MEASURING SYSTEMIC RISK USING CONTINGENT CLAIMS ANALYSIS (CCA)

Moisã ALTĂR¹ Adam-Nelu ALTĂR-SAMUEL² Ioana MARCU³

This paper dwells upon the contingent claims analysis (CCA) framework in order to quantify the risk of financial distress at the level of the sectors of economy (banking, sovereign and corporate sector). After the CCA risk indicators have been obtained for the three analyzed sectors, a global VAR is constructed for the analysis of spillover effects among the Central and Eastern European countries by determining whether a shock in one sector of a country would have a significant effect on the other analyzed sectors and countries and, especially, on the contraction of economic growth. In order to analyze the impact and spillover of shocks across sectors and countries, adverse shock scenarios are developed, particularly regarding the banking and sovereign risk. The methodology is applied on four Central and Eastern European Countries: Romania, Bulgaria, Hungary and Poland.

Keywords: risk monitoring, systemic risk, contingent claims analysis (CCA), global VAR

JEL Classification: C51, G13, G21, G28

Abstract

1. Introduction

Following the global financial crisis of the late 2000's, the interest in measuring systemic risk has increased substantially. The focus has been set on finding a framework that quantifies the risk taking into consideration the connections established between the sectors of the economy, as well as the transmission of risk across countries.

This paper focuses on studying systemic risk in a CCA Global VAR by applying the methodology proposed by Gray *et al.* (2013). After the CCA risk indicators are

¹ The Bucharest University of Economic Studies, The Romanian – American University – FINSYS, E-mail: altarm@gmail.com.

² The Romanian – American University - Mathematics, Statistics and Computer Science Department, E-mail: adamalt@gmail.com.

³ The Romanian – American University - FINSYS , E-mail: ioana_marcu@ymail.com.

obtained for the three analyzed sectors, a Global VAR is constructed for the analysis of risk transmission between the banking sector, corporate sector, sovereign sector, credit growth and real economic activity. Key to the framework is that the variables included in the GVAR model are combined in a fully endogenous setting, the weight matrix needed to construct the foreign variable vectors being estimated jointly with the GVAR's parameters.

An impulse response analysis is performed upon the GVAR model in order to determine whether a distress in the banking sector has a more severe effect upon the other sectors than a distress in the sovereign sector and to compare to which extent these shocks determine the contraction of economic growth.

2. Literature Review

The global financial crisis has renewed the interest of academics, regulatory bodies and Central Banks in the area of quantifying and mitigating systemic risk. The result was the enrichment of literature on this topic, leading to the publication of a wide array of papers regarding the measurement of systemic risk, its regulation and to the identification of threats to financial system stability.

There are various definitions of systemic risk, which all share some common features. However, there still is no agreement over a single systemic risk definition. In the context of this paper, systemic risk is defined as the risk that originates in, or spreads through, the financial sector, with a potential for severe adverse effects on financial intermediation and real output. Moreover, the spillover effects to other countries' financial systems are considered.

This paper focuses on studying systemic risk in a CCA Global VAR by applying the methodology proposed by Gray *et al.* (2013).

The CCA approach is used in general to measure corporate credit risk. This framework has been extended by Gray and Jobst (2011) to a Systemic CCA, considering the financial sector as a portfolio of individual contingent claims. Their results show that the joint expected losses reached the highest values during the Lehman Brothers collapse, a result that is in accordance with the economic situation that led to the recent financial crisis.

In a recent paper, Gray *et al.* (2013) have used the CCA framework to analyze the interactions between the banking, sovereign and corporate sectors risk, real economic activity and credit growth for 15 European countries and the USA. After applying the CCA methodology to individual institutions, the results were aggregated for each sector and then a Global VAR model was constructed in order to study the spillover of shocks between sectors and across countries and the impact upon economic growth. The results obtained by applying negative shocks to the banking and sovereign sectors of Spain and Italy showed that a shock to the sovereign sector has a greater overall impact than a shock to the banking sector.

Until recently, Global VAR models have been developed based on the methodology presented by Pesaran and Shin (1998), applications based on macroeconomic variables (GDP, inflation, interest rates, etc.) being employed. The standard approach

Romanian Journal of Economic Forecasting – XVII (4) 2014

was to use trade-based weight matrices for the construction of the foreign variables vectors. Gross (2013) shows that misspecified weights can bias the global model and decrease its forecast performance by constructing a GVAR model using a weight matrix that is estimated along with the model's parameters. Gross (2013) applied this methodology in contrast to the traditional trade weights method by analyzing GDP and personal expenditure price inflation based on a panel of 18 countries. The results obtained sustain the fact that the out-of-sample forecast performance of the GVAR improves when using weights that are estimated along with the model's parameters. Moreover, the author highlights the fact that this type of weight matrix is more adequate to be used when it is not obvious how weights could be otherwise constructed from data, as in the case when a GVAR is used for the analysis of mixed country and bank cross section.

The approach employed in this paper is the one used by Gray *et al.* (2013), pursuing to determine each sector's risk indicators using CCA, to analyze the interdependencies between sectors, the transmission of shocks across sectors and countries, as well as the impact of these shocks on economic growth. The weight matrix used to construct the foreign variable vectors is estimated along with the GVAR parameters, following the approach proposed by Gross (2013).



3.1. Contingent Claims Analysis

A contingent claim is any financial asset whose future payoff depends on the value of another asset.

The contingent claims analysis (CCA) is a generalization of the option pricing theory pioneered by Black-Scholes (1973) and Merton (1973). This approach is used to construct marked-to-market balance sheets that reflect the underlying risk by combining the balance sheet information with widely used finance and risk management tools. Option pricing tools are used to value the liabilities which are modeled as claims on stochastic assets.

The CCA is based on three principles: the values of liabilities are derived from assets, liabilities have different priority (i.e. senior and junior claims) and assets follow a stochastic process.

The prototypical contingent claim is an option. The CCA framework models equity as a call option on the company's assets, while risky debt is viewed as the difference between book value of debt and a put option on the firm's assets.

In its basic concept, CCA assumes that owners of corporate equity in leveraged firms hold a call option on the firm value after outstanding liabilities have been paid off. They also have the option to default if their firm's asset value falls below the present value of the notional amount of outstanding debt at maturity. Thus, bond holders receive a put option premium in the form of a credit spread above the risk-free rate in return to holding risky corporate debt (and bearing the potential loss) due to the limited liability of equity owners.

Romanian Journal of Economic Forecasting -XVII (4) 2014

According to this approach, a company's asset value, A(t) is equal to the sum of its equity market value, E(t) and its risky debt, D(t):

A(t) = E(t) + D(t)

The risky debt is equivalent in value to default free debt minus a guarantee against default. This guarantee can be calculated as the value of a put option on the assets with an exercise price equal to the promises payment, B.

$$D(t) = Be^{-rT} - P(t),$$

$$P(t) = Be^{-rT} N(-d_2) - A(t)N(-d_1)$$

As assets value and assets volatility are not directly observable, their value is determined solving the following non-linear system of two equations:

$$\begin{cases} E = A N(d_1) - Be^{-rT} N(d_2) \\ E \sigma_E = A \sigma_A N(d_1) \end{cases}$$

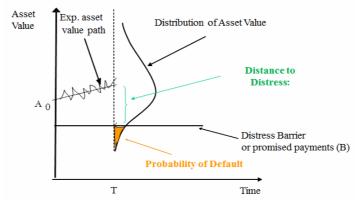
Default occurs if the assets are insufficient to meet the amount of debt owed to creditors at maturity, that is, when assets fall below a distress barrier comprising the total value of the company's liabilities. The driver of default risk is the uncertainty in the changes in the future asset value relative to promised payment on debt.

Default risk increases when the value of assets declines towards the distress barrier or when asset volatility increases such that the value of the assets becomes more uncertain and the probability of the value falling below the distress barrier becomes higher.

The relation between the value of the assets and the distress barrier at time T is presented below.

Figure 1

Distribution of Assets Value at Time T



Source: Authors' computations.

An important aspect of this type of model is that equity needs to be expressed in market value. This feature of the CCA framework highlights the main advantage of this approach, respectively the forward looking character of the model incorporated in capital market expectations through price and volatility movements.

Romanian Journal of Economic Forecasting – XVII (4) 2014

Moreover, the volatility of equity has to be computed bu means of the price evolution of company's shares. In this paper, equity volatility has been determined by a historical rolling window of 125 trading days.

The approach used to determine the distress barrier is a defining element of the CCA and has a great impact upon the model results. In most empirical applications employed in the corporate sector, the distress barrier used was the one computed by the Moody's/KMV Methodology, i.e. the total short-term debt and half of the long term debt:

$B_{CORPORATE SECTOR} =$ Short Term Debt + 0.5 Long Term Debt.

Applying the Moody's/KMV methodology to determine the distress barrier for the banking sector is more difficult due to the features of banks' balance sheet. The activities performed by commercial banks imply a higher debt to equity ratio than in the case of the corporate sector, as the loans rendered are mainly sustained through deposits. Moreover, in the recent years, financial market instability led to a decrease in the deposit maturity, determining an increase in the number of short term deposits compared to long term deposits. Also, considering the fact that most banks do not publish the term structure for deposits, another approach used in empirical studies applied to the banking sector was to establish the distress barrier as percentage of total liabilities. For example, Guerra *et al.* (2013) applied CCA to measure systemic risk for the Brasilian banking system, calculating the distress barrier as 85% of total liabilities. For the purpose of this paper, we consider that a bank experiences distress if the assets value falls below 70% of total liabilities:

$B_{\text{BANKING SECTOR}} = 0.7 \text{ Total Liabilities}$

Another step has to be made in order to obtain relevant risk indicators for the banking sector. Due to the fact that Romania, Bulgaria and Hungary do not have enough banks listed on the stock exchange to assess the banking system, one unlisted bank from each country has to be included in the analysis. In order to do so, the market capitalization and the price volatility have to be determined using proxies. For the market capitalization, the average between the bank's balance sheet equity and the market capitalization of the affiliated banking group has been used. For equity's volatility, a proxy has been used based on the average between the price volatility of the affiliated banking sector, determined as a weighted average of the price volatility of the local traded banks.

The application of the CCA to the sovereign sector implies an additional step related to the construction of a sovereign balance sheet that is common to the Government and the Monetary Authority. In order to do so, the approach employed by Gapen *et al.* (2008) was used. The elements included in the individual balance sheet of the Government and the Monetary Authority, as well as the aggregated balance sheet of the sovereign sector are presented in Table 1.

Through consolidation process, the Government claim on foreign currency reserves and credit to government net out. Moreover, in order to have only elements that are traceable to observable data on the liabilities side, Government's guarantees to tooimportant-to-fail entities are subtracted from the assets side. Therefore, an important aspect that needs to be highlighted is that public debt used in the model contains only

direct debt. The guaranteed debt falls into another category of liabilities, that is financial guarantees, which are subtracted from the assets value when the sovereign balance sheet is consolidated.

Table 1

Government Balance Sheet	
Assets	Liabilities
- Claim on a portion of International Reserves - Other Public Sector Assets	 Credit from the Monetary Authority Domestic Currency Debt Foreign Currency Debt
- Other Public Sector Assets	- Guarantees to "too- important-to-fail" entities
Monetary Authority Balance Sheet	
Assets	Liabilities
 International Reserves Credit to Government Other Assets 	 Base Money Government Claim on a portion of International Reserves
Sovereign Sector Consolidated Balance She	eet
Assets	Liabilities
 International Reserves Domestic currency assets: Other assets – Guarantees 	 Domestic Currency Liabilities (DCL): Base Money (M0); Domestic Currency Debt (DCD). Foreign Currency Debt (FCD).

Sovereign Sector Balance Sheet

Source: Authors' computations based on the approach proposed by Gapen et al. (2008).

In order to apply the CCA, liabilities need to be divided into junior claims (equity) and senior claims. Domestic currency liabilities (domestic currency debt and base money - DCL) are considered to be junior claims, because they have several equity-like features: money and local currency debt can be issued in large amounts, even if this causes a decrease in their value; domestic currency liabilities multiplied by the exchange rate can be seen as a "market capitalization" of the sovereign in the international financial market. Moreover, domestic currency debt is an important absorber of fiscal risk, similar to equity that is a cushion and risk absorber for firms. Another reason to consider domestic currency liabilities as junior claims is that in periods of stress governments try to meet primarily their foreign currency obligations, because domestic currency debt can be issued, repurchased and restructured much more easily than foreign currency debt.

Therefore, the equity used in the CCA for the corporate and banking sectors will be replaced in the sovereign case by domestic currency liabilities, denominated in euros.

Due to the fact that the method used by Gapen *et al.* (2008) to determine the volatility of domestic currency liabilities based on the volatility of exchange rates and variations in quantities of domestic currency debt and base money issued has proved to produce risk indicators that underestimate sovereign risk, the approach used in this paper for the volatility of domestic currency liabilities is the one proposed by Oshiro and Saruwatari (2005), that is the volatility of the representative stock market index. Moreover, this choice for computing the volatility is also made because it is important

Romanian Journal of Economic Forecasting – XVII (4) 2014

to include financial market information in the model, especially when no market data is used.

The distress barrier for the sovereign sector is computed by applying the Moody's/ KMW Methodology to foreign currency debt:

B_{SOVEREIGN_SECTOR} = Short Term FCD + 0.5 Long Term FCD

After determining the implied asset value and the implied asset volatility, the following risk indicators are calculated:

- Probability of default (PD) the probability that the future value of the assets would fall below the distress barrier. This is in fact a probability that the put option will be exercised at maturity: PD = N(-d2).
- Distance to distress (D2D) shows the number of standard deviations the assets

are from default: D2D =
$$\frac{\mathbf{A} - \mathbf{B}}{\mathbf{A} \sigma_{\mathbf{A}}}$$
.

The risk indicators are computed by applying the CCA methodology separately for each company and bank and for the sovereign sector as a whole. In order to obtain aggregated risk indicators for the corporate and for the banking sectors, the methodology used is based on the procedure employed by Gray *et al.* (2013), respectively by computing aggregated risk indicators using weighted averages based on assets market value.

3.2. Global VAR

After the CCA risk indicators have been obtained for the three sectors analyzed, a Global VAR is constructed for the analysis of risk transmission between the banking sector, sovereign sector, corporate sector, credit growth and real economic activity.

For the construction of the Global VAR (GVAR), it is assumed that the model comprises N+1 countries that are indexed by i=0,...,N. The set of country-specific endogenous variables are collected in a $k_i \times 1$ vector y_{it} , which is related to a number of autoregressive lags up to P, and a $k_i \times 1$ vector of weighted foreign variables $y_{it} \times 1$ that enters the model time contemporaneously with a number of lags up to Q, that is:

$$y_{it} = a_{i0} + a_{i1}t + \sum_{p=1}^{p} \emptyset_{ip} \, y_{i,t-p} + \sum_{q=1}^{Q} \vartheta_{iq} \, y^{*}_{i,t-q} + \Psi d_{t} + \varepsilon_{it}$$

where a_{i0} , a_{i1} , \mathcal{O}_{ip} , ϑ_{iq} and Ψ are coefficient matrices of size $k_i \ge 1$, $k_i \ge 1$, $k_i \ge k_i$, and $d_i \ge 1$ respectively. The vector d_t contains global weakly exogenous variables. It

is assumed that the idiosyncratic error vector \mathcal{E}_{ii} is i.i.d. and has zero mean and covariance matrix Σ_{ii} .

An important factor when constructing the local models of the GVAR is the weight matrix used to compute the foreign variable vectors. A particular feature of the applied methodology is that the weight matrix needed to construct the foreign variable vectors

in the GVAR model is estimated jointly with the GVAR parameters. This approach was developed by Gross (2013). Key to the framework is that the variables included in the GVAR are combined in a fully endogenous setting. The rationale for estimating the weights for the foreign variable vectors using the approach suggested by Gross (2013) is that there is no obvious choice for the weights that would link the analyzed sectors to economic growth and credit rendered to households.

The weight matrix is determined using a sequential quadratic programming method to minimize the sum of squared residuals from a local model subject to the constraints that its set of weight is non-negative and summing to unity. The minimization problem is:

$$\min_{\tau_{i}, w_{ijk}} \sum_{t=1}^{T} \varepsilon_{it}^{2}$$

subject to

$$w_{ijk} \ge 0, j = 0, ..., N, k = 1, ..., K$$

 $\sum_{j=0}^{N} w_{ijk} = 1, k = 1, ..., K$

where: τ_i comprises all local models coefficients contained in a_{i0} , a_{i1} , \emptyset_{ip} , ϑ_{iq} , Ψ and d_t . The minimization problem for item i would exclude w_{ii} and set it to zero.

After a stable model is obtained along with the estimated weight matrix, the GVAR model is used to analyze the impact and the spillover of shocks across sectors and countries. Adverse shock scenarios are tested, particularly to banking and sovereign risk.

The final step of the proposed methodology implies analyzing the results obtained using cumulative impulse response functions. Using the Toolbox provided by Gross (2013)⁴, the cumulative impulse responses are determined using external shocks scenarios. An impulse response analysis is conducted by applying simultaneous shocks to the banking and sovereign sectors of the countries included in the analysis. The size of the implied shocks is of one standard deviation (1 STD) calculated based on the values registered for each variable included in the model. The rest of the variables on which a shock is not applied are considered to be equal to their mean.

4. Data Description

This paper focuses on studying systemic risk in a CCA Global VAR by applying the methodology presented on the previous section on four Central and Eastern European Countries: Romania, Bulgaria, Hungary and Poland. The sample data used has a guarterly frequency and ranges from 2006 to 2013 (32 observations).

⁴ The Toolbox used for estimating and solving the GVAR model, including the weight estimation for the foreign variable vectors, as well as the codes used for computing impulse response functions have been provided by Mr. Gross upon request. For further information please refer to Gross (2013).

The data used to calculate the risk indicators for the corporate and banking sectors were collected from the Reuters Database. The individual balance sheet for each company and bank included in the analysis was needed to determine the distress barrier and daily price quotations were needed to calculate the price volatility. Table 2 presents how much of the corporate and the banking sectors has been covered by the analysis in each of the four countries analyzed. The table shows the average coverage percentage of total market capitalization for the corporate sector, as well as the average coverage percentage of total banking system assets for the banking sector. The number of companies and banks included in analysis is also presented.

Table 2

-	-	-	-		-
Se	ector/ Country	Romania	Bulgaria	Hungary	Poland
Corporate Sector	(average percentage of total market capitalization)	35%	23%	60%	22%
	number of companies	7	5	5	9
Banking Sector	(average percentage of total banking system assets)	41%	27%	44%	49%
	number of banks	4	4	3	8

Average Coverage Percentage for the Corporate and Banking Sectors

Source: Authors' calculations.

When computing the risk indicators for the corporate sector, the companies included in the analysis were non-financial companies with the highest market capitalization from each country's stock exchange.

As the CCA methodology requires the usage of market data, the banks included in the analysis were initially only those listed at the stock exchange. Because the coverage percentage of the total banking system assets was significantly greater in Poland as compared to the other three countries analyzed, one unlisted bank with significant asset value from each of these countries had to be included in the analysis. In order to do so, proxies have been used for the market capitalization and price volatility using information from the affiliated Banking Groups (Erste Group for Romania and Hungary, Unicredit Group for Bulgaria). The complete list of the companies and banks included in the analysis is presented in Appendix 1.

The GAVR model used to analyze the risk transmission between sectors and countries is therefore constructed based on 5 variables (corporate risk, banking risk, sovereign risk, economic growth and the dynamic of household credit growth) and four countries (Romania, Bulgaria, Hungary and Poland) using quarterly data for the period 2006-2013.

5. Results

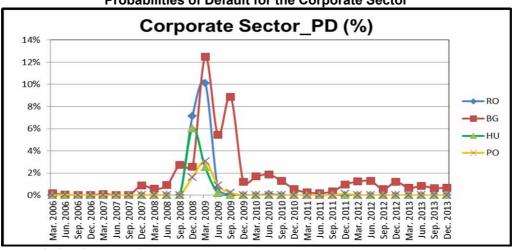
The first part of this section consists in the presentation of the CCA results for the three sectors analyzed: corporate, banking and sovereign.

Romanian Journal of Economic Forecasting -XVII (4) 2014

5.1. Probability of Default

The evolution of the probability of default for the corporate sector of the four countries analyzed is presented in Figure 2 below.





Probabilities of Default for the Corporate Sector

Source: Authors' computations.

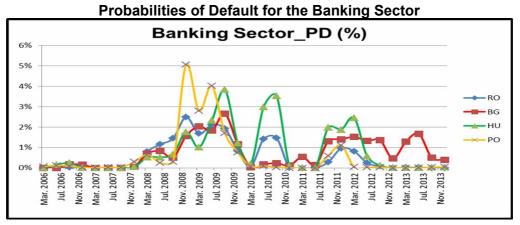
The analysis has been employed considering non-financial companies listed at the stock exchange that have shares traded for a period long enough to capture the impact of the financial crisis (at least 2007-2013). The composition of the aggregated corporate sector probabilities of default is presented in Appendix 2.

The CCA results obtained for the corporate sector show that the most severe consequences of the financial crisis were present in Bulgaria, with a probability of default of approximately 12.5% in the first quarter of 2009. Moreover, as compared to the other three countries analyzed, the probability of default for Bulgaria is significantly different from zero for a longer period. The probability of default for the Romanian corporate sector was close to the value registered in Bulgaria with a climax of approximately 10% in the first quarter of 2009. Poland reached the highest value of the corporate sector probability of default in the same period as Bulgaria and Romania, but at a smaller scale, having a 3% likelihood that the corporate sector assets would fall below the distress barrier. As for the situation in Hungary, the probability of default for the corporate sector reached the highest value of approximately 6% at the end of 2008, decreasing to approximately 2% in the first quarter of 2009.

The probability of default for the banking sector has been obtained following the same approach as for the corporate sector. The differences consist in the methodology used to determine the distress barrier and the assumptions made in order to include in the analysis three unlisted banks. The aggregated results for the banking sector are presented in Figure 3, while the risk indicators computed for individual banks are presented in Appendix 2.

Romanian Journal of Economic Forecasting - XVII (4) 2014





Source: Authors' computations.

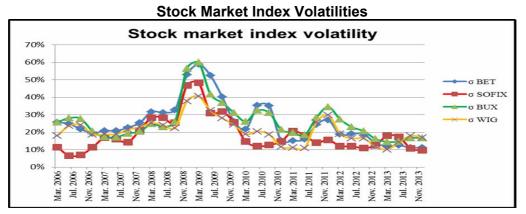
As the difficulties encountered at the level of the banking system in many countries was one of the first signs of the recent financial crisis, the probability of default for the banking sector showed signs of distress starting in the last quarter of 2007 and reached the highest values between the last quarter of 2008 and the third quarter of 2009. Another period of financial distress encountered by the banking sector began in the second semester of 2011 and ended in the third quarter of 2012. The cause for this period of distress could be considered the sovereign debt crisis that had a severe effect on many European countries.

After looking at Figure 4 above, one might conclude that the Polish banking sector was the riskiest one during the period 2008-2009. It must be taken into consideration the fact that Poland is the only country of the four countries analyzed that has enough banks listed at the stock exchange to assess a significant proportion of the banking system. However, the probabilities of default for the four countries analyzed were relatively close, reaching values between 2% and 5% during the period 2008-2009.

Another observation that shall be made based on the probabilities of default obtained for individual banks is that the banks with smaller asset values faced financial distress earlier than the rest of the banks included in the analysis. For example, one can see in the graphs presented in Appendix 2 that BCC, the smallest Romanian bank included in the analysis, was affected more seriously by the financial crisis than the other three banks analyzed, reaching a probability of default of approximately 7% in the second quarter of 2008 and continuing to encounter financial distress during 2013.

Romanian Journal of Economic Forecasting -XVII (4) 2014



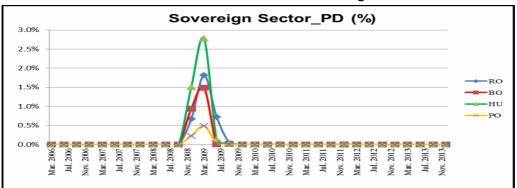


Source: Authors' computations.

When applying CCA to the sovereign sector, an important aspect consists in determining the volatility of domestic currency liabilities. In this paper, the volatility of the stock market index has been used. Figure 4 shows that the stock markets of the four countries analyzed bear the influences of the recent financial crisis, experiencing high volatilities in the period 2008-2009. Another episode of high volatility is outlined in Hungary, Romania and Poland between the second semester of 2011 and the end of 2012. This episode of market uncertainty has emerged in Bulgaria one quarter earlier and had a milder impact. Moreover, the highest volatilities of the stock market indexes are reached in Hungary and Romania. This result implies that the sovereign risk for Hungary and Romania will exceed the values recorded for two countries analyzed, a higher volatility leading to an increase in the probability of default.

The probabilities of default for the sovereign sector of the four countries included in the analysis are displayed in Figure 5.

Figure 5



Probabilities of Default for the Sovereign Sector

Source: Authors' computations.

Romanian Journal of Economic Forecasting - XVII (4) 2014

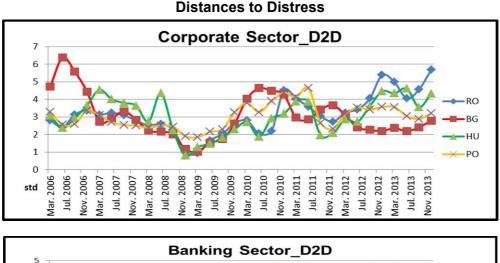
The first observation based on the results obtained is that the probabilities of default for the sovereign sector detect only the period with the highest likelihood that the total assets would fall below the distress barrier. Moreover, the values registered are relatively small, the probabilities of default being situated below 3%. The fact that the probabilities of default are significantly different from zero only during the period 2008-2009 might be problematic when studying the transmission of shocks between sectors and countries.

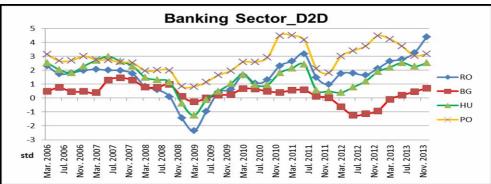
5.2. Distance to Distress

Due to the fact that probabilities of default are significantly different from zero only during periods of distress, this risk indicator cannot be used to measure the shock transmission across sectors and countries. A more suitable risk indicator proves to be the distance to distress (D2D).

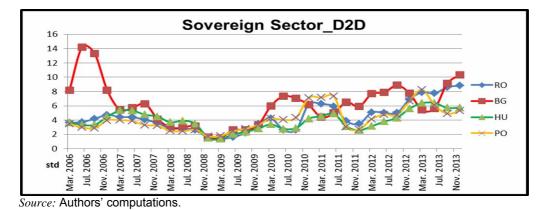
As it can be observed in Figure 6, the distances to distress risk indicator distinguishes two periods of increased financial distress: the global financial crisis that affected the European countries in 2008-2009 and the euro area debt crisis that impacted the countries included in the analysis in 2011-2012.







Measuring Systemic Risk Using Contingent Claims Analysis



A notable observation is that the banking sector was the only sector whose distance to distress risk indicator dropped below zero during the first quarter of 2009 for Romania, Hungary and Bulgaria, whilst the Polish banking sector maintained a positive distance to distress for the entire period analyzed.

Another observation that can be made based on the results obtained refers to the slightly distinctive evolution of the risk indicator for Bulgaria as compared to the results registered for the other three countries. The main difference consists in a significant increase in distances to distress in June 2006 for the Bulgarian corporate and sovereign sectors. This might be the result of a decrease in the market volatility caused by the introduction of a new set of rules meant to create a new subdivision of the official and unofficial markets already in existence. Moreover, the most severe period of distress for the Bulgarian banking sector was registered in 2012, being influenced by the fact that the Bulgarian sovereign sector was affected by the European debt crisis half a year in advance as compared to the other three countries analyzed. This might be a consequence of the fact that Bulgaria has a monetary council, which sets the exchange rate of the leva fixed to the euro, facilitating the contagion of the European debt crisis.

The evolution of distances to distress for Romania, Hungary and Poland is relatively similar in the period analyzed, the risk indicator identifying simultaneously periods of distress for each of the three sector included in the analysis.

5.3. Global VAR

In order to conduct systematic shock simulation and to measure the spillover potential within sectors and across countries, a Global Vector Autoregressive (GVAR) Model is constructed based on the distances to distress risk indicators for the corporate, banking and sovereign sectors, economic growth and household credit growth.

The local model equations for the five variables analyzed have been set to contain one autoregressive lag and one lag for the foreign variables.

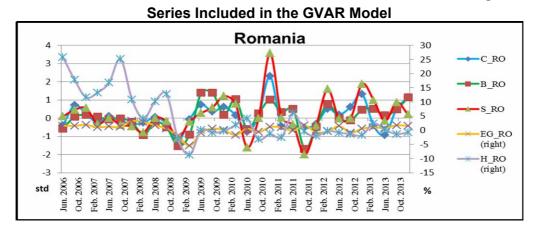
Due to the fact that the variables presented in the previous sections were not stationary, some adjustments had to be made in order to obtain a stable model. Therefore, the risk indicators for the three sectors analyzed were included in the

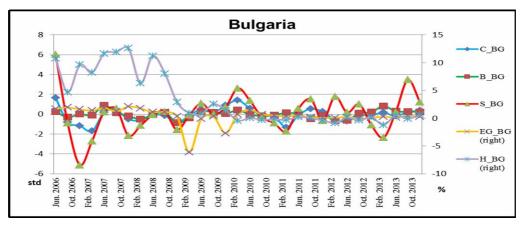
Romanian Journal of Economic Forecasting - XVII (4) 2014

Figure 7

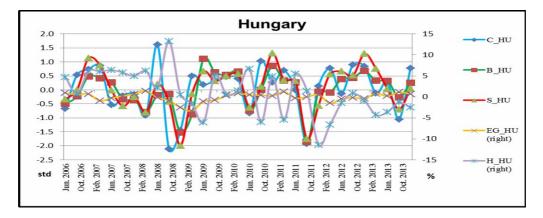
model as differences from quarter to quarter, reflecting the absolute changes in distances to distress (changes in the number of standard deviations of the assets from distress). In order to render it stationary, economic growth was measured as the dynamic of real GDP from quarter to quarter. For the household credit growth series, the rates were computed as quarter to quarter relative changes in the value of loans rendered to households.

Figure 7 illustrates the evolution of the series included in the GVAR model, aggregated by country. The risk indicators are expressed in assets standard deviations, while economic growth and household credit growth are expressed in percentages. The descriptive statistics of the series included in the GVAR model are presented in Appendix 3.





Measuring Systemic Risk Using Contingent Claims Analysis





Source: Authors' computations

The results obtained for Romania and Poland prove that the global financial crisis that affected the European countries in 2008-2009 had its roots in the banking sector, whilst the 2011-2012 episode of distress had a higher impact on the sovereign sector, as a consequence of the Euro Area sovereign debt crisis.

As it was previously mentioned, the weights for the foreign variable vectors have been estimated along with the GVAR's parameters. The results obtained are presented in Appendix 4. It can be observed that the countries that exercise the highest influence among the rest of the countries included in the analysis are Poland and Bulgaria. The variables from Poland have a high influence upon the Bulgarian and Hungarian variables, while the Bulgarian variables have a significant influence upon the evolution of the Romanian and Polish variables. Romania and Hungary are accountable for less than a third of the total foreign influence employed on the other countries included in the analysis. This might indicate that a shock in Romania or Hungary would not have a significant spillover effect among the countries included in the analysis, while a shock in Poland or Bulgaria would affect all the four countries included in the analysis. For better understanding how shocks are propagated across sectors and countries, a shock simulation shall be employed.

Romanian Journal of Economic Forecasting – XVII (4) 2014 —

5.4. Shock Transmission Analysis Using GVAR's IRFs

Before going further with the shock transmission analysis, it must be underlined that some of the most severe shocks that affected the analyzed countries were propagated from developed countries (e.g. USA, Germany), whose financial distress had a broader global impact due to their international connections (trading, investment). However, the purpose of this paper is to determine the spillover effects among Central and Eastern European countries by analyzing whether a distress in the banking sector has a more severe effect upon the other sectors than a distress in the sovereign sector and whether it generates a higher contraction of economic growth.

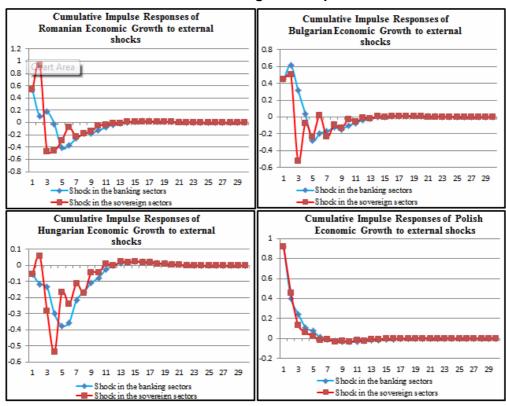
While the weight estimates presented in the previous section might be suggestive of how shocks might propagate, they do not provide an insight into either how significant shock responses would be or how the dynamic of the shock responses would look like. To address this issue, cumulative impulse response functions will be used.

Since an adverse scenario would imply a decrease in the distance to distress risk indicators, the shocks applied will be negative and their size will be equal to one standard deviation calculated for each series of absolute changes in distances to distress.

One of the most accurate indicators that can be used to measure the impact of a shock is the effect it implies upon economic growth. The results obtained using cumulative impulse response functions show that a general shock in the sovereign sectors leads to a more severe contraction of the economic growth, the highest drop being recorded two quarters after the onset of the shock for Romania, Bulgaria and Poland and a quarter later for Hungary. The effects of the shocks upon Poland's economic growth are reduced as compared to the results obtained for the other three countries, Poland being the only country which recorded a positive economic growth throughout the entire period analyzed. A graphic comparative illustration of the impact on economic growth by a general adverse shock of one standard deviation to the banking sector as opposed to the same type of shock applied to the sovereign sector is presented in Figure 8.

Figure 8 clearly shows that, in all the four countries analyzed, a shock of one standard deviation employed on the sovereign sector generates a greater impact than a shock of one standard deviation applied to the banking sector. This result is based on the fact that the fiscal measures implied in order to reduce the impact of a sovereign crisis are transmitted easier to economic growth than the monetary policy measures. For example, in order to reduce the government debt, a restrictive fiscal policy is applied, reducing budgetary expenses (e.g. salaries, subventions) and increasing taxes. This measure will generate a drop in consumption and ultimately a decrease in real GDP, which would be reflected in a decrease of the economic growth. The monetary policy mechanism seems to have a delayed effect as compared to the fiscal policy mechanism, more time being needed for an increase in the monetary policy rate to have an impact on economic growth.

Figure 8



Cumulative Impulse Responses of Economic Growth to Shocks in the Banking and Corporate Sectors

Source: Authors' computations.

Further on, the impact of a simultaneously shock to the sovereign and banking sectors of all the four countries is analyzed. As it was expected, the cumulative impulse response functions are more pronounced when a shock affects both the banking and sovereign sectors. For exemplification purposes, Figure 9 illustrates the impact employed on the Romanian economic growth by the shocks applied to the banking sector, sovereign sector, as well as on both sectors simultaneously.

The spillover effect between the banking and sovereign sectors is present at the level of the analyzed countries, a shock applied on one sector generating the most severe drop in the distance to distress risk indicator of the other sector approximately two quarters after the onset of the shock. The results show that Romania and Hungary are more exposed to spillover effects from other sectors and countries, while Poland and Bulgaria are affected in a much smaller extent.

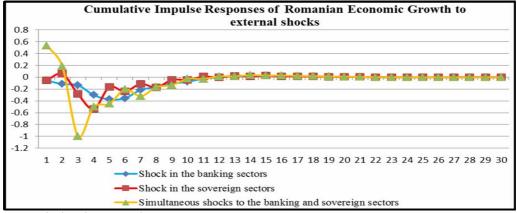
The Hungarian corporate sector bears the most significant influence from a shock employed to the sovereign sectors, whilst the most affected sector from a generalized

Romanian Journal of Economic Forecasting - XVII (4) 2014

shock to the banking sector is the Romanian corporate sector. However, the impact of a generalized shock to the sovereign sectors has a less severe impact on the corporate sectors than a generalized shock to the banking sectors.

Figure 9

Cumulative Impulse Responses of the Romanian Economic Growth to External Shocks



Source: Authors' computations.

40

As far as household credit growth is concerned, a shock in the sovereign sector does not have a significant effect. The adverse shocks applied to the banking sectors are reflected in the evolution of household credit growth, reducing the growth rate and generating a further decrease of the credits rendered to households after one and a half years from the onset of the shocks.

6. Conclusions

It is a known fact that systemic risk affects not only the banking sector, but the financial markets and other sectors as well, the ultimate effect being a decline in the economic growth. The systemic nature of the risk usually involves spillover effects to other countries' financial systems, depending on the magnitude of the shocks.

The purpose of the paper has been to determine the extent to which the banking, sovereign and corporate sectors of the four countries analyzed, along with economic growth and household credit growth, have been inter-dependent during the recent global financial crisis. The framework used in this paper for risk quantification purposes has been the Contingent Claims Analysis.

Since the obtained probabilities of default for the sovereign and corporate sectors were significantly different from zero only during periods of distress, it was not possible to use this risk indicator to measure the shock transmission across sectors and countries. A more suitable choice proved to be the distance to distress risk indicator.

The results showed that distances to distress capture the distress periods more accurately than the probabilities of default, distinguishing two periods of increased financial distress: the global financial crisis that affected the European countries in 2008-2009 and the Euro Area debt crisis that impacted the countries included in the analysis in 2011-2012.

A notable observation is that the banking sector was the only sector whose distance to distress risk indicator dropped below zero during the first quarter of 2009 for Romania, Hungary and Bulgaria. This means that due to increased market volatility, the

implied asset values dropped below the distress barrier. The Polish banking sector was the only one which maintained a positive distance to distress for the entire period analyzed.

In order to conduct systematic shock simulation and to measure the spillover potential within sectors and across countries, a Global Vector Autoregressive (GVAR) Model was constructed based on the distances to distress risk indicators for the corporate, banking and sovereign sectors, economic growth and household credit growth. The results obtained for Romania and Poland proved the fact that the global financial crisis that affected the European countries in 2008-2009 had its roots in the banking sector, whilst the 2011-2012 episode of distress had a higher impact on the sovereign sector, as a consequence of the euro area sovereign debt crisis.

The estimated weights for the foreign variables vectors illustrated that the countries with the highest influence among the rest of the countries included in the analysis were Poland and Bulgaria.

The results of the impulse response analysis showed that a shock of one standard deviation employed on the sovereign sector generates a greater impact upon economic growth than a shock of one standard deviation applied to the banking sector. Therefore, the impact of a sovereign crisis is transmitted easier to economic growth than the impact of a banking crisis, the monetary policy mechanism having a delayed effect as compared to the fiscal policy mechanism. As it was expected, the cumulative impulse response functions are more pronounced when a shock affects both the banking and sovereign sectors.

Before drawing final conclusions, we must consider the fact that some of the assumptions made might bias the results. Therefore, the contingent claims approach can be applied to study systemic risk but certain adjustments need to be made in order to overcome the model limitations, most of them caused by data availability.

However, integrating macroeconomic and financial variables into one framework, while using for some variables CCA indicators instead of accounting measures, is considered to be an improvement as compared to the existing empirical work in the literature. The framework developed here may be a useful tool to assess the combinations of policies that reduce risk for banking systems and sovereigns while increasing real GDP growth.

Acknowledgment

This work was supported by a grant of the Romanian National Authority for Scientific Research, CNCS – UEFISCDI, project number PN-II-ID-PCE-2011-3-1054.

Romanian Journal of Economic Forecasting – XVII (4) 2014

References

Altar, M. Samuel, J. and Altar-Samuel, A.N., 2012. A Study Of Sovereign Risk, Using Contingent Claims Analysis. World Finance & Banking Symposium -"Asian Finance & Banking", Shanghai, China

- Bisias, D. Flood, M. Lo, A.W. and Valavanis, S., 2012. A Survey of Systemic Risk Analytics. *Working Paper* 0001, Office of Financial Research;
- Blancher, N., et al., 2013. Systemic Risk Monitoring (SysMo) Toolkit A User Guide. *IMF Working Paper*, WP/13/168;
- Gapen, M.T. Gray, D. Lim, C.H. and Xiao, Y., 2008. Measuring and Analyzing Sovereign Risk with Contingent Claims. *IMF Staff Papers* Volume 55.
- Gray, D. Gross, M. Paredes, J. and Sydow, M., 2013. Modeling Banking, Sovereign, and Macro Risk in a CCA Global VAR. *IMF Working Paper*, WP/13/218;
- Gray, D., 2007. A New Framework for Sovereign Wealth Management. Sovereign Wealth Management, Central Bank Publications for the World Bank and Blackrock.
- Gray, D. and Jobst, A.A., 2011. Systemic CCA A Model Approach to Systemic Risk. Conference "Beyond the Financial Crisis: Systemic Risk, Spillovers and Regulation".
- Gray, D. and Walsh, J., 2008. Factor Model for Stress-testing with a Contingent Claims Model of the Chilean Banking System. *IMF Working Paper* 08/89. (Washington: International Monetary Fund);
- Gray, D. et al., 2011. Incorporating Financial Sector Risk into Monetary Policy Models: Application to Chile. *IMF Working Paper*, WP/11/228;
- Gray, D. Merton, R. and Bodie, Z., 2008. New Framework For Measuring And Managing Macrofinancial Risk And Financial Stability. Central Bank of Chile, *Working Papers* No. 541;
- Gray, Dale F. and Jobst, A.A., 2011. Modelling Systemic Financial Sector Risk and Sovereign Risk. *Economic Review*, 2, pp. 68-106.
- Gross, M., 2013. Estimating GVAR weight matrices. ECB, *Working Paper Series* No. 1523;
- Jobst, A.A. and Gray, D., 2013. Systemic Contingent Claims Analysis Estimating Market-Implied Systemic Risk. *IMF Working Paper*, WP/13/54;
- Merton, R.C., 1973. Theory of Rational Option Pricing. *Bell Journal of Economics and Management Science*, 4, pp. 141-83 (Chapter 8 in Continuous-Time Finance).
- Oshiro, N. and Saruwatari, Y., 2005. Quantification of sovereign risk: Using the information in equity market prices. *Emerging Markets Review*, 6, pp. 346-362
- Pesaran, M.H. Schuermann, T. and Weiner, S.M., 2004. Modelling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business and Economic Statistics*;
- Segoviano, M. A. and Goodhart, C., 2009. Banking Stability Measures. *IMF Working Paper*, WP/09/4.

Appendices

Appendix 1 – The List of Analyzed Companies and Banks

1. Corporate Sector

1.1. Romania

Company Name	Notation		Share in the Risk
		Capitalization	Indicators
OMV PETROM S.A.	SNP	26.9%	76.1%
ALRO S.A.	ALR	3.0%	8.4%
S.N.T.G.N. TRANSGAZ S.A.	TGN	2.0%	6.9%
C.N.T.E.E.	TEL	1.7%	4.8%
TRANSELECTRICA			
ANTIBIOTICE S.A.	ATB	0.6%	1.6%
ZENTIVA S.A.	SCD	0.5%	1.4%
BIOFARM S.A.	BIO	0.3%	0.8%

1.2. Bulgaria

Company Name	Notation	Percent of Market Capitalization	Share in the Risk Indicators
SOPHARMA AD-SOFIA	SHRM	6.9%	30.2%
CHIMINPORT AD-SOFIA	CHI	5.8%	22.3%
BULGARTABAC HOKDING AD-	BGH	3.9%	18.8%
SOFIA			
ALBENA AD-ALBENA	ALB	3.5%	15.8%
MONBAT AD-SOFIA	MBT	3.1%	13.0%

1.3. Hungary

Company Name	Notation	Percent of Market Capitalization	Share in the Risk Indicators
MOL Hungarian Oil and Gas Plc.	MOL	33.0%	55.3%
Gedeon Richter Plc.	RCH	12.7%	21.1%
Magyar Telekom Plc.	MTK	11.8%	20.0%
Tisza Chemical Group Plc.	TVK	1.5%	2.6%
Danubius Hotel and Spa Plc.	DNB	0.7%	1.1%

1.4. Poland

Company Name	Notation	Percent of Market Capitalization	Share in the Risk Indicators
PGNIG	PGN	5.6%	27.8%
PKN ORLEN	PKN	4.1%	20.7%
KGHM POLSKA MIEDŹ S.A.	KGH	4.3%	19.8%
PGE POLSKA GRUPA	PGE	4.0%	15.0%
ENERGETYCZNA S.A.			
LPP SA	LPP	1.0%	4.3%
CYFROWY POLSAT S.A.	CYFR	0.8%	3.4%
SYNTHOS S.A	SHOS	0.8%	3.2%

Romanian Journal of Economic Forecasting – XVII (4) 2014

TAURON POLSKA ENERGIA S.A.	TPE	0.8%	3.1%
EUROCASH S.A.	ECSH	0.7%	2.8%

2. Banking Sector

2.1. Romania

Bank Name	Notation	Percent of	Share in the
		Banking	Risk
		System Assets	Indicators
BANCA COMERCIALA ROMANA S.A	BCR	21.1%	50.9%
BRD - GROUPE SOCIETE GENERALE S.A.	BRD	13.4%	32.5%
BANCA TRANSILVANIA S.A.	TLV	5.8%	14.4%
BANCA COMERCIALA CARPATICA S.A.	BCC	0.9%	2.2%

2.2. Bulgaria

Bank Name	Notation	Percent of	Share in the
		Banking System	Risk
		Assets	Indicators
UNICREDIT BULBANK	UNIB	15.0%	57.4%
CB FIRST INVESTMENT BANK	FIB	5.8%	19.6%
CB CORPORATE COMMERCIAL BANK	CCOM	3.5%	11.5%
CB CENTRAL COOPERATIVE BANK	CCB	3.0%	11.6%

2.3. Hungary

Bank Name	Notation	Percent of Banking System	Share in the Risk
		Assets	Indicators
OTP BANK PLC.	OTP	32.3%	73.5%
ERSTE BANK HUNGARY ZRT	ERTH	9.1%	20.7%
FHB MORTGAGE BANK CO PLC.	FHB	2.5%	5.8%

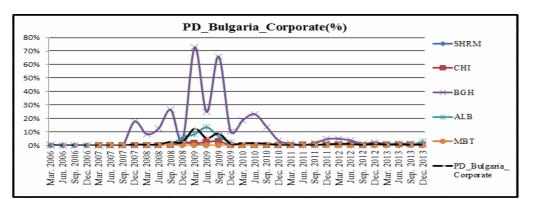
2.4. Poland

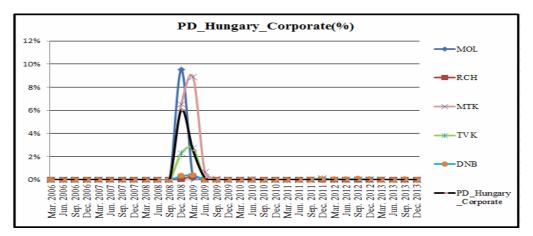
Bank Name	Notation	Percent of	Share in the
		Banking System	Risk
		Assets	Indicators
POWSZECHNA KASA OSZCZĘDNOŚCI BANK	PKOBP	12.3%	25.3%
POLSKI S.A.			
BANK POLSKA KASA OPIEKI S.A.	PEKAO	10.0%	20.5%
MBANK S.A.	MBANK	6.2%	12.9%
ING BANK ŚLĄSKI S.A.	ING	5.4%	11.0%
BANK ZACHODNI WBK S.A.	BZWBK	4.6%	9.3%
BANK HANDLOWY W WARSZAWIE S.A.	HNDLY	3.5%	7.1%
BANK MILLENNIUM S.A.	MLM	3.4%	7.1%
BANK BPH S.A.	BPH	3.4%	6.8%

1. Corporate Sector

Appendix 2 - Probabilities of Default for the Corporate and Banking Sectors

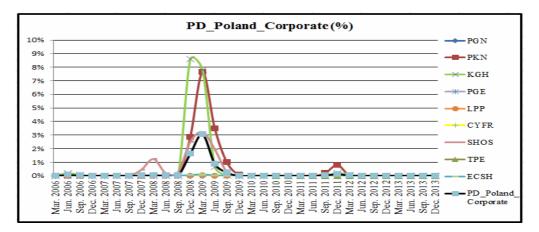
PD_Romania_Corporate(%) -SNP 25% ALR 20% TGN-15% TEL 10% -ATB 5% SCD 0% 2-2-2006 | 22006 | 22006 | 22006 | 22006 | 22007 | 22007 | 22007 | 22007 | 22007 | 22008 | 22008 | 22008 | 22009 | 22009 | 22009 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 22010 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | 1020 | -BIO PD_Romania Corporate



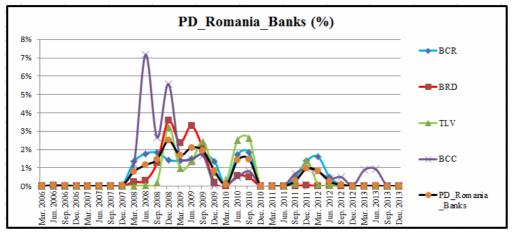


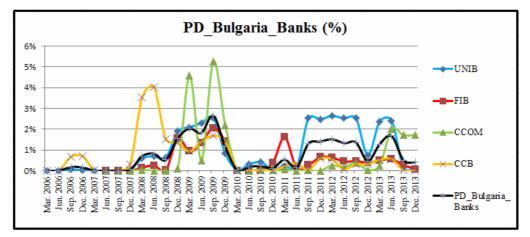
Romanian Journal of Economic Forecasting - XVII (4) 2014

Institute for Economic Forecasting

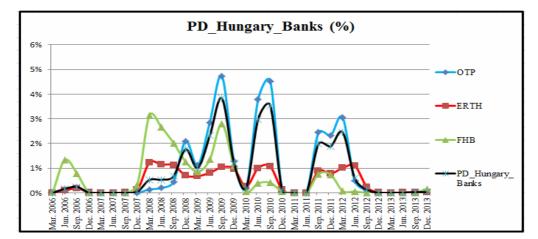


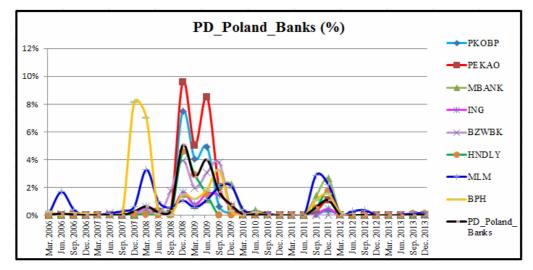
2. Banking Sector





Measuring Systemic Risk Using Contingent Claims Analysis





Appendix 3 – Descriptive Statistics for the Series Included in the GVAR

Statistic/Variable*	C_RO	C_BG	C_HU	C_PO	B_RO	B_BG	B_HU	B_PO
Mean	0.09	-0.06	0.04	0.00	0.07	0.01	0.00	0.00
Median	0.06	-0.10	0.27	-0.03	0.08	0.02	0.26	0.00
Maximum	2.31	1.66	1.62	0.97	1.39	0.91	1.10	1.56
Minimum	-1.26	-1.70	-2.11	-1.98	-1.69	-0.86	-1.86	-2.05
Std. Dev.	0.71	0.72	0.88	0.56	0.76	0.39	0.66	0.66
Skewness	0.90	0.09	-0.79	-1.11	-0.32	-0.01	-0.97	-0.53
Kurtosis	4.52	3.35	3.15	6.07	2.96	3.34	3.84	5.30

The values are expressed as absolute changes in the number of standard deviations the assets are from default.

Statistic/Variable*	S_RO	S_BG	S_HU	S_PO
Mean	0.17	0.07	0.07	0.06
Median	0.00	0.17	0.12	0.03
Maximum	3.57	6.03	1.31	2.77
Minimum	-2.00	-5.12	-1.99	-4.24
Std. Dev.	1.03	2.01	0.77	1.24
Skewness	0.93	0.33	-0.74	-1.06
Kurtosis	5.58	4.88	3.63	6.61

* The values are expressed as absolute changes in the number of standard deviations the assets are from default.

Statistic/Variable**	EG_RO	EG_BG	EG_HU	EG_PO	H_RO	H_BG	H_HU	H_PO
Mean	0.54	0.44	-0.05	0.92	4.36	3.26	1.03	4.30
Median	1.00	0.44	0.23	0.79	0.07	0.62	0.84	3.95
Maximum	3.27	2.10	1.41	2.20	25.84	12.58	13.27	12.37
Minimum	-5.48	-6.13	-3.33	-0.41	-8.76	-1.20	-11.48	-10.41
Std. Dev.	1.65	1.52	1.05	0.62	8.59	4.68	5.29	5.20
Skewness	-1.56	-2.84	-1.32	0.08	1.08	0.92	-0.18	-0.48
Kurtosis	6.87	12.75	4.85	2.40	3.32	2.21	2.85	3.43

** The values are expressed as relative changes from quarter to quarter (%).

Appendix 4 – Common Weights Matrix for the Foreign Variables Vectors

	RO	BG	HU	PO
RO	0.00	0.26	0.27	0.18
BG	0.48	0.00	0.22	0.59
HU	0.28	0.17	0.00	0.23
PO	0.24	0.57	0.51	0.00