Sudden Changes In Volatility In European Stock Markets

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ABSTRACT

This paper studies the volatility in ten European stock markets (Denmark, France, Germany, Ireland, Italy, Netherland, Spain, Sweden, Switzerland and United Kingdom) during the periods of financial crisis (East Asian currency crisis, Subprime crisis…) from 1990 to 2012. We apply Markov Regime Switching SW-GARCHmodel. Our results show that most of the European stock markets are closely interlinked to the U.S.

Keywords: Financial Crisis; SW-GARCH Model; Volatility; Stock Markets

1. INTRODUCTION

The question of volatility dynamics has always been the motivation of many researchers in the field of finance with objectives to ensure economic stability and to obtain higher rates of return for investors by portfolio diversification. Consequently, to financial crisis streaming, in the last few decades, a large literature has been focused on studying volatility. Hamao and *al.* (1991) found evidence of significant price-volatility spill over from US to London and Tokyo, and from London to Tokyo stock markets. Edwards and Naim (1998) observed a new style "Tequila Effect" of economic crises in Latin America. A similar crisis emerged, at the end of 1997, in Thailand which was far more severe and engulfed far more countries than its predecessor. It's bad character has been manifested by its contagion on whole region, for that reason it has been called Asian Crisis. The emergence of East Asian currency crisis in 1997 raised doubt about the lessons learned from Mexico by national and international policy makers, and economic analysts (Edwards & Naim, 1998). Then, again in 2007, the world witnessed the worst crisis in history after the Great Depression of 1929. The crisis appeared in U.S.A due to a complicated interaction of different variables, consisting principally on: 1) lower interest rates, 2) abundance of mortgage loans, 3) weak or no controls at an institutional level and an authoritative level, 4) and the use of securitization. In all the cases mentioned above, we observe lower rates of return, higher volatility, and the propagation of crisis to other stock markets, around the world, during the periods of turbulence.

The initial empirical literature on financial crises consists on a simple comparative analysis of Pearson's correlation coefficient between markets "tranquil vs. crisis" periods. Financial Crises are identified when significant increases of correlation coefficient occurred. King and Wadhwani (1990), and Lee and Kim (1993) employed the correlation coefficient between stock returns to test the impact of the 1987 US stock crash on the equity markets of several countries. Empirical findings show that the correlation coefficients between several markets had significantly increased during the crash. Hamao and *al.* (1990) estimated the conditional variance, during the crisis of 1987, witha GARCH model to test correlations between market volatilities. Edward and Susmel (2001), by using a switching ARCH model, tested the contagion effects for many Latin American equity markets, during the times of high market volatility. They showed a significant correlation between studied equity markets which proved the existence of contagion effects.

Gray (1996) was the first to introduce the Markov Regime Switching GARCH which had been applied to US Treasury bill rates from January 1979 to April 1994. In this word, he mentioned how an Exponential GARCH could be incorporated to estimate Markov Regime Switching EGARCH. This innovation led to a flood of research applications. Klaassen (2002) modified Gray's model by adopting the conditional expectation of the lagged conditional variance with broader information set. Fong and Koh (2002) applied a Markov Regime Switching EGARCH on Hong Kong stock market. They found a strong evidence of regime shifts in conditional volatility as well as significant volatility asymmetry in high volatility periods. Maheu and McCurdy (2004) applied Markov Regime Switching (MRS) with Auto-regression to study the volatility in U.S stock market. They found a strong evidence of: high mean and low volatility, and low mean and high volatility under two regimes. Edwards and Susmel (2003) studied the interest rate volatility in emerging markets by applying a modified version of MRS with ARCH and find evidence of regime shifts. Kanas (2005) applied Markov Switching with vector auto-regression (MS-VAR) to study the relationship between Mexican currency and six emerging stock markets. Hondroyiannis and Papapetrou (2006) studied the dynamic relationship between real stock returns and expected and unexpected inflation of Greece utilizing a MS-VAR. They found no evidence of relation between real stock returns and expected and unexpected inflation. Moore and Wang (2007) investigated the volatility in stock markets for the new European Union member states by applying MRS Model and revealed that there is a tendency in emerging stock markets to move from high volatility regime in the earlier period of transition into the lower volatility regime as they move into the European Union. Brunetti et *al.* (2008) analysed exchange rate turmoil in South Asia with a Time Varying Markov Switching GARCH model. They found that the real effective exchange rates, money supply relative to reserves, stock index returns, and bank stock index returns and the volatility contain relevance information in order to identify turbulence and ordinary periods. Wang and Theobald (2008) applied MS model to study the behaviour in the return-generating processes of six East Asian emerging stock markets. They found strong evidence of more than one regime in each stock market and mixed evidence regarding the impact of financial liberalization on return volatility. Cologni and Manera (2009) investigated the impact of oil price shocks on economic growth of developed countries (G7) by applying alternative switching models. Their empirical evidence supports the notion of lesser/ decreasing role of oil price shocks on the business cycles of G7 member countries.

In this research paper, we will study the behaviour of volatility in European stock markets. We apply Markov Regime Switching SW-GARCH model developed by Hamilton and Susmel (1994), Cai (1994) and Edwards and Susmel (2003) to study volatility of European stock markets under different regimes and under crisis period. The main attraction of using SW-GARCH Model lies in its ability to calculate changing variance under different regimes. The empirical literature on the application of SW-GARCH models to European stock markets is however very limited. In addition, we do not find any other research which has focused on the European countries at such as large scale.

The remaining of the paper is organized as follows. Section 2 presents the econometric method. Section3 reports and discusses the obtained results. Section 4 concludes the paper.

2. METHODOLOGY

The use of GARCH model and its different variants has become the standard for studying and analysing time varying conditional volatility where the conditional means and the variances of GARCH models are fixed for the entire sample period. Gray (1996) proposed a generalized regime-switching (GRS) model, which may be described as follows**:**

$$\begin{aligned} r_t &= \mu(S_t) + \varepsilon_t \\ \varepsilon_t &\to \varepsilon_t \sqrt{h_t(S_t)} \\ h_t(S_t) &= \alpha_0(S_t) + \alpha_1 \varepsilon_{t-1}^2 + \beta_1(S_t) h_{t-1} \end{aligned} \qquad (1)$$

where $S_t = 0$ or 1, $\mu(S_t)$ and $h_t(S_t)$ are the conditional mean and conditional variances respectively. Both are allowed to switch between two regimes. To confirm positivity of conditional variance in each regime, indispensible conditions are similar to the necessary conditions in uni-regime GARCH (1, 1) model. The unobserved regime variable S_t is governed by a first order Markov Chain with constant transition probabilities given by:

$$\begin{aligned} &\Pr(S_t = 0 / S_{t-1} = 0) = P_{00} \\ &\Pr(S_t = 1 / S_{t-1} = 1) = P_{11} \\ &\Pr(S_t = 0 / S_{t-1} = 1) = P_{10} = 1 - P_{11} \\ &\Pr(S_t = 1 / S_{t-1} = 0) = P_{01} = 1 - P_{00} \end{aligned} \tag{2}$$

In matrix notation,

$$P = \begin{bmatrix} P_{00} & 1 - P_{11} \\ 1 - P_{00} & P_{11} \end{bmatrix} \tag{3}$$

Then, conditional distribution of return series r_t becomes a mixture of distribution model in which mixing variable is *ex-ante* probability $\Pr(S_t = i / \pi_{t-1})$ denoted by P_{it},

$$r_t / \pi_{t-1} = \begin{cases} f(r_t / S_t = 0, \pi_{t-1}) \ \textit{with probability} \ p_{0t} \\ f(r_t / S_t = 1, \pi_{t-1}) \ \textit{with probability} \ p_{1t} = 1 - p_{0t} \end{cases} \tag{4}$$

where $f(r_t / S_t = 1, \pi_{t-1})$ denotes one of the assumed conditional distributions for errors: Normal, Student-t or GED. π_{t-1} denotes the information at time t-1. p_{0t} is the *ex-ante* probability of being in regime 0. The log-likelihood function for SW-GARCH model can be written as

$$L = \sum_{t=1}^{T} \ln\left[\sum_{S_t=1}^{2} f(r_t / S_t = 1, \pi_{t-1}) \ \Pr(S_t / \pi_{t-1})\right] = \sum_{t=1}^{T} \ln\left[f(r_t / S_t = 0, \pi_{t-1}) p_{0t} + f(r_t / S_t = 1, \pi_{t-1}) p_{1t}\right] \tag{5}$$

The $\Pr(S_t / \pi_{t-1})$ is the regime probability at time *t* based on the all information up to time t-1. Both Hamilton and Susmel (1994) and Cai (1994) limited their estimation to the Markov Regime Switching ARCH model. The reason is that there is an infinite path dependence problem inherent in SW-GARCH models.

In SW-ARCH models, the conditional variance at time t depends on past *q* squared residuals and past *q* regime variables $(S_t, .., S_{t-q})$. However, in SW- GARCH model, the conditional variance at time t depends on the conditional variance at time t-1 and regime variable (S_t) at time t. While the conditional variance at time t-1 depends on the conditional variance at time t-2 and regime variable (S_{t-1}) at time t-1, and so on. Therefore, the conditional variance at time t depends on the entire history of regimes up to time t. Both Hamilton and Susmel (1994) and Cai (1994) indicated that path dependence nature of SW-GARCH model makes estimation impossible for large sample size. In order to resolve problem of path dependence in SW-GARCH model, Gray (1996) proposed to use conditional expectation of the lagged conditional variance $E_{t-2}(h_{t-1})$ instead of lagged conditional variance h_{t-1}. This approach preserves the natural essential of the GARCH process and allows tractable estimation of model. Gray's approach recombines $h_{t-1}(S_{t-1}) = 0$ and $h_{t-1}(S_{t-1}) = 1$ into h_{t-1}, and recombines $\varepsilon_{t-1}(S_{t-1}) = 0$ and $\varepsilon_{t-1}(S_{t-1}) = 1$ into ε_{t-1} by taking conditional expectations of h_{t-1} and ε_{t-1} based on the ex-ante probabilities. That is,

$$
\begin{aligned}
h_{t-1} &= E_{t-1}(h_{t-1}) \\
&= E_{t-1}(r_{t-1}^2 / \pi_{t-2}) - \left[E_{t-1}(r_{t-1} / \pi_{t-2})\right]^2 \\
&= p_{1t-1}\left[\varepsilon^2(S_{t-1}=0) + h_{t-1}(S_{t-1}=0)\right](1-p_{1t-1})\left[\varepsilon^2(S_{t-1}=1) + h_{t-1}(S_{t-1}=1)\right]
\end{aligned} \tag{6}
$$

Similarly, error terms ε_{t-1} is given by

$$
\varepsilon_{t-1} = r_{t-1} - E(r_{t-1} / \pi_{t-2}) = r_{t-1} - p_{1t-1}\varepsilon(S_{t-1}=0) + (1-p_{1t-1})\varepsilon(S_{t-1}=1) \tag{7}
$$

Given equations (6) and (7), the conditional variance $h_t(S_t)$ in Gray's model can be written as

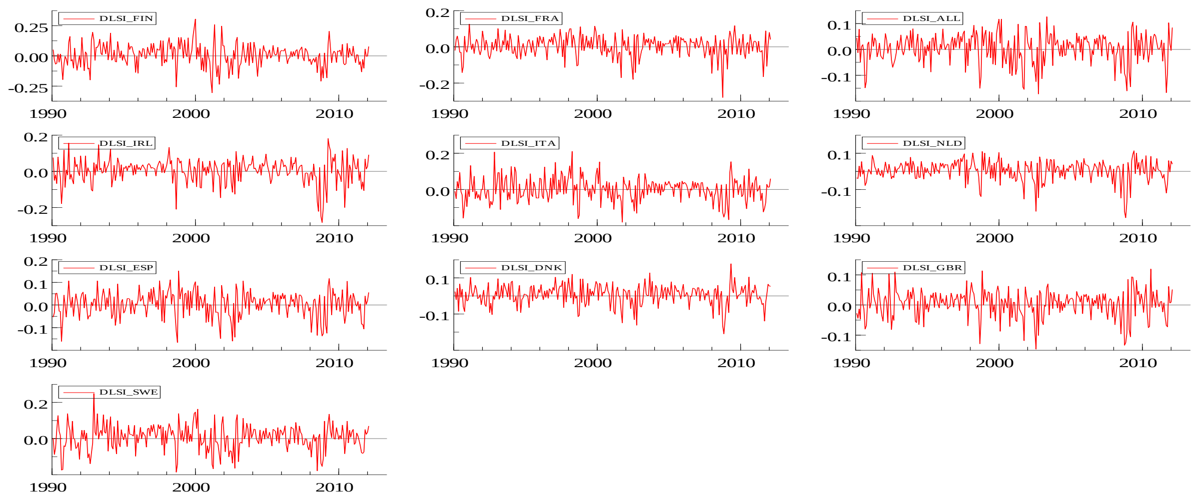
$$
h_t(S_t) = \alpha_0(S_t) + \alpha_1(S_t)\varepsilon_{t-1}^2 + \beta_1(S_t)h_{t-1} \tag{8}
$$

The procedure of conditional expectation of the lagged conditional variance $E_{t-2}(h_{t-1})$ instead of lagged conditional variance h_{t-1} makes conditional variance at time t depends on only current regime S_t and inference about S_{t-1}. Therefore, the Gray's collapsing procedure simplifies and makes tractable the estimation of SW-GARCH models. Given initial values for regime probabilities, conditional mean and conditional variance in each regime, the parameters of SW-GARCH model can be obtained by maximizing numerically the log-likelihood function given in equation (5). The log-likelihood function is constructed recursively similar to that in a uni-regime GARCH models.

3. DATA AND EMPIRICAL RESULTS

3.1 Data

The dataset includes monthly data for stock markets: Finland (Helsinki General), France (CAC 40), Germany (DAX 30), Ireland (ISEQ), Italy (Milan MIB), Netherlands (AEX), Spain (Madrid General Index), Denmark (KFX Copenhagen), Sweden (Stockholm Index), UK (FTSE 100) from 02/01/1990 to 01/03/2012. Stocks index are obtained from Datastream International database. Monthly stock returns are calculated (see figure 1) from stock market indices according to the formula $R_{it} = \ln(P_t / P_{t-1})$. Table 1 presents descriptive statistics for stock market returns. Average stock returns are positive for all considered countries and range from 0.1% (Italy) to 0.7% (Finland). United Kingdom is the least volatile market with a standard deviation of 4.5%, while the highest volatility is found for Finland (9.0%). Expect Italy, the coefficients of skewness are negatives which means that the return distributions are skewed to the left and the probability of observing extreme negative returns is higher than that of a normal distribution. Kurtosis coefficients are significant and greater than three in all cases and thus reveal the leptokurtic behavior of return distributions. Altogether, the non-normality of all the return series is clearly confirmed by the Jarque-Bera test. We also find the presence of ARCH effects for all the series.



Graphic 1: Stock Markets Returns

Table 1: Descriptive Statistics Of Return Series

	FRA	ITA	UK	ESP	IRL	DNK	SWE	FIN	GER	NLD
Mean	0,004	0,001	0,004	0,003	0,003	0,006	0,005	0,007	0,004	0,003
Median	0,011	0,001	0,010	0,008	0,015	0,010	0,013	0,006	0,009	0,010
Max.	0,125	0,210	0,119	0,150	0,181	0,178	0,183	0,305	0,126	0,114
Min.	-0,280	-0,181	-0,146	-0,166	-0,282	-0,209	-0,203	-0,305	-0,172	-0,256
St. Dev.	0,056	0,065	0,045	0,056	0,067	0,055	0,048	0,090	0,057	0,056
Skew.	-1,000	0,058	-0,518	-0,534	-1,000	-0,664	-0,818	-0,151	-0,718	-1,250
Kurt.	5,587	3,555	3,807	3,434	5,378	4,269	5,561	3,959	3,623	6,156
J.B	118,111^{+++}	3,557^{+++}	19,033^{+++}	14,686^{+++}	106,617^{+++}	37,271^{+++}	102,0^{+++}	11,156^{+++}	27,055^{+++}	178,96^{+++}
ARCH(1)	0,356^{+++}	0,169^{+++}	0,561^{+++}	0,896^{+++}	0,343^{+++}	0,289^{+++}	0,987^{+++}	0,111^{+++}	0,473^{+++}	0,221^{+++}

Notes: This table shows the basic statistics and the stochastic properties for stock returns $^{+++}$ indicate that the null hypothesis of normality, no autocorrelation and no ARCH effect is rejected at the 1% rate.

3.2 Discussion Results

Are there regime shifts in the return generating processes?

Several authors, such as Wang and Theobald (2008)**,** stressed that the identification of regime change is difficult as the search for the number of regimes cannot be observed through the use of simple Wald ratio and the test of likelihood ratio.

To resolve this problem, we have applied the likelihood ratio test developed by Garcia and Perron (1996) to verify the existence of regime change for each studied markets. However, we test the null hypothesis of no regime change for the stock market returns represented by the GARCH (1,1) model with a single regime against the SW-GARCH (1,1) specification, which implies the existence of more than one regime for each studied stock market. We start by determining the number of delays with the help of autoregressive model by applying the Akaike Information Criteria (1974) and of Hannan and Quinn (1977). The LR test is defined as $LR = 2\left|\ln L_{MS-GARCH} - \ln L_{GARCH}\right|$ and the critical value for model with two regime shifts is tabulated by Garcia and Perron (1996) and Garcia (1998) based on the study of Davies (1987). Table 2 shows that the LR test statistics are higher than the critical value for all markets. Hence**,** we can reject the null hypothesis of no regime change at a significance level of 1%. However, it is clear that stock market returns of the OECD are better described by a Markov Switching GARCH model compared to a GARCH (1,1) with a single regime.

Table 2: Likelihood Ratio Test

	$\ln L_{GARCH(1,1)}$	$\ln L_{MS-GARCH(1,1)}$	Test LR
France	-1704.54	-1682.98	22.02^{+++}
Italy	-1352.72	-1304.42	20.58^{+++}
United Kingdom	-1392.33	-1374.68	18.33^{+++}
Netherlands	-1631.19	-1608.4	22.79^{+++}
Spain	-1602.79	-1565.92	37.17^{+++}
Ireland	-1896.1	-1828.07	68.03^{+++}
Denmark	-1682.07	-1642.71	39.36^{+++}
Sweden	-1709.68	-1663.62	46.04^{+++}
Finland	-2244.68	-1789.62	455.06^{+++}
Germany	-1987.38	-1789.83	188.55^{+++}

Note: +++ indicate the null hypothesis of no regime switching volatility is rejected at the 1% level.

The results of the estimation of MS-GARCH model (table 3) allow us to identify types of regimes: A first regime with a positive average return with a low volatility for all studied markets and a second regime with higher volatility and positive average returns.

Referring to Maheu and McCurdy (2000), regime 0 is considered a “bull market”, while regime 1 is considered as "bear market". The average returns during regime 0 ranges from -0.026 for Spain to 0.50 for the UK. While the average return is positive for all markets for regime 1. The average ranges between 0.016 for Spain to 0.56 for UK. MS-GARCH model also shows that the probability that a day of low volatility will be followed by another day of low volatility. The probability of transition from regime 0 to regime 1 is 0.98 for the Netherland followed by Italy, Ireland and Sweden (0.97), while the UK has the lowest probability (0.43). The probability that a day of high volatility will be followed by another day of high volatility varies between 0.02 for Italy to 0.66 for the UK.

Table 3: MS-GARCH Results

	FRA	ITA	GBR	ESP	IRL	DNK	SWE	FIN	GER	NLD
$\mu(S_t=0)$	0.19	0.03	0.50	-0.026	0.11	0.17	0.12	0.14	0.11	0.096
	(0.26)	0.13	(0.13)	(0.013)	0.08	(0.15)	0.09	(0.10)	(0.09)	0.08
$\mu(S_t=1)$	0.25	0.08	0.56	0.016	0.42	0.29	0.18	0.21	0.19	0.101
	(0.06)	(0.06)	(0.20)	(0.003)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	0.104
$\sigma^2(S_t=0)$	0.03	0.03	0.03	0.07	0.08	0.07	0.04	0.05	0.07	0.05
	(0.01)	(0.003	(0.004)	(0.006)	(0.005)	(0.012)	(0.003)	(0.005)	(0.005)	(0.003)
$\sigma^2(S_t=1)$	0.05	0.07	0.04	0.08	0.09	0.09	0.08	0.107	0.09	0.07
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.005)	(0.006)	(0.007)	(0.002)	(0.002)
P_{00}	0.86	0.97	0.43	0.84	0.97	0.91	0.97	0.96	0.96	0.98
P_{11}	0.066	0.020	0.661	0.065	0.030	0.033	0.033	0.027	0.027	0.020
$E(D_0)$	8.44	54.00	2.78	7.44	40.50	23.67	44.33	31.25	29.25	49.00
$E(D_1)$	21.00	105.50	10.31	22	54.33	48.50	47.00	46.67	49.33	59.00
L. likelihood	405.91	363.41	456.12	405.53	368.49	99.47	347.83	281.26	401.12	474.63

Note: standard deviations are reported in parentheses

Table 4 reports the results from the Normality test and the ARCH test for conditional heteroscedasticity in the standardized residuals. The null hypothesis of ARCH effects is rejected at conventional levels for all markets. With regard to *Jarque-Bera* test, we confirm the acceptation of normality statistics. The empirical statistic of Portmanteau for autocorrelation reveals that the autocorrelations of the standardized residuals are no longer significant.

Table 4: Normality Test For Scaled Residuals

	FRA	ITA	GBR	ESP	IRL	DNK	SWE	FIN	GER	NLD
Skewness	0.11	-0.02	-0.20	-0.33	-0.26	-0.34	-0.21	-0.20	-0.43	-0.31
Ex. Kurtosis	-0.51	-0.07	-0.10	0.35	-0.02	-0.03	-0.43	-0.10	-0.45	0.17
χ^2 (2)	3.88	0.02	12.57	6.35	5.31	6.32	5.37	2.20	19.99	4.34
	[0.14]	[0.98]	[0.11]	[0.14]	[0.54]	[0.26]	[0.26]	[0.33]	[0.12]	[0.11]
ARCH (1)	0.04	0.053	-0.002	0.007	-0.02	-0.06	-0.01	-0.13	-0.051	0.24
	(0.06)	(0.06)	(0.006)	(0.006)	(0.02)	(0.06)	(0.26)	(0.16)	(0.06)	(0.26)
P. (36)	25.74	32.77	36.68	25.74	30.88	31.22	32.06	26.16	30.85	65.78
	[0.89]	[0.45]	[0.43]	[0.89]	[0.41]	[0.44]	[0.65]	[0.88]	[0.71]	[0.66]

Notes: χ^2 (2) and ARCH (1) refer to empirical statistics of the *Jarque-Bera*test to standardized residuals, and the ARCH test for conditional heteroscedasticity with 1 lag. Numbers in bracket are the associated *p*-values. P refers to empirical statistic of Portmanteau for autocorrelation of order 36 applied to standardized residuals.

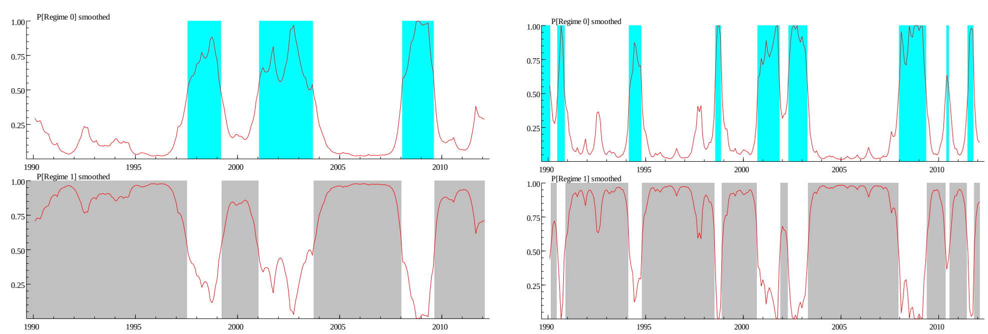
Volatility Behaviour Of Stock Markets Across Regimes

A close look on smoothed probabilities (see figure 2) indicates that there is no common pattern in the regime shift dates among stock markets considered. The unique exception is around the year of 2008, when the smoothed probability of high volatility state increases for all markets, thus reflecting the advent of the US subprime crisis followed by a global financial crisis. Other regime shifts tend to be coincided with several economic and political events occurring over the study period. We now focus on these specific patterns by performing a country by country analysis.

We find a similar pattern in the regime shifts for France, Spain and Switzerland since the three markets experienced a high volatility regime during the September 11 terrorist attack effects starting in 2001. For the Denmark, United Kingdom, Ireland and Netherland, the Japanese asset price bubble that started in 1991 marked the beginning of its first high volatility episode. Another high volatility regime is identified during the Russian and Brazilian financial crisis of 1998-1999. This finding indicates that the Spain, U.K, France, Sweden and Ireland stock markets are more likely to be affected by financial contagion and in crisis periods. The final episode of high volatility happened between 2008 and 2011 for all stock markets studied due to the Subprime crises.

1- Danmark

2 - Spain



3- Finnland

4 – GBR

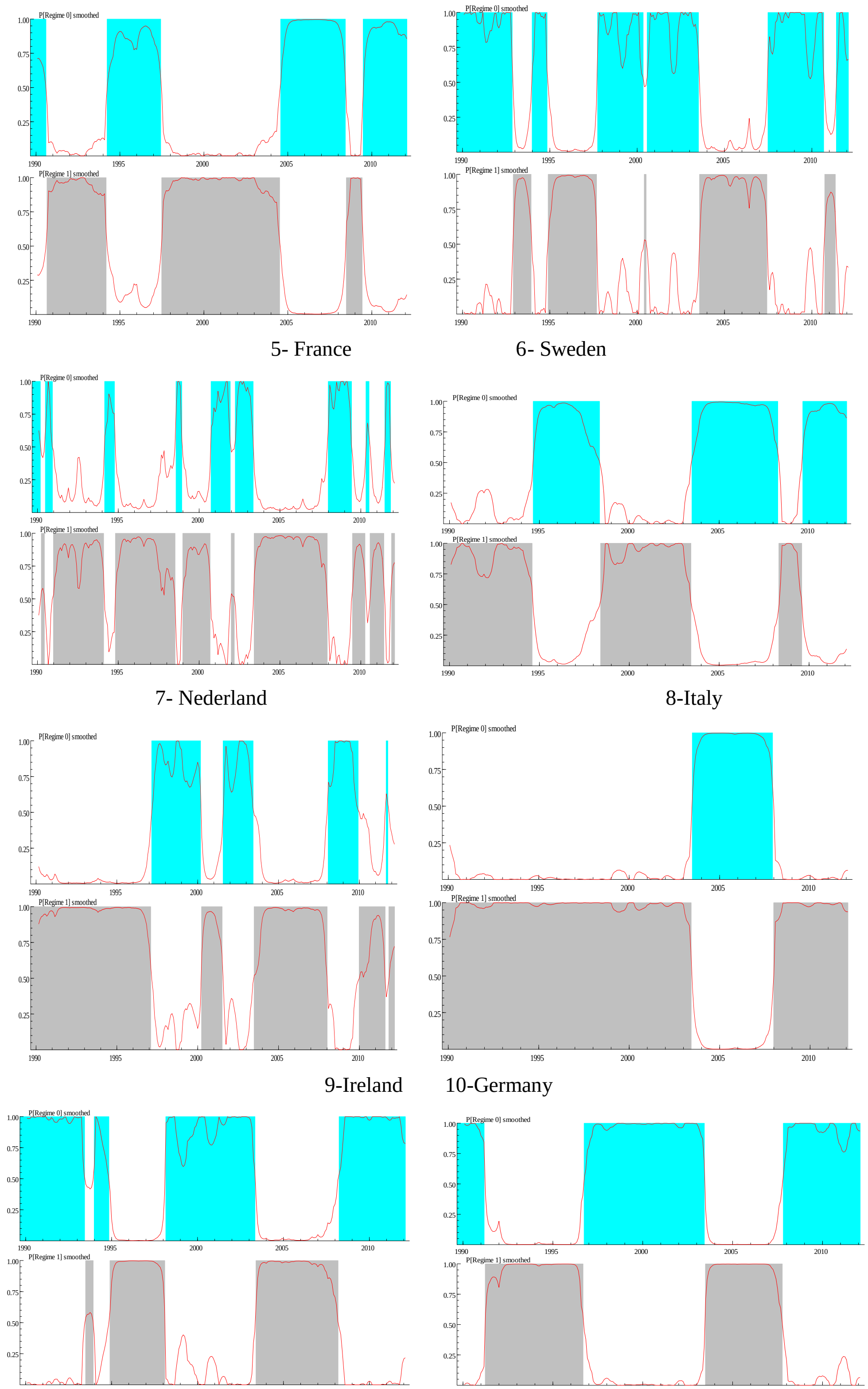


Figure 2: The Smooth Probability In Regime 1 And Regime 2

Finally, our results suggest that changes in the volatility level and regime duration vary across countries and types of event. Economic, political and social events**,** thus**,** cause each market's volatility to change differently, a finding that is consistent with that of Aggarwalandal. (1999).

4. CONCLUSION

In this paper, we studied the volatility of 10 European stock markets. We employed the MS-GARCH empirical approaches. We used the Markov regime shifts in order to study the behaviour of the European stock markets during the financial crises (1990-2012). We proved that most of the European stock markets are closely interlinked to the U.S. highlighting some contagion between markets. However, the relationship of correlation increased significantly during the periods of crises that have affected these markets.

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