Output Volatility and Its Transmission in Transition Economies: Implications for European Integration

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Abstract

Following the 2008 financial crisis, the world's attention was drawn to the periphery of the European Union, where economic openness and pegs to the Euro combined to destabilize the region. This study measures the output volatility of a set of Central and Eastern European countries from the early 1990s to 2011 using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and GARCH-in-Mean models. Volatility "spillovers" are then tested with Vector Autoregressive and Multivariate GARCH techniques. Overall, six countries can be modeled as a GARCH process, and for three of these, volatility significantly reduces output growth. Volatility comovements are particularly strong among the Visegrad countries, while Romania seems fairly insulated from external shocks. This asymmetry of responses to other CEE countries and to foreign shocks suggests that expanding the Eurozone may lead to adjustment problems.

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I. Introduction

Following the financial crisis of 2008, the Eurozone and its neighbors to the East have fallen victim to region-wide crises that have threatened to destabilize the entire area. While the financial and currency markets in a number of Central and Eastern European (CEE) countries received a great deal of attention due to fears of devaluation and resulting "contagious" currency crises, real fluctuations also have potential to spill over within the region. Trade linkages and currency regimes help drive this process.

Latvia, for example, defended its Euro peg at tremendous cost to its domestic level of output, and its wide current account deficit turned into a surplus. Its peg was required for Euro membership that would bring deeper integration and thus insulation from global shocks, but its ongoing defense could easily have a contractionary effect on the country's trading partners. As their exports drop, so do their GDPs—leading to increased variability that can travel from one country to another.

Is real macroeconomic volatility "contagious" in this part of the world? This study looks at macroeconomic volatility, and using monthly indices of industrial production, examines whether it does indeed spill over among CEE countries. We expect that those countries enjoying the deepest trade linkages will be most vulnerable to contagion, and that the choice of exchange-rate regime might also play a role in determining how exposed each country is to its neighbors' output shocks. Applying time-series methodologies to a set of CEE countries from 1992 to 2011, we find that this is indeed the case. This suggests that expanding the Euro Zone may lead to problems due to asymmetric adjustment.

A. Relationship to the Literature

For all their recent importance to the world economy, transition economies and the interconnections among volatility in their real economies have received relatively little attention. This is likely because of data limitations and the relatively short length of the transition process. While some studies (such as those by Artis *et al.*, 2008 and Hegerty, 2010) find evidence of co-movements among CEE business cycles, they do not address volatility itself. Rafiq (2011) does so, testing whether the Euro area had itself experienced a U.S.-style "Great Moderation." CEE countries are only considered peripherally as a single unit, which is proxied by the common business cycle of Hungary and Poland. Hakura (2009) specifically omits transition economies in an examination of the causes of output drops in developing countries.

Studies of output and other macroeconomic volatility instead tend to cover large panels of countries, focusing on either the causes or the effects of increased variability rather than on spillover effects or other interlinkages. One of the best-known analyses, by Ramey and Ramey

(1995), shows that for a large sample of 92 countries, as well as a set of OECD members, macroeconomic volatility tends to reduce output growth. These results are confirmed by Imbs (2007). It is important to note that transition economies are often omitted from these analyses. Ramey and Ramey (1995), for example, choose only countries for which data exist over the period from 1960 to 1985. This obviously does not cover the transition period, and only Yugoslavia is included in their analysis.

Many papers, both theoretical and empirical, isolate a number of causes of macroeconomic volatility. Karras and Song (1996) focus on economic openness, exchange-rate flexibility, fiscal policy, and shocks to the money supply and technology. Karras (2006) examines the role of economic openness and country size. His sample of more than 100 countries appears to include a few in Eastern Europe, although the time period begins as early as 1951. Other shocks that generally originate from abroad have also been found to be influential: Hirata *et al*. (2007) show terms of trade shocks to have an impact on Middle Eastern and North African volatility, while Kim (2007) focuses on volatility in the terms of trade of a group of countries.

The role of financial integration has also been studied extensively, since in theory, it might lead to increased risk-sharing opportunities that allow for the "smoothing" of macroeconomic fluctuations. On the other hand, increased exposure to trade and capital flows might also open channels by which one country's fluctuations might be transmitted to another. These are empirically studied by Kose *et al*. (2003), while Buch *et al*. (2005), Evans and Hnatkovska (2007), and Özbilgin (2009) develop the theory. Bayoumi and Swiston (2009), using Vector Autoregressive (VAR) methods to test for spillovers among a series of developed-country GDP growth rates and the rest of the world, find that the Euro Area serves as less of a source of worldwide shocks than does the United States.

This literature thus suggests that real as well as financial factors can explain volatility transmission (or the lack thereof) in this part of the world. The most likely real transmission channel is through demand and trade. Greater access to international financial markets might allow a country to circumvent a downturn, unless capital outflows precipitate a currency depreciation that leads to sharp changes in imports and exports. Finally, psychology may also be a factor if a shock to one country might lead to changes in buying decisions by people and firms who purchase goods and services in a neighboring country. All of these explanations are plausible, but difficult to model empirically.

This study tests for evidence of volatility transmissions in a set of CEE countries, rather than the underlying causes, using various time-series methods. Some, such as the VAR methodologies of Sims (1980) and Pesaran and Shin (1998), are said to be atheoretical—they examine only the statistical properties of a dataset without regard to the underlying process. In this case, because of the multiple possible transmission channels, as well as the limited availability of the necessary data required for a structural model at the appropriate frequency, this serves as a distinct advantage. In addition, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach of Engle (1982) and Bollerslev (1986) is applied to construct appropri-

ate measures of output volatility and test for interrelationships among a set of CEE countries' outputs.

This paper proceeds as follows: Section II outlines this methodology in further detail. Section III provides the results for a set of nine transition economies, six of which show evidence of time-varying output volatility. Section IV concludes.

II. Methodology

In this study, real output is proxied for GDP, as the monthly indices of industrial production in a set of transition and advanced economies. It is important to note that this series is likely to be more volatile than GDP, because it excludes services, but the gains brought by increased data frequency outweigh this cost. In addition, this volatility is itself interesting in its own right, as it is able to capture key events in these industrial economies.

The CEE countries' (log) output series are depicted in Figure 1. The group includes eight CEE EU members, as well as Russia, and also three foreign proxies to test for spillover effects. Data are taken from the International Financial Statistics of the International Monetary Fund over the period from as early as 1992 to mid-2011 (roughly 220 observations, varying by country). These deseasonalized indices are measured in natural logarithms.[1]

Volatility will be modeled using GARCH techniques as follows: First, each country's output series is tested for stationarity to determine the appropriate value of d (which turns out to be 1 in all cases), and then estimated with an ARIMA(p,d,q) model as in Equation (1a). The appropriate AR and MA values are chosen using the Box-Jenkins methodology.

$$\Delta y_t = c + \sum_{i=1}^{p} \rho_i \Delta y_{t-1} + \sum_{j=0}^{q} \theta_j \varepsilon_{t-j} \tag{1a}$$

This model is then tested for ARCH effects for each series. To deal with the problem of possible sensitivity of the ARCH test to the lag order, each country is estimated first at 12 lags and then re-estimated at the longest length that originally yielded a significant coefficient. Only those output series that show evidence of time-varying volatility at that lag are included in further analysis.

We then conduct both 'traditional' GARCH estimations, and GARCH-in-Mean (GARCH-M) models. Since output volatility has been shown in previous studies to lower economic growth, we estimate Equations (1a) and (1b), along with Equation (2), separately. We then choose the GARCH-M specification for those cases where volatility has a significant coeffi-

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[1] For all countries except Bulgaria, Latvia, Lithuania, Romania, Russia, and the AE index, deseasonalized data are available directly from the IFS. For these countries, the Census-X12 procedure was applied to the available data.

cient in the mean equation.

$$\Delta y_t = c + \gamma \sigma^2 + \sum_{i=1}^{p} \rho_i \Delta y_{t-1} + \sum_{j=0}^{q} \theta_j \varepsilon_{t-j} \tag{1b}$$

For each estimation, the error term is modeled as a GARCH(1,1) process as in Equation (2):

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{2},$$

In certain cases (particularly if the GARCH term is insignificant), we also estimate GARCH(2,1) and GARCH(1,2) models and select a model based on the significance of the coefficients. Once an appropriate model is found, volatility series are generated.

Next, we apply VAR methods to measure spillover effects both among the CEE countries themselves, and with the rest of the world. Volatility series for all transition economies that show ARCH effects, as well as an appropriate proxy for foreign volatility, are entered into a single vector. Impulse-Response Functions (IRFs) will then be generated for cross-country shocks.

Since the 'orthogonalized' VAR methods introduced by Sims (1980) are sensitive to the ordering of variables in the VAR, and since there is no logical order to this set of countries, the Generalized VAR methodology of Pesaran and Shin (1998) is used here. This avoids a problem encountered by Bayoumi and Swiston (2009), who devote considerable attention to the proper Cholesky ordering of their series of developed country GDP growth rates. Generalized IRFs (GIRFs) are insensitive to the ordering of variables, but will still be able to show whether there are indeed significant spillovers among the countries in question.

Finally, Multivariate GARCH (MGARCH) methods are applied to test these spillovers in a more formal setting. Each output growth series is evaluated as an AR(1) process as in Equation (3a), and each GARCH(1,1) process includes the other countries' error terms and variance series as in Equation (3b). Per Laopodis (2001, 2002, 2003), the constant conditional correlations are estimated in Equation (3c). Diagonal VECH is used for the estimation.

$$\Delta y_{i,t} = c + \rho_i \Delta y_{i,t-1} + \varepsilon_t \qquad \text{for all } i \tag{3a}$$

$$\ln \sigma_{i,t}^2 = \alpha_{i,0} + \sum_{j}^{8} \left(\alpha_{i,j} \phi_i \varepsilon_{i,t-1}^2 + \beta_{i,j} \ln \sigma_{j,t-1}^2 \right) \qquad \text{for all } i,j \tag{3b}$$

$$\sigma_{i,j,t} = \gamma_{i,j} \sigma_{i,t} \sigma_{j,t} \qquad \text{for all } i,j;\ i \neq j \tag{3c}$$

This combination of approaches will allow us to see which countries' monthly output growth rates demonstrate time-varying volatility, and to formally assess which of these economies might be prone to volatility spillovers. As is shown below, not all countries show evidence of ARCH effects, and of those that do, some countries show more evidence of international

volatility spillovers than do others.

III. Results

Monthly industrial production indices are studied for nine CEE countries, as well as three proxies for the rest of the world: The IMF's "Advanced Economies" index, the United States, and Germany. Table 1 shows the results of the Phillips-Perron (1988) stationarity test. This test is similar to the better-known Augmented Dickey-Fuller test, except that the Phillips-Perron test uses Newey-West (1987) standard errors to control for autocorrelated errors. As might be expected for output, all series are integrated of order 1, or are nonstationary in levels and stationary in first differences. As a result, the first differences of the log series (or rates of change) will be used in these models.

Next, each series is modeled as an ARIMA ($p,1,q$) process according to the Box-Jenkins methodology. The exact orders are also given in Table 1. The errors of each model are then tested for ARCH effects, or time-varying volatility, and these results are provided as well.

As can be seen, not every country's output volatility can be modeled as a GARCH process. We see that significant ARCH effects are found for six of the nine countries—the Czech Republic, Hungary, Lithuania, Poland, Romania, and Slovakia, as well as for Germany and the Advanced Economies index. There is no evidence for time-varying volatility in the output series of Bulgaria, Latvia, Russia, or the United States. We thus continue to study the volatility series and spillovers for six CEE economies, using both Germany and the Advanced Economies (AE) as alternatives for the foreign proxy. We expect these two countries' results to differ, since Germany has closer (but varying) connections to each country in the region, and the AE index, which is more diversified, is more of a proxy for truly 'global' events.

It is interesting to note that Bulgaria and Latvia have firm pegs to the euro, while Russia intervenes to maintain the ruble versus a dollar/euro basket. Perhaps a case can be made that exchange-rate management introduces fluctuations that make output less amenable to GARCH modeling. Lithuania, on the other hand, serves as a counterexample.

GARCH estimates of the six countries' volatility series are given in Table 2. One important result is that we find significant GARCH-M effects for three of the six CEE countries: Poland, Romania, and Slovakia. The remaining countries do not register an output drop in the face of increased volatility. There is very little obvious pattern to which countries exhibit these effects and which do not, but these findings do provide some support for the idea that volatility hurts a country's growth, and that fluctuations differ from country to country. We note that Slovakia and Poland, which were modeled as GARCH-M(1,2) processes, each have one negative β coefficient.

The other β coefficient in both estimations is larger however, suggesting that past volatility

has an overall positive effect on current volatility. All equations look correctly specified, with no evidence that an alternative (such as Integrated GARCH, which might be advisable if the α and β coefficients summed to one) would be preferable. In addition, there is no remaining ARCH error in any specification.

Figure 2 shows the GARCH or GARCH-M variance series (for those with a significant γ coefficient) for the six CEE countries and for the Germany and the Advanced Economies index. These series all show a spike that corresponds to the international financial crisis of 2008. They also demonstrate movement throughout the sample period, particularly for the Czech Republic (throughout the entire period) and Romania (in the late 1990s).

Slovakia, the only country in this group to join the euro, shows higher volatility around the time of its 2004 EU accession. Lithuania, on the other hand, seems to have experienced a reduction in output volatility, with more fluctuations in the late 1990s and early 2000s than during the 2008 crisis. Finally, both foreign proxies appear to have been part of the "Great Moderation"—until the onset of the global financial crisis, when volatility skyrocketed. Whether these countries' volatility spikes or general movements are related among countries, however, is the subject of this empirical study.

We next analyze these countries using the VAR and MGARCH methodologies described above. For the first multivariate analysis of volatility spillovers among these CEE countries, as well as from the rest of the world to these countries, GIRFs are generated for a vector that contains the GARCH variance series of the Czech Republic, Hungary, Poland, Romania, Slovakia, and a foreign proxy. In one (separate) vector, we include the Advanced Economies index, in the other we include Germany. We omit Lithuania because of its relatively short sample length, although results from an estimation that contained this country produced broadly similar results. A VAR(1) is chosen for both vectors by minimizing the Schwarz criterion out of a maximum of 12 lags in each. The GIRFs are shown in Figure 3, with ±2 standard error bands to show whether the responses are significant at 5 percent.

The GIRF results differ between the two specifications only for the CEE countries' responses to shocks in the advanced economy. The within-region responses are very similar in both. We begin by looking at these results.

One interesting result involves which countries serve as sources of volatility shocks, and which are most susceptible to volatility transmission. For example, the four Visegrad countries are interlinked, but not symmetrically; the Czech Republic responds strongly to volatility in Poland and weakly to volatility in Slovakia, with some evidence of a negative response from events in Hungary. At the same time, Hungarian volatility is affected by shocks in Poland and Slovakia, but not the Czech Republic. Slovakia responds to increased volatility primarily in Poland, with perhaps weak effects emanating from the Czech Republic. Hungary seems to be a less likely source of volatility spillovers in the region than its recent turmoil might suggest.

Poland serves much more as a source of shocks than as a recipient. The only country to escape a recession during the global financial crisis, it responds negatively to shocks in harder-hit

Hungary, and positively only to Slovakia. On the other hand, Romania responds to shocks in Slovakia, Poland and the Czech Republic, but not to those in Hungary, while itself serving less as a source of volatility transmissions. Possible economic factors behind these differences are given below.

Looking at the CEE countries' responses to external shocks, we find that the choice of proxy leads to substantially different results. Shocks to Germany only affect fluctuations in Hungary and Slovakia, but not in Poland, Romania, or the Czech Republic. Volatility in the broader index shows more evidence of leading to increased fluctuations in all five countries.

For a more elaborate analysis of these interlinkages, we turn to the Multivariate GARCH results in Table 3. Over the common sample period of 1993m3-2011m5, these are estimated separately for equations that include the Advanced Economies (top panel) and Germany (bottom panel). The signs and significance of most coefficients are the same regardless of the choice of external economy. While the Akaike Information Criterion points us towards choosing the Advanced Economies over the German one, examining both yields some interesting conclusions.

It is clear that most countries' variance series are indeed affected by the others' lagged error terms, while fewer show significant responses to foreign volatility itself at five percent. We find similar connections among the Visegrad countries here as we saw in the VAR analysis. Again, higher Hungarian volatility does not lead to increased fluctuations elsewhere. Slovakia, likewise, registers spillovers from the Czech Republic and Poland, and the Czech Republic has significant GARCH coefficients for volatility in Poland (only in the German specification) and Slovakia.

Romania, the only country that lies outside this region, again seems fairly insulated from outside shocks and only seems to be affected by volatility in Slovakia. As shown previously, Poland appears to be most strongly influenced by events in Slovakia.

Turning to the conditional correlations, we again see that the only major differences between specifications involve linkages to the foreign proxy. Hungarian output is correlated with that of Germany, (also shown via the VAR analysis), but is not correlated with the Advanced Economies output volatility. On the other hand, Poland is only tied to the broader Advanced Economies index. Romania shows no connection with either foreign proxy. While the Czech Republic and Slovakia are correlated with both proxies, the coefficients are larger using the Advanced Economies.

In summary, both methods produce three findings. First, Romanian GDP volatility is insulated from events originating in its neighbors' economies. Second, the four remaining Visegrad countries show stronger connections among each other, but these are asymmetric—with Poland causing volatility spillovers while not responding to variability elsewhere, and Hungary responsible for relatively little volatility transmission. Finally, the two 'external' proxies, Germany and the Advanced Economies, exhibit differing connections to these countries.

A. Underlying Economic Factors

What factors might underlie these differences among countries? Obviously, Romania stands out as the only Balkan country in this sub-sample, and its location and industrial structure are not very similar to the others, but within the Visegrad region, there is still considerable economic diversity. Hungary's relatively poor performance led to a bailout and political turmoil, while Poland serves as a model for the rest of the EU after weathering the global financial crisis.

Trade linkages within the region, which vary in degree from partner to partner, might be partially responsible. While Germany is by far each country's largest partner, pairs such as Poland and the Czech Republic do make up a significant proportion of each other's exports. We only find a one-way propagation of shocks, particularly in the VAR analysis, from Poland to its smaller neighbor. Hungary's relatively small level of trade with its Visegrad neighbors (compared to trade with Western Europe)[2] might help explain its limited impact on regional volatility. However, other strong interconnections, such as between the Czech Republic and Slovakia, do not seem to result in differences in volatility spillovers.

Trade connections affect these countries' susceptibility to external contagion even more. The divergence in impact of Germany and the Advanced Economies index might have to do with the differing proportion of non-German OECD countries among each nation's major partners. For example, the combined share of EU countries such as France, the UK, and Italy in Poland's overall exports is almost as large as Germany's, and oftentimes the Advanced Economies index has a stronger impact on Poland's volatility series. A similar effect occurs in Romania's impulse responses. Perhaps the fact that distant Germany makes up less than 20 percent of the Balkan nation's trade (18 percent of the country's 2010 exports), is responsible.

Economic size might also play a role in these results, while financial depth might not. Examining GDP (in dollars) and the M2/GDP ratio for 2007 using IFS data (available upon request), we confirm that Romania has the smallest economy and the least financial depth. This Balkan country is more susceptible to volatility transmission than Poland, which has this group's largest GDP. The M2/GDP ratio is highest in the Czech Republic however, but the country is not particularly well insulated from outside shocks. Poland's size might therefore matter more, explaining its one-way volatility transmission to the Czech Republic.

IV. Conclusion

The financial crisis that began in 2008, exposed a series of real and financial linkages by

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[2] Source: UN Trade statistics, 2010.

which turmoil in one country could lead to contagion elsewhere. The transition economies of Central and Eastern Europe were at the center of the crisis early on, and only a set of well implemented and often painful policy prescriptions was able to contain the situation. While an outright collapse was avoided, macroeconomic shocks were shown to be "contagious" among the countries of the region.

This study applies GARCH methods to model the output volatility of nine transition economies, using monthly series of industrial production from 1992 to 2011. Focusing on the six countries whose series showed evidence of time-varying volatility, a multivariate analysis is conducted to examine whether shocks to output volatility are capable of spreading within the region as well as outside it. Vector Autoregressive techniques (namely Generalized Impulse-Response Functions) as well as multivariate GARCH methods, help us arrive at three key results.

First, of the nine CEE countries studied, Bulgaria, Latvia, and Russia do not exhibit significant ARCH effects. These countries are all further removed from the center of Europe, and all manage their exchange rates. Further research would be necessary to determine whether fixed exchange rates make a country's output series less likely to exhibit time-varying volatility, but here only one of the three currency boards studied can be modeled as a GARCH process.

Secondly, of the six CEE countries that follow such a process, three have a significantly negative GARCH-M coefficient, suggesting that output volatility reduces output growth. This evidence was not found for the other three countries. Nevertheless, it provides updated support for the conclusions of earlier work by Ramey and Ramey (1995) and others.

These differences among countries lead us to our third main conclusion, that both among regions and within each region (the Baltics, Balkans, and Visegrad Countries), each country behaves differently from its neighbors. For example, the relatively advanced nations in Central Europe seem to be more integrated than the Balkans. At the same time (within their respective regions), Romania and Bulgaria, and Latvia and Lithuania produce disparate results from one another. Each country also responds uniquely to shocks that originate abroad.

These results have implications for European integration. As Mundell's (1961) Optimum Currency Area theory suggests, the elimination of monetary adjustment mechanisms under a common currency requires that other methods (such as labor movements and fiscal transfers) take their place. It also suggests that asymmetric shocks might not be effectively addressed using a "one size fits all" monetary policy. Should certain areas experience economic shocks that other parts of the union do not, it will be impossible to implement a single policy that will work for everyone. In addition, fiscal transfers in Europe are small compared to the United States, and studies such as Brenke (2011) note that labor is less mobile in the region than might be expected. This means that an important alternative adjustment mechanism is lacking.

Asymmetric adjustment may happen if spillovers from abroad lead to increased volatility in only certain countries on the periphery of the Eurozone. The varying susceptibility to outside shocks shown here suggests that the addition of these new members may make the EU even

less of an Optimum Currency Area. Perhaps eventual monetary union will help new member states achieve further financial integration with the EU, but real differences persist. If labor mobility is limited due to migration restrictions, these countries will be exposed to asymmetric shocks for the near future.

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Figure 1. Log (Industrial Production Series)
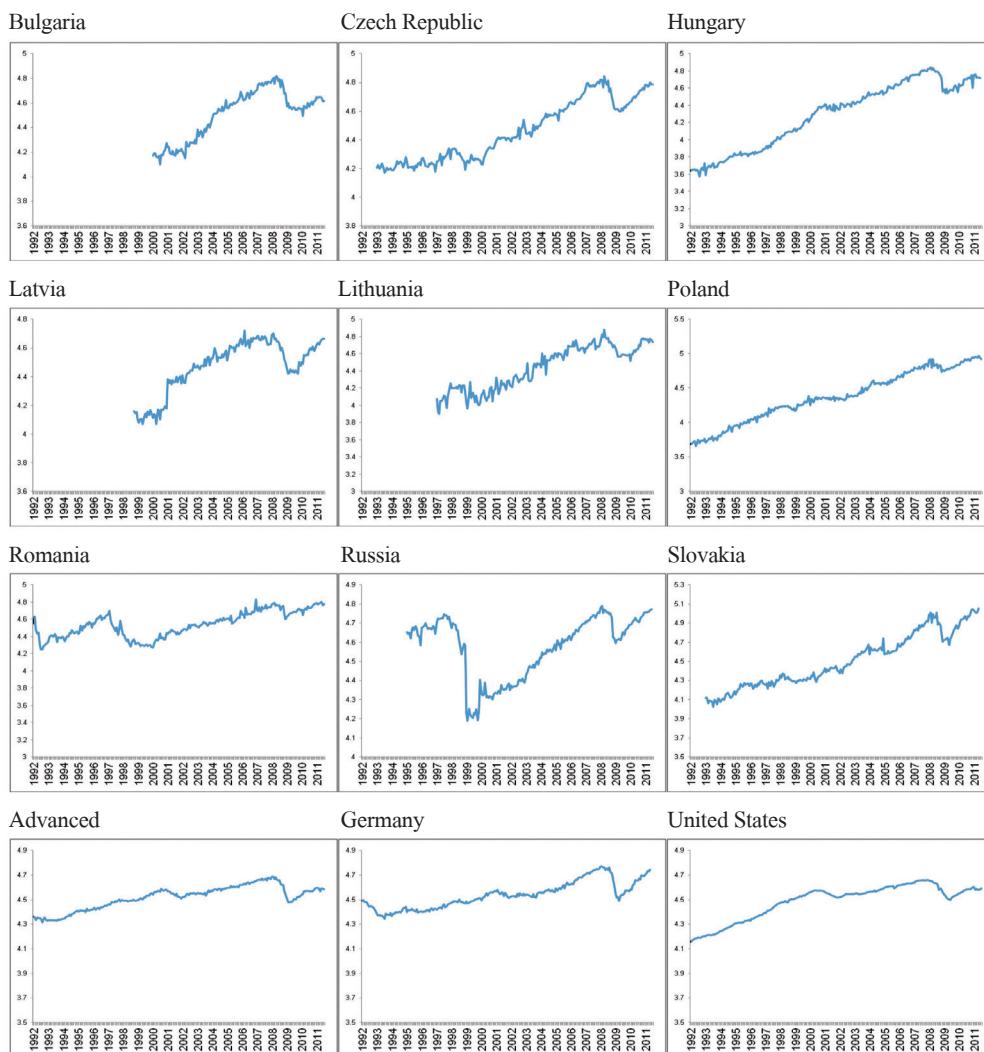
(Source) International Financial Statistics of the IMF.

Table 1. Stationarity and ARCH Test Results.

Country	Phillips-Perron test statistic (p-value)		ARCH test (Lagrange Multiplier)		ARMA(p,q)
	Level	Difference	ORDER	TR^2 (p-value)	ARMA Order
Bulgaria	-1.580 (0.493)	-17.846 (0.000)	9	10.328 (0.325)	(1,3)
Czech Republic	-0.405 (0.909)	-20.360 (0.000)	4	20.514 (0.000)	(1,0)
Hungary	-1.366 (0.598)	-23.610 (0.000)	1	7.344 (0.007)	(1,0)
Lithuania	-1.320 (0.620)	-20.986 (0.000)	8	18.106 (0.020)	(4,0)
Latvia	-1.466 (0.550)	-17.822 (0.000)	1	0.087 (0.768)	(2,1)
Poland	-1.239 (0.657)	-32.871 (0.000)	11	23.344 (0.016)	(2,0)
Romania	-1.319 (0.620)	-19.720 (0.000)	8	26.335 (0.001)	(0,1)
Russia	-1.258 (0.648)	-14.857 (0.000)	1	1.065 (0.302)	(1,0)
Slovakia	-0.002 (0.958)	-21.742 (0.000)	11	39.732 (0.000)	(1,2)
Advanced	-1.453 (0.556)	-17.817 (0.000)	8	51.307 (0.000)	(3,0)
Germany	-0.552 (0.881)	-16.334 (0.000)	1	43.639 (0.000)	(1,2)
United States	-2.697 (0.590)	-14.495 (0.000)	10	8.757 (0.553)	(1,2)

Table 2. GARCH Estimates.

Panel A: No GARCH-In-Mean

	Czech Rep.*	Hungary*	Lithuania*	Poland	Romania	Slovakia	Advanced*	Germany*
χ	0.003 (0.005)	0.005 (0.000)	0.004 (0.094)	0.005 (0.000)	0.003 (0.037)	0.005 (0.001)	0.002 (0.000)	0.002 (0.007)
ρ_1	-0.218 (0.007)	-0.332 (0.000)	-0.379 (0.000)	-1.014 (0.000)	-0.342 (0.000)	0.652 (0.001)	-0.400 (0.000)	0.855 (0.000)
ρ_2			-0.206 (0.013)	-0.594 (0.000)	-0.176 (0.009)		0.011 (0.842)	
ρ_3			-0.232 (0.004)				0.497 (0.000)	
ρ_4			-0.169 (0.010)					
θ_1				0.304 (0.006)		-1.145 (0.000)		-1.256 (0.000)
θ_2						0.408 (0.000)		0.402 (0.000)
α	0.000 (0.003)	0.000 (0.622)	0.001 (0.103)	0.000 (0.000)	0.000 (0.138)	0.001 (0.000)	0.000 (0.008)	0.000 (0.429)
α_1	0.502 (0.000)	0.654 (0.011)	0.217 (0.014)	0.246 (0.023)	0.114 (0.122)	0.421 (0.001)	0.343 (0.001)	0.579 (0.000)
α_2		-0.549 (0.093)						-0.459 (0.004)
β_1	0.254 (0.048)	0.880 (0.000)	0.537 (0.004)	0.580 (0.014)	0.745 (0.000)	-0.171 (0.000)	0.465 (0.000)	0.825 (0.000)
β_2				-0.356 (0.012)				
Q(4)	2.14 (0.543)	5.716 (0.126)	0.601 (0.438)	6.003 (0.014)	2.052 (0.358)	4.691 (0.030)	3.338 (0.068)	6.193 (0.013)
TR^2	4.071 (0.254)	16.806 (0.157)	13.937 (0.176)	14.100 (0.294)	1.103 (0.294)	11.166 (0.515)	0.312 (0.576)	3.231 (0.664)

Panel B: GARCH-In-Mean

	Czech R.	Hungary	Lithuania	Poland*	Romania*	Slovakia*	Advanced	Germany
γ	-2.526 (0.290)	1.276 (0.306)	0.783 (0.653)	**-3.105 (0.024)**	**-8.968 (0.022)**	**-4.920 (0.044)**	-0.250 (0.263)	-1.171 (0.719)
c	0.004 (0.008)	0.004 (0.008)	0.001 (0.909)	0.008 (0.000)	0.013 (0.007)	0.011 (0.000)	0.004 (0.043)	0.002 (0.013)
ρ_1	-0.222 (0.007)	-0.318 (0.000)	-0.379 (0.000)	-1.051 (0.000)	-0.365 (0.000)	0.409 (0.181)	-0.424 (0.000)	0.855 (0.000)
ρ_2			-0.203 (0.014)	-0.593 (0.000)	-0.185 (0.005)		-0.007 (0.904)	
ρ_3			-0.232 (0.004)				0.492 (0.000)	
ρ_4			-0.168 (0.010)					
θ_1				0.331 (0.002)		-0.926 (0.002)		-1.259 (0.000)
θ_2						0.270 (0.025)		0.405 (0.000)
α	0.000 (0.003)	0.000 (0.610)	0.001 (0.097)	0.001 (0.000)	0.000 (0.106)	0.001 (0.000)	0.000 (0.005)	0.000 (0.454)
α_1	0.497 (0.000)	0.675 (0.009)	0.218 (0.012)	0.272 (0.007)	0.101 (0.179)	0.297 (0.008)	0.323 (0.001)	0.576 (0.000)

α_2		-0.565 (0.088)					-0.452 (0.006)
β_1	0.270 (0.023)	0.876 (0.000)	0.549 (0.001)	0.469 (0.000)	0.733 (0.000)	-0.309 (0.000)	0.503 (0.000)	0.817 (0.000)
β_2				-0.378 (0.000)		0.388 (0.000)	
Q(4)	2.12 (0.547)	6.009 (0.111)	0.638 (0.424)	1.063 (0.302)	2.072 (0.355)	5.005 (0.025)	3.900 (0.048)	6.308 (0.012)
TR^2	19.218 (0.083)	16.985 (0.150)	11.102 (0.196)	9.509 (0.659)	3.136 (0.679)	7.826 (0.251)	0.252 (0.616)	3.248 (0.662)

(Notes) 1) Bollerslev-Wooldridge Standard Errors applied; p-values in parentheses.

    2) Bold: Significant GARCH-in-Mean Coefficient; * = chosen as GARCH process for a particular country.

    3) Q(4) is the Ljung-Box statistic for serial correlation. It is distributed as a $\chi 2$ with 4 degrees of freedom

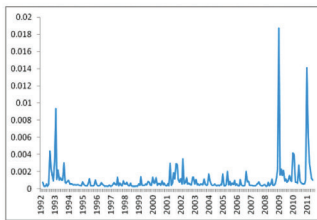   4) TR^2 is the statistic for the ARCH test.

    5) A dummy to account for the 1999 output drop was included in the Russian specification.
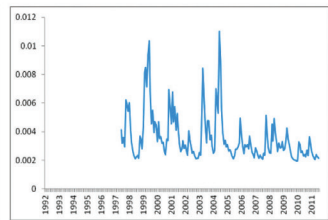
Figure 2. GARCH Variance Series
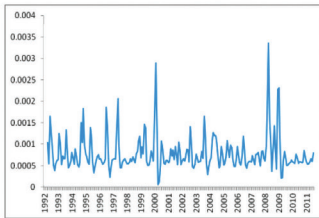

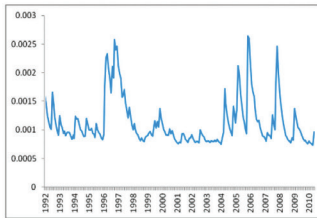Czech Republic (1993m3~2011m7)
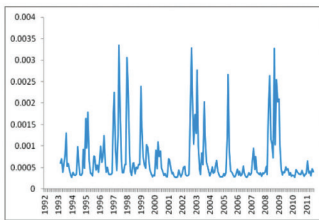
Hungary (1992m3~2011m6)
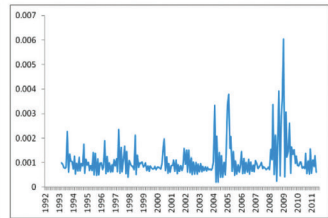
Lithuania (1997m6~2011m7)
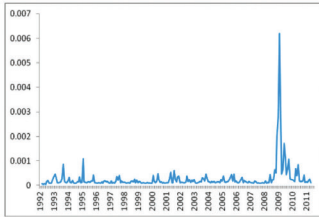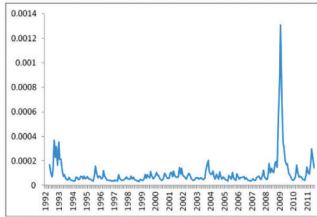
Poland (1992m4~2011m7)

Romania (1992m4~2011m7)

Slovakia (1993m3~2011m5)

Germany (1992m3~2011m5)

Advanced (1992m5~2011m8)

**Figure 3a. Generalized Impulse-Response Functions (with ±2 s.e. Bands)
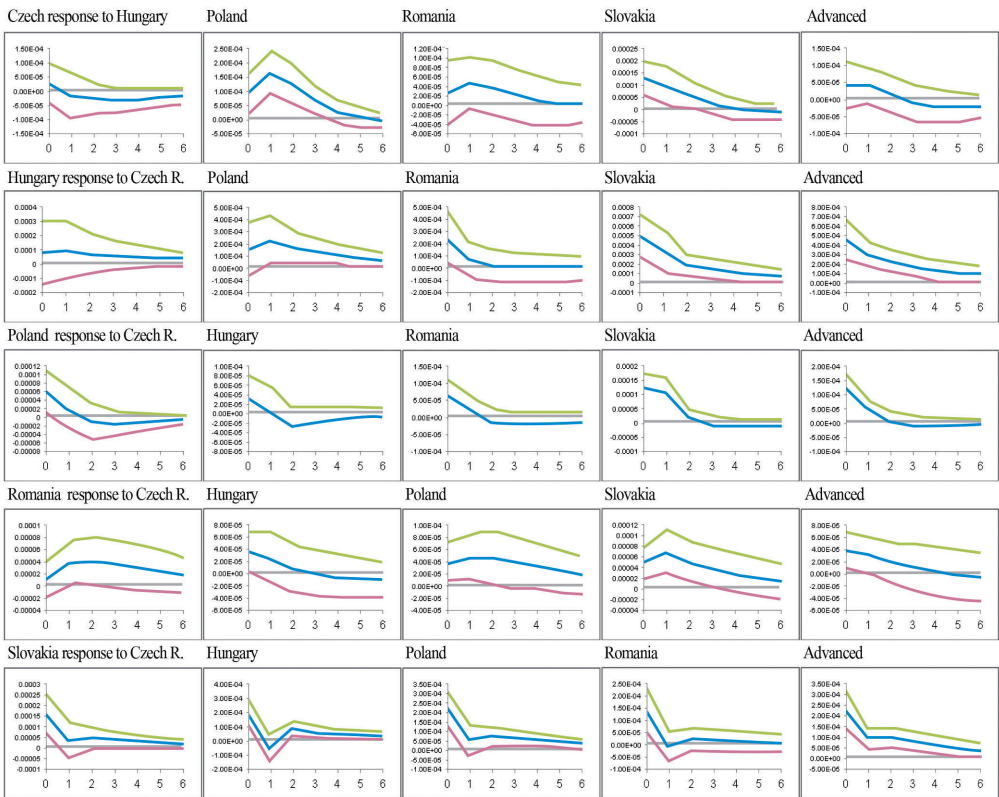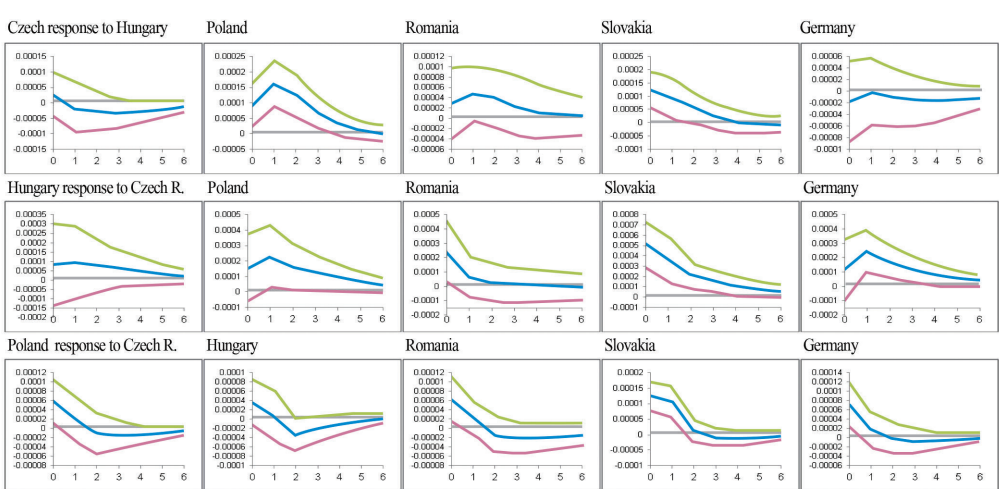: Including Advanced Economies**

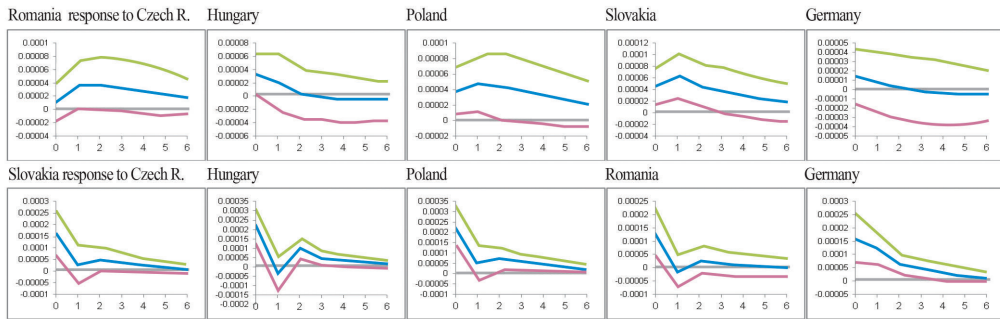**Figure 3b. Generalized Impulse-Response Functions (with ±2 s.e. Bands)：Including Germany**

Romania response to Czech R.   Hungary   Poland   Slovakia   Germany

Slovakia response to Czech R.   Hungary   Poland   Romania   Germany

Table 3. Multivariate GARCH Results

GARCH Coefficients

	Czech Republic		Hungary		Poland		Romania		Slovakia	
Constant	0.003 (0.015)		0.006 (0.000)		0.006 (0.000)		0.003 (0.051)		0.006 (0.000)	
AR(1)	-0.246 (0.000)		-0.257 (0.000)		-0.518 (0.000)		-0.262 (0.000)		-0.368 (0.000)	
Caused by	ARCH	GARCH	ARCH	GARCH	ARCH	GARCH	ARCH	GARCH	ARCH	GARCH
Czech Rep.	0.613 (0.000)	0.313 (0.000)	0.538 (0.000)	0.083 (0.223)	0.285 (0.000)	0.282 (0.061)	0.268 (0.010)	0.045 (0.811)	0.295 (0.000)	0.225 (0.019)
Hungary	0.499 (0.000)	0.098 (0.158)	0.721 (0.000)	0.024 (0.449)	0.344 (0.010)	0.045 (0.777)	0.290 (0.011)	0.011 (0.918)	0.459 (0.000)	0.013 (0.677)
Poland	0.209 (0.000)	0.214 (0.300)	0.266 (0.000)	0.073 (0.417)	0.244 (0.000)	0.513 (0.000)	0.229 (0.009)	0.186 (0.372)	0.309 (0.000)	0.378 (0.000)
Romania	0.203 (0.041)	-0.025 (0.916)	0.184 (0.103)	-0.010 (0.947)	0.198 (0.004)	0.233 (0.219)	0.339 (0.003)	0.061 (0.743)	0.265 (0.000)	0.154 (0.213)
Slovakia	0.218 (0.000)	0.224 (0.099)	0.439 (0.000)	0.005 (0.864)	0.305 (0.000)	0.383 (0.000)	0.232 (0.000)	0.170 (0.261)	0.346 (0.000)	0.148 (0.069)
Advanced	0.157 (0.003)	0.476 (0.001)	0.284 (0.001)	0.231 (0.237)	0.169 (0.000)	0.674 (0.000)	0.161 (0.014)	0.200 (0.593)	0.254 (0.000)	0.356 (0.001)

AIC = -28.428

	Czech Republic		Hungary		Poland		Romania		Slovakia	
Constant	0.003 (0.006)		0.005 (0.000)		0.005 (0.000)		0.003 (0.046)		0.005 (0.000)	
AR(1)	-0.228 (0.000)		-0.221 (0.001)		-0.526 (0.000)		-0.259 (0.000)		-0.365 (0.000)	
Caused by	ARCH	GARCH	ARCH	GARCH	ARCH	GARCH	ARCH	GARCH	ARCH	GARCH
Czech Rep.	0.652 (0.000)	0.290 (0.001)	0.513 (0.000)	0.190 (0.021)	0.245 (0.000)	0.265 (0.147)	0.200 (0.028)	-0.156 (0.413)	0.219 (0.001)	0.210 (0.026)
Hungary	0.525 (0.000)	0.169 (0.054)	0.747 (0.000)	0.049 (0.350)	0.334 (0.046)	0.137 (0.490)	0.161 (0.277)	-0.058 (0.783)	0.425 (0.000)	0.055 (0.145)
Poland	0.257 (0.000)	0.278 (0.076)	0.347 (0.017)	0.127 (0.476)	0.231 (0.000)	0.543 (0.000)	0.191 (0.044)	0.308 (0.065)	0.301 (0.000)	0.401 (0.000)
Romania	0.218 (0.025)	-0.058 (0.760)	0.192 (0.117)	-0.075 (0.709)	0.195 (0.010)	0.232 (0.268)	0.360 (0.000)	0.053 (0.709)	0.234 (0.000)	0.262 (0.043)
Slovakia	0.244 (0.000)	0.199 (0.046)	0.447 (0.000)	0.035 (0.449)	0.304 (0.000)	0.398 (0.000)	0.255 (0.000)	0.237 (0.033)	0.365 (0.000)	0.154 (0.050)
Germany	0.244 (0.002)	0.096 (0.698)	0.342 (0.002)	0.115 (0.502)	0.266 (0.000)	0.442 (0.000)	0.254 (0.005)	-0.024 (0.935)	0.328 (0.000)	0.191 (0.068)

AIC = -27.163

Conditional Correlations (p-values)

	Hungary	Poland	Romania	Slovakia	Advanced
Czech Rep.	0.120 (0.043)	0.323 (0.000)	0.160 (0.012)	0.371 (0.000)	0.242 (0.001)
Hungary		0.061 (0.333)	0.139 (0.021)	0.042 (0.602)	0.085 (0.258)
Poland			0.009 (0.919)	0.343 (0.000)	0.636 (0.000)
Romania				0.109 (0.209)	0.015 (0.858)
Slovakia					0.359 (0.000)

	Hungary	Poland	Romania	Slovakia	Germany
Czech Rep.	0.129 (0.030)	0.363 (0.000)	0.147 (0.020)	0.397 (0.000)	0.184 (0.003)
Hungary		0.077 (0.227)	0.132 (0.033)	0.045 (0.569)	0.234 (0.000)
Poland			0.007 (0.933)	0.364 (0.000)	0.048 (0.545)
Romania				0.093 (0.286)	0.089 (0.195)
Slovakia					0.189 (0.015)

(Notes) 1) Bollerslev-Wooldridge Standard Errors applied; p-values in parentheses.

2) $ARCH = \alpha_{i,j}$ and $GARCH = \beta_{i,j}$ in Equation (3b)