# Stock Market Volatility Spillovers Among The EU Members

**by**

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**and have found that it is complete and satisfactory in all respects,**
**and that any and all revisions required by the final**
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# Abstract

In this thesis, I analyze volatility spillovers across eight European stock markets from March 19, 2001 to July 21, 2010. Following recent contributions to the literature on financial spillovers, I use the variance decompositions from a generalized vector autoregression model of stock market volatilities. The results illustrate that there had been substantial volatility spillovers among the eight European stock markets, especially during the current global financial crisis. The results also show that German and French stock markets have been net volatility transmitters to Eastern European stock markets both in non-crisis and crisis periods.



Key words: Volatility, Spillover, Stock Market, Interdependence, Variance Decomposition, Financial Crisis

# Özet

Son yıllarda küreselleşmenin etkisiyle artan oynaklık yayılmaları, birçok araştırmaya konu olmuştur.

Bu çalışma 2001 ve 2010 yılları arasındaki dönemde günlük oynaklıkları kullanarak Avrupa ülkeleri arasındaki oynaklık yayılmalarını incelemiştir. Bu araştırma genelleştirilmiş VAR modelinden elde edilen varyans ayrıştırmasına dayananarak yapılmıştır. Elde edilen sonuçlara göre, oynaklık yayılmalarının ekonomik olaylara bağlı olduğu ortaya konmuş, özellikle finansal kriz zamanlarında çok fazla artış gösterdiği anlaşılmıştır. Ayrıca sonuçlar, Almanya ve Fransa piyasalarında oluşan oynaklıkların diğer Avrupa ülkelerine daha fazla yayıldığını göstermiştir.


Anahtar Kelimeler: Oynaklık, Finansal Kriz, Finansal Piyasalar, Oynaklık yayılması, Varyans Ayrıştırması

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# 1. Introduction and Literature Review:

The global financial crisis which firstly originated in the U.S. subprime mortgage market was transformed into a global one with the collapse of Lehman Brothers in September 2008. Financial markets crashed all around the world and began impacting each other with increased volatility.

The recent financial crisis was not the first one in the history. After the 1990s, the financial market crises have become more frequent with the impact of globalization. During these crises, financial market volatility rises faster due to globalization and increased integration between markets. An understanding of volatility in financial markets is crucial for assessing these financial crises and showing how these volatilities spill over to other markets.

Several studies have researched how the increase in financial market volatility spreads over to other markets. Many of these studies illustrate that interdependence between financial markets increase by the impact of globalization, financial reforms, advances in computer technology, and information processing. This stimulates economists to show the integration of markets and how financial market volatility changes across markets.

Edwards and Susmel (2001) found volatility dependence and contagion in emerging equity markets in Latin America and Asia during 1989-1999. They analyzed whether the degree of financial instability rose during last several years. Furthermore, they assessed whether periods of increased stock market volatility matched for these countries. They used both univariate and bivariate switching volatility models such as Hamilton and Susmel's (1994) SWARCH methodology. Their univariate results indicated that high volatility periods were related to international crises. Moreover, there were interdependent volatility processes in Latin American markets.

Forbes and Rigobon (2002) measured stock market comovements to show that there was evidence of interdependence or contagion. To prove their claim, they defined contagion and interdependence. Contagion was defined as an increase in cross-market linkages after a shock to one country (or group of countries). Nevertheless, interdependence was defined as strong linkages between two economies that existed in all states of the world. They focused on tests for contagion based on cross-market correlation coefficients. The purpose of this focus was to show that these tests were biased and inaccurate due to heteroscedasticity. They stated that there was no increase in the unconditional correlation coefficients (no contagion) during 1997 East Asian Crisis, 1994 Mexico Peso Crisis, and 1987 U.S. Stock Market Crash. Consequently, they concluded that high cross-market coefficients were caused by only interdependence that was the continuation of strong linkages that occur in all states of the world during 1997 East Asian Crisis, 1994 Mexico Peso Crisis, and 1987 U.S. Stock Market Crash.

Researchers used different methodologies to show the interdependence across markets. For example, Baele (2005) demonstrated that the impact of globalization and regional integration caused an increase in equity market interdependence. He used regime-switching spillover model which was the extension of Bekaert and Harvey (1997). He distinguished between two regional sources of shocks instead of one world shock and allowed for regime switches in the spillover parameters. Baele analyzed 13 Western European equity markets by this new measure. He found that spillover intensity of shocks from European (Regional) and U.S. (global) increased over the 1980s and 1990s. The increase in spillovers from the EU was more pronounced. He linked this increase in EU spillovers to an increase in equity market development, low inflation, and a rise in trade integration. Moreover, he concluded that there was a contagion effect from U.S. market to a number of European equity markets during high world market volatility periods.

Measuring the volatility and showing the integration among financial markets during non-crisis and crisis periods attract the attention of the researchers since it is crucial to determine the cost of capital during global integration of financial markets. Chukwuogor and Feridun (2007) showed return volatilities in both emerging and developed European stock markets by applying a set of parametric and non-parametric tests to test the equality of mean returns and standard deviations of the returns. They found that there were high volatility returns in these markets during 1997-2004. During this period, Japan and United States played important roles for all economies because there was a slowdown in economies of Japan and the US. Due to this fact, stock markets fell during this period. Sharp declines in stock markets were not only due to this slowdown, but also consequences of dotcom bubble and September 11 attacks.

Diebold and Yılmaz (2009) contributed to the literature by defining a new index. To measure interdependence, Diebold and Yılmaz (2009) proposed a spillover index which was based on forecast error variance decompositions from vector autoregressions (VARs) and Cholesky-factor identification of VARs. They analyzed return and volatility spillovers from 1992 to 2007 across nineteen global equity markets. Their results were based on full sample analysis and rolling sample analysis. They concluded that volatility spillover displayed no trend and increased during crisis periods. In addition, return spillover had an increasing trend due to an increase in international financial market integration.

Yılmaz (2010) applied same procedure of the DY (2009) spillover index to measure interdependence between East Asian equity markets during 1992-2009. He found that volatility spillover index rose during major market crises such as the current crisis, East Asian crisis while return spillover index revealed an increased integration over time among these markets. Furthermore, both of them reached their peaks during the global financial crisis.

Diebold and Yılmaz (2009) used the DY (2009) spillover index framework to assess return and volatility spillovers across five equity markets in Americas during 1992-2008. They concluded that volatility spillovers were clearly correlated to economic events, and they displayed bursts. Whereas, return spillovers gradually changed over time and did not show bursts.

Diebold and Yılmaz developed their spillover index by using generalized vector autoregressive framework in which forecast-error variance decompositions were not changed according to variable ordering. This framework also included the directional volatility spillovers. This new spillover index was called as the DY (2010). Diebold and Yılmaz (2010) used this framework to measure interdependence between stock, bond, foreign exchange, and commodities markets during 1999-2010. They found that significant volatility changes in all markets were limited until the current financial crisis. However, volatility spillovers increased when the global crisis deepened. Moreover, volatility spillovers from stock markets to other markets were higher than volatility spillovers from other markets.

As mentioned above, Diebold and Yılmaz analyzed volatility spillover among Latin American and Asian stock markets. I want to study how volatility spillover has taken place in the European continent. In this thesis, I focus on eight European countries. Many of these economies became powerful in the global economy due to joining to the European Union. Therefore, it is very fascinating to show how these markets influence each other and how the volatility spills over.

I follow Diebold and Yılmaz methodology in this thesis. However, there are some limitations for the first version of Diebold and Yılmaz index. The DY (2009) depends on Cholesky ordering at which variance decompositions are based on variable ordering. Moreover, this index only evaluates total spillovers (from/to each market i, to/from all other markets, added across i). Another limitation of the DY (2009) is that it only measures spillovers for across equity markets in different countries.

To enhance these limitations, DY (2010) uses generalized vector autoregression framework. This new framework is based on forecast-error variance decompositions in which are robust to variable orderings. As the variance decomposition is robust to the ordering of the markets, the generalized VAR framework allows one to study the directional volatility spillovers.

I use the DY (2010) to analyze daily volatility spillovers across eight stock markets of European countries between March 2001 and July 2010.

The rest of the thesis is structured as follows: Section 2 explains the methodology followed and presented the data used. Section 3 presents the analysis of the findings of this study. Section 4 concludes the thesis. References are explained in section 5 and appendix is included in the last section.

## 2. Methodology and Data:

### Spillover Methodology:

As stated above, the DY (2009) index is based on simple VAR famework which uses Cholesky ordering. However, the DY (2010) index is extended with using generalized VAR framework and adding directional volatility spillovers. The reason generalized VAR framework is used is that it is invariant to variable-ordering.

Consider a covariance stationary N-variable VAR(p):

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$$

and where $\varepsilon \sim (0, \sum)$ is a vector of IID disturbances.

MA representation is shown as

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$$

where $A_i$ is NxN coefficient matrices and they satisfy

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + ...... + \Phi_p A_{i-p}$$

with $A_o$ an NxN identity matrix and $A_i = 0$ for i<0.

MA coefficients represent impulse-response functions, or variance decompositions. They are crucial to understand spillover frameworks. Variance decompositions are the key points to parse forecast error variances of each variable into attributable parts to shocks. They are important to evaluate the H-step-ahead error variance in predicting $x_i$ due to shocks to $x_j$, $\forall i \neq j$ for each i.

I use generalized VAR framework of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), KPPS. It allows me to use variance decompositions which do not depend on variable-ordering. However, simple VAR framework which depends on Cholesky ordering uses orthogonal innovations, generalized VAR uses correlated shocks but accounts for them appropriately using the historically observed distribution of the errors. As orthogonality is not used, the sum of the contributions to variance of forecast error is not necessarily equal to 1.

**Variance shares:**

*Own variance shares* are defined as fractions of H-step-ahead error variances in forecasting $x_i$ due to shocks to $x_i$, for i=1,2,….N

Cross variance shares (spillovers) are defined as fractions of H-step-ahead error variances in forecasting $x_i$ due to shocks to $x_j$, for i=1,2,…..N and i≠j.

KPPS H-step-ahead error variance decompositions are denoted by $\theta_{ij}^{g}(H)$ for H=1,2,……. and it is given as

$$\theta^{g}{}_{ij}(H) = \frac{\sigma^{-1}{}_{ii} \sum_{h=0}^{H-1} (e'_i A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e'_i A_h \Sigma A'_h e_j)} \tag{1}$$

Where $\Sigma$ , $\sigma_{ii}$ , $e_i$ are the variance matrix for error vector, the standard deviation of error term for i th equation and the selection vector with one as i th element and zeros elsewhere.

As it is known that $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$

To calculate the spillover index, each entry of variance decomposition matrix is normalized by a row sum:

$$\tilde{\theta}^{g}{}_{ij}(H) = \frac{\theta^{g}{}_{ij}(H)}{\sum_{j=1}^{N} \theta^{g}{}_{ij}(H)} \tag{2}$$

$$\sum_{j=1}^{N} \tilde{\theta}^{g}{}_{ij}(H) = 1 \quad \text{and} \quad \sum_{i,j=1}^{N} \tilde{\theta}^{g}{}_{ij}(H) = N$$

**Total Spillovers:**

The total volatility spillover index is set by:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}^{g}{}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^{g}{}_{ij}(H)} .100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}^{g}{}_{ij}(H)}{N} .100 \tag{3}$$

Total volatility spillover index explains the contribution of spillovers of volatility shocks across eight stock markets to the total forecast error variance. It is the KPPS analog of Cholesky factor based on DY (2009).

**Directional Spillovers:**

Generalized VAR framework allows me to see the direction of volatility spillovers across eight stock markets. Directional spillovers are constructed according to generalized variance decomposition matrix because they are invariant to variable-ordering.

Directional volatility spillovers received by market i from all other markets j:

$$S_{i.}{}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}^{g}{}_{ij}(H)}{\sum_{j=1}^{N} \tilde{\theta}^{g}{}_{ij}(H)} .100 \tag{4}$$

Directional volatility spillovers transmitted by market i to all other markets j:

$$S_{.i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}^{g}{}_{ji}(H)}{\sum_{j=1}^{N} \tilde{\theta}^{g}{}_{ji}(H)} .100 \qquad (5)$$

**Net Spillovers:**

Net volatility spillover from market i to all other markets j:

$$S_{i}^{g} = S_{.i}^{g} - S_{i.}^{g} \qquad (6)$$

Net volatility spillover means the difference between gross volatility shocks transmitted to all other markets and gross volaility shocks received from all other markets. Net volatility spillover gives information about how much each market affects other markets in net terms.

**Net Pairwise Spillovers:**

Net Pairwise Spillover between markets i and j is defined as the difference between gross volatility shocks transmitted from i to j and gross volatility shocks transmitted from j to i, so it is calculated by using equation 6 as followed:

$$S_{ij}^{g}(H) = \left( \frac{\tilde{\theta}^{g}{}_{ij}(H)}{\sum_{k=1}^{N} \tilde{\theta}^{g}{}_{ik}(H)} - \frac{\tilde{\theta}^{g}{}_{ji}(H)}{\sum_{k=1}^{N} \tilde{\theta}^{g}{}_{jk}(H)} \right) .100 \qquad (7)$$

**Data:**

My analysis includes stock market indices for eight European countries: Germany (DAX), Greece (ASE), France (CAC40), United Kingdom (FTSE), Hungary (BUX), Czech Republic (PX), Poland (WIG), and Estonia (TALSE) from March 19, 2001 through July 21, 2010.

I estimate daily stock volatilities by using daily high, low, open, and close prices. The method is based on the findings of Garman and Klass (1980) and Alizadeh et al. (2002). The formula is defined as:

$$\tilde{\sigma}^2 = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2$$

where H is the daily high, L is the daily low, C is the daily close, and O is the daily open price (all in natural logarithms). I find the corresponding estimate of annualized daily percent standard deviation by using

$$\hat{\sigma}_{1t} = 100\sqrt{365\tilde{\sigma}_{1t}{}^2}$$

The plots of volatilities and summary statistics of log volatilies are seen in Figure 1 and Table 1. All volatilities are high during the global financial crisis according to Figure 1.

In my thesis, I use second-order vector autoregressions (VAR) with 10-step ahead forecasts for 8 markets. Time variation in spillovers is also provided by re-assessing VAR daily, using 200-day rolling estimation window.

After finding the daily stock volatility, I take natural logarithm of daily stock volatility, which is more close to normal distribution, and normality is required to obtain the generalized variance decompositions. Moreover, since these log volatility series are stationary according to Philips Perron test at full-samples as well as rolling window sub-samples, it is appropriate to use VAR instead of a VEC model. Stationarity results of the rolling samples are given in Figure A1. There are no observations higher than t-critical at 5% level, so all of them are stationary.

## 3. Empirical Results:

### 3.1 Full-Sample Volatility Spillover Table:

Table 2 is known as the volatility spillover table whose $ij^{th}$ entry shows the estimated contribution to the forecast error variance of market i coming from innovations to market j. Therefore, the off-diagonal column sums reflect the "to" directional spillovers, and the off-diagonal row sums show the "from" directional spillovers. Net volatility spillover is the difference between "Directional TO Others" and the "Directional FROM Others". In addition, the total volatility spillover index is also shown in Table 2. It is the total off-diagonal column sum relative to the total column sum including diagonals.

The whole analysis is based on vector autoregressions of order 2 and generalized variance decompositions of 10-day-ahead forecast errors.

According to the directional spillovers transmitted to others over the full sample, France transmitted the most of spillovers to other countries' forecast error variance (85.5 points, which is equivalent to 10.7% of the total forecast error variance to be explained). It is followed by the UK (80.2 points, which is equivalent to 10% of the total forecast error variance). However, Estonia and Hungary contributed the least to other countries' forecast error variance (2.2% and 3%, respectively)

In terms of the directonal spillovers received from others, Estonia is the country that received the most of the spillovers from other countries (33 points, which is equivalent to 4.1% of the total forecast error variance). It is followed by Hungary. France received the most of spillovers from other countries' (65.4 points, which is equivalent to 8.1% of the total forecast error variance)

In the case of net volatility spillovers, France is a net transmitter of spillovers to other countries' (2.5% of the total forecast error variance). It is followed by the UK (2% of the total forecast error variance).

Up to this point, I analyzed the directional volatility spillovers. Now I look into the total (non-directional) volatility spillover, which is seen in the lower right corner of Table 2. It indicates that 49.3 percent of volatility forecast error variance in all eight markets comes from spillovers for whole sample.

### 3.2 Rolling-sample total volatility plot:

After the 1990s, financial markets experienced capital movements, advances in computer technology, information processing, and financial reforms. These factors resulted in increasing domestic markets' ability to react to global news and shocks. Therefore, the linkage among stock markets around the world was getting stronger.

To show the interdependence between stock markets around the world is important. However, assessing this interdependence by the fixed-parameter over the entire sample period does not give accurate results. Therefore, full-sample spillover table assembled above does not show the dynamic behavior of the spillovers. To encounter this problem, volatility spillovers are re-estimated by using 200-day rolling samples. The reason I use 200-day rolling samples is that the increase in the number of data provides more realistic results for time-series models. Moreover, the shocks in the stock markets have long-term impacts. Therefore, using 200-day rolling samples allows me to capture these shocks. By using the rolling samples, time variation is well captured. The name of this re-estimation by using rolling samples is total spillover that is seen in Figure 2. The total spillover is used to measure the contribution of spillovers of volatility shocks across eight stock markets. The result is based on vector autoregressions of order 2 and generalized variance decompositions of 10-day-ahead volatility forecast errors.

In order to check the robustness of the results to the choice of the order of VAR, I re-calculated the spillover index for orders 2 through 6. I obtained the maximum, the minimum, and the median values showed in Figure A3. Moreover, I re-calculated the spillover index for forecast horizons varying 5 to 10 days. Figure A2 shows the maximum, the minimum, and the median values according to this change. Both Figure A2 and Figure A3 show that the results are not sensitive to the change of the order of VAR and the forecast horizon.

There are some steep jumps in the total volatility spillover. The volatility spillovers increase sharply in 2006, 2007, and 2008. I ramify these periods according to the crisis time. For example, I name the periods between July 2007 and April 2010 as the global financial crisis period. Therefore, there are two periods to mention about the steep jumps in the total volatility spillover index. The first one is during 2002-2006; the other one is during the global financial crisis period.

**a) Total volatility spillover plot analysis during 2002-2006:**

There is an increasing trend of the total volatility spillover after 2004 due to the electronic trading, a rise in hedge funds, and increased capital mobility. The total volatility spillover index is approximately forty percent in the first window and changes between 25 and 55 percent during this period. However, there are some huge fluctuations: The total volatility spillover increases steeply during July 2002, July 2005, and May-July 2006.

These oscillations are seen in the total volatility spillover plot. The first one happened during mid-2002. This oscillation was a result of the stock market downturn all around the world. The stock market downturn, which was caused by a sharp decline in stock markets around the world, especially the U.S. and Europe, was also known as telecoms' crash. The reason of the sharp decline in stock markets was enormous spending and debts of telecom companies. Total volatility spillovers reached 43 percent during telecoms' crash, before dropping back to 33 percent at the end of July 2002.

After the total volatility spillover started to increase in 2004, the spillover index recorded an upward move in July 2005 due to the bombings in London. The impacts of these suicide attacks were also seen as losses in German, French, and the UK stock markets. During this period, the total spillover index increased 5 percent.

The second oscillation occurred during May and July of 2006 after the increasing trend of total volatility spillover continued. This cycle was caused by the strong signals from U.S. Federal Reserve of additional hikes in the Federal Funds Rate. Followed by these signals, there was the reversal of capital flows from emerging markets. After the reversal, the total spillover index increased from 35 percent at the beginning of May 2006 to 54 percent in July 2006. Furthermore, global imbalances, inflation pressures, and tightening monetary policies contributed to an increase in stock markets' volatilities in Poland, the Czech Republic, Hungary, and Greece, the volatilities that spilled over to other markets.

**b) Global Financial Crisis Period:**

The global financial crisis period is the most attractive part of the total spillover plot because there are tremendous upward moves respecting the key waves during this crisis. Figure 2 shows these swings which occurred during July-August 2007, January-March 2008, September 2008, and March-May 2010.

The year 2007 considered an unprecedented period for global economies after the Great Depression. The stock markets around the world experienced the losses due to the recent financial crisis originated in the U.S. subprime mortgage market. The initial problems of this subprime mortgage crisis and the risk of credit crunch began during July and August of 2007. These concerns snowballed with the losses of Northern Rock, BNP Paribas, and Bear Sterns. After this news was announced around the world, the total spillover index recorded a huge jump of 12 percent.

After the first signs of the global financial crisis, the increasing trend of the total spillover continued until the beginning of 2008. The total spillover showed a sharp increase of 8 percent during January and March of 2008 due to the announcement of the credit crunch, the takeover of Bear Sterns by JP Morgan.  The recent financial crisis deepened with the collapse of Lehman Brothers during September 2008. The collapse was followed by the start of the credit crunch in Europe, bailout of Dexia, Hypo Real Estate, and rescue plans around the world. After these news, the total spillover index, which increased roughly 15 percent, reached its peak during October 2008.

Towards the end of 2009, Greece faced a debt crisis. The initial impacts of this Greek crisis did not put a big pressure on the rest of the Europe. The reason this crisis had a limited effect on Europe was that it was a problem of fiscal sustainability of Greece and it generally affected Bulgaria, Serbia, and Romania because four large Greek banks Eurobank EFG, National Bank of Greece, Piraeus Bank, and Alpha Bank held a market share of 29% in Bulgarian banking sector and 16% in Serbia, and Romania. Therefore, the total spillover index showed a small increase in the beginning of the Greek crisis.

After the Greek debt crisis deepened and transformed into an European debt crisis, the pressure on euro started to rise with the concern of the failure of Greece to pay its debt and the fear of the spread to Spain, Portugal, Ireland, and the UK. In addition, the losses in the euro, the rise in the fear of the contagion, and the downgrades of Greece, Portugal, Spain were followed by an increase of 5 percent in the total spillover index.

### 3.3 Rolling-Sample Gross Directional Volatility Plots:

After discussing the total spillover plot, which does not provide directional information, now I concentrate on directional spillovers across European markets. The directional spillovers, which are the key elements to understand the direction of the volatility transmission among stock markets, provide this directional information. The directional information is included in the "Directional TO Others"row (in equation 4) and the "Directional FROM Others" column (in equation 5).

In Figure A4, I show the directional volatility spillovers from each of the stock markets to other markets. The directional spillovers from Estonia to others are smaller than the spillovers from other seven markets over the entire sample period. Whereas, the directional spillovers from Germany, the UK, and France are bigger than the spillovers from other markets. During the global financial crisis, the spillovers from each market not only reached their peaks but also indicated an increase close to 10 percent.

In Figure A5, I illustrate the directional volatility spillovers from others to each of the eight stock markets. They change over time. During the global financial crisis, they recorded upward moves. The directional volatility spillovers from others to France, Germany and, the UK were roughly 9 percent during this crisis. Furthermore, France, Germany, and the UK are affected mostly by the spillovers from others over the sample period. Conversely, gross directional volatility spillovers from others to Estonia are smaller than the spillovers to other markets.

### 3.4 Rolling-Sample Net Directional Volatility Spillover Plots:

The background underlying the analysis of the net directional spillover plots showed on Figure 3 are the gross spillover plots mentioned above. The graphs in Figure 3 are found according to equation 6 in the methodology. They correspond to the the difference between "Contribution from" column sum and the "Contribution to" row sum and are used to obtain information about how much each market contibutes to volatility in other markets in net terms.

According to Figure 3, until the global financial crisis, Greece, Poland, the UK, and the Czech Republic were at both the giving and receiving ends of net volatility transmissions. Over the entire sample period, the volatilities from France and Germany generally were transmitted to other markets, whereas Estonia and Hungary received net volatility spillovers from other markets.

Germany's net transmitter role is seen in Figure 3d. After the dotcom bubble burst, Germany struggled to get out of difficulties such as the decline in the exports, high budget deficit, and the trouble in major German banks. Furthermore, the creditworthiness news of CommerzBank, the third biggest bank in Germany, caused a problem in international stock markets. Being the first-largest economy in the Euro area, the Germany's fragile economy influenced mostly other markets in the Euro area during this period. Figure 3d showed that net volatility spillovers reached 5 percent during this period. Moreover, during the Iraqi war and the economic crisis which ended up the highest unemployment rate in Germany in 2005, Germany continued its net transmitter role.

During the global financial crisis, big economies such as Germany and France generally affected other markets. They were volatility transmitters due to being the main economies in the Euro area. The impacts of the bailouts of major German banks such as

SachsenLB, IKB Deutsche Industriebank, and HRE were observed in the rest of the Euro area. After this deterioration in Germany, the volatility from Germany was transmitted to other markets during the global financial crisis. The UK came after France and Germany as the volatility transmitter in the Euro area during this crisis.

Nevertheless, the UK was at both the giving and receiving ends of net volatility transmissions until the global financial crisis. Until 2004, the UK was a volatility transmitter to other European markets. Net volatility spillovers from the UK reached 2 percent during this period, when there were the concerns of the Iraqi War, grim economic news from the U.S., the surge in oil price, and huge losses in the FTSE index.

In the case of Greece, net volatility spillovers from Greece had equal magnitudes in terms of giving and receiving net volatility transmissions. Until mid-2006, Greece generally received sizeable net volatility spillovers from other markets. Nonetheless, between mid-2006 and January 2007, Greece became a net transmitter of the spillovers. During this period, there was a substantial boost in the Athens Stock Exchange. This was due to becoming a more open economy, the increase in the attraction of foreign companies, the rise in the privatizations, and the entry of the foreign banks such as the Credit Agricole. After this boost, the Greek banks undertook the leading role in Southeast Europe and Greece drove growth in the Euro area. This was followed by the increase in the net volatility spillover transmitted from Greece that reached 3 percent during this period. Since mid-2007, Greece continued to be net transmitter of volatility spillovers until mid-2008. After the recent financial crisis deepened, Greece began getting negatively impacted by the volatility spillovers from other markets.

According to the Figure 3b, Estonia was generally a net recipient of the spillovers from other markets. The Hungarian case was commonly similar to the Estonian case. However, Hungary and the Czech Republic were net transmitters of the spillovers resulted from high exposure of western banks to emerging Europe between mid-2008 and mid-2009. This high exposure was connected to the foreign ownership in the banking sector of the Czech Republic and Hungary. When the recent crisis deepened in these countries, these western banks recorded huge losses because Austria, Germany, France, Sweden, Belgium, and Italy hold 84 percent of total western European banks’s claims on emerging Europe. Moreover, the percentage of foreign ownership in the Czech and the Hungarian banking sectors were about 97 and 68 percent, respectively. Consequently, the fragile economies of the Czech Republic and Hungary caused the spillover transmissions to other stock markets. During this period, net volatility spillovers from the Czech Republic and Hungary were approximately 3 percent.

### 3.5 Rolling Sample Net Pair-wise Directional Volatility Spillover Plot:

The net volatility spillover methodology also provides me to analyze the net pair-wise directional spillovers which state information about how much market i contributes the volatility to the market j in net terms. They are found according to equation 7 in the methodology.

According to Figure 4, there were three important episodes of net volatility spillovers from the Czech Republic to other markets: during mid-2003 through the first quarter of 2004, from the last quarter of 2006 through the second quarter of 2007, and from February 2008 through the end of 2009. During the first episode, the Czech Republic was the transmitter of the volatility to Hungary, Poland, and Germany. However, the Czech Republic was a net receiver of volatility from the UK due to the impacts of the Iraqi war on the UK. In the second episode, the Czech Republic was a net transmitter to France, Germany, the UK, and Hungary. Until the first concerns of the global financial crisis, the Czech Republic was influenced by the volatility transmitted from Greece.

The third episode was more important than the first two episodes because it correlated to the recent crisis. While following this episode, the total volatility spillover index started to increase after the collapse of Lehman Brothers on September 2008. Until February 2009, the total spillover index recorded a huge jump of 15 percent after the collapse of Lehman Brothers. During this episode, the Czech Republic was a volatility receiver from the UK and Germany because they were the main economies in the Euro area. Nevertheless, the Czech Republic was a volatility transmitter to Estonia and Poland. The Czech Republic and France had approximately the same effects on each other for this period.

In the case of Poland, I analyzed four episodes of positive net spillovers: during March 2003 through August 2003, October 2005 through October 2006, the beginning of

2007 through mid-2007, and mid-2009 through the end of 2009. In the first episode, the volatility from Poland spilled over to France, Germany, Greece, Estonia, and Hungary. In the second episode, total spillover index increased around 20 percent due to the reversal of capital flows from emerging markets. During this period, the volatility in Poland generally spilled over to other markets, especially to the UK. When the first concerns of the recent crisis rose in the third episode, Poland was influenced mostly by France. However, the volatility in Poland spilled over to Germany and Hungary. In the last episode, Poland was a net volatility transmitter to France, Germany, Greece, Estonia, and the UK.

In the case of France, there were three episodes of positive net spillovers: early 2002 through the beginning of 2004, mid-2004 through the end of 2006, March 2007 through May 2010. During the Iraqi War, the volatility shocks in Germany, Greece, and the UK mostly spilled over to France due to the sharp decline in the stock markets, and the surge in oil price. In the second episode, the total volatility spillover index increased around 25 percent which was caused by the reversal of the capital flows from emerging markets. France was a net receiver of the volatility from Germany. Nonetheless, France's volatility transmission to the UK was higher than the UK's volatility transmission to France in this episode.

Analyzing the third episode was interesting because this episode took place during the global financial crisis. During this period, the total spillover index jumped from 49 percent from March 2007 to 62 percent in February 2008 and was approximately 70 percent after the collapse of Lehman Brothers. Until Greek debt crisis deepened, the volatility in France transmitted to Greece. However, after it deepened, Greece became a net transmitter to France because French banks had an exposure of 79 billion dollars to Greece. At the same time, France became a net receiver of the volatility from Germany in consequence of the trade imbalances caused by the fear of contagion from Greece.

In the Estonian case, there was only one episode of positive net spillovers: the end of 2004 through the end of 2005. During this period, Estonia was a net transmitter of volatility to Greece, the UK, Hungary, and the Czech Republic. While following this episode, the total volatility spillover index had an increasing trend.

I identified four episodes of net volatility spillovers from the UK: early 2002 through the end of 2003, mid-2006 through the first quarter of 2007, August 2007 through the end of first quarter of 2008, August 2008 through late 2009. In the first episode, the UK was a volatility transmitter to France. During the Iraqi War, the sharp declines in the FTSE index, and the surge in oil price caused the volatility transmissions from the UK. For this reason, the volatilities from the UK were transmitted to Germany and France. During the second episode, the total volatility spillover increased 10 percent due to the initial signs of the global financial crisis. The UK's transmission role to France continued during this episode. The third period coincided with the beginning of the global financial crisis. During this period, the total spillover index increased about 15 percent, and the UK became a net recipient of volatility from France. However, the last episode corresponded to the worst phases of the global financial crisis. Therefore, the total spillover index increased 15 percent. The volatility in the UK spilled over to Germany, Greece, Estonia, and Hungary.

From 2002 to 2010, there were only two episodes of net spillovers taking place from Hungary to other markets:  August 2008 through May 2009, December 2009 through May 2010. The total spillover index increased 8 percent in the first episode due to the worst financial crisis. In this episode, Hungary faced a debt crisis. While following this episode, Hungary was generally a volatility transmitter to Germany and Greece. In the second episode, the volatility in France, Germany, Poland, the Czech Republic, and the UK spilled over to Hungary.

According to Figure 4, Germany was generally the volatility transmitter to other markets over the entire sample period due to being the biggest economy in Euro area. Until 2007, France received net volatility spillovers from Germany. However, during the global financial crisis, Germany began getting negatively impacted by France. However, Germany continued to be one of the main locomotives in the Euro area during this crisis.

I identified two episodes of net volatility spillovers from Greece: mid-2006 through the end of 2007, and mid-2007 through mid-2008. In the first episode, Greece was a net transmitter to all of the other markets due to the boost in Athens Stock Exchange mentioned above. The second episode coincided with the worst financial crisis. During this period, the volatility in Greece generally transmitted to other markets.

## 4. Conclusion:

In this thesis, I analyze volatility spillovers across eight European stock markets from March 19, 2001 to July 21, 2010. I use the methodology developed by Diebold and Yılmaz. This methodology uses the variance decompositions from a generalized vector autoregression model, which is not based on variable ordering. Moreover, this methodology also includes directional volatility spillovers.

Empirical results suggest that the spillover index has an increasing trend after 2004. This is linked to globalization, increased financial mobility, the entry of electronic trading, and the advances in technology. This confirms Baele's (2005) finding that interdependence across markets increases due to the impact of globalization.

The spillover index captures the features of the current crisis. There have been substantial volatility spillovers during the recent financial crisis. For instance, it records a sharp increase during the first signs of the global financial crisis. Furthermore, the spillover index reaches its peak during the collapse of Lehman Brothers. During the European debt crisis, it also has an increasing trend. This result supports Edward and Susmel's (2001) finding that high volatility period and volatility comovements are related to international crises. Moreover, the result endorses Diebold and Yılmaz (2009)'s and Yılmaz (2010)'s findings that the spillover index experiences significant bursts during major market crises and corresponds to economic events.

The directional spillover measures allow me to identify gross and/or net transmitters of the volatility shocks to other markets. Moreover, the directional spillovers are used to show the gross recipients of the volatility shocks from other markets. According to the directional spillover measures, France and Germany are main net volatility transmitters to other markets over the sample period. However, Estonia is affected mostly by the volatility shocks in other markets. In the case of the global financial crisis, the volatility shocks in France spill over to other markets more than the volatility shocks in Germany. The UK comes after France and Germany as the volatility transmitter.

In the case of emerging markets such as Hungary and the Czech Republic, they are only transmitters of the sizeable volatility to other markets during mid-2008 through mid-2009 because the financial crisis in emerging Europe has an impact on big economies due to their exposure to the banking sector in emerging Europe.

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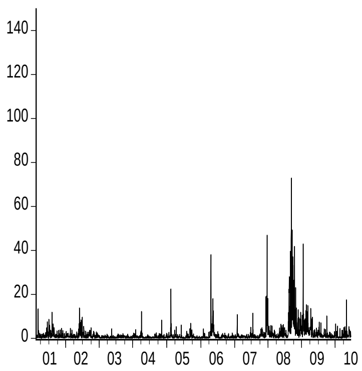
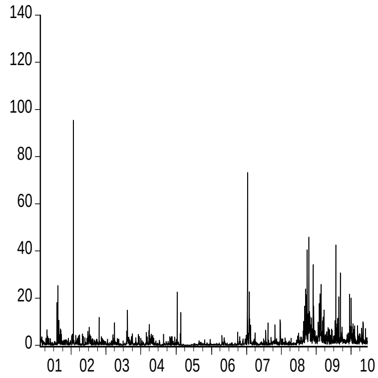
## 6. Figures and Tables:

**Figure 1: Daily Financial Market Volatilities** (Annualized Standard Deviation, Percent)

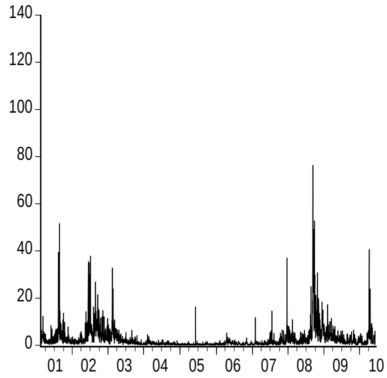
a) The Czech Republic



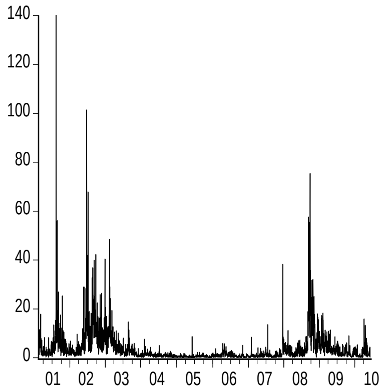

b) Estonia



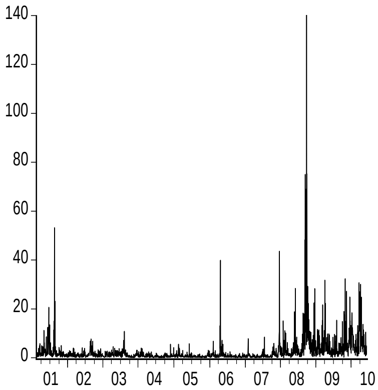

c) France



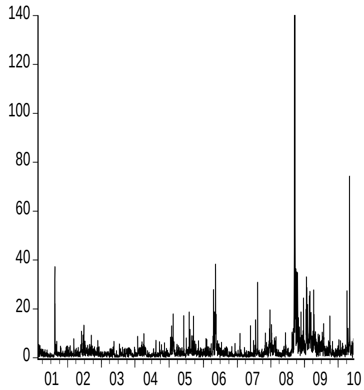

d) Germany



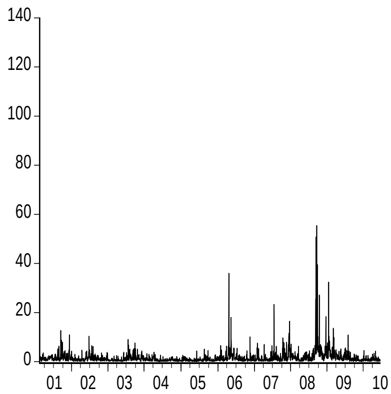

e) Greece




f) Hungary




g) Poland




h) the UK

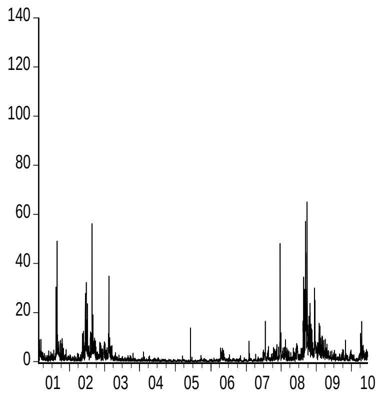


**Table 1:**

Log Volatility Summary Statictics, Eight Stock Markets

| | CZECH REPUBLIC | ESTONIA | FRANCE | GERMANY | GREECE | HUNGARY | POLAND | UK |
|---|---|---|---|---|---|---|---|---|
| Mean | -9.97 | -10.17 | -9.53 | -9.29 | -9.60 | -9.18 | -9.78 | -9.77 |
| Median | -10.05 | -10.17 | -9.58 | -9.33 | -9.68 | -9.23 | -9.83 | -9.82 |
| Maximum | -5.52 | -5.25 | -5.48 | -4.87 | -4.68 | -4.27 | -5.80 | -5.64 |
| Minimum | -14.04 | -15.26 | -13.02 | -12.64 | -12.48 | -11.90 | -12.65 | -13.05 |
| Std. Dev. | 1.16 | 1.37 | 1.19 | 1.24 | 1.15 | 0.93 | 0.93 | 1.20 |
| Skewness | 0.37 | -0.09 | 0.17 | 0.19 | 0.40 | 0.50 | 0.36 | 0.23 |
| Kurtosis | 3.46 | 3.25 | 2.86 | 2.82 | 3.09 | 3.89 | 3.43 | 2.90 |

**Table 2: Volatility Spillover Table, Eight Stock Markets**

| | France | Germany | Greece | UK | Estonia | Hungary | Czech Republic | Poland | Directional FROM Others |
|---|---|---|---|---|---|---|---|---|---|
| **France** | 34.6 | 28.0 | 5.7 | 21.2 | 2.5 | 1.7 | 3.3 | 3.0 | 65.4 |
| **Germany** | 27.7 | 40.5 | 4.5 | 18.6 | 1.7 | 1.4 | 2.5 | 3.1 | 59.5 |
| **Greece** | 9.2 | 6.5 | 58.6 | 9.3 | 4.6 | 2.4 | 5.7 | 3.7 | 41.4 |
| **UK** | 23.6 | 21.7 | 5.9 | 35.9 | 2.9 | 1.8 | 4.8 | 3.4 | 64.1 |
| **Estonia** | 5.8 | 3.9 | 7.0 | 7.5 | 67.0 | 1.6 | 3.6 | 3.5 | 33.0 |
| **Hungary** | 4.7 | 3.9 | 4.0 | 5.8 | 1.8 | 59.5 | 11.1 | 9.3 | 40.5 |
| **Czech Republic** | 8.3 | 5.6 | 6.5 | 10.8 | 2.8 | 7.5 | 50.4 | 8.1 | 49.6 |
| **Poland** | 6.2 | 6.4 | 3.7 | 6.9 | 1.5 | 7.9 | 8.7 | 58.8 | 41.2 |
| **Directional TO others** | 85.5 | 76.0 | 37.1 | 80.2 | 17.8 | 24.3 | 39.9 | 34.0 | |
| **Directional Including own** | 120.1 | 116.6 | 95.7 | 116.0 | 84.8 | 83.8 | 90.2 | 92.8 | **Total Spillover Index 49.3%** |

**Figure 2: Total Volatility Spillovers, Eight Stock Markets**

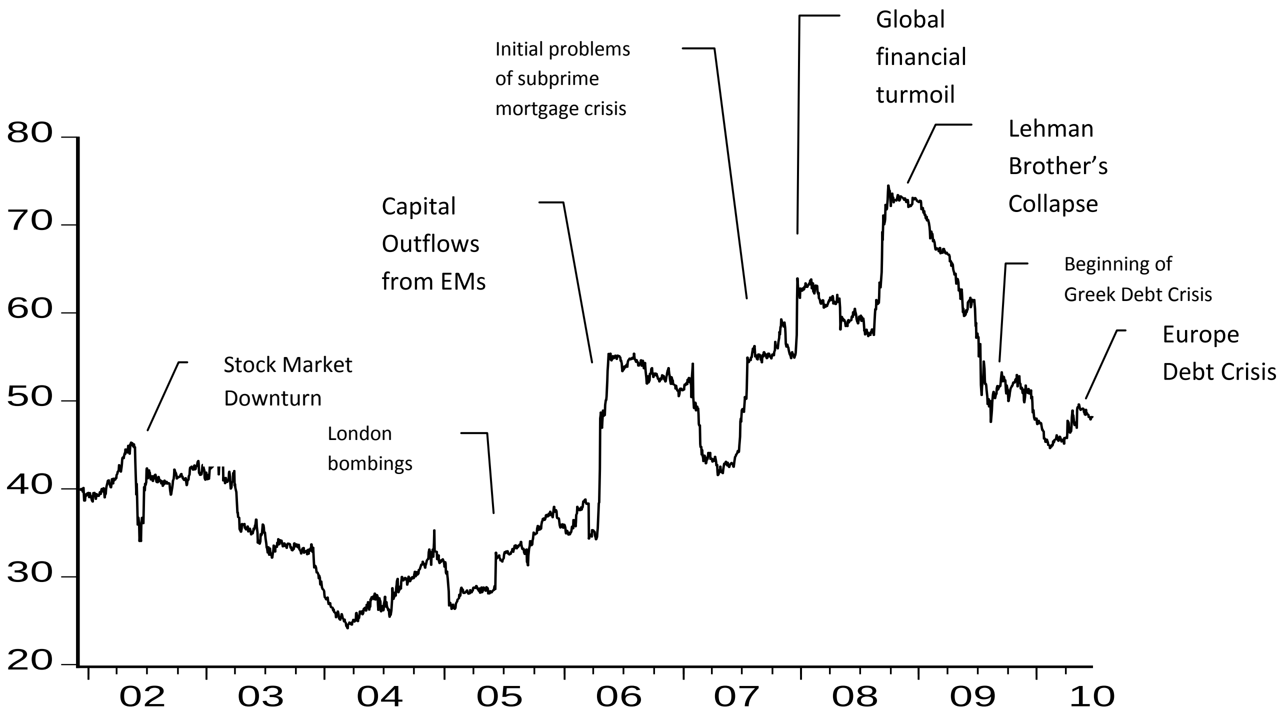


**Figure 3: Net Volatility Spillovers for eight stock markets:**

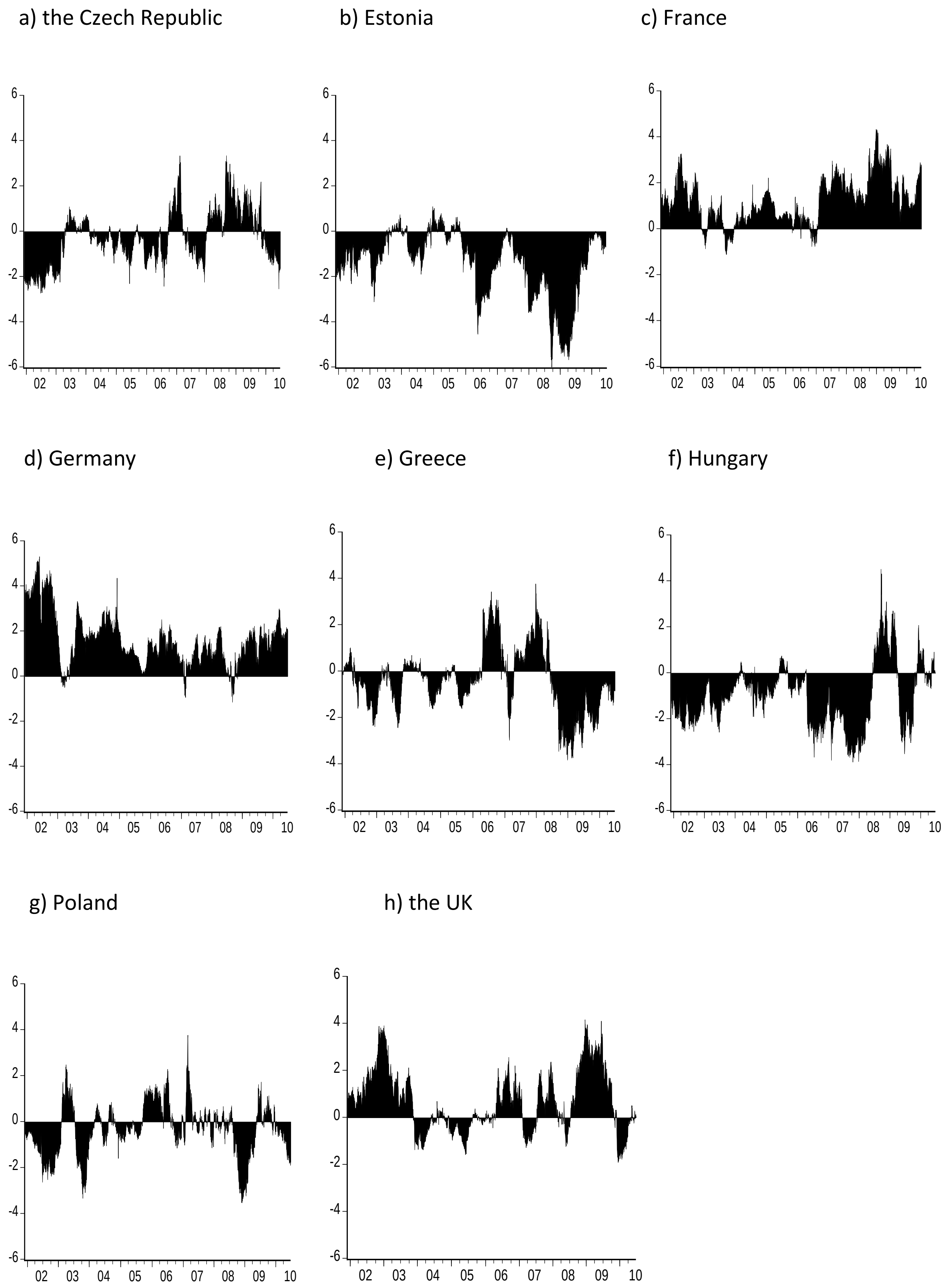
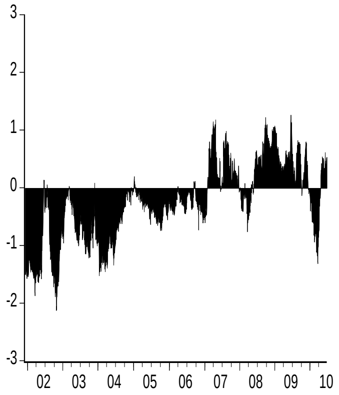
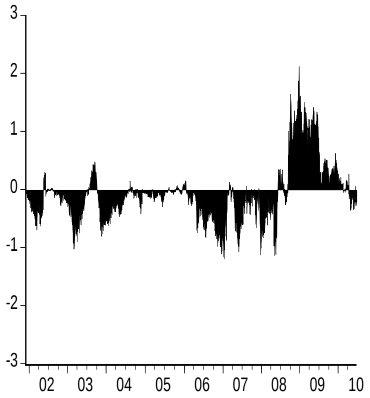


**Figure 4: Net Pair-wise Volatility Spillovers Plot:**

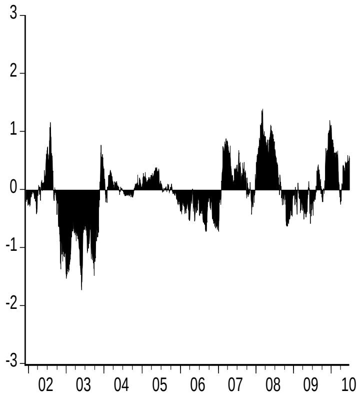
a) France-Germany



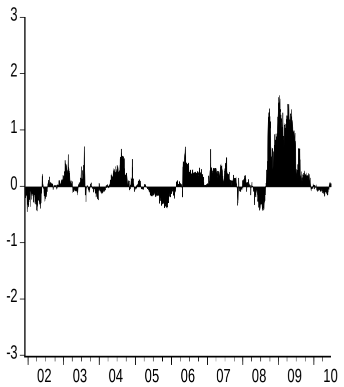

b) France-Greece



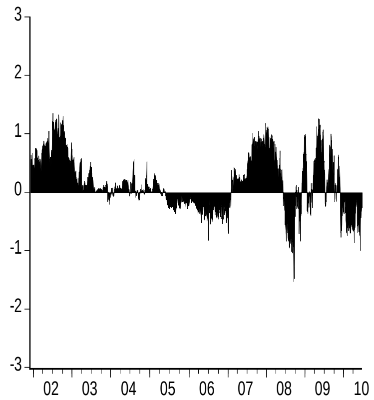

c) France-UK



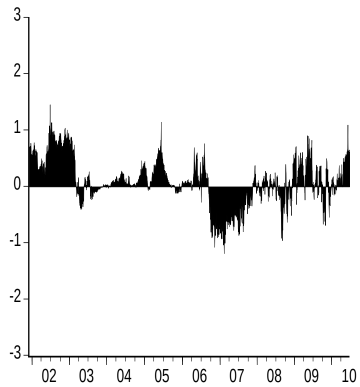

d) France-Estonia



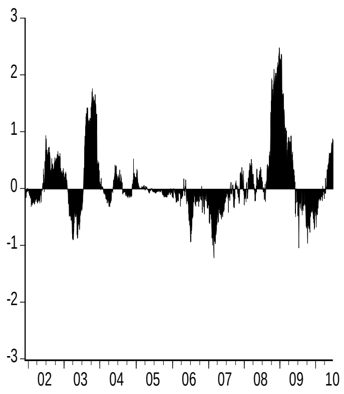

e) France-Hungary



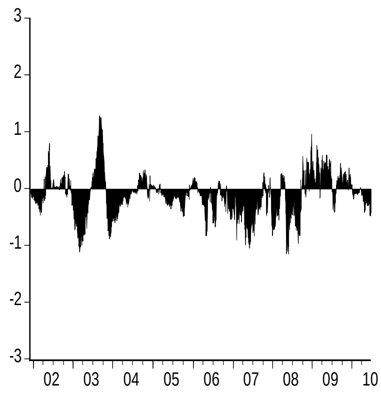

f) France-Czech Republic




g) France-Poland




h) Germany-Greece




i) Germany-UK

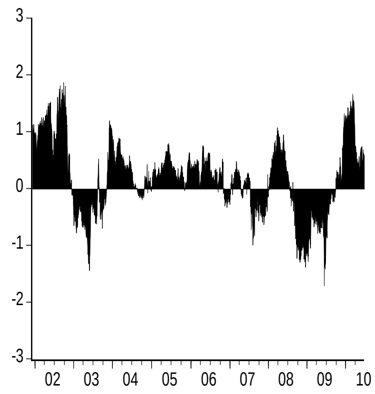
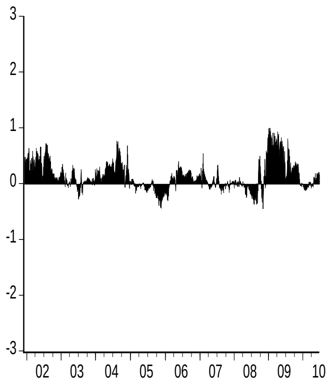
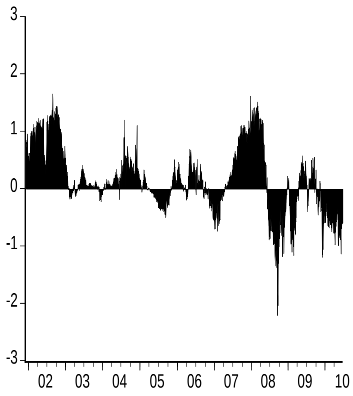


**Figure 4 continued:**

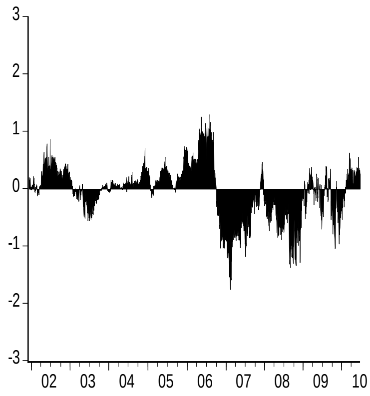
i) Germany-Estonia



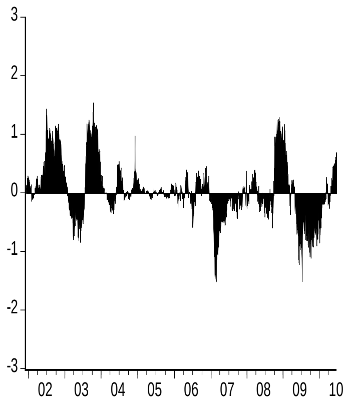

j) Germany-Hungary



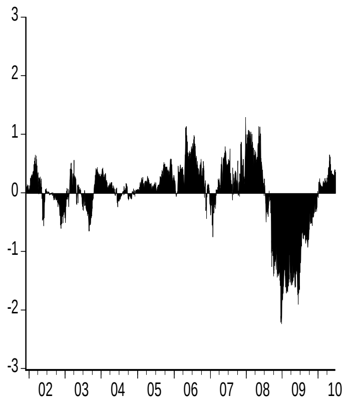

k) Germany-Czech Republic



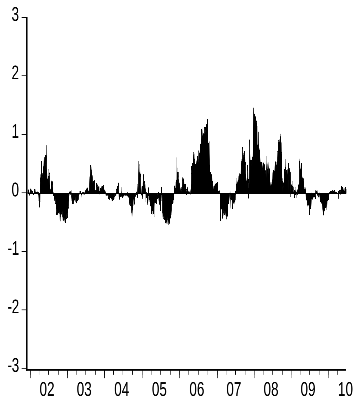

l) Germany-Poland



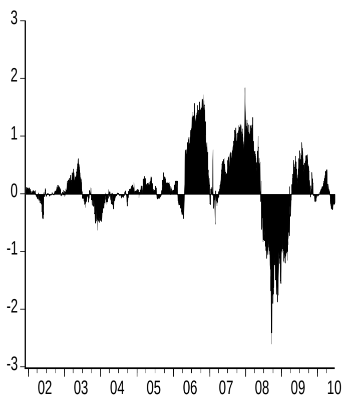

m) Greece-UK



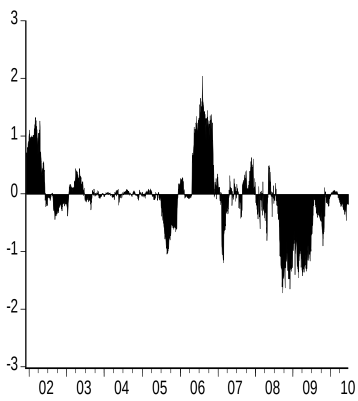

n) Greece-Estonia




o) Greece-Hungary




p) Greece-Czech Republic




r) Greece-Poland

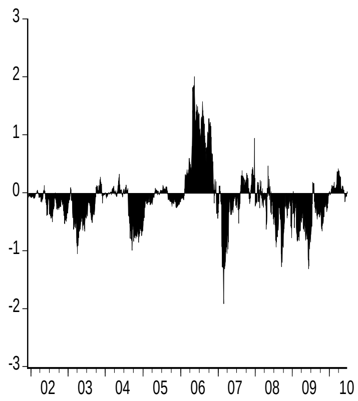
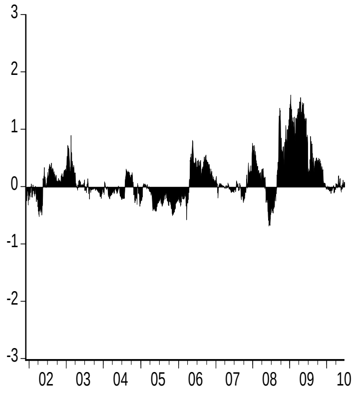
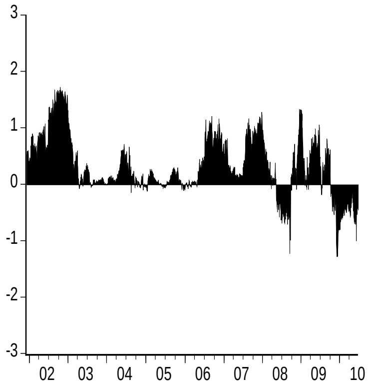


**Figure 4 continued:**

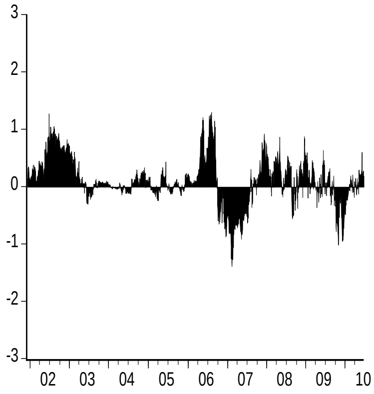
s) UK-Estonia



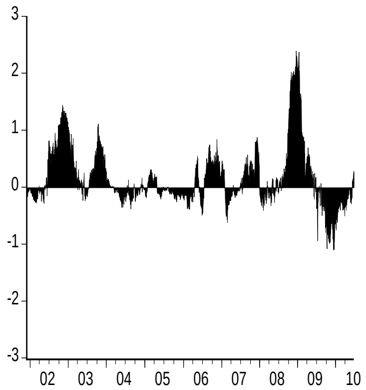

t) UK-Hungary



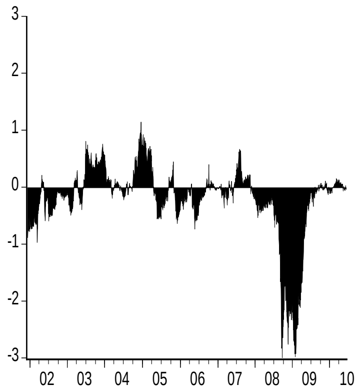

u) UK-Czech Republic



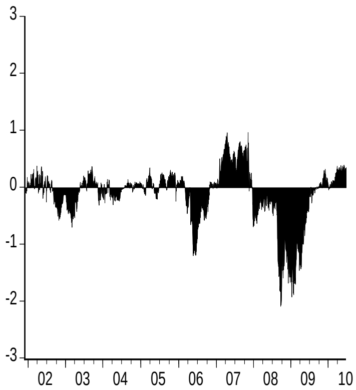

v) UK-Poland



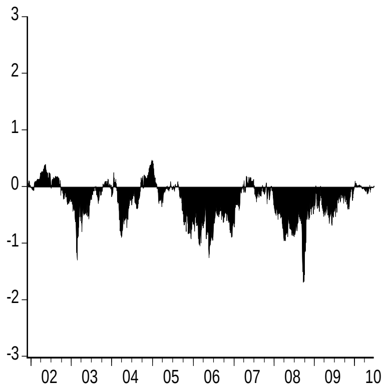

y) Estonia-Hungary



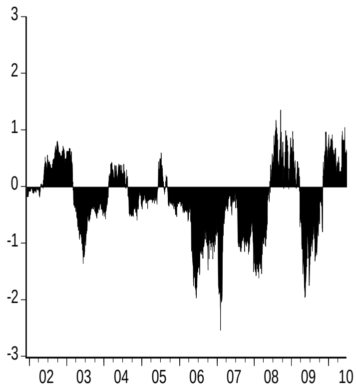

z) Estonia-Czech Republic




w) Estonia-Poland




x) Hungary-Czech Republic




q) Hungary-Poland

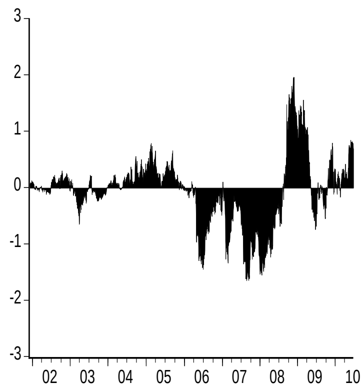
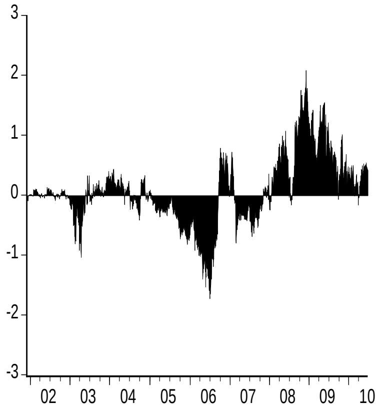


**Figure 4 continued:**

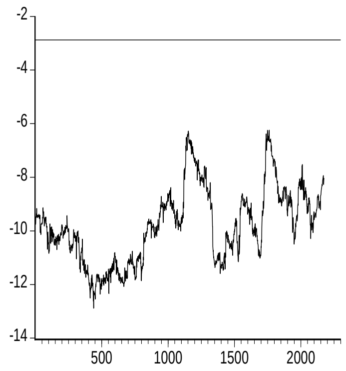
aa) Czech Republic-Poland



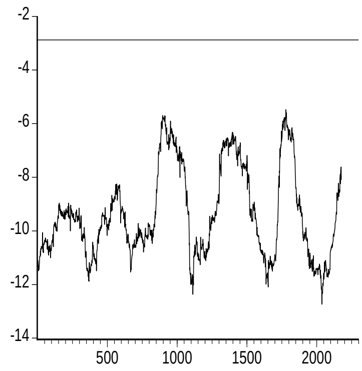
# 7. Appendix:

**Figure A1: Stationarity tests results of Rolling-samples:**

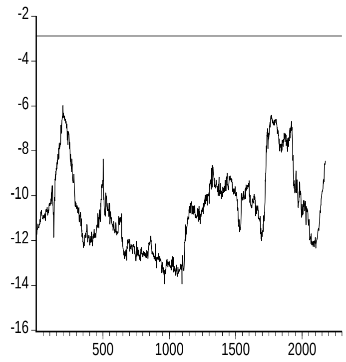
a) The Czech Republic



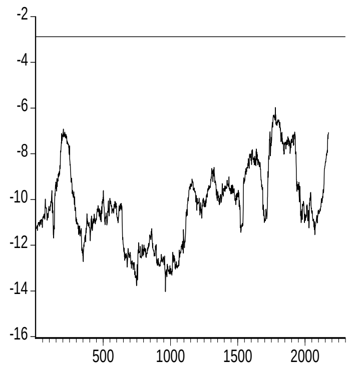

b) Estonia



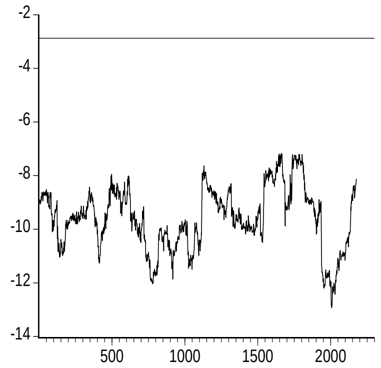

c) France



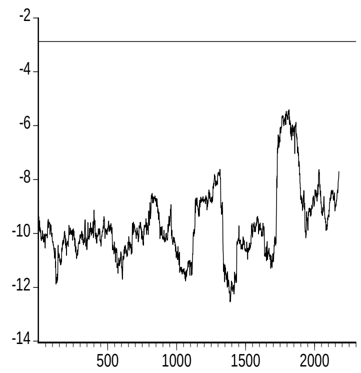

d) Germany



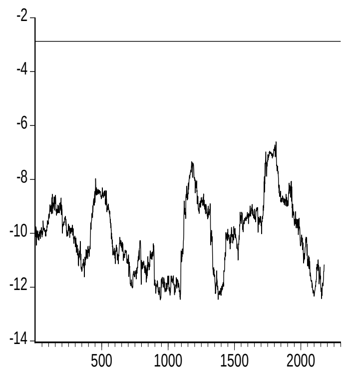

e) Greece




f) Hungary




g) Poland




h) the UK

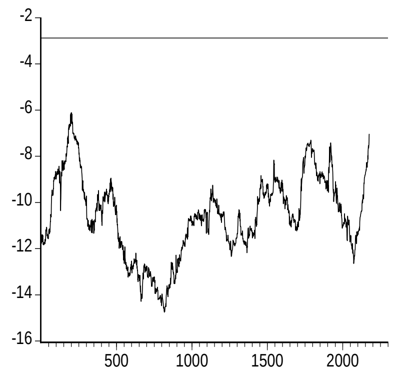


**Figure A2: Sensivity of the Spillover index to Forecast Horizon (Max, Min and Median values over 5 to 10-day horizons)**

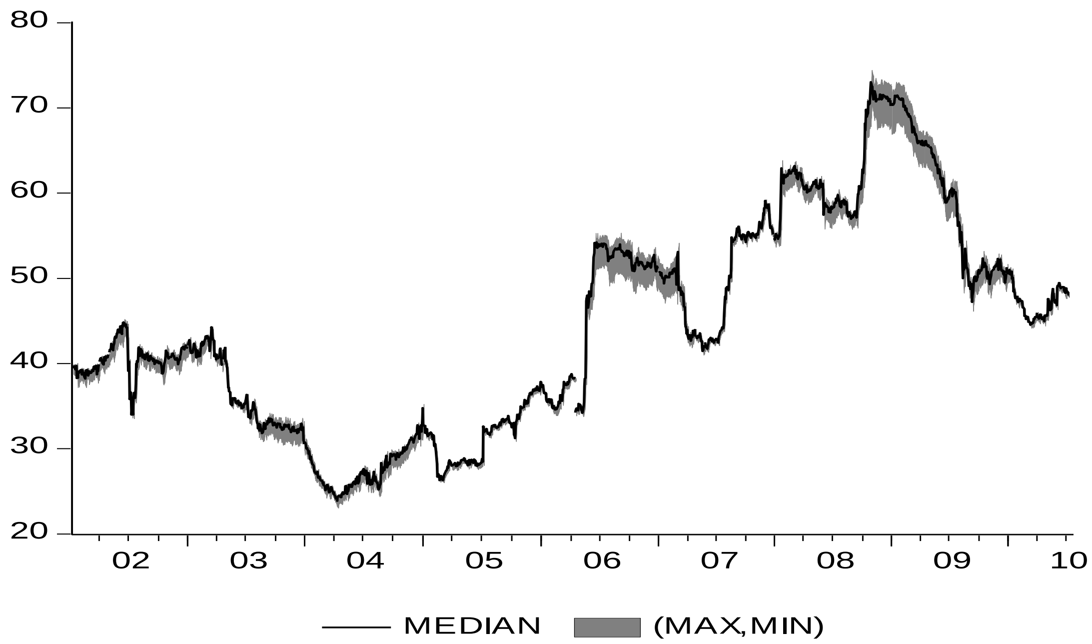



**Figure A3: Sensivity of Spillover index to VAR lag structure (Max, Min and Median values of the index for VAR order of 2 through 6)**

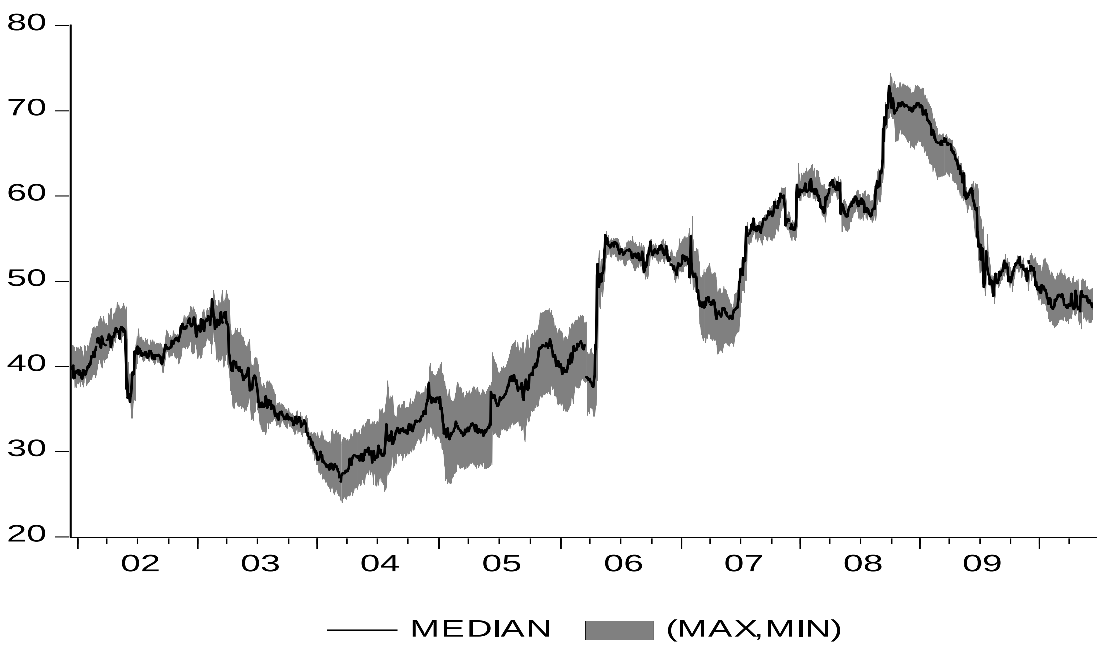
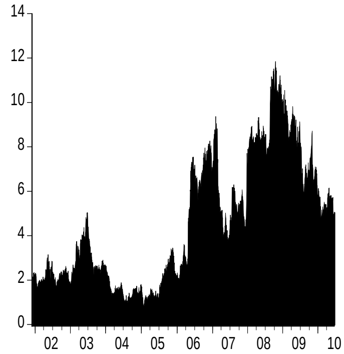
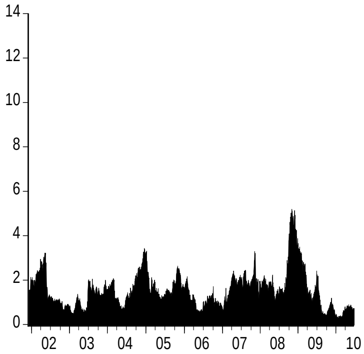


**Figure A4: Directional Volatility Spillovers from each country TO others:**

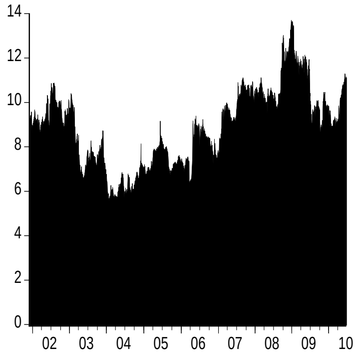
a) The Czech Republic



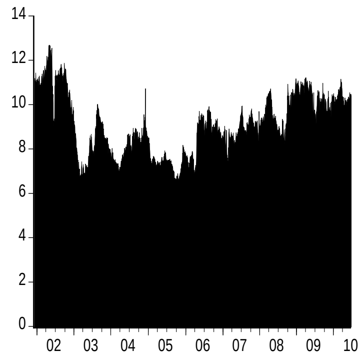

b) Estonia



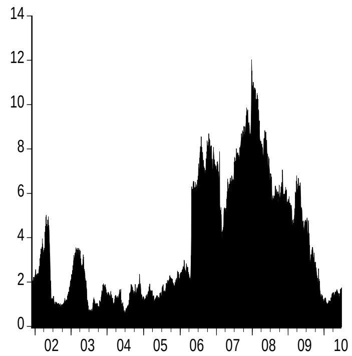

c) France



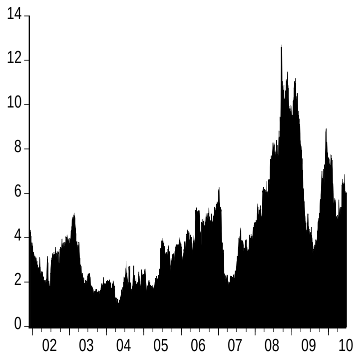

d) Germany



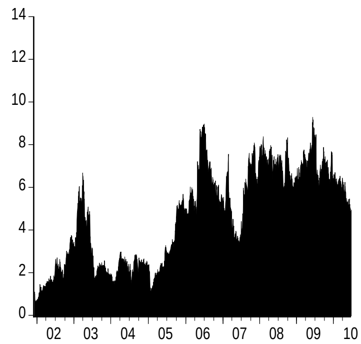

e) Greece




f) Hungary




g) Poland




h) the UK

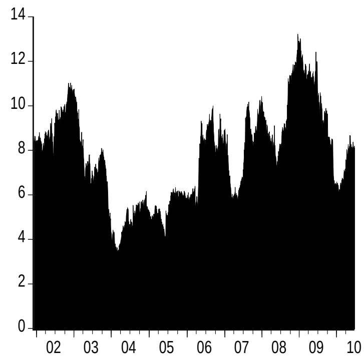
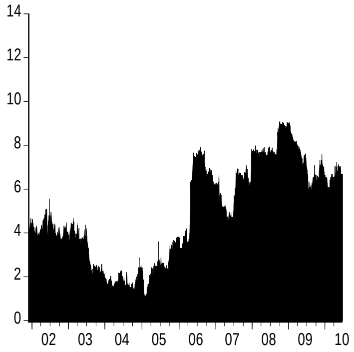
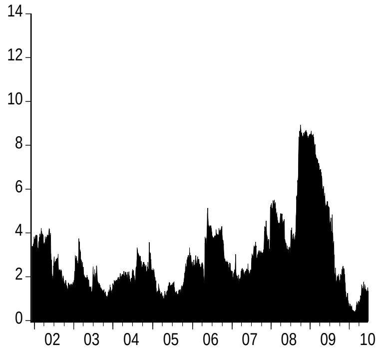


**Figure A5: Directional Volatility Spillovers from others to each markets:**

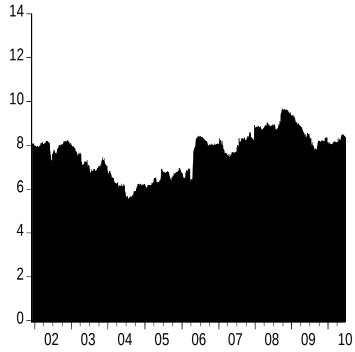
a) the Czech Republic



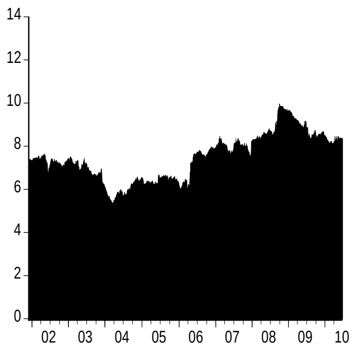

b) Estonia



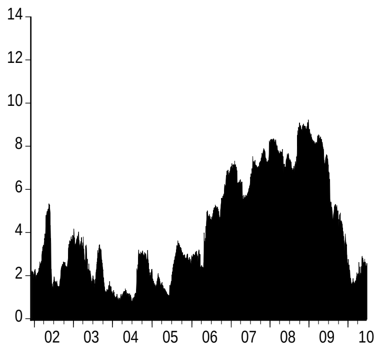

c) France



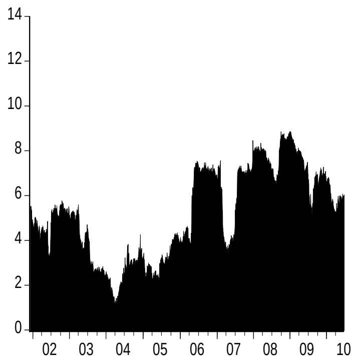

d) Germany



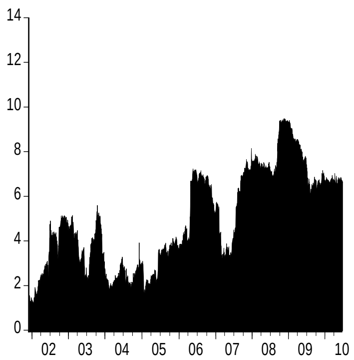

e) Greece




f) Hungary




g) Poland




e) the UK