STOCKHOLM SCHOOL OF ECONOMICS
Department of Finance
Bachelor Thesis in Finance
Spring 2010

Tutor: Cristian Huse
Presentation: June 3, 2010
Opponents: Eric Mercado Olofsson
and Vincent Vennberg

Global Stock Market Contagion

A study of the transmission mechanism of shocks during the 2008 financial crisis

Henrik Ohlsén
21194@student.hhs.se

Anders Skarholt
21014@student.hhs.se

ABSTRACT

Tests for contagion between international equity markets have usually been based on the assumption of constant cross-market correlation. Due to time-varying correlations, these tests can generate biased results. We use a test that focuses on the transmission mechanism of shocks directly, searching for evidence of mean and volatility contagion during the two months following the bankruptcy of Lehman Brothers in September 2008. Empirical results for ten different European and American markets show strong evidence of mean contagion in five cases, but no volatility contagion. We find evidence of mean contagion for countries in Western Europe as well as for emerging market indices in Latin America and Eastern Europe.

Key words: Contagion; Correlation; Comovement; Spillover

Table of contents

1. INTRODUCTION 3

2. PREVIOUS LITERATURE 5

3. THEORY AND METHOD 10

3.1 BIAS IN THE CORRELATION COEFFICIENT 10
3.2 MODELLING CONTAGION 11
3.2.1 Mean contagion 12
3.2.2 Volatility contagion 12
3.2.3 Full model 14

4. DATA 15

4.1 DATA DESCRIPTION 15
4.2 TIME ZONE ISSUES 17

5. EMPIRICAL RESULTS 19

6. DISCUSSION 21

7. CONCLUSION 23

REFERENCES 24

APPENDIX 25

1. Introduction

In an increasingly global market environment, knowledge of the international equity market structure is becoming more and more essential. First, worldwide equity co-movement structure is important to economists as it influences investment, capital flows and consumption decisions. Second, investors looking to improve their return-risk ratio are interested in comovement structures for portfolio diversification purposes. Though criticized, international diversification is still regarded as one of the best ways to improve portfolio performance. The risk reduction possibilities available to portfolio managers through international diversification depend largely on the expected correlation between stock markets. However, it is only quite recently that increasing investment activity in emerging markets and through hedge funds has called attention to the fact that risk parameters are unstable and that international equity correlations can change quickly and dramatically (Ray, 2000). The US stock market crash of October 1987 and its effect on stock markets worldwide led to increased research interest into financial market contagion, i.e. how financial disturbances transmit from one market to another. This resulted in a more cautious attitude towards international diversification as a risk management tool. The gradual removal of barriers to international investment has led to more integrated financial markets. This in turn is likely to lead to international stock markets becoming more correlated, thereby further reducing the advantages of international diversification in the future. Furthermore, a number of studies (e.g. Longin and Solnik, 1995) have shown that the case for international diversification may have been exaggerated, since correlation between markets in multi-country portfolios seem to increase during times of high market volatility and extreme negative price movements. When risk protection is needed at most, correlations go up. This phenomenon, known as *correlation breakdown,* casts doubt on the usefulness of diversifying portfolios based on historic correlations, since they may be inaccurate when they are most desired.

Experience shows that it is clear that dramatic movements in one stock market can have a significant impact on markets of very different sizes and structures across the world. What is unclear though, is whether these periods of highly correlated stock market movements provide evidence of contagion. In order to answer this, it is necessary to define contagion. There is some confusion and disagreement about the meaning of contagion, but in this paper we use the narrow definition of the term, defined by Forbes and Rigobon (2002). They define contagion as “a significant increase in cross-market linkages after a shock to one country (or group of countries)”. According to their definition, two markets showing a high degree of comovement during periods of stability and continuing being highly correlated after a shock to one market does not imply contagion. Only if cross-market comovement increases significantly after a shock is it to be considered contagion. If the comovement does not increase significantly after a shock, then a continued high level of correlation between the markets is only a sign of the strong market linkages that exists between the two economies during all states. Forbes and Rigobon refer to this situation as interdependence, and we use the same term in this paper.

Focusing on the definition of Forbes and Rigobon (2002), we use a model for testing for contagion introduced by Baur (2003). We show that simple correlation comparisons can be misleading when correlations are not constant, but time-varying, and that heteroskedasticity is a source of contagion. Thus the correlation coefficient is a poor measure of analyzing a non-symmetric phenomenon as contagion and, on the basis of Baur (2003), we advocate focusing on the transmission mechanism of shocks directly. The remainder of this paper is organized as follows Section 2 reviews the more recent research on market correlation and contagion. Section 3 explains the issue with heteroskedastic returns and introduces the model used to test mean and volatility contagion. In Section 4 we discuss the data used in our study. The empirical results for contagion during the financial crisis of 2008 are presented in Section 6, and we discuss these results in Section 6. Section 7 concludes.

2. Previous literature

The correlation between stock markets of different economies has long been subject to investigation by financial economists. Today there exist a large number of empirical studies on how shocks transmit between international markets and how common contagion is. A number of different methods of testing for correlation have been used, and some of these have later been criticised for not taking into account the time-varying nature of correlation or inadequately adjusting for this.

Early tests for contagion use comparisons of cross-market correlation coefficients, which is the most straightforward approach to test for contagion. These tests measure the correlation in returns between two markets during a stable period and then test for a significant increase in this correlation coefficient after a shock. An increased correlation coefficient during a crisis is interpreted as a strengthened transmission mechanism and an evidence of contagion. In one of the first papers using this approach, King and Wadhwani (1990) test for an increase in stock market correlations between the US, the UK, and Japan after the U.S. market crash in 1987. They conclude that cross-market correlations increased significantly during the crisis. Lee and Kim (1993) use a similar framework to test for contagion in 12 major markets in connection with the 1987 crash and find that average weekly cross-market correlations increased from 0.23 to 0.39. The approach was also used by Calvo and Reinhart (1996) to test for contagion after the Mexican peso crisis in 1994, and they also find that cross-market correlations increased for many emerging markets during the crisis. A statistically significant increase in cross-market correlation coefficients during the crisis in question is shown in each of the above studies, and this was interpreted as evidence of market contagion. However, Loretan and English (2000), among others, argue that the differences reflect time-varying sampling volatility, resulting in a bias due to the heteroskedasticity of returns. Increases in the volatility of returns are generally accompanied by an increase in sampling correlations even when the true correlations are constant, which we will show with an example below.

Another approach for analyzing market comovement is to use an ARCH or GARCH (Generalised Autoregressive Conditional Heteroskedasticity) framework to estimate the variance-covariance transmission mechanisms between different economies. Hamao, Masulis, and Ng (1990) use this method to test for contagion after the 1987 crash and find evidence of price-volatility spillover from the US to the UK and Japan as well as from the UK to Japan. It is also used by Edwards (1998) in connection with the Mexican crisis, showing increased bond market linkages between Mexico and Argentina, but not between Mexico and Chile. As put forward by Forbes and Rigobon (2002), both of these papers show that market volatility is transmitted across countries, but do not explicitly test if this transmission changes significantly after the relevant shock or crisis. Therefore, although these papers provide important evidence that volatility is transmitted across markets, they do not explicitly test for contagion according to our definition.

Boyer, Gibson, and Loretan (1999), Loretan and English (2000) and Forbes and Rigobon (2002) all compare cross-market correlation coefficients and use similar methods for adjusting for the bias caused by time-varying volatility. This adjustment is based on a number of simplifying assumptions, but provides a relatively good approximation of the unconditional correlation coefficient if the change in the variance is large and it is possible to identify the country where the shock originates (Forbes and Rigobon, 2002).

Baur (2003) criticizes Forbes' and Rigobon's method, arguing that results can be misleading when (i) correlations are not constant, but time-varying in nature (such as a long-term trend of increasing cross-market correlation); (ii) heteroskedasticity is a source of contagion; and (iii) the crisis period is too short, meaning that the test does not have enough power to detect contagion. Forbes and Rigobon (2002) base their test for contagion on comparing correlation coefficients during a stable period (the average over the period) with correlations coefficients during a crisis, equating correlation with cross-market linkage. Baur argues that the correlation coefficient is poor measure to analyze a non-symmetric phenomenon like contagion and recommends looking into the transmission mechanism of shocks directly.

Forbes' and Rigobon' test is based on an unconditional correlation coefficient. There are a number of situations where this could lead to strongly biased test results (Baur, 2003). First, assume a period of steadily increasing market correlation between two economies. If the crisis is in the beginning of a period like this, averaging such a trend could lead to the false conclusion that no contagion has taken place when in fact it has. The same is true the other way around – a crisis period at the end of a trend period could falsely indicate contagion, when no contagion has in fact taken place. Figure 1 clearly shows these two possible scenarios. Second, if the correlation between two markets varies due to different business cycles or different periods of capital in- and outflows, correlations can show a cyclical behaviour with one peak or multiple extremes (Baur, 2003). Contagion can falsely be identified depending on the particular time of the crisis, as shown in Figure 2. In light of these examples, Baur points out the importance of assessing the dynamic structure of correlation-based tests for contagion, arguing that any test assuming constant correlation can produce false results. An important question to ask then is how common time-varying correlation is in the markets as well as the magnitude of the variation over time. A number of studies (e.g. Longin and Solnik, 1995, Karolyi and Stulz, 1996; Longin and Solnik, 2001) show that correlations are seldom constant.

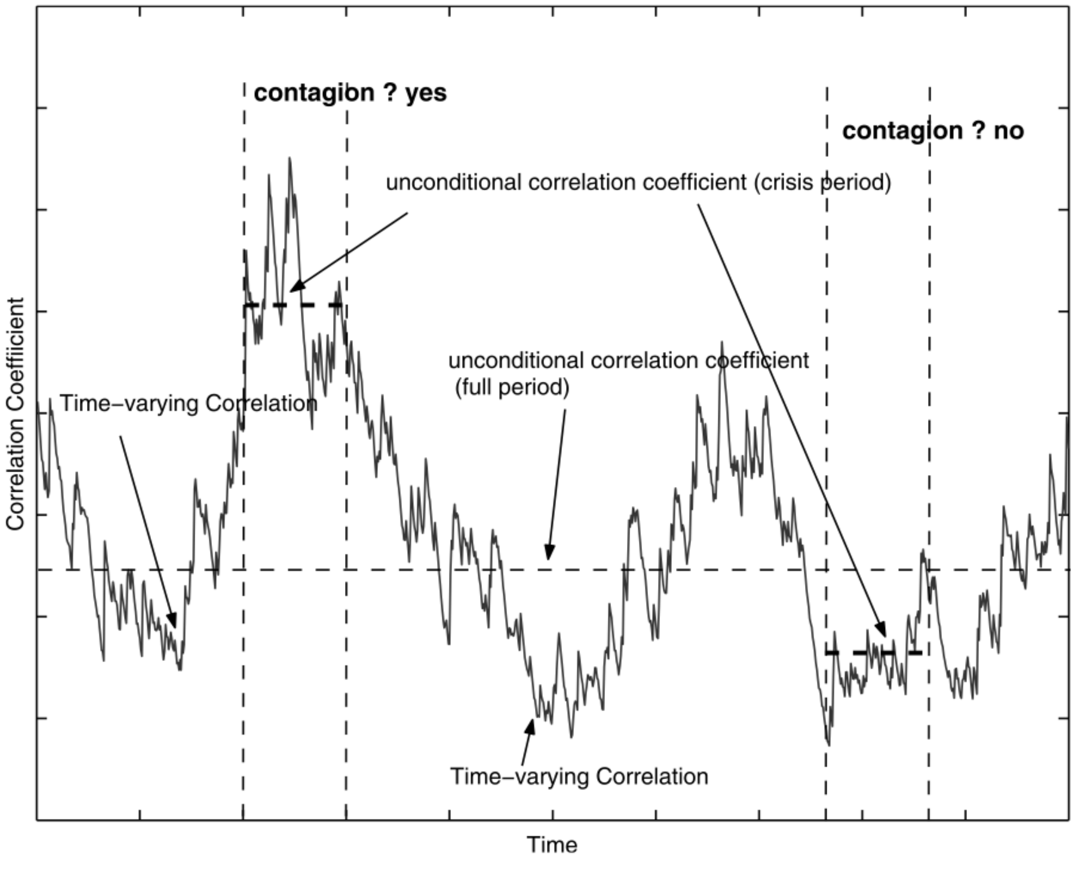

Figure 1, Baur (2003)

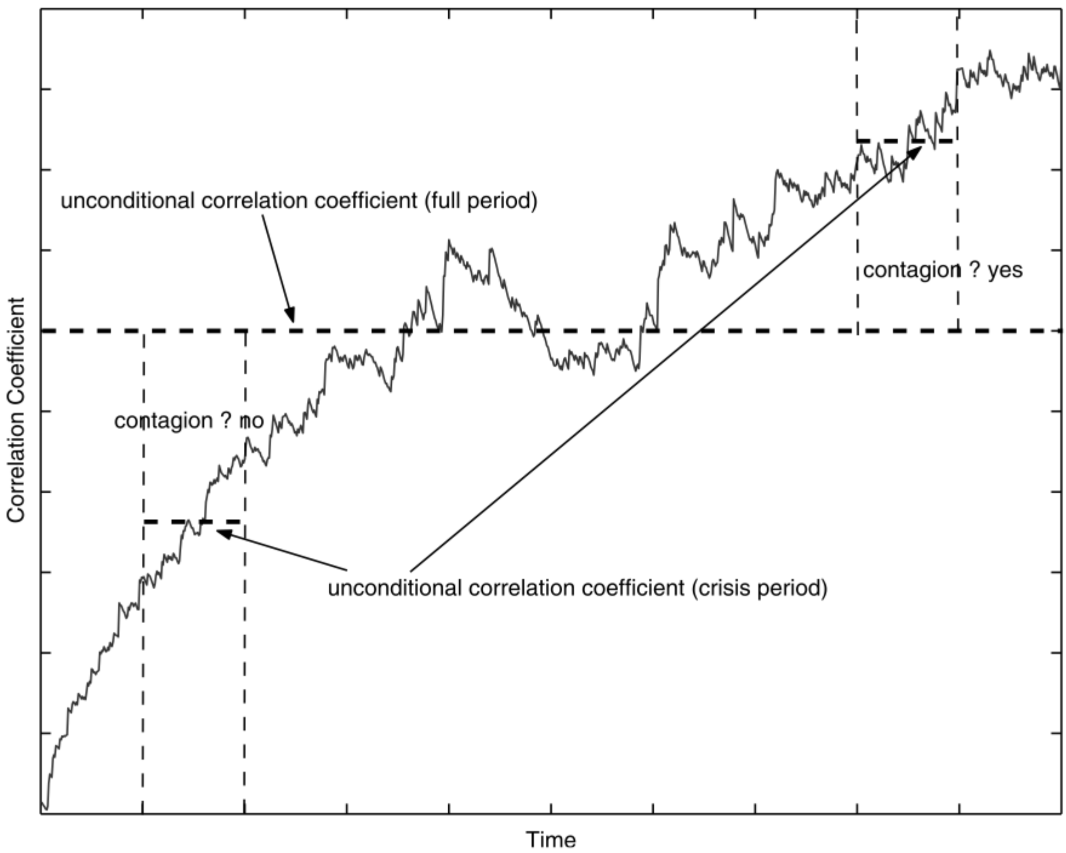

Figure 2, Baur (2003)

Baur (2003) also points out a number of other potential shortcomings of the concept proposed by Forbes and Rigobon (2002). The issue with biased correlation coefficient during periods of high volatility (explained in greater detail in section XXX below) and the adjustment used to correct for this bias by Forbes and Rigobon can be misleading if volatility is a major source of contagion. Furthermore, Baur objects to the use of correlation coefficients as a proxy for market linkages, since they are a symmetric measure, whereas contagion should be modelled in an asymmetric way, like a virus submitted from one market to the next. Also, as put forward by Bae et al. (2002), the correlation coefficient is a linear measure and hence not suitable given that contagion most likely is a non-linear phenomenon.

To eliminate these shortcomings, Baur advocates the use of a different test for contagion, based on a modified model by Corsetti et al. (2001). Since Corsetti's model does not capture any change in the transmission mechanism beyond the transmission which is expected in normal times, Baur modifies the model and allows for a change in the transmission mechanism during a crisis period relative to a tranquil period. One parameter captures the normal effect of shocks from one market while another parameter indicates whether there is an additional effect (beyond what is normally expected) in a particular crisis period, which is interpreted as the level of mean contagion. Baur also introduces the concept of volatility contagion and tests for these types of contagion during the Asian crisis of 1997. We use Baur's framework to test for contagion during the financial crisis of 2008, and this method is explained in greater detail in the section 3.2.

3. Theory and method

3.1 *Bias in the Correlation Coefficient*

In this section we show that tests for contagion that compare correlation coefficients before and in conjunction with a crisis are inadequate due to heteroskedasticity of returns. We show an imaginary numerical example that explains this point. Proofs of the bias together with suggestions for correcting it have been presented by Forbes and Rigobon (2002), Boyer, Gibson, and Loretan (1999) and Loretan and English (2000), but the ways of correcting for it are basically all the same.

The setup of our numerical example is shown in the table below, with the purpose of showing how heteroskedasticity can bias cross-market correlation coefficients. Under normal non-crisis times, the daily return of the US stock market is assumed to be a uniformly distributed random number between -1 percent and 1 percent. During a period of financial instability though, the volatility of the stock market increases and the same news (a rate change by the Fed for example) has a 10-fold increased impact on stock market return (the return is a random number between -10 and 10 percent).

Simulated Example: Heteroskedasticity and Cross-Market Correlations

	Low volatility scenario	High volatility scenario
Variance of domestic Canadian financial sector	1.33	1.33
Variance of US financial sector	0.33	33.33
Variance of the Canadian stock market	1.35	2.67
Variance of the US stock market	0.33	33.33
Covariance between the two indexes	0.07	6.67
Estimated cross-market correlation	10%	71%

Table 1 – As seen in this table, changes in market volatility (heteroskedastic returns) will change the cross-index volatility and correlation even if the fundamental linkages between the two markets in question remain the same. Based on the same setup used by Forbes and Rigobon (2002), in the low volatility scenario, the return of the US market is assumed to be a uniformly distributed, random number ranging from -1 to 1 percent. In the high volatility scenario, the return on the US market is multiplied by 10 and therefore ranges from -10 to 10 percent. The return on the Canadian market is calculated as the value of a Canadian domestic shock (which is a uniformly distributed, random number ranging from -2 to 2 percent), plus 20 percent of US return.

The Canadian stock market is assumed to be influenced by two factors. The first is domestic Canadian shocks causing the market returns range from -2 to 2 percent on a daily basis. The second factor is based on developments in the US markets and equals 20 percent of the US return on the day in question.

Hence, when volatility is moderate, most of the variance of the Canadian stock market is caused by domestic idiosyncratic shocks. In our low volatility scenario, the variance in Canada is four times greater than the variance in the US. Under this scenario, the resulting the correlation coefficient in returns between the US and Canada is only 10 percent.

During volatile periods of the US market, the proportion of the variance of the Canada market caused by movements in the US market increases considerably. When shocks from the US are uniformly distributed from -10 to 10 percent, the variance of these shocks is 25 times the variance of the domestic shocks to the Canadian market. Now, movements in the US markets explain around 50 percent of the Canadian stock market variance. The cross-market correlation has increased to a high 70 percent. Although this is a simulated and simplified example, it shows quite clearly how increased market volatility can have dramatic effects on cross-market correlation (from 10 percent under the normal low volatility conditions to the 70 percent, even though the transmission mechanism is unchanged (a constant 20 percent under both low and high volatility scenarios) and no contagion has taken place according to our definition.

3.2 Modelling Contagion

Prior literature often characterizes contagion as a financial crisis spreading from one market to another. However, the literature is not consistent on exactly how the crisis is spreading and certainly not how to measure and test for it. Methods focusing on changes in the correlation coefficient and volatility spillover seem to be dominant in the literature.

The method used in this thesis is based on Baur (2003). The idea is that financial contagion can be seen as a virus that has one origin market, which then contaminates other markets in an asymmetric way. As noted earlier, previous studies have tested whether correlation is constant or time-varying, and in general these find that correlation between market returns is not constant over time. Since the method does not consider the correlation coefficients themselves, but focuses directly on the transmission mechanism, it has the advantage of allowing for time-varying correlations. This is in contrast to most studies on the subject before Baur (2003). The model takes into account two different forms of contagion: mean and volatility contagion.

3.2.1 Mean contagion

In the model for mean contagion a shock in one market becomes regional or global and has an effect on at least one other market (Baur, 2003). The model is expressed as follows:

$$r_{2t} = \mu_2 + b_1 r_1 + b_2 r_1 D_{crisis} + u_{2t}$$

where r_1 is the origin country, and r_2 is the potentially infected market. u_2 denotes the mean daily return of the affected country's market. D_{crisis} is a dummy variable that takes the value one in the defined crisis period and zero otherwise. The parameter b_1 provides the expected effect of shocks from one market to the other market, and a positive coefficient indicates a positive correlation of index returns between the two markets. The parameter b_2 is the contagion coefficient, which indicates whether there is an increased effect the crisis period. We view a positive b_2 with a p-value less than 5 percent as a statistically significant evidence of mean contagion, which implies that the comovement between the two countries (coefficient b_1) increases during the particular crisis.

The contagion effects are estimated using the maximum-likelihood (ML) method. We test the null-hypothesis that there is no increase in the comovement against the alternative that there is an increase in comovement between the two markets during the defined crisis period.

As mentioned above, one particular economy is considered the origin of the crisis, while one or several other markets are the 'recipients' or the infected markets. It is probably a strong assumption to assume that only one country affects another country, and the variable r_1 cannot be assumed to be exogenous during tranquil times. This implies that b_1 does not necessarily measure an asymmetric relationship. However, we assume that r_1 is exogenous during the crisis, which is a plausible assumption during a crisis, at least if the correct crisis origin is defined, and the crisis period is constrained to a relatively short period of time (Baur, 2003). If r_1 is exogenous during a crisis, we get an asymmetric transmission of shocks in the crisis period and an unbiased estimation of the contagion coefficient b_2.

3.2.2 Volatility contagion

Another way to test for contagion is through the volatility spillover effect in stock index returns (Piplack, 2004). A volatility spillover occurs when a change in volatility of returns in one market has a lagged impact on volatility of returns in one or several other markets (Tansuchat et al, 2010). Spillover effects can be tested by modelling the conditional variance of returns in one country, with the squared residuals (or returns) from the assumed origin country as an exogenous variable in the equation. The squared residuals of the other countries can be interpreted as 'volatility surprises'; the size of the parameters determines the magnitude of the spillover. Previous literature have considered volatility spillover effects as proof of volatility contagion, but Baur (2003) argues that these should be treated as two different phenomena. While volatility spillover consists of shocks that transmit from one market to others at every instance, he argues that volatility contagion is an increase in this effect during a certain period of time. This definition of volatility contagion is coherent with our previous discussion of mean contagion.

To test for volatility contagion we have to model the conditional variance, and since the variance is assumed to be time-varying, the heteroskedasticity problem has to be taken into account. First we decompose the error term:

$$u_{2t} = z_{2t}\sigma_{2t}$$

z_{2t} is normally distributed with mean zero and variance of one, while σ_{2t} is the conditional variance of r_{2t}. Then we can model the conditional variance as follows:

$$\sigma_{2t} = a_0 + b_0 u_{2t-1}^2 + c_0 h_{2t-1} + d_1 r_{1t-1}^2 + d_2 r_{1t-1}^2 D_{Crisis,t-1}$$

where σ_{2t} is the conditional variance for the return of country two. The conditional variance is a GARCH(1,1) model with two additional explanatory variables. The first (r_{1t-1}^2) captures the increase in volatility in country two after an increase in volatility in country one in the tranquil period. This is called a volatility spillover, a shock in volatility that transmits to another market at any time. The second regressor ($d_2 r_{1t-1}^2 D_{Crisis,t-1}$) shows if there exists volatility contagion - an increase in volatility spillovers during the period of crisis.

There is an estimation problem by using GARCH in our model, as negative coefficients in the GARCH model would risk negative volatility in the estimation process (Baur, 2003). However, there is a chance that the coefficient d_2 should be negative, because it is not unlikely that the volatility actually is lower during the period of crisis. To avoid this problem we can use the EGARCH (exponential GARCH) model, as this model still account for our heteroskedasticity problem but do not restrict the parameters to be non-negative. The EGARCH model can be expressed as follows (Baur, 2003):

$$u_{2t} = z_{2t}\sigma_{2t}$$

$$\sigma_{2t} = \exp\left(c + \theta z_{2t-1} + y(|z_{2t-1}|E|z_{2t-1}|)\right) + \delta \log\left(\sigma^2_{2t-1}\right) + d_1 r^2_{1t-1} + d_2 r^2_{1t-1} D_{Crisis,t-1}$$

The parts that are left from the GARCH expression are the two additional regressors. d_1 shows spillover effects in volatility from market one to market two, while $d_2$shows if there exists any similar volatility contagion effects.

3.2.3 Full model

The full model for estimating mean and volatility contagion is then given by:

$$r_{2t} = c + b_1 r_1 + b_2 r_1 D_{crisis} + u_{2t}$$

$$\sigma_{2t} = \exp\left(c + \theta z_{2t-1} + y(|z_{2t-1}|E|z_{2t-1}|)\right) + \delta \log\left(\sigma^2_{2t-1}\right) + d_1 r^2_{1t-1} + d_2 r^2_{1t-1} D_{Crisis,t-1}$$

The full model is estimated with an EGARCH approach, where the first equation is the mean equation in the estimation. After the estimation we can test for spillover and contagion effects. If b_1 or d_1 are larger than zero we have positive spillover effects, while we observe contagion effects when either b_2 or d_2 are significantly larger than zero.

The null hypothesis of no mean contagion is H_0: $b_2 > 0$ against the alternative hypothesis H_1: $b_2 \leq 0$, while the null hypothesis of no volatility contagion is H_0: $d_2 > 0$ against the alternative H_1: $d_2 \leq 0$

4. Data

4.1 Data description

We use continuously compounded returns from six different MSCI indexes, retrieved from Datastream. We use the following markets in this paper: US, Sweden, France, Germany, Italy, Canada, UK, Norway, Switzerland, Latin America and Eastern Europe. The final two are MSCI emerging markets indices, comprising emerging markets in each continent[1]. The time period range from 1st November 2003 until 14th November 2008. The period consists of 1317 observations. We have chosen indices denominated in US dollars. Figure 3 graphs five of the stock market indices during the full time period.

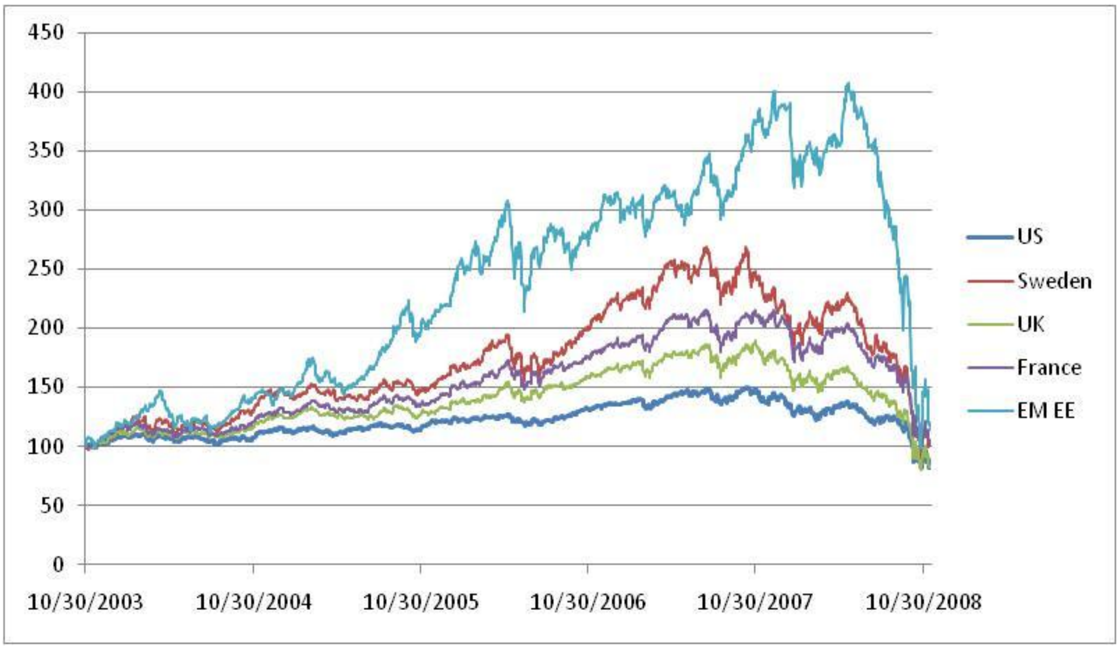

Figure 3 – Stock market movements during full sample period

The start date of the crisis is set to 15th September 2008, the day Lehman Brothers filed for bankruptcy. The US index was nowhere near its peak at this day, and the financial

[1] The MSCI EM (Emerging Markets) Latin America Index is a free float-adjusted market capitalization weighted index that is designed to measure the equity market performance of emerging markets in Latin America. As of June 2007 the MSCI EM Latin America Index consists of the following 5 emerging market country indices: Brazil, Chile, Colombia, Mexico, and Peru. The MSCI EM Eastern Europe is a similar index, consisting of Russia, Poland, Hungary and the Czech Republic

sector had already gone through some turbulence before this date, but it marked the start of an unprecedented and extremely volatile period in the international stock markets. Studying Figure 4, it is clearly visible that the stock markets become more volatile after Lehman Brothers filed for bankruptcy (15th September 2008), even though some would claim a prior beginning of the financial crisis.

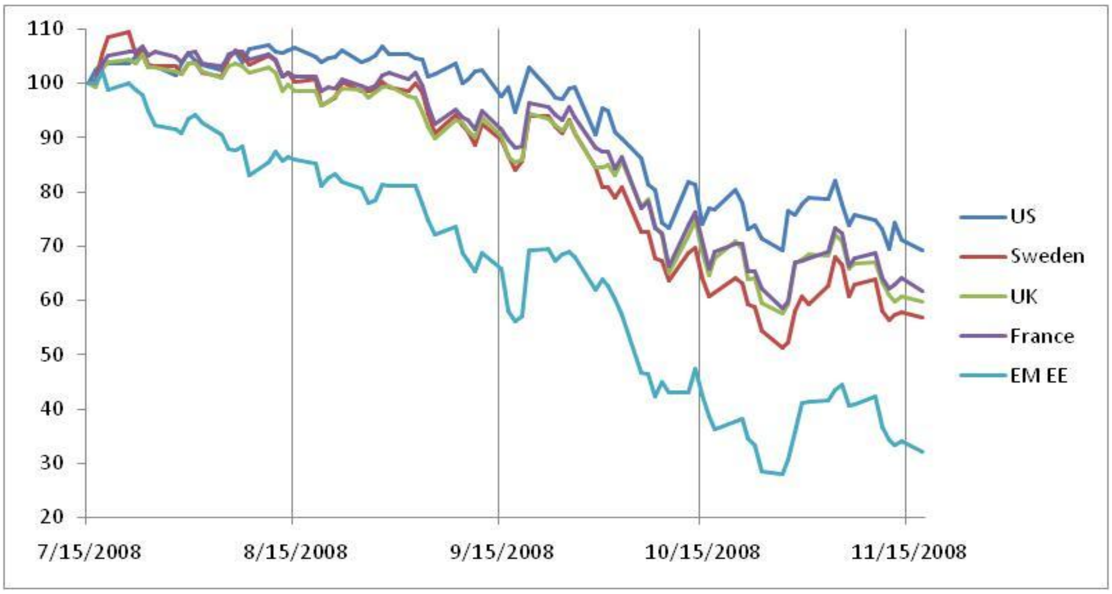

Figure 4 – Stock market movements two months prior and following the collapse of Lehman Brothers

The US market is consequently set as the origin country; its return is denoted r_1 in the estimations. The continuously compounded returns results from taking the logarithmic difference of daily index values. The software package E-views is used for calculations.

Table 2 shows descriptive statistics for the daily stock market returns, while Table 3 shows the unconditional correlation coefficients between the United States and the other markets during the tranquil period, the crisis period and for the whole dataset respectively.

Descriptive statistics

	Stable period		Crisis period		Full period	
	Mean	St.dev	Mean	St.dev	Mean	St.dev
US	0.000149	0.008535	-0.008129	0.046126	-0.000134	0.011992
EM Latin America	0.001019	0.015855	-0.012406	0.070061	0.000560	0.020322
UK	0.000209	0.010492	-0.009642	0.050949	-0.000128	0.014014
Sweden	0.000393	0.013950	-0.010471	0.050521	0.000021	0.016650
Germany	0.000480	0.011198	-0.009179	0.046293	0.000150	0.013996
Canada	0.000597	0.011083	-0.010672	0.053538	0.000211	0.014792

EM eastern Europe	0.000681	0.015779	-0.015605	0.079994	0.000124	0.021529
France	0.000364	0.011127	-0.008749	0.049931	0.000053	0.014346
Italy	0.000219	0.010092	-0.009015	0.051198	-0.000097	0.013746
Norway	0.000731	0.016066	-0.015621	0.067435	0.000172	0.020258
Switzerland	0.000394	0.009552	-0.006188	0.037822	0.000169	0.011724

Table 2 – Mean and std. deviation of returns in the stable, crisis and full period respectively

The statistics show that the mean returns for all countries during the stable period are positive, opposed to negative mean returns for all countries during the financial crisis. As expected all examined markets are clearly more volatile during the crisis.

Cross-market correlations

		EM LA	Germany	Sweden	UK	Canada	EM EE	France	Italy	Norway	Switzerland
	Stable period	0.60	0.39	0.34	0.39	0.54	0.22	0.40	0.36	0.20	0.31
US	Crisis period	0.81	0.65	0.56	0.53	0.71	0.39	0.54	0.45	0.53	0.55
	Full period	0.70	0.51	0.43	0.46	0.62	0.32	0.47	0.42	0.36	0.42

Table 3 – Unconditional correlation coefficients between the US and the other examined markets

From Table 3 we note a rather large increase in the unconditional correlation coefficient between all indices and the US market during the financial crisis, however this is not evidence of contagion, as the increase could be a consequence of time-varying volatility and resulting heteroskedastic returns.

4.2 Time zone issues

We have deliberately chosen to use daily returns in each market in order to have a large sample set, which is particularly important during the two-month period following the Lehman bankruptcy. Using weekly returns, for example, would only have provided 9 data points for the crisis period and would have produced weak test statistics. However, a major concern that arises when using daily data is that of differences in time zones. Since the US market opens and closes after the European market (even though there is an overlap here) and the US stock markets often is a dominant force in international market movements, shocks occurring in the US will sometimes only affect other markets when they open the day after. Given that we are particularly interested in contagion originating in the US in connection with the collapse of Lehman Brothers, this could raise cause for concern. One option is to compare the daily US return with one-day-lagged returns of European and Asian indices. This does indeed generate a higher cross-market correlation for Asian indices and some European indices. However, we would then miss the effect of US morning shocks in favour of including the afternoon shocks. It would also generate problems when comparing our regression results for European and Asian markets with those of Canada and Latin America. We have instead decided to only use indices for markets that have overlapping opening hours, thus completely excluding any Asian markets. The cross-market correlation coefficients between the US and other countries shown in Table 3 are decidedly lower than would have been the case using weekly or monthly stock markets returns.

5. Empirical results

Table 4 presents results based on our model for mean and volatility contagion. The p-value of each estimator is shown below it.

Estimation results

	c	b1	b2	C2	γ	Θ	δ	d1	d2
Canada	0.000629	0.698769	0.165293	-1.426832	0.090552	-0.085268	0.861927	698.3465	-507.3913
	0.0106	0.0000	0.0567	0.0000	0.0048	0.0000	0.0000	0.0000	0.0000
Germany	0.000513	0.530548	0.168227	-1.49742	0.179234	-0.08653	0.861211	872.9669	-677.442
	0.0376	0.0000	0.0900	0.0000	0.0000	0.0003	0.0000	0.0000	0.0000
UK	0.000271	0.449426	0.19613	-1.73524	0.159341	-0.10871	0.84232	1390.171	-1119.17
	0.2211	0.0000	0.0103	0.0000	0.0000	0.0009	0.0000	0.0000	0.0000
Sweden	0.000355	0.533048	0.166269	-1.26036	0.108097	-0.13258	0.873411	782.2698	-616.03
	0.2646	0.0000	0.1355	0.0000	0.0034	0.0000	0.0000	0.0000	0.0000
France	0.000343	0.538446	0.109174	-1.837093	0.159618	-0.094671	0.827601	1248.371	-972.8609
	0.1526	0.0000	0.3006	0.0000	0.0000	0.0013	0.0000	0.0000	0.0000
Italy	0.000387	0.449003	0.151716	-1.683247	0.149405	-0.063837	0.843993	1118.696	-839.8281
	0.0948	0.0000	0.1020	0.0000	0.0000	0.0200	0.0000	0.0000	0.0000
Norway	0.00107	0.388087	0.486954	-1.018967	0.189229	-0.100654	0.902219	557.5888	-429.7786
	0.0043	0.0000	0.0008	0.0000	0.0000	0.0000	0.0000	0.0001	0.0009
Switzerland	0.000359	0.364537	0.134084	-1.953006	0.124046	-0.04669	0.8145	1166.948	-921.222
	0.1127	0.0000	0.0381	0.0000	0.0006	0.1103	0.0000	0.0000	0.0000
Emerging markets Latin America	0.000985	1.114317	0.179924	-2.02044	0.222742	-0.13236	0.800686	1033.225	-813.983
	0.0011	0.0000	0.0361	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Emerging markets Eastern Europe	0.001012	0.341913	0.346748	-1.102636	0.173174	-0.119235	0.889091	420.4276	-238.0711
	0.0076	0.0000	0.0173	0.0000	0.0000	0.0000	0.0000	0.0000	0.0017

Table 4 – EGARCH(1,1) regression results. Coefficients with p-values below.

The strongly significant b_1 values indicate the high degree of comovement of international equity market. It clearly suggests that shocks clearly are transmitted in some way between the US and the examined markets, even though it doesn't necessarily specify the direction of these shocks. The magnitude of the b_1-values is not surprising - as we have already shown, the unconditional correlation coefficients are strongly positive both in the stable and in the unstable period. The parameter of particular interest to us is b_2, since a positive value implies mean contagion during the studied crisis period. As shown in table 3, the b_2 value is positive for all examined markets, but only significant on a 5 percent level for the UK, Norway, Switzerland and emerging markets in Latin America and Eastern Europe. Canada, Germany, Italy, Sweden and France (in order of p-value, starting with the lowest) are not significant at a 5 percent level, but still exhibit quite strong positive signs of contagion.

The statistically significant d_1-values clearly implicate volatility spillovers from the US to all other markets, which is not surprising. It is evident that increased volatility in the US leads to increased volatility in the other examined markets. However, the coefficient for volatility contagion d_2 is negative for all markets, which can be interpreted as less transmission of volatility shocks during the crisis than expected in tranquil times. The results give no support to the hypothesis of volatility contagion. The sum of the coefficients ($d_1 + d_2$) is still positive for all countries, which indicates positive spillover effects even during the crisis. However, the spillover effects are considerably lower than what would be expected with the same volatility during the stable period (of course, the stable period would not be stable with that kind of consistently high volatility, but ceteris paribus the statement holds true).

Another interesting aspect of our results is the relationship between b_1 and b_2 for each of the indices. Are countries with markets closely correlated with the US market more prone to contagion than less correlated ones? In this particular crisis and with the relatively small sample of economies studied, there are rather signs that the opposite is true. The economies with the lowest b_1-values and correlation with the US market (Norway and Eastern Europe) are the ones exhibiting the highest level of contagion, both doubling the total shock transmission mechanism ($b_1 + b_2$) during the crisis compared to before b_1. As seen in Table 2, the correlation between Norway and the US increases from a mere 0.20 to a full 0.53 and between Eastern Europe and the US from 0.22 to 0.39. This is a very clear indication (but not, as repeatedly pointed out, evidence due to heteroskedasticity of returns) of contagion.

6. Discussion

Compared to Baur's (2003) study of the 1997 Asian crisis (the Thai and Hong Kong crises in particular), we find much stronger evidence of mean contagion. Baur finds positive b_2 -values for three out of ten Asian countries regressing on Honk Kong returns during the crisis and four out of ten for the Thai crisis, but not a single result is significant at a 5 percent level. Baur interprets all positive results as evidences of contagion, irrespective of significance level. We believe that our much stronger indications of mean contagion is due to a more severe international financial crisis, originating in the US, the single most influential force on the international equity markets. To us, the presence of contagion in connection with the global financial crisis is clear – not only did cross-market correlation coefficients with the US rise sharply during the crisis for all markets in our study, but also the shock transmission mechanism itself rose for all countries, albeit not statistically significantly for some. This is true both for developed Western markets like the UK and Switzerland, as well as for emerging markets in Eastern Europe and Latin America.

The presence of contagion and correlation breakdown has far-reaching consequences for portfolio management strategies. It means that the advantages of international diversification are smaller than the historic cross-market correlations coefficients suggest. We have also found indication that economies with low correlation can be more affected by contagion than others, calling into question the usefulness of diversifying into these markets. Our two emerging market

The negative parameters for volatility contagion are more difficult to interpret. It seems that a relatively small volatility increase during the stable period constitutes a considerable increase in volatility spillover, which results in a very large spillover coefficient (d_1). In the crisis period volatility increases dramatically (see Table 2), and the large d_1-coefficient implies an equally large (linear relationship) increase in volatility spillover effects. The increase in volatility spillover is evidently not as dramatic as the volatility increase itself during the 2008 financial crisis for any of the economies in our study. That is our interpretation of the seemingly large negative d_2-values. Most of the d_2-values in Baur's study are also negative, but not of the same magnitude and significance as our results. Once again, we believe this to be because of the severity of the 2008 crisis and the sharp increase in volatility in September 2008.

The fact that we get different results for mean and volatility contagion does not necessarily challenge our model, as a greater impact of shocks to the mean of a return does not have to increase the effect on the volatility, while volatility contagion do not need to have an increased effect on the mean of returns (Baur, 2003).

7. Conclusion

Since its introduction, the concept of financial contagion and the difficulty of testing for it has been a frequently debated subject. Studies focusing on changes in the correlation coefficient are dominating the literature, but we have shown that it can lead to false conclusions when the correlation is not constant over time, but time-varying in nature. In this study we have used a regression approach to test for mean and volatility contagion in the 2008 financial crisis, a model introduced by Baur (2003).

Our empirical results serve as evidence of contagion in the two-month period after the collapse of Lehman brothers, in the form of mean contagion from the US to five different markets, including the UK, Norway, Switzerland and emerging markets in Latin America and in Eastern Europe. Other tested markets also points in the direction of mean contagion, although the parameters are not statistically significant. We believe that these results should be taken into account by investors seeking to diversify their portfolio internationally. The volatility spillover effects from the US to the other markets are large in the full period, but clearly decreasing during the financial crisis.

A significant contribution of this paper is the highly significant mean contagion from the US to both emerging market regions tested, as we have not found any prior research on this particular subject. We suggest that future research could focus even more on emerging markets, as these are becoming more and more interesting from an investor's point of view.

References

Ang, A. & Bekaert, G. 2002, "International Asset Allocation with Regime Shifts", The Review of Financial Studies, vol. 15, no. 4, pp. 1137-1187.

Bae, K.H., Karolyi, G.A. & Stulz, R.M. 2003, "A new approach to measuring financial contagion", Review of Financial Studies, vol. 16, no. 3, pp. 717.

Baur, D. 2003, "Testing for contagion—mean and volatility contagion", Journal of Multinational Financial Management, vol. 13, no. 4-5, pp. 405-422.

Boyer, B.H., Gibson, M.S. & Loretan, M. 1997, "Pitfalls in tests for changes in correlations", International Finance Discussion Papers, vol. 597.

Calvo, S. Capital flows to Latin America is there evidence of contagion effects? .

Chang, C., McAleer, M. & Tansuchat, R. 2010, "Analyzing and Forecasting Volatility Spillovers and Asymmetries in Major Crude Oil Spot, Forward and Futures Markets", .

Corsetti, G., Pericoli, M. & Sbracia, M. 2001, "Correlation analysis of financial contagion: what one should know before running a test", Working Papers, .

Edwards, S. 1998, "Interest rate volatility, capital controls and contagion", .

Eichengreen, B., Rose, A. & Wyplosz, C. 1996, "Contagious currency crises: first tests", The Scandinavian Journal of Economics, vol. 98, no. 4, pp. 463-484.

Forbes, K.J. & Rigobon, R. 2002, "No Contagion, Only Interdependence: Measuring Stock Market Comovements", The Journal of Finance, vol. 57, no. 5, pp. 2223-2 Market Correlations*", The Journal of Business, vol. 78, no. 1.

Hamao, Y., Masulis, R.W. & Ng, V. 1990, "Correlations in price changes and volatility across international stock markets", Review of Financial Studies, vol. 3, no. 2, pp. 281-307.

Karolyi, G.A. & Stulz, R.M. 1996, "Why do markets move together? An investigation of US-Japan stock return comovements", Journal of Finance, vol. 51, no. 3, pp. 951-986.

King, M.A. & Wadhwani, S. 1990, "Transmission of Volatility between Stock Markets", The Review of Financial Studies, vol. 3, no. 1, National Bureau of Economic Research Conference: Stock Market Volatility and the Crash, Dorado Beach, March 16-18, 1989, pp. 5-33.

Lee, S.B. & Kim, K.J. 1993, "Does the October 1987 crash strengthen the co-movements among national stock markets", Review of Financial Economics, vol. 3, no. 1, pp. 89-102.

Longin, F. & Solnik, B. 2002, "Extreme correlation of international equity markets", The Journal of Finance, vol. 56, no. 2, pp. 649-676.

Longin, F. & Solnik, B. 1995, "Is the correlation in international equity returns constant: 1960-1990?", Journal of International Money and Finance, vol. 14, no. 1, pp. 3-26.

Longin, F.S. & Solnik, B. "B.(2001). Extreme correlation of international equity markets", Journal of Finance, vol. 56, pp. 649-676.

Loretan, M. & English, W.B. 2000, "Evaluating" correlation breakdowns" during periods of market volatility", International Finance Discussion Papers, vol. 658.

Piplack, J. 2004, Volatility Contagion and East Asian Equity Markets: A Markov-Switching SWARCH Analysis, http://www.personeel.unimaas.nl/j.piplack/Thesis_Complete_Master_Final_2.pdf, 2010-05-21

Rey, D.M. 2000, "Time-varying stock market correlations and correlation breakdown", Financial Markets and Portfolio Management, vol. 14, pp. 387-412.

Appendix

Complete descriptive statistics

Full period

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
US	-0.000137	0.000403	0.110426	-0.095137	0.011996	-0.209608	22.016740
EM Latin Am.	0.000563	0.002017	0.153640	-0.150601	0.020330	-0.828635	14.366430
Germany	0.000151	0.001009	0.113339	-0.096373	0.014001	-0.419050	16.337730
Sweden	0.000031	0.000555	0.104409	-0.105336	0.016653	-0.414125	9.945921
UK	-0.000124	0.000325	0.121605	-0.104311	0.014018	-0.446566	19.606510
Canada	0.000211	0.001220	0.102792	-0.105364	0.014792	-0.863178	15.326370
EM EE	0.000124	0.001890	0.191191	-0.207765	0.021529	-0.911530	23.900560
FM CEE	0.000219	0.000887	0.079377	-0.090818	0.013563	-0.688937	11.521920
France	0.000053	0.000577	0.114615	-0.115657	0.014346	-0.522386	18.056560
Italy	-0.000097	0.000580	0.124698	-0.108873	0.013746	-0.115270	21.503070
Norway	0.000172	0.001653	0.103311	-0.142249	0.020258	-1.375469	11.720340
Switzerland	0.000169	0.000334	0.097346	-0.074871	0.011724	-0.024719	13.112160

Stable period

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
US	0.000146	0.000485	0.041034	-0.035165	0.008538	-0.233227	5.266656
EM Latin Am.	0.001022	0.002117	0.066315	-0.085821	0.015861	-0.533498	5.222315
Germany	0.000481	0.001104	0.067991	-0.083856	0.011202	-0.460630	7.479293
Sweden	0.000403	0.000672	0.059717	-0.063639	0.013950	-0.183923	5.247559
UK	0.000213	0.000362	0.057294	-0.060261	0.010495	-0.225719	6.510920
Canada	0.000597	0.001345	0.048981	-0.052842	0.011083	-0.506990	4.767019
EM EE	0.000681	0.001942	0.067516	-0.087747	0.015779	-0.725982	6.298249
FM CEE	0.000603	0.000941	0.043740	-0.056210	0.010814	-0.150334	5.480079
France	0.000364	0.000615	0.068144	-0.078883	0.011127	-0.362475	7.237329
Italy	0.000219	0.000644	0.048983	-0.062286	0.010092	-0.378191	5.730288
Norway	0.000731	0.001658	0.070332	-0.083914	0.016066	-0.514936	5.216696
Switzerland	0.000394	0.000439	0.047340	-0.055385	0.009552	-0.188320	5.347437

Crisis period

	Mean	Median		Minimum	Std. Dev.	Skewness	Kurtosis

			Maximum				
US	-0.008129	-0.011288	0.110426	-0.095137	0.046126	0.444439	3.019019
EM Latin Am.	-0.012406	-0.006564	0.153640	-0.150601	0.070061	0.107998	2.577826
Germany	-0.009179	-0.008905	0.113339	-0.096373	0.046293	0.423623	3.515792
Sweden	-0.010471	-0.012836	0.104409	-0.105336	0.050521	0.255921	2.635100
UK	-0.009642	-0.009243	0.121605	-0.104311	0.050949	0.325616	3.115673
Canada	-0.010672	-0.007209	0.102792	-0.105364	0.053538	0.179911	2.363566
EM EE	-0.015605	-0.015304	0.191191	-0.207765	0.079994	0.206681	3.475831
FM CEE	-0.010611	-0.011822	0.079377	-0.090818	0.044678	0.186437	2.251738
France	-0.008749	-0.007101	0.114615	-0.115657	0.049931	0.256240	3.222809
Italy	-0.009015	-0.007566	0.124698	-0.108873	0.051198	0.530063	3.343707
Norway	-0.015621	-0.010098	0.103311	-0.142249	0.067435	-0.240176	1.856690
Switzerland	-0.006188	-0.007247	0.097346	-0.074871	0.037822	0.547814	3.253626