent with the findings by Nivet (1997) on the development of the exchange from 1991 to 1994. In addition, Gordon and Rittenberg (1995) analyse the behaviour of stock prices for the period of 1 June 1993 to 27 July 1994 on Warsaw stock exchange in light of alternative models of market inefficiency. The Gordon-Rittenberg study finds that the EMH provides an inadequate explanation of investor behaviour and its effect on stock price volatility in the Polish market. Moreover, Poshakwale and Wood (1998), using daily data from two main indices and equally weighted portfolio of 17 stocks in the Warsaw market, report the presence of persistent volatility and non-linearity in returns. For the Hungarian market, Dockery and Vergari (1997) examine the random walk hypothesis using variance test ratio on weekly returns and find that the Budapest stock exchange is a random walk market. However, the results of the above research studies indicate a need for further investigation of the nature of volatility, given the evolution of the Central and East European markets as documented by Rotyis (1992) and Meszaros (1993).

This paper provides evidence on the main features of volatility in the Central and East European emerging stock markets of Croatia, Czech Republic, Hungary, Poland, Russia and Slovakia.[4] The paper makes several contributions to the existing knowledge. First, the paper uses robust econometric procedure. For example, after testing for presence of non-linearity in the indexes through the Brock, Dechert, Scheinkman and Le Baron (1996) - hereafter, BDSL - statistic, the presence of conditional heteroskedasticity is investigated using LM tests. Thereafter, the GARCH models can incorporate non-linear effects and outperform conventional OLS models as shown by Theodossiou and Lee (1995). Also, GARCH-in-Mean

[4] 4 Our rationale for the choice of the six stock markets, among the other emerging markets in Central Eastern Europe, was purely due to data availability.

(GARCH-M) modelling is used to provide a convenient and reliable measure of the relationship between expected returns and volatility. Asymmetric Exponential GARCH and Threshold GARCH models are also employed to test whether volatility follows an asymmetric process. Second, the paper fills important gaps in the literature by exploring some key volatility characteristics of six Central and Eastern European stock markets: for example, whether or not the volatility follows a process of conditional heteroskedaticity; the possibility that the market prices the conditional volatility; investigation of asymmetric volatility; a test of the martingale hypothesis; and the nature of day-of-the-week effects. The third important contribution of the paper is that in general, an examination of the nature of volatility of stock returns in the six transition economies offers a number of worthwhile theoretical and practical insights.[5]

The remainder of this paper is structured into two sections. The modelling procedures and empirical results are presented in Section 2. Section 3 summarises the main conclusions.

2. Modelling Procedures and Results

2.1 The database

We use daily closing prices from the main indices of each of the six emerging stock markets in the sample. For the Croatian stock market, we use the *kuna*-based CROBEX index for the period 25 December 1997 to 5 April 2000. The base date for the CROBEX index is 1 July 1997 = 1000. The Prague Stock Exchange's PX-50 index is used for the Czech market, for the period 12 May 1994 to 5 April 2000. The base date for the PX-50 index is 1 April 1994 = 1000. For the Polish stock market, we use the Warsaw General In-

[5] 5 We argue that evidence on the main features of volatility of stock returns in the six Central and Eastern European markets offers a number of worthwhile theoretical and practical insights. However, the paper does not distinguish between market volatility, fundamental volatility and excess volatity (see Green, Maggioni and Murinde, 2000).

dex of 20 (WIG-20) for the period 13 July 1994 to 5 April 2000. The WIG-20 has a base date of 16 April 1994 = 1000. The BUX index is used for the Budapest Stock Exchange (BSE), for the period 18 November 1991 to 5 April 2000. The base date for the BSE BUX is 2 January 1991 = 1000. For the Slovakian stock market, we use the SAX index, for the period 7 June 1994 – 5 April 2000. The base date for the SAX index is 1 December 1993 = 1000. Finally, for the Russian market, we use ASPG index, for the period 3 July 1995 to 5 April 2000. The base date for the index is 20 June 1994 = 1000. All the data are obtained from Datastream International.

2.2 Non–linearity and other properties of the data

Using each of the six stock market indices, we first calculate corresponding daily logarithmic returns and squared returns. The returns are then tested for the presence of autocorrelation and stationarity; the results are reported in Tables 1a and 1b, respectively.[6] The descriptive statistics show that the returns exhibit skewness and significant kurtosis. Russia has the highest standard deviation and is out of range with the rest of the sample markets. In addition, Russia exhibits the highest kurtosis and Jarque-Bera statistic. The returns and squared returns in the market indices show autocorrelation with significant coefficients at various lag lengths. We thus reject the null hypothesis of no serial correlation and homoskedastic daily returns (uncorrelated squared returns). These characteristics of high kurtosis and variance clustering observed in the autocorrelation coefficients suggest that the ARCH specification provides a good approximation for investigating the structure of conditional volatility of daily returns in the six emerging equity markets (Diebold, 1986).

[6] 6 Daily logarithmic returns are calculated as $ln(P_t / P_{t-1})$, where P is the stock market index.

Table 1a: *Descriptive Statistics for Daily Logarithmic Returns*

	Croatia	Czech	Poland	Hungary	Slovakia	Russia
Mean	–0.00	–0.02	0.05	0.11	–0.07	0.31
Median	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	17.47	5.82	11.57	13.62	13.08	101.95
Minimum	–11.09	–7.08	–10.32	–18.03	–28.08	–23.55
Std. Deviation	2.41	1.17	2.25	1.90	1.66	4.11
Skewness	0.36	–0.23	–0.09	–0.52	–3.11	12.26
Kurtosis	10.89	7.34	5.84	17.30	64.25	306.15
Jarque–Bera	1554.77	1220.32	503.39	18718.77	240181.5	478704
ACF (Lag1)	0.03	0.18	0.10	0.03	–0.02	0.08
Q–Statistic	(0.42)	(52.6***)	(15.1***)	(2.05)	(0.40)	(8.30)
ACF (Lag 5)	0.04	–0.03	0.003	0.015	0.05	–0.04
Q–Statistic	(8.41)	(84.8***)	(15.8***)	(6.68)	(8.83)	(13.3**)
ACF (Lag 10)	0.05	0.06	0.03	0.081	–0.10	–0.01
Q–Statistic	(20.99**)	(93.5***)	(24.5***)	(33.8***)	(11.89)	(18.16*)
ACF (Lag15)	0.10	0.03	–0.008	0.03	–0.11	0.00
Q–Statistic	(29.94**)	(100***)	(36.2***)	(71.0***)	(45.3***)	(21.29)
ACF (Lag22)	–0.00	–0.03	0.045	–0.03	–0.02	0.09
	(33.43*)	(107***)	(43.5***)	(78.0***)	(46.6***)	(36.0**)
Augmented Dickey Fuller (ADF) Test Statistic						
ADF Statistic	–10.00***	–16.35***	–17.00***	–20.23***	–16.62***	–15.97***
AR 1	–0.88***	–0.75***	–0.92***	–0.93***	–0.91***	–0.93
Intercept	–1.34	–0.19*	–0.07	0.08	0.08	–0.35
Trend	0.00	0.00*	0.00	0.00	0.00	0.00
Observation	589	1534	1490	2182	1516	1237

Table 1b: *Descriptive Statistics of Squared Returns*

	Croatia	Czech	Poland	Hungary	Slovakia	Russia
Mean	5.82	1.37	5.06	3.63	2.75	17.00
Median	0.43	0.22	1.25	0.32	0.13	0.62
Maximum	305.25	50.09	133.88	325.19	788.67	10392.75
Minimum	0.00	0.00	0.00	0.00	0.00	0.00
Std. Deviation	18.33	3.44	11.12	14.56	21.94	297.28
Skewness	9.59	5.90	5.39	10.95	30.90	34.30
Kurtosis	134.57	52.97	43.99	175.20	1087.75	1196.68
Jarque–Bera	437532	169058	111924	2745853	74813888	73980742
ACF (Lag1)	0.23	0.13	0.20	0.28	-0.00	0.00
Q–Statistic	(32.8***)	(24.9***)	(58.2***)	(173.3***)	(0.01)	(0.02)
ACF (Lag 5)	0.35	0.20	0.12	0.16	0.03	0.00
Q–Statistic	(146.6***)	(170.5***)	(191.6***)	(322.6***)	(2.82)	(1.00)
ACF (Lag 10)	0.11	0.15	0.07	0.11	0.09	0.00
Q–Statistic	(183.7***)	(305.6***)	(223.8***)	(475.2***)	(15.02)	(1.00)
ACF (Lag15)	0.08	0.11	0.03	0.06	0.18	0.00

Q–Statistic	(199.4**)	(399.6***)	(241.2***)	(667.7***)	(73.34***)	(1.00)
ACF (Lag22)	0.07	0.09	0.03	0.06	0.00	0.02
	(208.6***)	(483.4***)	(251.2***)	(766.4***)	(73.88***)	(1.00)
Augmented Dickey Fuller (ADF) Test Statistic						
ADF Statistic	–6.05***	12.05***	–13.49***	–15.54***	–22.19***	–15.55***
AR 1	–0.40***	0.54***	–0.57***	–0.54***	–0.86***	–0.98***
Intercept	1.11	0.17	3.39***	0.59	1.05	30.44
Trend	0.00	0.00*	0.00	0.00***	0.00	0.00
Observation	589	1534	1490	2182	1516	1237

*Significant ***1%, **5%, and *10%.*

We test for non-stationarity using the unit root test of Dickey and Fuller (1979).[7] The Augmented Dickey Fuller (ADF) statistics in Table 1a suggest that the logarithmic forms of the daily stock returns are I(0) when first differenced and hence I(1) in levels; Table 1b shows that similar results hold for squared returns.

We first use ARIMA models which enable us to compare the performance of the conventional OLS model with GARCH models. In the context of Box and Jenkins (1976), the ADF results reported in Tables 1a and 1b suggest that ARMA model can be used.

Table 2: *ARIMA Estimates*

	Croatia	Czech	Poland	Hungary	Slovakia	Russia
Constant	–0.002	–0.015	0.045	0.096	–0.069	0.275
	(–0.024)	(–0.522)	(0.778)	(2.172**)	(–1.797*)	(2.231**)
AR	–0.126 (Lag 6)	0.185 (Lag 1)	0.100 (Lag 1)	0.077 (lag 10)	0.066 (Lag 4)	0.077 (Lag 1)

[7] [7] The ADF is used with a constant and trend. We also experiment with the ADF version with no constant as well as the ADF version with a constant but no trend; the results, which are available from the authors, are consistent with those reported in this paper.

	(-3.015***)	(5.465***)	(2.738***)	(0.031**)	(2.453**)	(0.117)
Adjusted R Square	0.021	0.034	0.009	0.01	0.017	0.005
Log Likelihood	-1336.82	-2395.21	-3319.49	-4476.26	-2696.93	-3498.75
Engle's LM Statistic	97.11***	32.26***	61.77***	267.40***	22.10	0.086

*Significant at ***1%, **5%, and *10%, t statistics in parentheses.*

The estimation results for the ARMA model are reported in Table 2. The results indicate that the coefficients for the autoregression are statistically significant in the market returns for Croatia, Czech, Poland, Hungary and Slovakia, but not for Russia.[8] To test for heteroskedasticity, the ARCH-LM test is applied to the residuals. The test is based on the regression of squared residuals on lagged squared residuals. The statistic is asymptotically distributed as χ^2, with degrees of freedom equal to the number of lagged squared residuals, and provides a test of the hypothesis that the coefficient of the lagged squared residuals are all zero; that is, there is no ARCH effect. The ARCH-LM statistic in Table 2 indicates presence of heteroskedasticity in the index returns for the markets in Croatia, Czech, Poland and Hungary, suggesting that the ARMA model does not remove heteroskedasticity with respect to these markets.

We then investigate non-linearity in daily returns using the BDSL test.[9] The test is capable of locating many types of departures from independent and identical distribution, such as nonstationarity, non-linearity and deterministic chaos, any of which imply that the conditional distribution is different from the unconditional distribution. Specifically, the null hypothesis under the BDSL test is that the data are identically and independently distributed (IID). Rejec-

[8] 8 The results are not reported here but are available on request to the authors.

[9] 9 The basis of the BDSL test is the concept of correlation dimensions (CD); see the seminal work by Grassberger and Procaccia (1983) and the asymptotic distribution of the test statistic by Brock, Hsieh and Le Baron (1991).

tion of IID hypothesis would suggest that the time series is non-linear or has chaotic characteristics.

Table 3: *BDS Test Statistics for Residuals from ARIMA Models*

M	Croatia	Czech	Poland	Hungary	Slovakia	Russia
2	0.436	1.072	0.408	1.712	0.340	0.95
3	0.701	1.345	0.393	2.135*	0.635	1.547
4	0.829	1.165	0.28	1.933	0.605	1.705
5	0.776	0.902	0.157	1.610	0.514	1.808
6	0.720	0.645	0.081	1.222	0.379	1.75
7	0.637	0.443	0.041	0.900	0.276	1.612
8	0.569	0.293	0.022	0.661	0.198	1.471
9	0.507	0.193	0.011	0.479	0.137	1.354
10	0.466	0.129	0.006	0.348	0.092	1.233
2	0.477	1.131	0.864	1.963*	0.223	0.452
3	1.055	2.164*	1.375	3.470*	0.753	1.042
4	1.440	2.786*	1.621	4.489*	1.018	1.566
5	1.505	3.053*	1.558	5.038*	1.147	2.001*
6	1.468	3.012*	1.372	5.208*	1.166	2.287*
7	1.351	2.772*	1.125	5.162*	1.115	2.448*
8	1.231	2.494*	0.898	4.997*	1.043	2.578*
9	1.112	2.206*	0.702	4.733*	0.928	2.67*
10	1.009	1.919	0.548	4.415*	0.797	2.687*
2	0.501	0.745	0.871	1.385	0.191	0.381
3	1.094	1.766	1.762	2.781*	0.688	0.896
4	1.625	2.658*	2.599*	4.099*	1.083	1.386
5	2.005*	3.372*	3.14*	5.249*	1.401	1.831

6	2.307*	3.878*	3.439*	6.210*	1.635	2.203*
7	2.458*	4.140*	3.502*	6.959*	1.779	2.497*
8	2.494*	4.305*	3.463*	7.465*	1.914	2.722*
9	2.486*	4.375*	3.319*	7.780*	1.996*	2.893*
10	2.411*	4.341*	3.138*	7.951*	1.993*	3.033*
2	0.357	0.463	0.639	0.948	0.114	0.306
3	0.797	1.249	1.468	2.032*	0.463	0.778
4	1.305	2.049*	2.4*	3.203*	0.804	1.27
5	1.792	2.856*	3.228*	4.333*	1.161	1.745
6	2.231*	3.623*	3.932*	5.474*	1.475	2.176*
7	2.597*	4.220*	4.452*	6.484*	1.724	2.57*
8	2.883*	4.701*	4.881*	7.358*	2.004*	2.923*
9	3.102*	5.117*	5.18*	8.116*	2.274*	3.243*
10	3.224*	5.422*	5.386*	8.734*	2.467*	3.536*

**Significant at 5%. Marginal significance level of the statistics for a two tailed test is 1.960*

To be able to detect and remove any linear dependence before testing for non-linearity, the BDSL test is applied on the residuals of the ARMA model. As suggested by Hsieh (1991, 1993), we use embedding dimensions of 2 to 10 and epsilons ranging from half to two times the standard deviation. The results in Table 3 indicate significant BDSL statistics for the indices of all the six markets (but very weak for Slovakia), suggesting the presence of low dimension non-linearity. The evidence also suggests that the ARMA model does not fully capture non-linear dependencies.

2.3 Conditional volatility

In order to explore the nature of volatility, we initially apply the Autoregressive Conditional Heteroskedasticity (ARCH) model, given that Engle (1982) and Sumel and Engle (1994), among other studies, indicate that the ARCH appropriately accounts for volatility clustering in the error terms that are serially uncorrelated and have fat tailed distributions. Previous evidence suggests that the ARCH process can well represent time-varying stock return volatility and fat tailed distribution parsimoniously, while incorporating autocorrelation (see Bollerslev, Chou and Kroner, 1992).

The likelihood ratio (LR), computed using the Akaike Information Criterion (AIC) and the Shwartz Bayesian Criterion (SBC) is used in comparing the performance of models. The LR statistic is based on the log likelihood value at the estimated vector and LR of the restricted to the unrestricted model is distributed as χ^2 (k) where k is the number of restricted parameters. Specifically, we estimate models with one restriction imposed at a time, and thus use the LR test for comparing two models, with k = 1. The AIC and SBC are functions of the log likelihood values as well as the number of free parameters in estimation and they incorporate a penalty for a large number of parameters, which gives us a bias towards more parsimonious specifications. If a model contains k free parameters, the AIC is $\frac{2}{T}(LogL + 2K)$ and the SBC is $\frac{2}{T}(LogL + (LogT/2)K)$.

We also test the martingale hypothesis, *i.e.* changes in stock prices from period t–1 to period t are innovations which are orthogonal to the information available at period t–1, (See McCurdy and Morgan, 1988). The estimation equation is expressed as:

$$\Delta P_t = \gamma_0 + \sum_{i=1}^{n} \gamma_i \Delta P_{t-i} + \sum_{j=1}^{m} \delta_j D_{tj} + \varepsilon_t \qquad (1)$$

where ΔP_t is defined as the difference in logarithms of daily stock price index; D is a seasonal dummy variable which takes the value of one for a given day of the week and zero otherwise. Under the null hypothesis, if changes in daily stock prices are independent of the previously available information, parameters γ_i and δ_j are expected to equal zero, and errors ε_t are uncorrelated with a zero mean, but are not necessarily homoskedastic.

The results of the ARCH-LM test (earlier reported in Table 2) show significant heteroskedasticity (at 5%) in the residuals in daily returns from the ARMA model. The presence of ARCH effects, together with the results obtained using the AIC and SBC as well as the BDSL tests, give rise to the possibility that return volatility may be modelled as a GARCH process.

In the GARCH(p,q) specification, we model the conditional variance of daily stock returns h_t as a linear function of its own lagged p conditional variances and the lagged q squared residuals:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j h_t \qquad (2)$$

where α and β are parameters to be estimated. For $p = 0$, equation (2) becomes the ARCH(q) process, and for $p = q = 0$ the variance of daily stock returns is simply a white noise process. In this linear GARCH(p,q) procedure, shocks to the current volatility of stock returns persist if $\sum \alpha_i + \sum \beta_j = 1$ which indicates that current information remains important for forecasts of the conditional variance for all horizons (See Engle and Bollerslev, 1986 and Bollerslev, Chou and Kroner, 1992).

Table 4 reports the estimation and testing results for the GARCH model, alongside OLS estimates, with dummy seasonals for all the six markets. The OLS results indicate significant first order autoregression for the market indices for Croatia, Czech and Poland, but not for Hungary, Slovakia and Russia. In addition, none of the dummy variables for the day-of-the-week effect are significant for Croatia, Czech Slovakia and Russia. For the Polish index, coefficients for the Tuesday, Wednesday and Friday dummy variables are significant; while for the Hungarian stock market, only coefficients for the Thursday dummy variable is statistically significant. Overall, it is interesting to note that the well known day-of-the-week anomaly, in the form of negative Monday returns and higher positive returns for Friday is not present in all the six emerging stock markets.

The parameter estimates from the GARCH models for the six markets are also reported in Table 4. The LR shows marginal improvement in the GARCH model compared to its OLS counterpart. Coefficients for ARCH and GARCH are highly significant, confirming the presence of significant heteroskedasticity in daily returns. For Poland, Hungary and Slovakia, skeweness and kurtosis decline in the GARCH model compared to the OLS counterpart; this suggests that the GARCH model successfully accounts for the volatility clustering in returns and is superior to the conventional OLS model. Only one dummy variable for the day-of-the-week effect is significant in the ARCH model, namely the dummy for Tuesday in the Polish market. Otherwise, like in the OLS results, the well known day-of-the-week anomaly, in the form of negative Monday returns and higher positive returns for Friday is not detected by the ARCH model in all the six emerging stock markets.

However, for all the six markets, both OLS and GARCH models provide low values of the adjusted $R^{2.}$ This suggests that although daily returns show conditional heteroskedasticity, the actual extent of dependence is not significant enough for predicting future volatility.

The variance estimates for the Czech, Polish, Hungarian and Slovakian markets show significant ARCH and GARCH effects with $\sum \alpha_i$ close to unity. For the Croatian and Russian markets, however, the effects are not significant. When $\sum \alpha_i$ is close to unity, the ARCH model is integrated in variance and analogous to a unit root in conditional mean; this evidence suggests that the return generating process is characterised by a high degree of persistence in conditional variance. Consequently for the Czech, Polish, Hungarian and Slovakian markets, the high aggregate value of α's in the ARCH suggest that shocks to the variance have substantial persistence. The computed asymptotic t-statistics indicate that prior day's return or variance has a significant effect on the current daily return.

Overall, the results show the presence of significant autoregressive conditional heteroskedasticity, suggesting that daily returns do not conform to the random walk model in all the six markets. For Hungary, therefore, our results contradict the findings of Dockery and Vergari (1997) who, using variance-ratio tests on weekly data, find that the Budapest stock exchange is a random walk market.

Clearly, the ARCH procedure does not normalise residuals as indicated by the presence of skeweness, kurtosis and autocorrelation. In this context, it is interesting to investigate whether the residuals even though not normal, are identically and independently distributed and are free from non-linearity. The residuals from the OLS and ARCH procedures are, therefore, tested for non-linearity using the BDSL test. It is found that for the Hungarian, Polish, Slovakian, and Russian markets, significant BDSL statistics for the residuals from the ARCH models occur at epsilon one and half and two times the standard deviation and they are larger for the higher embedding dimensions shown in Table 5. However, non-linearity is not present in the residuals from the ARCH models for Croatia and Czech markets. This suggests that the non-linearity caused by volatility clustering is captured by the GARCH models for Croatian and Czech markets.

The conditional volatility of the Croatian market estimated by the GARCH model is shown in Figure 1. Significant volatility is shown for the period 14 August – 17 September 1998, with a peak on 3 September 1998. The peak may be explained by the turbulent August – September 1998 period associated with the financial crisis in Russia. Average conditional volatility is 9.25%, which is higher than those for the Czech, Polish, Hungarian and Slovakian markets.

Figure 2 shows the conditional volatility in the Czech market. The pattern exhibits various peak and troughs, with significant volatility during 28 August – 7 October 1998 as well as 12 May – 1 June 1999. Average conditional volatility is 1.73%, which is the lowest in the six markets.

The conditional volatility of the WIG-20 and the BUX estimated by the GARCH model is shown in Figures 3 and 4, respectively. For the WIG-20, the volatility shows a cyclical pattern; significant volatility is detected for the periods 15-28 July 1994 and 7-16 September 1994. Average conditional volatility is 5.32%. For the BUX, the pattern exhibits various peak and troughs, with significant volatility during August 1993, October 1997 and September 1998. Average conditional volatility is 6.45%. The evidence on the WIG-20 and the BUX suggests that in both Hungarian and Polish markets, the risk premium required by the investors for undiversifiable risk should be time-varying.

Figures 5 and 6 show the conditional volatility of the Slovakian and Russian markets, respectively, estimated by the GARCH model. For the former, significant volatility is observed only for the period 9 June - 5 July 1994. Average conditional volatility is 2.33%. For the Russian market, there is considerable volatility, in October 1996 and October 1998. The average conditional volatility is 22.16%, which is the highest in the six markets covered in this paper. As indicated in Section 2 of this paper, the high volatility may be explained by the Russian financial crisis.

2.4 Conditional volatility and expected returns: GARCH–in–Mean

We extend the GARCH model to the GARCH-in-Mean (GARCH-M) with an aim to examine whether conditional volatility is priced (see the seminal work by Engle, Lilien and Robins 1987). If conditional variance $h^{1/2}$ given the available information at time t-1 is included in Equation (1):

$$\Delta P_t = \gamma_0 + \sum_{i=1}^{n} P_i \Delta_{t-i} + \sum_{j-1}^{m} D_j {}_{tj} \theta + h \sqrt{{}_t} \varepsilon + {}_t \qquad (3)$$

where the conditional variance ht is defined by equation (2). Chou (1988) uses the GARCH–M model in examining the risk premium assumptions, while Bollerslev, Engle and Wooldridge (1988) use a multivariate GARCH–M model to test for time-varying risk premiums. Due to non-availability of data on risk-free returns in many emerging markets, empirical testing of the risk premium hypothesis is indirect. GARCH–M specification provides a convenient and robust measure since it connects conditional volatility and expected returns described in equation (3) which is used as a proxy for risk premium if the hypothesis of time-varying risk premium is true.

Our testing procedure for the GARCH-M model closely follows Theodossiou and Lee (1995) by testing the hypothesised relationship between conditional volatility and expected returns, as specified in equation 3. Table 6 reports the estimation and testing with and without inclusion of lagged values and dummy variables. For all the six stock markets in this study, the insignificant coefficients for (θ) suggest that there is no relationship between conditional volatility and expected (future) returns. This result also suggests that the GARCH-M model does not connect time varying volatility to the mean of daily stock returns. Overall, therefore, the evidence rejects the hypothesis that conditional volatility is priced in the Croatian, Czech, Polish, Hungarian, Slovakian and Russian emerging stock markets.

2.5 Exponential GARCH (EGARCH) and Asymmetric Threshold ARCH (ATARCH)

It is often observed that the impact of the most recent news is exponential rather than quadratic (see, Nelson, 1991). Moreover, Black (1976), Pagan et al. (1990), Sentena (1992), and Engle and Ng (1993) provide evidence that a negative shock to stock returns generates more volatility than a positive shock of equal magnitude. Christie (1982) argues that the weight of the debt in the capital structure rises with the fall in stock prices and this leads the equity shareholders to anticipate higher returns due to increase in risk. We therefore employ the EGARCH and TARCH models to test for the asymmetric effects in volatility.

Under EGARCH the specification for the variance is:

$$log\left(\sigma_t^2\right) = \omega + \beta \log\left(\sigma_{t-1}^2\right) + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{4}$$

The variance has asymmetric effect if $\gamma \neq 0$. Because of the log transformation, there is no possibility of a negative variance and the impact of the most recent residual is exponential rather than quadratic.

Threshold ARCH (see, Rabemanajara & Zakoian, 1993 and Zakoian, 1994) models variance as:

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

where $d_1 = 1$ if $\varepsilon_t < 0$and 0 otherwise.

Good news has an impact of α while bad news has an impact of $\alpha + \gamma$. If γ is significantly different from zero, then leverage effect exists.

The results reported in Table 7 suggest that the γ which captures the asymmetric effects is statistically significant only for Slovakia and Russia (only in EGARCH) suggesting presence of leverage effects in these markets. For all other markets γ is not significantly different from 0. However, persistence parameter β is highly significant for all markets (except in EGARCH for Russia), indicating that volatility effects in these markets are persistent and any shock tends to die out slowly. The coefficient for first order autoregression φ is highly significant for Czech, Poland, and Hungary whereas, the ARCH term α is found significant in almost all markets suggesting that the ARCH effects are not fully captured by EGARCH and TARCH models. Both EGARCH and TARCH perform poorly with very low adjusted R^2 and fail to eliminate high kurtosis from the residual particularly in case of Russia.

As a further test of these models, BDSL statistics are calculated from the residuals. As can be seem from Table 8, EGARCH and TARCH fail to capture non-linear effects in stock returns as significant BDSL statistics are observed for various embedding dimensions for all markets.

3. Concluding Remarks

In this paper, we empirically study the main features of stock market volatility in the emerging markets of Central and Eastern Europe using daily indexes. Starting with the universe of all the emerging markets in the European transition economies, we use the criterion of data availability to obtain the sample of six stock markets used in the empirical analysis: these are Croatia, Czech Republic, Hungary, Poland, Russia and Slovakia.

In general, the empirical results identify the key volatility characteristics of the six emerging stock markets. The results suggest that in all six markets, daily return volatility exhibit significant conditional heteroskedasticity and non-linear effects. The GARCH model is able to capture non-linearity only in Croatian and Czech markets suggesting that non-linearity caused by shocks is reflected in the heteroskedastic behaviour. Although they outperform the conventional OLS models, GARCH models are not able to fully capture non-linear patterns for all six markets. The well-known day-of-the-week effect, reflected in significantly positive Friday and/or negative Monday returns and commonly found in most markets, do not appear to be present in all the six emerging stock markets. Broadly, the evidence suggests that the martingale hypothesis, that future changes of the daily stock prices in each of the six markets are orthogonal to the past information, can be significantly rejected.

Finally, volatility seems to be of a persistent nature, however, no asymmetric effects are found for most of the markets. Moreover, in all six markets, as measured by a GARCH-M model, volatility does not explain expected returns. Although GARCH appears to be most appropriate process in characterising volatility, the explanation provided by the model is not significant enough for predicting future volatility.

However, while we test for volatility using the main standard techniques, based on ARCH and GARCH models and their extensions, it is possible that some novel techniques for testing for volatility could have uncovered some non-conventional results. For example, Shields (1997) proposes and implements a double-censored tobit GARCH to investigate whether the asymmetry commonly found in developed stock markets, in which negative shocks entering the market lead to a larger return volatility than positive shocks of a similar magnitude, holds true in two emerging stock markets in Eastern Europe. The evidence suggests that no such asymmetry exists on either the Warsaw Stock Exchange or the Budapest Stock Exchange. Clearly, Shield's double-censored tobit GARCH technique is useful for further research on valitility in selected East European emerging stock markets. In particular, further research should be able to address the problem of consored returns on the Warsaw and Moscow stock exchanges, which we could not explain adequately in this paper.

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