Modeling Financial Market Volatility in Transition Markets: A Multivariate Case

by Leoni Eleni OIKONOMIKOU[1]

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[1] PhD Candidate at Georg-August University of Goettingen, Germany,

Contact address: 22, Svoronou str., 60100, Katerini, Greece,

e-mail: leoni-eleni.oikonomikou@wiwi.uni-goettingen.de

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Abstract:

This paper presents evidence of linkages across equity markets in the following transition economies: Russia, Ukraine, Poland and Czech Republic from beginning of January 2005 till the end of December 2014. I apply a multivariate asymmetric EGARCH model. Empirical results indicate significant return and volatility spillover effects during the full sample, the Russian Great Recession and Ukrainian crisis episodes. Over the full sample period, there is evidence of return co-movements, and strong volatility persistence. During the Russian Great Recession subsample, the own-return effects of the markets are stronger than the cross-market effects and their correlations have increased. Finally, the Ukrainian political crisis indicated no clear information producer, whereas, evidence of returns co-movement still exists. The markets in question are mainly partially integrated and the volatility transmission linkages across them are not that strong in crises periods, thus confirming previous literature on the particularities of emerging and frontier markets.

Keywords: Multivariate EGARCH models, spillover effects, transition markets, equity markets.

Section 1 Introduction

Volatility is a crucial factor for assessing the performance of financial markets with very volatile ones being perceived as not functioning effectively towards channeling savings into investment (Park and Linton, 2012). Therefore, a good modelization of the sources, magnitude and persistence of volatility in equity markets is crucial in making informative investment decisions about pricing local securities, implementing appropriate hedging and asset allocation strategies, as well as developing and implementing regulatory recommendations to restrict international capital flows.

Motivated by the ongoing Ukrainian political crisis, the purpose of this paper is to uncover whether financial market shocks are transmitted across equity markets in the region. Specifically, we focus on several transition equity markets, since there is a lack of empirical studies focusing on this region and in particular on the Ukrainian frontier transition market. My paper aims to answer the following research questions: Is the volatility of a market leading the volatility of other markets? Does the shock on a market increase the volatility in another market? Do the correlations between stock market returns vary over time? Are they higher during periods of higher volatility (usually linked with financial crises)? Are the markets in the region interdependent or driven by their own-volatility effects, in a longer time horizon?

In this vein, a large number of theoretical and empirical studies have attempted to better understand comovements, interdependencies and linkages across equity markets. Beirne, *et al.* (2010) assess global and regional spillover effects in 41 emerging markets in Europe, Asia, Latin America and Middle East. Their results indicate the existence of spillovers to regional and global markets in most of the emerging markets. However, although spillovers in mean returns are present in emerging Asia and Latin America, spillovers in variance play a major role in Emerging Europe.

My contribution in the literature is three fold. First, I focus on transition markets where there is limited empirical literature. Second, I examine potential transmission effects of the regional financial crises, Great Russian Recession and Ukrainian political crisis. This has implications for investors interested in investing in the region as well as on the frontier Ukrainian market in particular. Frontier markets by definition are supposed to be less correlated with the other markets and mainly driven by their own-effects, therefore they can be used by investors for portfolio diversification purposes. Third, my methodological approach follows Koutmos (1996) methodological approach which has not been applied to an emerging/frontier market context.

The paper is organized as follows. Section 2 presents an overview of the related literature and Section 3 provides a description and analysis of the data used in this study. Section 4 describes the methodology and Section 5 analyzes the empirical results. Finally Section 5 concludes and summarizes the key findings.

Section 2 Literature Review

In the empirical finance literature, an extensive body of studies explores how financial crises are transmitted to domestic and international markets, usually referred as *contagion* (Forbes and Rigobon, 2002; Karanasos *et al.*, 2014; Kenourgios *et al.*, 2011).

As previously mentioned, another strand in the literature examines linkages and interdependences across international financial markets. These terms are usually referring to normal periods. Hamao *et al.*(1990) examine the interdependence of returns volatility across three developed stock markets and provide evidence of unidirectional volatility spillovers from US to Japanese stock market. Conversely, Lin, *et al.* (1994) find bidirectional linkages between the former two stock markets. Koutmos and Booth (1995) assess the linkages among US, Japanese and UK stock markets by applying an asymmetric Multivariate EGARCH model that differentiates between good and bad news effects. Their findings suggest that volatility spillovers are higher when news is bad and when prices fall in the latest market to trade before opening. Booth *et al.* (1997) applied the same methodology and provided evidence on price and volatility spillovers among Scandinavian stock markets. Their findings are also in line with Koutmos and Booth (1995) that volatility transmission is asymmetric with negative news having larger importance than positive ones.

Factor models such as the ones developed by Bekaert and Harvey (1997) and Ng (2000) are also alternative methods of modeling the volatility behavior in equity markets. Cuadro-Sáez *et al.* (2009) analyze the transmission of emerging market shocks to global equity markets. Using a large dataset with both mature and emerging markets, they find that emerging market shocks have a statistically and economically significant impact to global equity markets, thus confirming their initial assumption of systemic importance of the emerging market economies as drivers of global asset price developments. Scheicher (2001) examines whether the equity markets in Poland, Hungary and Czech Republic are regionally and globally integrated by estimating a vector autoregression with a multivariate GARCH component. His empirical findings suggest that volatility innovations have a regional character whereas returns are influenced by both regional and global shocks. Li and Mayeroska (2008) examine the linkages among Warsaw, Budapest, Frankfurt and US stock markets by using an asymmetric multivariate GARCH model. They find evidence of unidirectional return and volatility spillovers from developed to emerging markets, thus suggesting portfolio diversification benefits from risk reduction and low correlation of emerging markets with their developed counterparts. Saleem (2009) examines international linkages of Russian equity market with the rest of the world and international transmission effects of 1998 Russian financial crisis. He provides evidence of direct linkages of Russia with the rest of the world but these linkages are weak indicating partial integration of Russian equity market. His estimated results also confirm contagion effects during the Russian financial crisis with the rest of the markets.

Section 3 Data Analysis

I use stock market indices from three emerging and one frontier market in transition. These stock market indices are the following: Russian Trading System Index (RTS), PFTS Index of Ukraine (PFTS), Warsaw Stock Exchange WIG Index of Poland and PX Index of Czech Republic. All data are sourced from DATASTREAM. The full sample period under study is from January 1, 2005 through December 31, 2014. The selection of this sample period has been done in order to include the financial crises of 2008-2009 (Great Recession in Russia) and the Ukrainian political crisis. My aim is to investigate the sources, magnitude and persistence in volatility among the equity markets.

I use daily data in order to capture more information, such as potential financial shocks that may last for a couple of days. Holidays or Non-Trading Days in at least one of the stock exchanges under study, are excluded from the sample for all markets. Therefore, I have a total number of 2187 observations (excluding public holidays and non-trading days). The number of observations for the Russian Great Recession subsample is 434 and for the Ukrainian crisis one is 247 observations. In addition, since all countries are geographically close, they have adjacent time zones. This does not influence the prices in their stock markets.

The selected stock market indices represent the benchmark stock index and track the overall performance of the largest-capitalization firms in the corresponding country. The RTS Index is a capitalization weighted composite index and is calculated based on prices of the 50 most liquid Russian stocks trading on the Moscow Exchange.

The index was launched on September 1, 1995 at base value 100 and is denominated in US$[2]. PFTS Index is the benchmark stock index of the PFTS Ukraine Stock Exchange. It was created on October 1st, 1997, as a capital-weighted price index of the 20 major and most liquid Ukrainian stocks trading at PFTS Ukraine Stock Exchange[3]. Warsaw Stock Exchange WIG Index is a free-float total return index that includes dividends and pre-emptive rights (subscription rights). The Index was launched on April 16, 1991, with base value 1000. It includes 361 companies listed and trading on Warsaw Stock Exchange (excluding foreign companies and investment funds) as of February 28, 2011[4]. Finally, PX Index is the benchmark index of Prague Stock Exchange. It was first calculated on March 20, 2006, after having replaced PX50 and PX-D Indices and taking over all the historical values of PX50 Index (was initially launched on April 5, 1994, with a base value of 1000 points)[5].

Figure A.1 in the Appendix shows the adjusting closing prices for all seven stock market indices. Each index has a trough during 2008-2009 indicating that all these markets have been affected by the financial crisis during that period. By the end of 2013-2014 the Russian market is clearly affected by the Ukrainian crisis, and the Ukrainian and Czech equity markets show some signs of influence, as well.

I transform the stock market indices to continuously compounded daily returns for each stock market by multiplying the ratio of the logarithm of stock market indices by 100:

[2]fs.rts.ru/files/4114/4937

[3]http://www.pfts.ua/en/indexes/

[4]http://www.gpw.pl/pub/files/PDF/opisy_indeksow_en/WIGopis_ang.pdf;
http://www.gpw.pl/opis_indeksu_WIG_en

[5] http://www.pse.cz/dokument.aspx?k=Burzovni-Indexy

$$r_t = \ln\left(P_t / P_{t-1}\right) * 100, \qquad (1)$$

where P_t is the stock market price index at time t. Figure A.2 shows the stock market returns for all stock market indices during the whole sample period. Figure A.3 shows the sample volatilities and the monthly "slowly-changing" variances for all four stock market returns. The latter is calculated based on the following formula:

$$\sigma_t^2 = \frac{1}{W} \sum_{s=t-W+1}^{t} r(s)^2 \qquad (2)$$

In this case the volatility is estimated via a moving/rolling window with width $W = 20$ which does repeated calculations using the most recent W data points.

Table 1 presents the main descriptive statistics of stock market returns for all four indices over the full sample and the two subsample periods. Apart from the mean returns of Czech Republic which is negative, all the other mean returns of the three indices are slightly positive. In terms of stock market performance, Poland has the highest annualized mean returns (7.60032), while Czech Republic has the worst performance based on its annualized mean returns (-0.99288). Russian and Ukrainian stock index price returns, which remain at the center of attention in this study, are the ones that exhibit the highest volatility with annualized standard deviation 38.6242 and 32.36812 accordingly. Czech Republic and Polish stock index price returns follow with annualized standard deviations of 25.68486 and 22.45275 respectively. Based on skewness statistics, Russia, Poland and Czech Republic have slight negative skewness highlighting that large negative returns are more frequent than large positive returns. Contrary to the previous statistics, Ukraine, has positive skewness (0.4813). Further, all the return series have excess kurtosis, namely are leptokurtic, which is quite common with financial time series at these frequencies. The one that has the lowest kurtosis (7.071) is Poland.

Jarque - Bera statistics test (Jarque and Bera, 1987) is also presented. It is computed via the following formula:

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4} \right), \tag{3}$$

where S is skewness and K is kurtosis. The Test (p-value) indicates that we should reject the null hypothesis of normality at the one percent of significance for all return series. Table 1 also presents Q-statistics, Qs-statistics and their corresponding p-values for Ljung-Box (1979) test. The Q_{LB}-statistic at lag m is a test statistic with null hypothesis that there is no autocorrelation up to order m and is computed as:

$$Q_{LB} = n(n+2)\sum_{k=1}^{m} \frac{\hat{\rho}_k^2}{n-k}, \tag{4}$$

where n is the number of observations, $\hat{\rho}_k$ is the sample autocorrelation at lag k and m is the number of lags being tested. Under H_o, the statistic Q follows a $\chi^2_{(m)}$. For significance level α, the critical region for rejection of the hypothesis of randomness is $Q \succ \chi^2_{1-\alpha,h}$, where $\chi^2_{1-\alpha,h}$ is the α-quantile of the chi-squared distribution with h degrees of freedom.

Table 1 : Descriptive Summary Statistics - Full sample period

	FULL SAMPLE PERIOD			
Country	RS	UKR	POL	CZR
Mean	0.012	0.0182	0.0302	-0.004
Median	0.116	0.075	0.0796	0.05
Maximum	20.204	19.674	6.301	12.364
Minimum	-24.668	-15.183	-10.186	-12.52
Std. Dev.	2.433	2.039	1.414	1.618
Skewness	-0.796	0.4813	-0.541	-0.415
Kurtosis	16.831	15.702	7.071	12.429
J-B	17671.84	14792.28	1617.57	8167.03
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
# of days	2187	2187	2187	2187
LB-Q(12)*	577.914	373.119	562.601	1325.72
(p-value)	(0.0000)	(0.0000)	(0.0019)	(0.0000)
LB-Q(24)*	105.717	205.805	38.624	107.793
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LB-Qs(12)**	577.914	373.119	562.601	1325.72
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)
LB-Qs(24)**	1198.832	524.288	831.427	1700.101
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)

* LB-Q(12) and LB-Q(24) represent the Ljung-Box Q-statistics test for return series up to 12 and 24 lags.
** LB-Qs(12) and LB-Qs(24) represent the Ljung-Box Qs-statistics for the squared return series up to the same number of lags.

Based on Q and Qs-statistics reported by Table 1, we strongly reject the null hypothesis of independence at five percent of significance which means that all return series and their squared returns are serially dependent. The rejection of the null at the squared return series shows that the returns exhibit "volatility clustering" which is also visually apparent (via the returns graphs in Figure A.2 in the Appendix) and confirms the appropriateness of introduction of GARCH-type models.

Another aspect that has to be reported is whether time series are stationary since non-stationary might lead to spurious regressions. In this study, we apply three tests to test whether time series are stationary. The first one is the Augmented Dickey-Fuller

(ADF) test proposed by Said & Dickey (1984) who improved the Dickey-Fuller (DF) test (Dickey & Fuller, 1979) to allow the time series to be autocorrelated at higher order lags. The null hypothesis for an ADF test is that the series tested has a unit root. The second one is the PP test (Phillips & Perron, 1988) and is similar in logic with ADF test. However, unlike ADF test, it makes a non-parametric correction to the t-test statistic. The third one is the KPSS test (Kwiatkowski, *et al.* 1992) which tests whether the return series is stationary rather than the opposite. The results of these two tests are reported in Table 2. The results from the unit root tests demonstrate that the stock market indices series are not stationary in level, but they are stationary in first differences (returns series). This also means that all series have the same order of integration I(1).

Table 2: ADF, PP, and KPSS unit root tests.

	LEVELS			FIRST DIFFERENCES		
Test	ADF*	PP*	KPSS*	ADF*	PP*	KPSS*
RS	-0.41473	-1.95566	2.385778	-34.6431**	-34.6258**	0.393201
	Accept	Accept	Reject	Reject	Reject	Accept
UKR	-0.31969	-1.33032	4.857905	-30.8714**	-31.0054**	0.327808
	Accept	Accept	Reject	Reject	Reject	Accept
POL	0.49443	-2.14174	5.773275	-37.9637**	-37.9981**	0.156032
	Accept	Accept	Reject	Reject	Reject	Accept
CZR	-0.42697	-2.45739	21.54885	-38.5683**	-38.5926**	0.131061
	Accept	Accept	Reject	Reject	Reject	Accept

* Critical values for the unit root tests are -3.437 (ADF and PP) and 0.739 (KPSS), without intercept and trend for ADF and PP tests, and with intercept for KPSS test.

** We reject the null hypothesis of existence of Unit Root at 1% for ADF and PP tests and accept the null for KPSS test for the same level of significance.

Section 4 Description of Methodology

The objective in this paper is to uncover potential return and volatility interdependencies and/or spillovers among the following financial markets, namely Russia, Poland, Czech Republic and Ukraine. Taking into account the summary statistics of the previous section, a Multivariate EGARCH (MGARCH) model is deemed as appropriate. Our methodological analysis and modelization follows Koutmos (1996).

For the mean equation, we employ a Vector Autoregressive model (VAR), which became well known by Sims (1980) and later applied by Hamilton(1994). The VAR model allows us to analyze the return spillovers among stock markets. We use information criteria (AIC, BIC, HQ) to consider upon the most appropriate lag for our VAR model.

We proceed to a simultaneous estimation of the mean equation and the variance-covariance equations. Based on the VAR lag selection criteria and the multivariate residual diagnostics tests we adopt a VAR(1) for the full sample period and the two subsample periods. The purpose of this choice for the lag is twofold: the small lag reduces the number of parameters in the model, thus making it faster to estimate and easier to interpret later on. In addition, based on the information criteria for lag selection (results of the lag selection criteria are not reported for the sake of brevity) one lag is deemed as sufficient.

In the standard VAR modelization, the disturbance vector is assumed to be an unobservable zero mean white noise vector process, with a time invariant covariance matrix. However, since our financial data exhibit 'volatility clustering' patterns (Fama, 1965; Mandelbrot, 1963) we consider of modeling time-varying second-order moments.

Our modelization on Multivariate VAR-EGARCH modeling is the following: Let $r_t = (r_{1,t}, r_{2,t}, r_{3,t}, r_{4,t})'$ denote the continuously compounded percentage return for market $\boldsymbol{i}$ where, $\boldsymbol{i = 1, 2, 3, 4}$ $(\boldsymbol{1 = Russia, 2 = Ukraine, 3 = Poland, 4 = Czech\ Republic})$**:**

$$r_{i,t} = \beta_{i,0} + \sum_{j=1}^{4} \beta_{i,j} r_{j,t-1} + \varepsilon_{i,t},\ for\ i, j = 1, 2, 3, 4 \quad (5)$$

$$\sigma_{i,j}^2 = \exp\{a_{i,0} + \sum_{j=1}^{4} a_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)\} \quad for\ i, j = 1, 2, 3, 4 \quad (6)$$

$$f_j(z_{j,t-1}) = (|z_{j,t-1}| - E(|z_{j,t-1}| + \delta_j z_{j,t-1}) \quad for\ j = 1, 2, 3, 4 \quad (7)$$

$$\sigma_{i,j,t} = \rho_{i,j} \sigma_{i,t} \sigma_{j,t} \quad for\ i, j = 1, 2, 3, 4\ and\ i \neq j \quad (8)$$

where Ω_{t-1} is the σ- field generated by all the information available at time $t-1$, $\mu_{i,t}$ and $\sigma_{i,j,t}$ the conditional covariance between markets i and j, $\varepsilon_{i,t}$ the innovation at time t, $\varepsilon_{i,t} = r_{i,t} - \mu_{i,t}$ and $z_{i,t}$ the standardized innovation (residuals) where $z_{i,t} = \varepsilon_{i,t} / \sigma_{i,t}$.

The equation (5) represents the return spillovers as a VAR, in which the conditional mean in each market is a function of past own returns and cross-market past returns (Koutmos, 1996). The coefficient $\beta_{i,j}$ captures the lead/lag relationships where a significant $\beta_{i,j}$ coefficient illustrates that market i leads market j or, alternatively, current returns in market j can be used to forecast future returns in market i.

Equation (6) describes the conditional variance of returns as an exponential function of past own as well as cross-market standardized innovations. Equation (7) demonstrates its specific form which allows standardized own and cross-market innovations to influence the conditional variance in each market in an asymmetric way. For instance, for $z_{j,t} > 0$ the slope of equation (7) becomes $1+\delta_j$, whereas for $z_{j,t-1} < 0$, it becomes $-1+\delta_j$. Furthermore, the term $(\left|z_{j,t-1}\right| - E\left|z_{j,t-1}\right|)$ measures the effect of magnitude. In a similar way, the term $\delta_j z_{t-1}$ measures the sign effect. Based on the coefficient sign and the innovation sign, the sign effect may be reinforcing or partially offsetting the magnitude effect.

The relative importance of the asymmetry, or leverage effect is captured by the ratio $\left|-1+\delta_j\right| / (1+\delta_j)$. Volatility spillovers and/or interactions among markets are measured by $a_{i,j}$. The persistence of volatility shown in equation (6) is γ_i.

The conditional covariance specification given by (8) illustrates that the correlation of the returns of markets i and j is constant. This assumption simplifies the estimation of the model. However, even with significant simplifications, the number of parameters to be estimated is fifty four.

Under the normality assumption, the log likelihood for the multivariate VAR-EGARCH model (Koutmos, 1996) is the following:

$$L(\Theta) = -0.5(\mathrm{NT})\ln(2\pi) - 0.5\sum_{t=1}^{T}(\ln\left|S_t\right| + \varepsilon_t^{'} S_t^{-1}\varepsilon_t) \qquad (9)$$

where N is the number of equations, T is the number of observations, Θ is 54×1 parameter vector to be estimated, $\varepsilon_t^{'}=\left[\varepsilon_{1,t},\varepsilon_{2,t},\varepsilon_{3,t}\varepsilon_{4,t}\right]$ is 1×4 vector of innovations at time t, S_t is the 4×4 time-varying conditional variance covariance matrix with diagonal elements given by equation (6) for $i=1,2,3,4$ and $i\neq j$. Due to the fact that the log-likelihood is highly non-linear the BFGS algorithm (Broyden, 1970; Fletcher, 1970; Goldfarb, 1970; and Shanno, 1970) is then employed to obtain the final estimates and their corresponding p-values.

Section 5 Empirical Results

This section analyzes the estimation results for the overall sample period (2005-2014) and the two sub-samples, namely the Russian Great Recession of 2008-2009 and the Ukrainian Crisis (11/21/2013 - 12/31/2014) periods. Our study includes three emerging and one frontier market. We employ a four-variable asymmetric multivariate EGARCH model in order to analyze the financial market interdependencies and potential contagion effects during the analyzed period.

The correct specification of the model is tested via a Multivariate Ljung-Box Q test for the residuals and their squared residuals. This test was first presented by Hosking (1981) to test for white noise in a set of time series. Therefore, if mean and variance equations are correctly specified, all Q-statistics for the standardized residuals and Qs-statistics for the squared standardized residuals should not be statistically significant. Their test statistics and p-values are presented in the Appendix Tables A.5~1-3. We choose to report the 24^{th} and 36^{th} lag order statistics. This choice has been done in order to account for the lag selection problem mentioned by Harvey (1981) that a test with small lag may not detect any potential serial correlation and testing with higher-order lag may lower the power of the test. These statistics clearly show that we cannot reject the null hypothesis for both tests and confirm that we have the appropriate specification for all countries.

5.1 *Evidence of financial market linkages in full sample period*

The overall sample period comprises of 10 years. The estimated coefficients for the variance covariance matrix of equations using the benchmark stock indices for each country are presented in the Appendix Tables A.5.~1-3 We obtain the coefficient estimates via Maximum Likelihood. As previously mentioned the coefficients $\beta_{i,j}$ measure the lead/lag relationships, respectively.

In the full sample period, there are statistically significant lead/lag relationships. More specifically, such a relationship exists among the following pairs: Russia-Czech Republic, Ukraine-Poland, Ukraine-Czech Republic, Poland-Czech Republic, Czech Republic-Russia and Czech Republic-Poland, with the causality running from market i to market j. This effect demonstrates that current returns in market j can be used to predict future returns in market i. As expected, almost all countries exhibit a lead/lag relationship and this is interpreted by their close geographic proximity and their financial market relations, especially among Russia-Ukraine-Poland as well as the fact that their expected returns are time-varying. The results also indicate that these markets are driven by their own return effects. Both empirical results imply the speed one market reflects new information relative to the other and how well these markets are connected. The cross-market return coefficients are relatively low compared to the own return coefficients. This implies that own return effects are stronger than the cross-market return ones. However, it is clear that no market plays the role of information producer and current returns are correlated with past returns among several markets.

The second moment interdependencies are taken into account by the coefficients $\alpha_{i,j}$, γ_i and δ_i. These coefficients measure the volatility interactions or spillovers, volatility persistence and asymmetry, accordingly. In particular, the coefficients γ_i are all highly persistent (close to unity) and statistically significant. The coefficients δ_i also indicate the degree of asymmetry which is higher in the case of Russia and Poland (2.48 and 2.34 respectively) and lower in the Ukrainian case (0.897). This relative importance of the asymmetry is alternatively interpreted as that negative innovations increase the volatility about 2.48 times more than positive innovations in the case of Russia. Similar holds for Poland. However, in the case of Ukraine, positive innovations increase the volatility about 0.897 times more than negative innovations, indicating that positive news influence more the volatility than negative news. Therefore both the size and the sign of the innovations matter for the transmission of volatility across the markets. The coefficients $a_{i,j}$ in combination with the previous ones demonstrate the multidirectional volatility spillovers among the tested markets and the extent to which the asymmetries can be evaluated.

In addition, the volatility persistence may be connected with the correlation structure presented. The correlation coefficients are all statistically significant at one percent and indicate strong correlation relationship among the following pairs: Russia-Poland, Russia-Czech Republic, Poland-Czech Republic, whereas the correlation is weaker among Russia-Ukraine, Ukraine-Poland, Ukraine-Czech Republic. This confirms previous literature that frontier markets, as it is the case with Ukraine are less correlated with developed and emerging markets and can be used for portfolio diversification purposes. Frontier markets are also accounted as not being influenced by global shocks and be mainly influenced by local or sometimes regional shocks. Indeed, in our case, investors can select the Ukrainian stock market in order to invest and mitigate their portfolio risk, across the full sample period (in a longer horizon).

Multivariate residual diagnostic tests indicate that the model is robust up to 24 and 36 lags accordingly.

5.2 Evidence of financial market linkages in financial crisis sub-sample period

During the Russian Great Recession sub-sample, empirical results demonstrate multidirectional return spillovers and lead/lag relationships among the following pairs: Ukraine-Russia, Ukraine-Czech Republic, Poland-Ukraine, Czech Republic-Russia (weakly statistically significant) and Czech Republic-Ukraine. As in the full sample period, there is no clear information producer, although current returns in Ukraine are correlated with past returns in Russia and Czech Republic. The same holds with Czech Republic stock market returns which are also correlated with Russian and Ukrainian stock market returns during the Russian Great Recession financial crisis period. This can be perceived as evidence of co-movement effect among these regional stock markets.

Turning to second moment spillovers, there is significant evidence of strong volatility persistence (very close to unity, except from Ukraine, which is somewhat lower but still highly persistent). This can be interpreted that these markets are weak-form efficient (although more evidence is needed in order to arrive to such a result) and there is an asymmetric impact of past innovations on current volatility. The degree of asymmetry in terms of the estimated coefficients δ_i is statistically significant in the case of Ukraine which means that positive innovations increase volatility about 0.596 times more than negative innovations. It is also perceived as evidence that the sign of innovations in Ukraine is important for the volatility transmission.

The combination between the coefficients $a_{i,j}$ and δ_i is also quite informative. For instance, in the case of positive $a_{i,j}$ the impact of the lagged standardized residuals on the current conditional variance will be positive if the magnitude of the lagged standardized residuals is greater than its expected value. Therefore, as previously mentioned, the size of innovations matter as well.

Moreover, the markets exhibit stronger correlations during the financial crisis period, which is in line with previous literature and might be perceived as an evidence of a contagion effect. Once more, multivariate residual tests pass the diagnostic tests for lags up to 24 and 36.

5.3 Evidence of financial market linkages in Ukrainian crisis sub-sample period

Finally, in the Ukrainian crisis there is evidence of return interactions, mainly between the following pairs: Russia-Czech Republic, Poland-Russia and Poland-Ukraine. In all three sample periods, no market is leading as information producer. However, Russia and Poland seem to play an important role in disseminating the information in financial returns across the region. One of the reasons is that they hold the largest market share in the region; Poland is the largest financial market in Central and Eastern Europe and Russia is the largest financial market in the Eastern European and Eurasian region.

Concerning the second moment interdependencies, a positive $a_{i,j}$ and a negative δ_i imply that negative innovations in market j have a higher impact on the volatility of market i than positive innovations. The relative importance of the asymmetry or leverage effect for the Ukrainian stock market is 1.76 (higher than in the Russian Great Recession crisis subsample) which means that negative innovations increase the volatility about 1.76 times more than positive innovations highlighting the importance of the crisis event for the market as well as the fact that this crisis might have existed to a lesser extent during 2008-2009 (the ratio is 0.59 for the Russian Great Recession crisis subsample).

The volatility is also persistent, but to a lesser extent, in particular, concerning the Polish market. Indeed, the correlations among this period are lower than in the previous subsample period possibly indicating the lower severity of the event compared to the Russian Great Recession of 2008-2009. However, surprisingly, the correlation between Polish and Czech stock markets has increased to almost 53 percent which demonstrates the high correlation between these two regional financial markets.

In addition, the multivariate residual tests confirm the robustness of the model for lags up to 24 and 36.

Section 6 Concluding Remarks

This paper examines the financial market linkages and regional spillover effects among transition markets from January 2005 to December 2014. We applied a multivariate EGARCH model to the daily benchmark stock index returns and found evidence of asymmetry, return spillovers and persistence of the effects.

The empirical results demonstrate no leading market as information producer. However, there exists strong return linkages across the markets during the overall sample period and the two sub-sample periods. Significant volatility spillover effects exist among almost all the financial markets, during the Russian Great Recession (2008-2009), in particular between Russia to Poland and Czech Republic, highlighting the regional importance about the Russian economic performance, as well as concerns on geopolitical risks, after the war in Georgia. During the Ukrainian crisis, there exists regional co-movements in returns between Russia and Czech Republic, Poland and Russia and Poland and Czech Republic indicating the important role Russian and Polish financial markets play in disseminating the information across the markets in the region. Finally, volatility spillovers are apparent in Ukrainian crisis subsample. Conversely, volatility spillovers are both unidirectional and bidirectional with high degree of persistence in some cases. There is also evidence that correlations among these markets are statistically significant and time-varying. In addition, the volatility became highly persistent during the Russian Great Recession.

The central message from these findings is that transition markets seem to be regionally integrated within the full sample period but within the crises periods are less driven by regional return and volatility spillovers from the region. A characteristic example is the Ukrainian stock market which is a frontier market and is less affected by the shocks in the region, thus confirming previous literature on investing in frontier markets in a longer time horizon. This conclusion is also in line with previous literature where less developed markets derive more of their volatility persistence from their domestic market (Worthington & Higgs, 2001). However, it is clear that in crises periods, they exhibit signs of correlation and interdependency.

Therefore, as demonstrated by the empirical results, longer term investors can benefit from including assets from emerging or even less-correlated frontier markets in their portfolios due to their weak regional integration. However, they have to consider implementing appropriate diversification and hedging strategies in crises periods, in order to be protected against political, economic and financial shocks. Further research, by applying different approaches, and exploring various asset classes, such as bonds, alternative investments and exchange rates can additionally enrich our understanding of the impact of the regional shocks and/or crises for portfolio management and asset allocation decisions.

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Section 7 Appendix

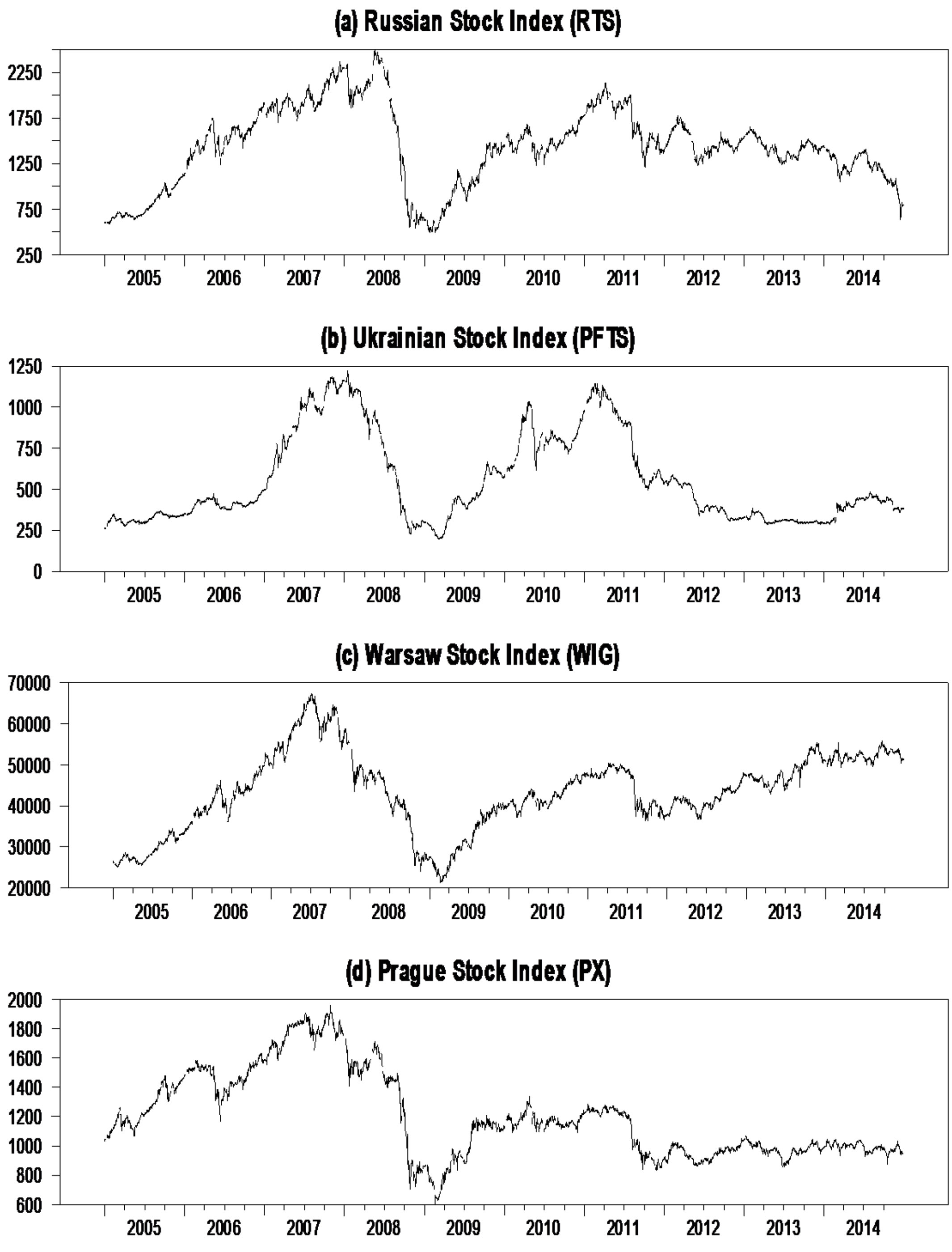

Figure A.1: Adjusted Closing Prices for all Four Stock Market Indices.

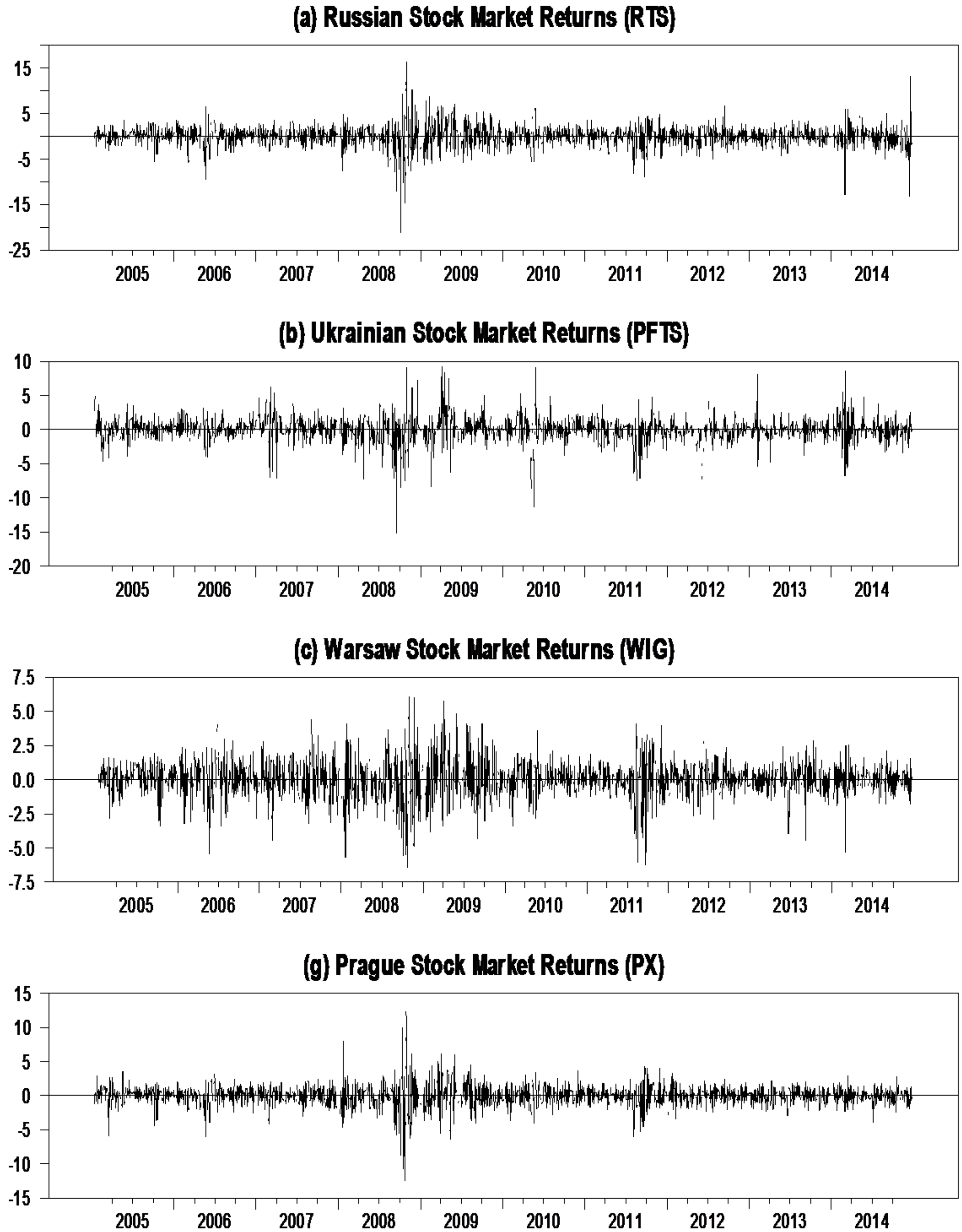

Figure A.2: Stock Market Returns for all Four Stock Market Indices

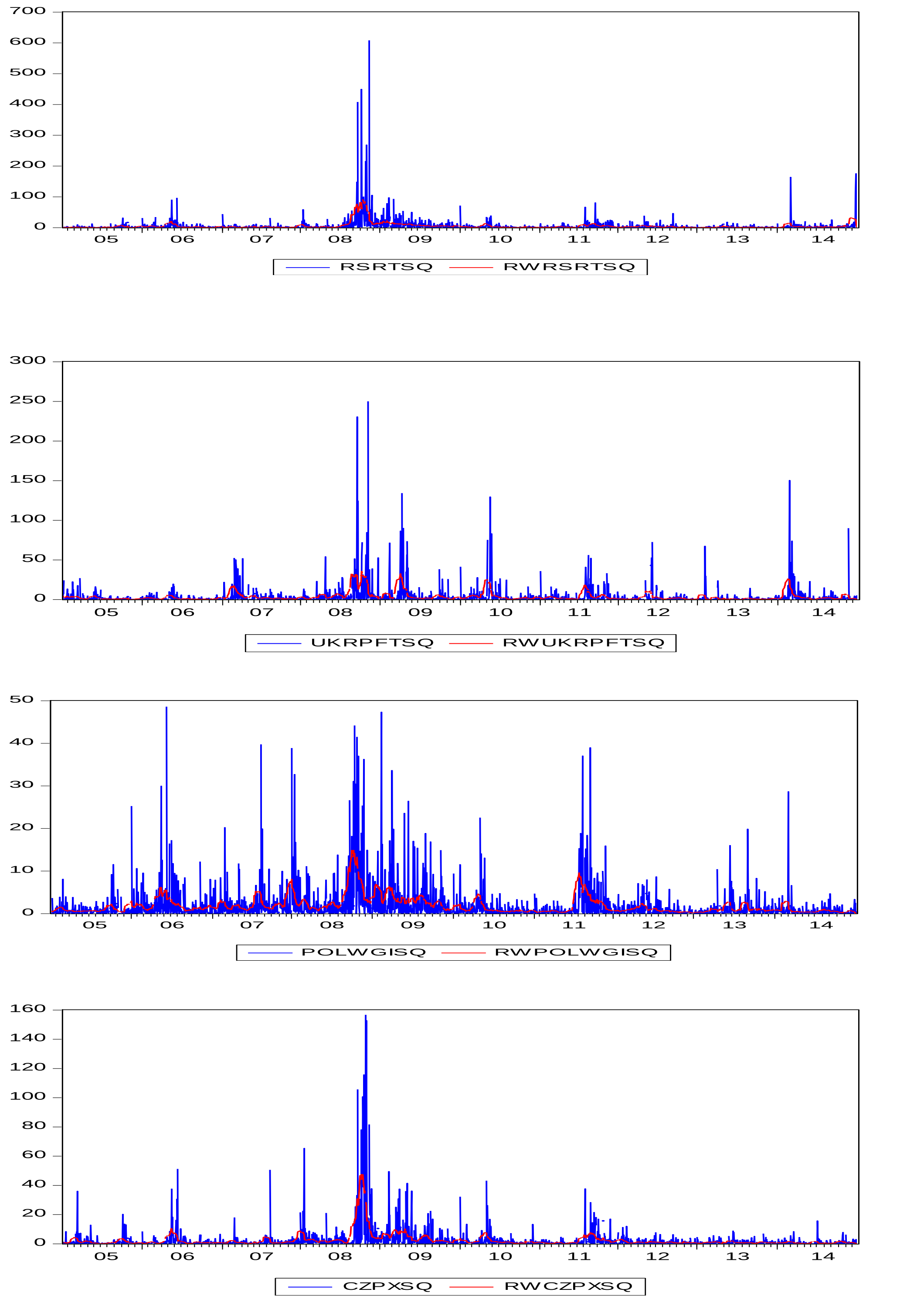

Figure A.3: Sample Volatilities and Monthly Rolling Window Volatilities of Stock Market Returns for all Four Stock Market Indices

Table A.4.1 : Correlation Table for the Full sample period

	RS	UKR	POL	CZR
RS	1.00000			
UKR	0.435483	1.00000		
POL	0.637165	0.340663	1.00000	
CZR	0.675337	0.377684	0.679606	1.0000

Table A.4.2 : Correlation Table for the Russian Great Recession crisis Subsample Period

	RS	UKR	POL	CZR
RS	1.00000			
UKR	0.56798	1.00000		
POL	0.672831	0.44344	1.00000	
CZR	0.738475	0.510957	0.753564	1.00000

Table A.4.3 : Correlation Table for the Ukrainian Crisis Subsample Period

	RS	UKR	POL	CZR
RS	1.0000			
UKR	0.148911	1.0000		
POL	0.483545	0.147134	1.0000	
CZR	0.38116	-0.00188	0.518668	1.0000

Table A.5.1 : Full Sample period estimation results

	RS(i=1)		UKR(i=2)		POL(i=3)		CZR(i=4)	
$\beta_{i,j}$(j=1)	0.0865	(0.000)	0.0051	(0.556)	0.0139	(0.183)	0.021	(0.06)
$\beta_{i,j}$(j=2)	-0.0005	(0.977)	0.2441	(0.000)	-0.0137	(0.219)	-0.0167	(0.104)
$\beta_{i,j}$(j=3)	0.0058	(0.836)	0.0353	(0.038)	0.0404	(0.027)	0.053	(0.001)
$\beta_{i,j}$(j=4)	-0.0712	(0.0001)	0.0526	(0.000)	-0.0484	(0.000)	-0.0329	(0.028)
Const. (β_0)	0.0501	(0.089)	0.024	(0.327)	0.0486	(0.012)	0.0207	(0.2606)
$\alpha_{i,j=1}$	0.0639	(0.000)	0.0195	(0.2952)	-0.0068	(0.522)	0.0028	(0.852)
$\alpha_{i,j=2}$	0.1161	(0.000)	0.4064	(0.000)	-0.0034	(0.787)	-0.0164	(0.295)
$\alpha_{i,j=3}$	0.0306	(0.031)	0.0657	(0.0015)	0.1252	(0.000)	0.0747	(0.000)
$\alpha_{i,j=4}$	-0.0179	(0.283)	-0.0359	(0.1447)	-0.0242	(0.152)	0.1344	(0.000)
Const. (α_0)	0.0639	(0.000)	0.158	(0.000)	0.0157	(0.000)	-0.0303	(0.000)
δ_i	-0.4256	(0.000)	0.0542	(0.027)	-0.4013	(0.000)	-0.0743	(0.154)
γ_i	0.9603	(0.000)	0.878	(0.000)	0.9726	(0.000)	0.9565	(0.000)

CORRELATION MATRIX

	RS	UKR	POL	CZR
RS	1.000	0.3674	0.6066	0.603
		(0.000)	(0.000)	(0.000)
UKR		1.000	0.2909	0.2904
			(0.000)	(0.000)
POL			1.000	0.6397
				(0.000)
CZR				1.000

MULTIVARIATE RESIDUAL TESTS

MVLB-Q(24)	410.8	(0.166)
MVLB-Q(36)	611.2	(0.15)
MVLB-Qs (24)	386.3	(0.457)
MVLB-Qs (36)	554.4	(0.734)

Table A.5.2 : Russian Great Recession crisis subsample estimation results

	RS(i=1)		UKR(i=2)		POL(i=3)		CZR(i=4)	
$\beta_{i,\,j}$(j=1)	0.1323	(0.573)	0.095	(0.001)	-0.0217	(0.509)	0.0653	(0.078)
$\beta_{i,\,j}$(j=2)	-0.0667	(0.127)	0.1533	(0.000)	-0.0646	(0.023)	-0.1182	(0.002)
$\beta_{i,\,j}$(j=3)	0.0115	(0.886)	0.0607	(0.236)	0.0647	(0.26)	0.0301	(0.646)
$\beta_{i,\,j}$(j=4)	-0.1062	(0.166)	-0.0875	(0.033)	-0.02	(0.704)	-0.0122	(0.846)
Const. (β_0)	0.0546	(0.573)	-0.1403	(0.014)	-0.047	(0.472)	-0.0095	(0.894)
$\alpha_{i,j=1}$	0.0543	(0.08)	-0.0331	(0.484)	0.0346	(0.286)	0.013	(0.817)
$\alpha_{i,j=2}$	0.1088	(0.000)	0.6764	(0.000)	-0.0085	(0.75)	0.0894	(0.01)
$\alpha_{i,j=3}$	-0.0014	(0.78)	0.0319	(0.756)	0.0079	(0.746)	0.0247	(0.763)
$\alpha_{i,j=4}$	-0.05	(0.071)	0.0181	(0.791)	0.07	(0.031)	0.1258	(0.047)
Const. (α_0)	0.0437	(0.032)	-0.3689	(0.000)	0.0373	(0.024)	-0,098	(0.009)
δ_i	-0.9259	(0.233)	0.2524	(0.000)	-6.2147	(0.764)	0.6443	(0.261)
γ_i	0.9826	(0.000)	0.797	(0.000)	0.973	(0.000)	0.9444	(0.000)

CORRELATION MATRIX

	RS	UKR	POL	CZR
RS	1.000	0.5586	0.6752	0.6929
		(0.000)	(0.000)	(0.000)
UKR		1.000	0.4895	0.5166
			(0.000)	(0.000)
POL			1.000	0.7622
				(0.000)
CZR				1.000

MULTIVARIATE RESIDUAL TESTS

MVLB-Q(24)	403.6	(0.236)
MVLB-Q(36)	604.6	(0.198)
MVLB-Qs (24)	344.1	(0.929)
MVLB-Qs (36)	578.8	(0.459)

Table A.5.3: Ukrainian Crisis subsample estimation results

	RS(i=1)		UKR(i=2)		POL(i=3)		CZR(i=4)	
$\beta_{i,j}$(j=1)	0.0812	(0.169)	-0.0555	(0.176)	0.0398	(0.047)	0.0158	(0.55)
$\beta_{i,j}$(j=2)	-0.0106	(0.84)	0.1632	(0.009)	-0.014	(0.000)	-0.0063	(0.763)
$\beta_{i,j}$(j=3)	-0.0799	(0.597)	-0.1608	(0.107)	0.0759	(0.108)	0.0652	(0.347)
$\beta_{i,j}$(j=4)	-0.2417	(0.032)	0.1272	(0.093)	-0.0496	(0.456)	-0.0761	(0.294)
Const. (β_0)	-0.2403	(0.003)	0.0712	(0.349)	-0.0033	(0.027)	-0.0432	(0.292)
$\alpha_{i,j=1}$	0.189	(0.074)	0.2624	(0.169)	0.057	(0.356)	-0.0531	(0.23)
$\alpha_{i,j=2}$	0.228	(0.001)	0.465	(0.000)	0.4738	(0.000)	0.0592	(0.451)
$\alpha_{i,j=3}$	-0.286	(0.000)	-0.0633	(0.762)	-0.2094	(0.067)	-0.0237	(0.617)
$\alpha_{i,j=4}$	0.013	(0.355)	-0.0408	(0.432)	0.0024	(0.832)	0.0185	(0.252)
Const. (α_0)	0.1034	(0.003)	0.21	(0.000)	-0.104	(0.027)	-0.0082	(0.504)
δ_i	-0.7439	(0.155)	0.2765	(0.034)	-0.3137	(0.191)	-7.1876	(0.23)
γ_i	0.9335	(0.000)	0.846	(0.000)	0.6458	(0.000)	0.9225	(0.000)

CORRELATION MATRIX

	RS	UKR	POL	CZR
RS	1.000	0.182	0.472	0.4114
		(0.001)	(0.000)	(0.000)
UKR		1.000	0.139	0.0149
			(0.004)	(0.754)
POL			1.000	0.5346
				(0.000)
CZR				1.000

MULTIVARIATE RESIDUAL TESTS

MVLB-Q (24)	382.9	(0.506)
MVLB-Q (36)	562.8	(0.645)
MVLB-Qs (24)	403.8	(0.234)
MVLB-Qs (36)	584.2	(0.398)