I.D.H.E.

Institutions et Dynamiques
Historiques de l'Economie
UMR CNRS 8533

M.O.R.A.

Modélisation non-linéaire
Risques et Applications

New Technology Stock Market Indexes Contagion: A VAR-dccMVGARCH Approach

Ryan LEMAND

Note de Recherche IDHE-MORA n^o 2003-03

Ecole Normale Supérieure de Cachan - Bâtiment Laplace -
61, avenue du Président Wilson - 94235 CACHAN Cedex
Tél. : + 33 (1) 47 40 68 40 - Fax : + 33 (1) 47 40 68 42
morey@idhe.ens-cachan.fr

NEW TECHNOLOGY STOCK MARKET INDEXES CONTAGION: A VAR-DCCMVGARCH APPROACH

RYAN LEMAND

ABSTRACT. The episodes of stock market crises in Europe and the U.S.A. since the year 2000, and the fragility of the New Technology sector after the explosion of the speculative bubble, have sparked the interest of researchers in understanding and in modeling this market's high volatility to prevent against crises. The strong linkage of the American and European New Technology sectors has brought up the co-movement and the contagion hypothesis, especially after the fall in new technology stock prices in Europe following the explosion of the IT speculative bubble in the U.S.A. In this article, we attempt to show that the NASDAQ-100 is a major origin for the shocks that the IT.CAC and the NEMAX undergo. We construct a VAR model with GARCH errors to show this linkage and we find that the NASDAQ-100 has a strong effect on the French IT.CAC; this approach is an original work on contagion in the case of stock market indexes.

1. INTRODUCTION

We can speak of the IT[1] speculative bubble as any other speculative bubble. A speculative bubble with a particularly fast development that spread over all the continents in one year. In other words, it was the first speculative bubble of the globalization process. The effect of this bubble went way beyond the frontiers of the stock market. The speculative movements not only dragged investors into this sector, but also created a massive wave of IT companies creation everywhere in the world. It suddenly attracted thousands of workers seduced by the innovative aspect of this sector and by the fast gain they can get through stock options. The traditional economy sector had to improvise new strategies into the Internet to seduce back investors and financial analysts who lost interest in it. People of all backgrounds and all levels got into the IT sector and invested in start-ups and this is what makes it an even like no other in the world of financial markets.

The peak of the world's interest in this sector arose just before the year 2000. The year 2000 bug[2] was a threat to all of the computers in the world, especially that most of the world's goods and services are computer dependent. So the world

[1]Affiliation: Ecole Normale Supérieure, Cachan, Adress: 132, rue de la Convention, 75015 Paris, France, Email: ryansuleiman@aol.com, Tel/Fax:+33145572544.

Date: March 2003.

1991 *Mathematics Subject Classification.* C22, C32, C52, G15.

Key words and phrases. Conditional Variance, Regime Changes, New Technologies, Contagion, Volatility, VAR, Causality.

I would like to thank Mme Dominique Guegan for her support and her comments in order to complete this paper.

[1]Information and Technology.

[2]The year 2000 bug makes the computers consider passing from the year 1999 to the year 2000 as passing to the year 1900.

realized its computer dependency and its need for computer engineers with the approach of the year 2000, which created the technology snow ball, especially that the year 2000 bug was avoided very smoothly.

In a previous article, we studied the co-movement hypothesis between the NASDAQ-100 and the IT.CAC (Lemand, 2002). We used several conditional variance models with changes in regime to show that there is co-movement between those markets. In fact, we show that the two IT indexes are both either in a high volatility state in or both in a low volatility state and never in a low-high or high-low volatility states. This suggests that the time the contagion takes to spread is quite short (a few days or a few weeks only). Having shown the co-movement hypothesis, we attempt to show in this article, that there is a one way co-movement in the case of the American NASDAQ-100, the French IT.CAC and the German NEMAX50. We proceed using VAR models with heteroskedastic errors and we examine the impulse response function in addition to making a causality test to check the direction of the contagion.

Using daily data of the three IT indexes, we find that there is a one way co-movement from the NASDAQ-100 to the French and German indexes and we find that a shock equal to one standard deviation on the NASDAQ-100 is transmitted quite rapidly onto the IT.CAC, which makes the American index responsible of a large part of the French's volatility; this can be clearly seen once we make the variance decomposition. In fact, the American IT sector is the birth place of IT sectors in the Europe, which gives it a strong influence on the French and German IT sectors that are quite small in size compared to the NASDAQ-100. It has been observed that most of the shocks that the NASDAQ-100 has undergone were transmitted quite rapidly to the French and German stock markets, for example with the Enron and WorldCom cases in the U.S.A., French companies were strongly affected and the public had doubts concerning them; this situation had a great influence on the IT.CAC which includes many companies similar to Enron and WorldCom.

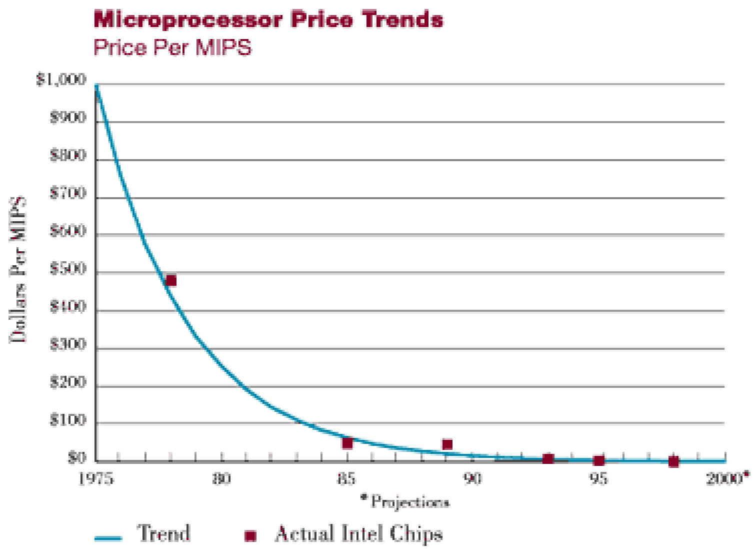
This paper is an original work in combining VAR models with dcc-MVGARCH[3] models with an application to European and American IT stock market indexes to study contagion.
The paper is organized in the following manner: section 2 provides a historical perspective of the IT crises. Section 3 reviews the theoretical and empirical literature on contagion. Data and estimation techniques are discussed in section 4. Section 5 reports the results of cross-country contagion and cross-market contagion results. Finally, the conclusion is drawn in section 6.

2. Historical perspective of the IT crises

The explosion of the Internet traffic is generally presented as the first sign of the new economy's birth. This explosion became possible following the progress realized in data processing and in telecommunication. It should be pointed out that Internet's development is prior to the emergence of micro-computers. Even though the first email message was sent in 1969 by the American army, the first

[3]Dynamic Correlation Multivariate Garch model (Engle and Sheppard, 2001).

micro-computer, *Altaïr*, was manufactured in the U.S.A. in 1975. Hardware companies like Apple, IBM, Compaq... appeared on the market, as well as software producing companies like Microsoft. There were 2000 computers worldwide in the 1950s and 200 million forty years later. Computer data processing speed went from 10000 operations per second to 100000000 operations per second, and this speed is doubling every 18 months. Parallely to the quick rise in microprocessors' power, the price of those microprocessors keeps falling, with an average of 25% per year (see figure below[4]).



This impressive fall in prices is basically due to the progress realized in the manufacturing methods. Economies of scale in general, played a very important role in lowering the prices of the final goods.

The realization of a considerable progress in telecommunication technology was waited for, in order to connect a network of a constantly growing number of computers. As of the end of the 1970s, the progressive usage of optical fibers allowed for high speed and low cost data transmission. The transmission costs of a bit of data over one kilometer of optical fibers has been divided by four between the year 1977[5] and the year 1995[6]. So the industry of computers has evolved through three parallel axis: data processing, networking and software to link the preceding two. Those three axis constitute today what we call the IT sector.

As can be expected, the stock markets realized the importance of this growing market and wanted to take part of it. So speculators bought IT stocks massively

[4]MIPS: Millions of Instructions Per Second. Source: www.neweconomyindex.org.
[5]The year when the first transmission using optical fibers was made in Chicago, U.S.A.
[6]Source: The New Economy Index, www.neweconomyindex.org.

and speculative valorization of IT companies broke records. Even though those companies were still young and weak and were making modest revenues, their market capitalization reached the equal of U.K.'s GNP[7]. In fact, most of the financial models value a company based on the dividends that the investor would expect to get. The problem is that most of the IT companies would have had to grow at a rate of 30 to 40 % over the next 20 years in order to be able to make sufficient revenues and distribute dividends. So most financial models fail to account for this problem since stock prices bear little or no relationship to the value of the IT company. In fact, Joseph Schumpeter discussed a similar phenomenon and introduced the concept of *creative destruction* to help explain the business cycle. This theory, which has become a mantra to venture capitalists and high-tech entrepreneurs, puts forth that economic fluctuations are caused by the introduction of new technology that destroys the value of existing investments built on old technology. Schumpeter took this line of thinking further and foresaw that the creative process of capitalism itself, "sows the seeds of its own destruction". Furhermore, Schumpeter talks about successive waves of innovation that would result in severe economic fluctuations.

The following table illustrates the gap between the American IT companies' market capitalization and their accounting situation: The scenario that took place in the

Table 1. Development of certain IT stocks from their introduction until 9/12/1999 (Capitalization and net revenues in millions of dollars)

Comp.	Stock price	Capit.	Net rev.	Int. date	Int. price	Var.%
AOL	84.17	92607	762	19.3.1992	11.22	650
Lycos	83.5	7159	-52	1.4.1996	15.61	435
Yahoo!	331.81	85204	26	13.4.1996	12.69	2515
Amazon	101.13	36171	-125	15.5.1997	17.57	467
eBay	156.75	19879	2.4	24.9.1998	17.57	792
Terra	48.82	13546	-3.8	17.10.1999	13	276

U.S.A. got repeated almost at the same time all over the major market places, all over the world, and especially in France and in Germany where a French and a German technology indexes (IT.CAC and NEMAX respectively) were created to account for this sector. Europe witnessed also the creation of a large number of IT companies which also "suffered" from a very high market capitalization versus quite modest revenues. Figure 1 shows the parallel explosion of the NASDAQ-100, the IT.CAC and the NEMAX's respective volatilities around the year 2000 using the RSD as a preliminary measure of those volatilities[8].

In table 2 we can see the correlation coefficients of the three indexes's volatilities measured using the RSD over 21 days.

Based on the above correlation matrix, we can make a preliminary hypothesis that the IT indexes's volatilities are highly correlated, which reflects the reality

[7]For IT companies based in the U.S.A.

[8]Rolling standard deviation (RSD) over 21 days: $\sigma(r_t) = [253 \sum_{k=1}^{2} 1(r_{t-k} - \mu)^2/20]^{\frac{1}{2}}$, where μ is the mean of the observations over 21 days (Schwert, 2002).

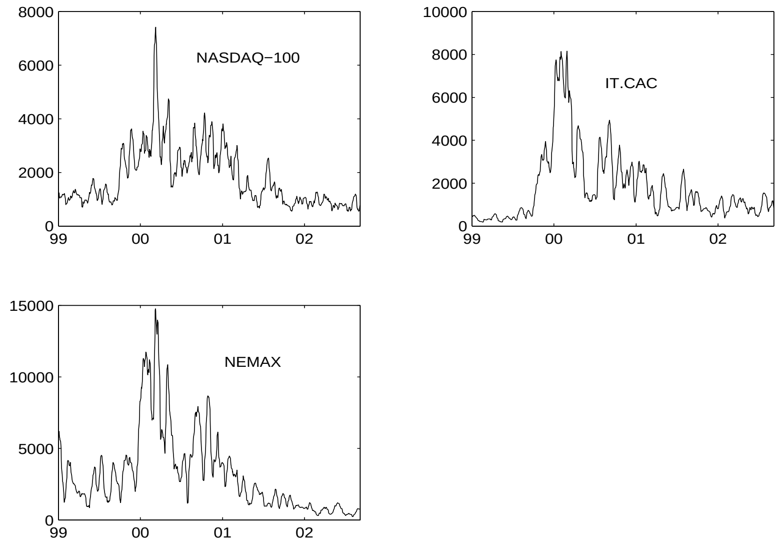


FIGURE 1. Rolling 21-day standard deviation for the 3 indexes

TABLE 2. Correlation coefficients of the indexes' 21-day RSD

	NASDAQ-100	IT.CAC	NEMAX
NASDAQ-100	1	0.74	0.77
IT.CAC	0.74	1	0.78
NEMAX	0.77	0.78	1

seen in the close relationship between the American and the European IT markets.

The rise of the new technology sector's volatility all over the world has taken place mainly because of technology itself. It seems all speculative bubbles are associated with some new gimmick, some new investment vehicle or technology. Many of these new market technologies of the past, have persisted as important market tools. However, their excessive over use in the short run contributed to speculation. Today's gimmick is probably the availability of on-line trading.

Today anyone can buy and sell stock at very low commissions with the click of a mouse. This wonderful technology represents several potential problems for unhealthy speculation. First, it makes it easy for anyone to get into the market. In the past, all the hassle of going to a broker to open an account probably prevented many people from diving in. Additionally, the broker probably represented an important double check on an investor's speculative euphoria. Brokers have a legal obligation to qualify their clients in an attempt to help people invest in securities appropriate to their circumstances. Though this system is far from perfect, a broker is a better filter than a computer. Finally, on-line trading has resulted in an explosion of day-traders. No one knows how many day-traders there are or how much money they actually represent. but it is getting to be substantial.

Unfortunately, many of them are really gambling; they do not truly have a rational and disciplined approach to trading. If they understood the true volatility of stocks, and especially how the dealers and floor specialists work they would realize that for all their apparent on-line access the odds, are terribly stacked against them.

A second reason why the IT sector's volatility exploded in the recent years is the heavy use of margin, especially in France. Margin is a term for borrowing money to buy stock. If an investor borrows and buys a stock that goes up, his profits increase. If the stock declines, his losses increase. Thus, margin increases the risk in owning stock. Margin rises during speculative bubbles. The Wall Street Journal reported recently that in February, margin debt hit $265.2 billion up 45% in just four months. And this number probably understates the amount of leveraged speculation that is going on. There is evidence that in addition to regular margin debt, people are borrowing against the equity in their homes and even their credit cards to invest. This is not healthy.

And finally, a third reason is a phenomenon known as an *information mirage* in which traders ignore their own information and instead look to "follow the herd". In an information mirage, also known as a *reverse information cascade*, an individual trader who can be certain that his or her own information is reliable is likely nonetheless to follow other traders, even if he or she knows that everyone else are badly trading based on these information. Such a behavior may play a role in bubble formation and in creating a contagion effect, national or international.

3. Financial market contagion: Literature survey

The phenomenon of global stock market contagion is now too familiar and serious to ignore and has become an integral part of the stock market activity. International spread of a financial crisis is no new phenomenon and dates back to the Mississippi and the South Sea bubbles. The collapse of the Mississippi scheme in the Netherlands during 1719-1720 led to the quick demise of the South Sea Company in England within one year in 1720.

The impact of the October 1987 crash was even more widespread. The 21.50% fall in the Dow resulted in a 44% decline in Australia, 22.20% in Canada, 21.70% in the UK, 18.60% in France and 17.70% in Germany. This is despite the fact that the indicators of economic conditions varied widely among the countries. Surprisingly, the impact was very little in the Italian and the Japanese markets.

However, the contagion effect has become more pronounced in recent years because of the rapid global economic integration. It may also be observed that the phenomenon of global stock market contagion always comes for debate only when a major crisis hits the US market.

Theoretical work on international propagation of shocks can be broadly categorized as focusing on three different mechanisms: aggregate shocks which affect the economic fundamentals of more than one country, country-specific shocks which affects the economic fundamentals of other countries, and shocks which are not explained by fundamentals and are categorized as pure contagion (Masson, 1996).

The first mechanism focuses on aggregate or global shocks which simultaneously affect the fundamentals of several economies. For example, a rise in international interest rate, a contraction of the international supply of capital, or a decline in international demand could simultaneously slow growth in a number of countries. The stock markets in any countries affected by this aggregate shock would move together (at least to some degree), so that directly after the shock, cross-market correlations between any affected countries could increase.

The second mechanism explains how a shock to one country (or group of countries) could affect fundamentals in other countries (Eichengreen, Rose and Wypolsz, 1996). This mechanism could work through a number of real linkages, such as trade or policy coordination. Trade could link economies because a devaluation in one country would increase the competitiveness of that country's goods, potentially decreasing the competitiveness of other countries. This could not only have a direct effect on a country's sales and output, but if the loss in competitiveness is severe enough, it could increase expectations of an exchange rate devaluation and/or lead to an attack on a country's currency. Policy coordination could link economies because one country's response to an economic or financial shock could force another country to follow similar policies. For example, a trade agreement might include a clause in which lax monetary policy in one country would force other trade member countries to raise trade barriers.

The final propagation mechanism, contagion, is defined as any increase in market co-movement which cannot be explained by the previous two channels, so contagion in this case is treated as a residual and which will be the case in our article. For example, Mullainathan (1998) focuses on investor psychology and argues that investors imperfectly recall past events. A crisis in one country could trigger a memory of past crises, which would cause investors to recompute their priors (on variables such as debt default) and assign a higher probability to a bad state. The resulting downward co-movement in prices would occur because memories instead of fundamentals are correlated.

The cross-market linkages during a crisis are different than during relatively stable periods. In fact, international propagation mechanisms are strengthened during a crisis and this shift is not driven by real economic linkages.

Now if we examine the IT sector in general, we can conclude that it does not belong to the first two propagation mechanisms. As a consequence we will treat contagion as a residual and we define it as a significant increase in cross-market linkages after a shock to one country (or group of countries), similarly to the literature (Forbes and Rigobon 2002).

Motivated by the lack of evidence on countrys economic fundamentals as determinants of contagion, researchers sought explanations in investment holding patterns. Kodres and Prisker (2002) develop a theoretical model of financial contagion through cross-market hedging. This hedging model predicts market co-movements should be symmetrical in market upturns and downturns. Kyle and Xiong (2001) suggest that contagion occurs through the wealth effects of investors. When investors undergo a large loss in investment in the crisis country, they may have to liquidate their positions in other countries, thus causing equity prices to depreciate elsewhere. Moreover, Calvo (1999) and Yuan (2000) find that wealth effects persist even when only a small fraction of investors are wealth-constrained, as long as they are relatively more informed. They argue that uninformed rational investors would not be able to discern the purpose of informed investors, and would not be able to distinguish between selling based on liquidity shocks and selling based on fundamental shocks. In the presence of margin-constrained, informed investors, it is possible for contagion to result from confused uninformed investors. Kyle and Xiong (2001), Calvo (1999), and Yuan (2000) predict that crises are spread to stock markets by their wealth-constrained investors, and that correlations among markets are greater in market down- turns. Although theoretically convincing, there is little empirical evidence for the investor-induced contagion hypothesis.

Empirical literature, in general, finds support for a case of currency contagion. For example a group of economists detected contagion in case of Tequila crisis in Latin America initiated by a crash of Mexican peso in 1994. Eichengreen, Rose and Wyplosz (1996) used thirty years panel data for 20 industrialized countries and argue that currency contagion spread more easily to countries which were closely tied by international trade linkages than to countries in similar macroeconomics conditions. Using data from emerging markets, Glick and Rose (1999) concluded that trade was the important channel for contagion. Using a time-varying transition probability Markov-switching model, Cerra and Saxena (2000) found empirical evidence suggesting contagion (pressures on exchange rate emerging from Thailand) as one source of crisis in Indonesia along with other factors such as domestic financial conditions and political instability. Ahluwalia (2000) twisted the argument of common macroeconomic weaknesses to important similarities between countries but found support for contagion in a sample of 19 countries Asia and Latin America. Rijckeghem and Weder (1999) argue that financial market linkages are an important source of spillovers from shock-originating country to the other countries in the 11 regions. Using Mexico, Thailand and Russia as the crisis originating countries, they found support for financial market linkages as the source of spillovers. There is also an argument based on common creditor problem, which may lead to unexpected capital outflows independent of macroeconomic fundamentals. Aizenman and Hoffmaiser (1999) found strong support for contagion of bank lending spreads and output fluctuations in Argentina.

Biag and Goldfajn (1998) used a VAR model to analyze data from a sample of seven Asian countries and found support for cross-boarder contagion in the currency and equity markets. Chan (1999), using a SURE framework for nine Asian economies, found both contagion and economic fundamentals to be important source of spread of crisis in the region. Dungey and Martin (1999) decomposed the exchange rate movements into idiosyncratic, common shocks, spillover effect and contagion effects and found empirical evidence suggesting that contagion from Thailand during the 1997 Asian crisis accounted for 15 percent volatility in Indonesia, 10% in Malaysia and less than 1 percent for South Korea.

Forbes and Rigobon (1999a), however, argue that cross-country correlation during the crisis may have a tendency to increase. Therefore, attributing such correlation as contagion may be biased unless some adjustment for such co-movements is made. Their empirical tests based on data from a sample of countries in Asian and Latin American regions and the United states suggest that adjusted coefficients do not have any contagion. However, the same data when applied to unadjusted coefficients reflect evidence of contagion. In a later paper, Forbes and Rigobon (1999b) suggest another definition of contagion, called shift-contagion. Shift-contagion occurs when cross-market linkages increase significantly after a shock to an individual country. Using this definition, they claim that most of evidence of contagion may not be classified as shift contagion. In this sense, the countries are highly interdependent, as the cross-country linkages remain stable even after the crisis.

Fratzscher (1998) compares the spread of Latin American crises and the Asian crises to other emerging economies. Using different definitions of contagion, he found that high financial and trade integration were central to the spread of crises across the regional economies. Masih and Masih (1999) examined the long and short-term dynamic linkages among international and Asian emerging stock markets. They found strong support for the role of contagion among Asian markets.

It is evident from above discussion that the interest in contagion has increased after two recent episodes of regional crises namely, the 1997 Asian crisis and the 1998 Russian crisis.

4. Data and Estimation Techniques

The main objective of this paper is to study the contagion effect between the three IT indexes that we study, namely the American NASDAQ-100, the French IT.CAC and the German NEMAX (see figure 2 for the three indexes' graphs).

4.1. Data and some preliminary analysis.

In fact, in a previous article we used a multivariate SWARCH model (Edwards and Susmel, 1998) to show that the IT indexes are simultaneously in high volatility regime or in a low volatility regime, but never in a high-low volatility regime. The coincidence of the indexes volatility states along with the high correlation coefficients (see table 3) the indexes have, lead us to draw the conclusion that there is a co-movement between them.

Table 3. Correlation coefficients matrix of the three indexes

	NASDAQ100	IT.CAC	NEMAX
NASDAQ100	1	0.89	0.93
IT.CAC	0.89	1	0.79
NEMAX	0.93	0.79	1

Our aim is to show that there is a one way co-movement between the three IT indexes and that the NASDAQ-100 is the originator of the shocks. On the other hand we will attempt to reach the conclusion that there is a relationship between international correlation of the three indexes and stock market turbulence.

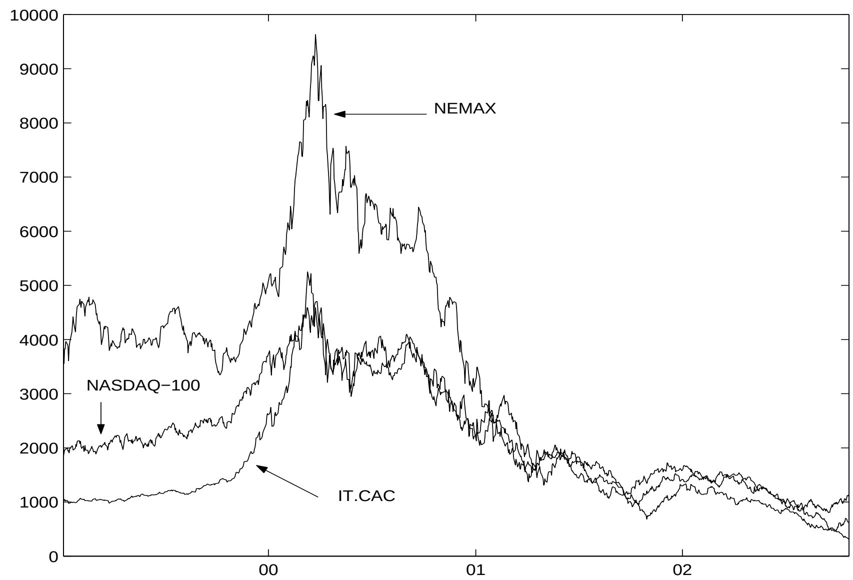


FIGURE 2. Graphs of the NASDAQ-100, the IT.CAC and the NEMAX

We use weekly stock returns of the three indexes, starting on the 6th of January 1999 till the 9th of October 2002[9]. A summary of the indexes weekly stock returns can be found in Table 4 below.

TABLE 4. Descriptive statistics of the three indexes weekly stock returns

	DNASDAQ-100	DIT.CAC	DNEMAX
Mean	-6.20388	-2.63094	-24.7852
Median	-3.29	-6.04	-31.61
Maximum	732.25	1052.93	1389.66
Minimum	-822.3	-1096.7	-1996.23
Std. Dev.	174.7744	196.9647	334.7201
Skewness	-0.29906	0.287231	-0.29903
Kurtosis	5.239088	9.621564	6.850925
Jarque-Bera	217.7603	1790.933	615.7182
Probability	0	0	0

The average weekly return is negative for the three indexes. Standard deviations reveal that the NASDAQ-100 has the smallest one whereas the German NEMAX has a standard deviation that is almost the double of the NASDAQ-100's. As for the skewness, which is the measure of the distributions asymmetry of returns, we find that the NASDAQ-100 and the NEMAX returns exhibit a negative one, which suggests that crashes are more likely than booms, whereas the IT.CAC's skewness

[9]We use weekly stock returns since they are less noisy than daily stock returns and allow for us to keep more information in the series than the first order differencing.

is positive. As for the kurtosis, which measures the heaviness of tails compared to a measure of three for the normal distribution, we find that the three indexes exhibit excess kurtosis (larger than 3), therefore their distributions have fatter tails than the normal one. The Jarque-Bera test statistic strongly rejects the normality hypothesis of stock returns for the three indexes. Those preliminary descriptive statistics confirm the widespread results in the financial literature on stock returns: negative skewness (except for the IT.CAC) and fat tails.

We next consider the presence of return serial correlation. We consider the Ljung-Box statistic. The Ljung-Box (LB) statistic with 36 lags is distributed as a χ^2_{36}. The LB statistic shows significant linear dependencies of returns for the three markets investigated.

Next we consider heteroskedasticity by regressing squared returns on past squared returns (up to 12 lags). The TR^2 Engle statistic, where R^2 is the quality of the fit coefficient, is distributed as a χ^2_{12} under the null hypothesis of homoskedasticity. The Engle statistic takes very large values for each market, and strongly rejects the homoskedasticity null hypothesis, which indicates strong non-linear (second moment) dependencies. We therefore conclude that there is a fair amount of heteroskedasticity in the data.

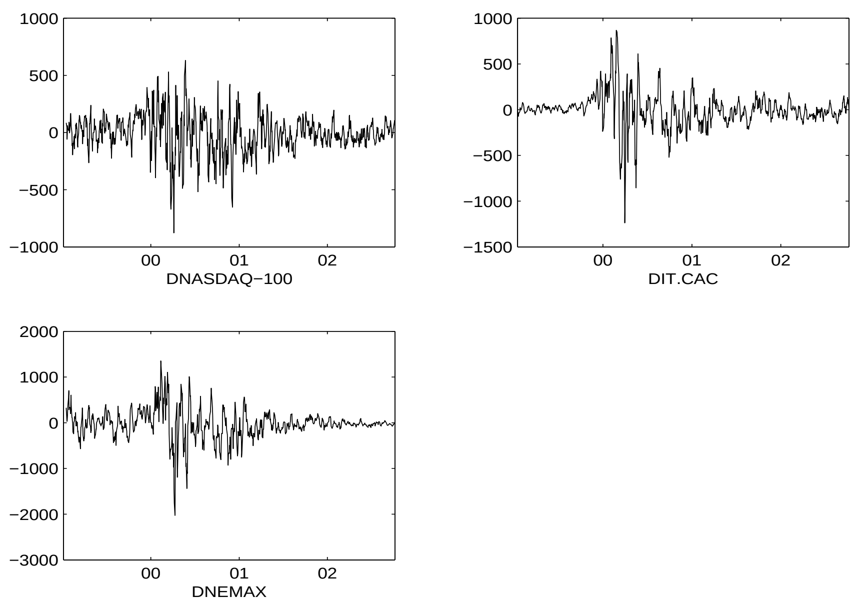


FIGURE 3. Graphs of the weekly returns for the NASDAQ-100, the IT.CAC and the NEMAX

Table 5 reports unconditional correlation coefficients between indexes returns and the unconditional variances over three subperiods. The first subperiod covers the year that preceded the IT crash (15/1/1999 till 31/12/1999) and the second subperiod (3/1/2000 till 29/12/00) covers the year of the IT crash. If we compare, we can clearly see that the unconditional variances grew out of proportions in the second subperiod compared to the first subperiod. Furthermore, the unconditional correlations between the NEMAX and the NASDAQ-100 more than doubled from the first subperiod to the second subperiod. Curiously, the unconditional correlations of the NASDAQ-100 and the IT.CAC did not increase in the second subperiod, but rather decreased. In fact, if we examine the graphs of the three indexes' weekly returns in figure 3 and the unconditional variances in table 5, we can see that in the period that followed the crash, the IT.CAC and the NEMAX weekly returns had a very high volatility for short period of a few months and then this volatility decreased dramatically afterwards. The NASDAQ-100 weekly returns on the other hand, exhibited a high increase in volatility after the crash and sustained this high volatility for a much longer time than the other two indexes. Looking back again at table 3, we can see that the unconditional correlation coefficients of the three indexes in levels show very high values and reach maximums around the year 2000 when the three indexes exhibited very high volatilities in a very turbulent period.

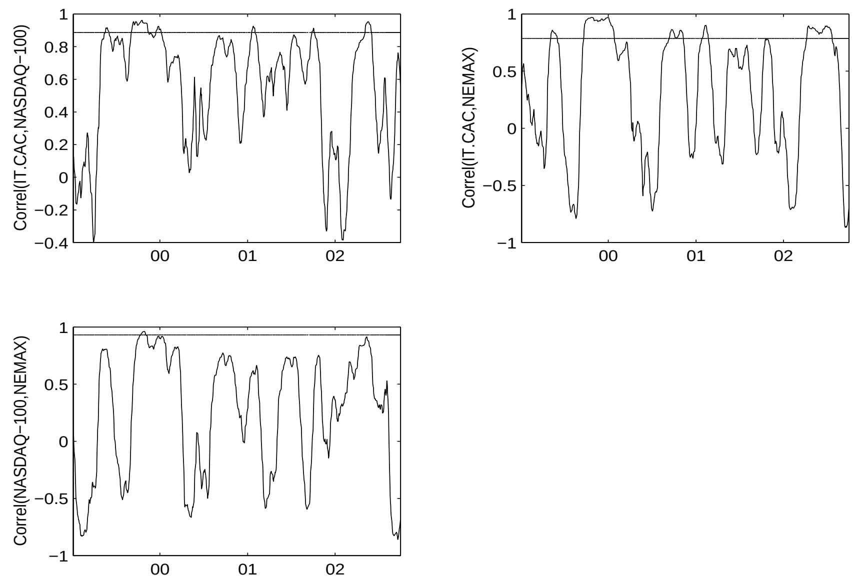


Figure 4. Conditional correlation coefficients over 100 days of the three IT indexes in levels

If we examine the conditional correlation coefficients[10] of the three indexes over 100 days in figure 4 above, we can see that those correlations are far from constant. The solid lines show the unconditional correlation coefficients of the three indexes and if compared with the conditional ones, we can see that those correlations exhibit dramatic fluctuations. Now if we examine the correlation coefficients matrix of the rolling 21-day standard deviations of the three indexes, as a preliminary

[10]Using the classical formula $\hat{\rho}_{12,t} = \frac{\sum_{s=t-n-1}^{t-1} r_{1,s} r_{2,s}}{\sqrt{(\sum_{t-n-1}^{t-1} r_{1,s}^2)(\sum_{t-n-1}^{t-1} r_{2,s}^2)}}$. This estimator gives equal weights to all observations less than n periods in the past and zero weight on older observations. This estimator will always lie in the $[-1, 1]$ interval. This estimator is also called moving average (MA) estimator for rolling conditional correlations.

Table 5. Unconditional correlation matrices and variances over various sub-periods of the three IT indexes' weekly returns

	Correlation matrix			variance
	DNASDAQ-100	DIT.CAC	DNEMAX	
15/1/99-31/12/99				
DNASDAQ-100	1	0.36	0.07	12389.25
DIT.CAC	0.36	1	0.25	6499.178
DNEMAX	0.07	0.25	1	49019.44
3/1/00-29/12/00				
DNASDAQ-100	1	0.20	0.19	67863.71
DIT.CAC	0.20	1	0.13	97527.53
DNEMAX	0.19	0.13	1	275789.8
1/1/01-8/10/02				
DNASDAQ-100	1	0.19	-0.11	11302.01
DIT.CAC	0.19	1	0.09	9360.779
DNEMAX	-0.11	0.09	1	17511.98

measure of volatility (figure 1), we can see that the correlation coefficients are quite high (table 2).

Furthermore, if we establish a Granger causality test over the three series of the rolling 21-day standard deviations (table 7 below), we can see that the NASDAQ-100 Granger causes the two European IT indexes (IT.CAC and NEMAX) and that it is a one way causality. We also find that there is a two-way causality between the IT.CAC and the NEMAX. Therefore we conclude that there might be a volatility contagion channel between these indexes and specifically from the NASDAQ-100 towards the IT.CAC and the NEMAX.

Table 6. Granger causality test for the three series of the rolling 21-day standard deviations for the NASDAQ-100, the IT.CAC and the NEMAX

Pairwise Granger Causality Tests		
Null Hypothesis:	F-Statistic	Probability
RSDcac doesn't Granger Cause RSDnas	1.42	0.23 (accept H_0)
RSDnas doesn't Granger Cause RSDcac	5.60	0.02 (reject H_0)
RSDnem doesn't Granger Cause RSDnas	0.96	0.33 (accept H_0)
RSDnas doesn't Granger Cause RSDnem	31.53	0.00 (reject H_0)
RSDnem doesn't Granger Cause RSDcac	14.64	0.00 (reject H_0)
RSDcac doesn't Granger Cause RSDnem	62.03	0.00 (reject H_0)

Based on the facts that the indexes are linearly dependent (LB test), show high levels of heteroskedasticity (Engle's test) and exhibit dynamic correlations, our approach in using a VAR model with heteroskedastic errors along with time variable conditional correlations is justified. Since the dynamic correlations that we estimated do not show remarkably high levels, we also establish the hypothesis of cointegration of the indexes.

4.2. **Estimation techniques.** We start by performing an augmented Dickey Fuller test (ADF) in order to identify the presence of a unit root in the data. The result would help us decide on the cointegration order of the three indexes and to construct a Vector Error Correction Model (VECM). The results of the ADF test, show that the three series are non-stationary and have a unit root $I(1)$.

A vector error correction model (VECM) is a restricted VAR designed for use with non-stationary series that are known to be cointegrated. The VEC has cointegration relations built into the specification so that it restricts the long-run behavior of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is known as the correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments.

Table 7 below shows the results of the Johansen cointegration test to determine the number of cointegration equations (CE) to include in the VEC model. The test reveals the presence of a single cointegration equation between the indexes.

Table 7. Unrestricted Johansen cointegration rank test for the three series to determine the number of cointegration equations

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5% Critical Value	1% Critical value
None	0.051752	61.65296	29.68	35.65
At most 1	0.00971	9.841828	15.41	20.04
At most 2	0.000337	0.328232	3.76	6.65

The VEC model can be represented as follows:

$$\Delta Y_t = \sum_{i=1}^{p-1} D_i \Delta Y_{t-i} + \alpha\beta' Y_{t-1} + \epsilon_t, \tag{4.1}$$

with the cointegration equation defined as a β linear equation between the first variable on one hand and the other two variables on the other hand and so on depending on the number of cointegration equations. Y_t with $t = 1, 2, ..., T$ is the vector of dimension s ($s = 3$ in our case) of the series in question, Δ is the usual difference operator and $\Delta Y_t = r_t$ the weekly returns (Y_t being the indexes in levels), α and β are matrices of full rank of dimensions $s \times r$ (r is the number of cointegration relations and $0 < r < s$), D_i is a matrix of parameters to be estimated of dimensions $s \times s$, and ϵ_t is a vector of innovations.

It is very important to determine the lag length before estimating the VECM. Therefore we use the Akaike information criteria(AIC), the Schwartz information criteria (SIC) and the likelihood ratio test (LR) to determine the lag length.

The main objective of estimating the VECM in this study is to identify any casual relationship among the three different IT markets across the U.S.A., France and Germany. In fact, we are interested in showing that the disturbances in the French and the German IT markets are primarily caused by the American NASDAQ-100 along with the intrinsic events of each IT market. We establish a Granger causality test for the three series (table 8) and we find that the NASDAQ-100 disturbances indeed cause the disturbances in the IT.CAC and the NEMAX.

Table 8. Granger causality test for the three IT weekly stock returns series

Pairwise Granger Causality Tests		
Null Hypothesis:	F-Statistic	Probability
DIT.CAC doesn't Granger Cause DNASDAQ-100	2.37	0.06 (accept H_0)
DNASDAQ-100 doesn't Granger Cause DIT.CAC	33.19	0.00 (reject H_0)
DNEMAX doesn't Granger Cause DNASDAQ-100	2.56	0.05 (accept H_0)
DNASDAQ-100 doesn't Granger Cause DNEMAX	4.75	0.00 (reject H_0)
DNEMAX doesn't Granger Cause DIT.CAC	6.08	0.00 (reject H_0)
DIT.CAC doesn't Granger Cause DNEMAX	19.93	0.00(reject H_0)

Next, we carry on with the VEC model estimation using ordinary least squares (OLS), and we use AIC, SC and LR to determine the most convenient lag length and we establish a lag exclusion test after estimation to eliminate unnecessary lags. We carry on a Pairwise Granger Causality/Block Exogeneity Wald Tests after estimation of the VECM to determine if there are any index to be considered as exogenous to the system; the results are reported in table (9).

We can see from table (9) that all six hypotheses are rejected, which means that the three indexes in the three VECM equations are significantly different from zero and that they are endogenous to the system, none should be considered as exogenous.

The surprising result in table (9) is the first part in it, where the test suggests that D(IT.CAC) and D(NEMAX) are not to be excluded from the D(NASDAQ-100) equation, which means that the D(NASDAQ-100) has, to a certain extent to be determined, a dependency on the two European indexes. The extent of this dependency will be determined next based on the impulse-response functions and on the variance decomposition of the three indexes.

4.2.1. *Impulse-Response Functions and Variance Decomposition.* The impulse response function traces the effect of a shock equal to one standard deviation to one of the innovations on current and future values of the endogenous variables. A shock to the i-th variable directly affects the i-th variable, and is also transmitted to all of the endogenous variables through the dynamic structure of the VAR. Since innovations are usually correlated, they have a common component, which cannot be associated with a specific variable.

The dynamic analysis of VECMs is usually carried out using the orthogonalized

Table 9. VECM Pairwise Granger Causality/Block Exogeneity Wald Tests for the Three Indexes

Dependent variable: D(NASDAQ-100)			
Exclude	Chi-sq	df	Prob.
D(IT.CAC)	86.98	29	0
D(NEMAX)	102.41	29	0
All	190.29	58	0

Dependent variable: D(IT.CAC)			
Exclude	Chi-sq	df	Prob.
D(NASDAQ-100)	111.61	29	0
D(NEMAX)	77.86	29	0
All	195.83	58	0

Dependent variable: D(NEMAX)			
Exclude	Chi-sq	df	Prob.
D(NASDAQ-100)	74.40	29	0
D(IT.CAC)	319.46	29	0
All	474.00	58	0

impulse-responses. as suggested by Sims (1980). Accordingly, Cholesky decomposition is normally used in the literature where errors are orthogonalized in such a way that the covariance matrix of the resulting innovations is diagonal.

We first introduce a shock to the NASDAQ-100 and we analyze the impact within and across the markets over 30 days. We repeat the same in the other two markets namely, the IT.CAC and the NEMAX. Figure (5) shows the different graphs of the accumulated impulse-response functions.

If we look at the first column of graphs, which represent a shock to the NASDAQ-100, we can see that the effect on the IT.CAC is almost immediate (3 days after the shock took place) and rises rapidly, whereas the response of the NEMAX is delayed with relatively to the IT.CAC and the response rises after the 10th days. If we compare the shock to the NASDAQ-100 and its effect on the other two indexes with the shocks to the IT.CAC and the NEMAX and their effect, we can clearly see that the NASDAQ's shock has considerable effect on the other two indexes compared with the IT.CAC's and the NEMAX's shocks. This suggests a contagion effect coming from the NASDAQ-100 and affecting the two European indexes.

Next, we consider the variance decomposition for the three indexes. While impulse response functions trace the effects of a shock to one endogenous variable on to the other variables in the VAR, variance decomposition separates the variation in an endogenous variable into the component shocks to the VAR. Thus, the variance decomposition provides information about the relative importance of each random innovation in affecting the variables in the VAR. The first column in figure (6) shows the percent of variance due to the NASDAQ-100 in each of the three indexes and so on for the other two columns.

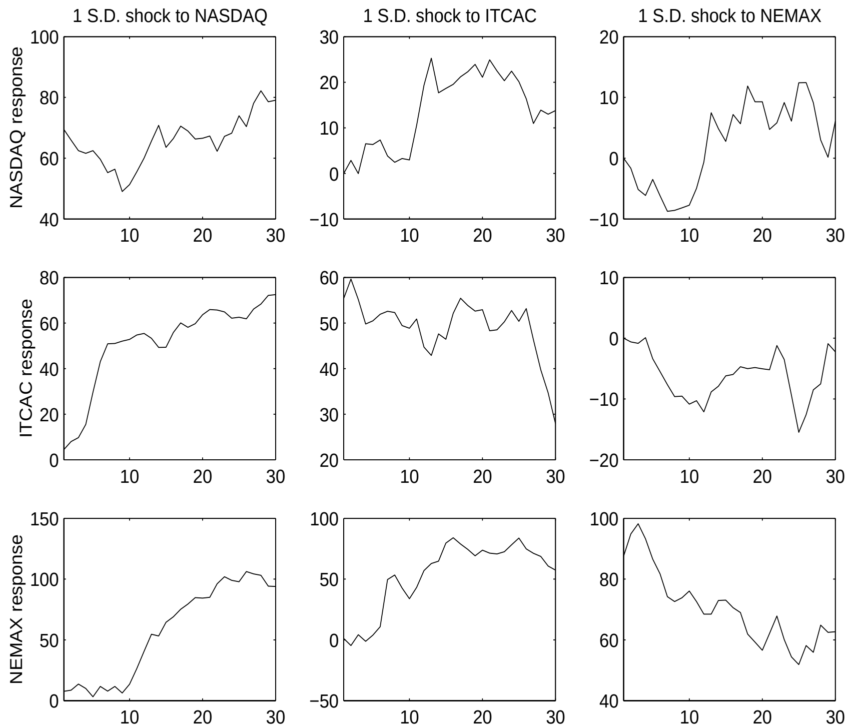


FIGURE 5. Accumulated impulse-reponse functions over 30 days for the three indexes

If we examine the variance decomposition graphs for the three indexes we can see that the contagion hypothesis is confirmed. In fact, if we look at the first column and see the variance decomposition of the IT.CAC and the NEMAX, we can conclude that the NASDAQ-100 is responsible for a considerable part of the IT.CAC's and the NEMAX's variances. After a shock, the NASDAQ's variability is transmitted at a rate of almost 40% after one week of the shock. On the other hand, the effects of shocks to the IT.CAC and the NEMAX on the variances of the three indexes are much less significant. This drives us to conclude that the contagion effect is indeed coming from the NASDAQ-100 to the IT.CAC and the NEMAX.

4.2.2. *Analysis of the residuals.* We next examine the residuals of the VEC model in order to see if the VEC model has captured the linearity in the data and to see if the residuals are heteroskedastic as it can be expected. We first test the residuals for serial correlation using an LM test for different lags (6, 12 and 18 lags). The results are reported in table (10).

We reject the hypothesis of a presence of serial correlation in the VECM residuals for the three lags, 6, 12 and 18. This means that the VEC model captures all of the linearity that was present in the three indexes. Then, we test the residuals' normality using a multivariate normal test. The results of the test are reported in table (11).

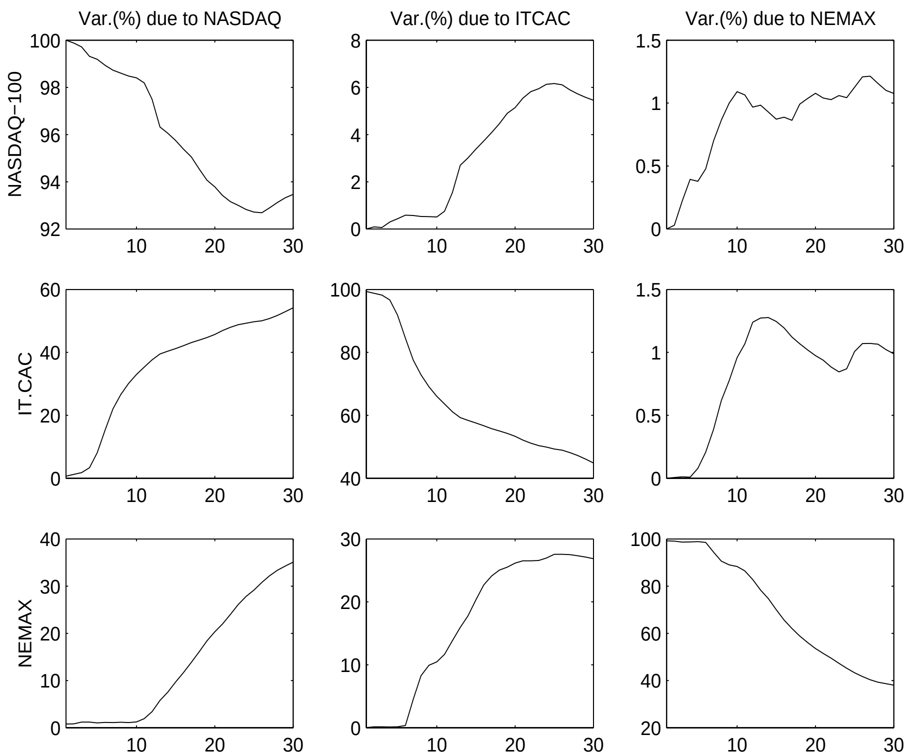


FIGURE 6. Variance decomposition in percentage over 30 days for the three indexes

TABLE 10. VECM Residual Serial Correlation LM Test (H0:no serial correlation at lag order h)

Lags(h)	LM-Stat	Prob
6	10.76	0.29
12	13.66	0.14
18	12.66	0.18

The test reveals that the NASDAQ-100's and the NEMAX's residuals are symmetrical and show no skewness, whereas the IT.CAC's residuals are positively skewed since the test rejects the hypothesis that its skewness is null. The three indexes's residuals show excess kurtosis, which is typical in the case of financial data. Finally the Jarque-Bera normality test strongly rejects multivariate normality for the three residuals.

We finally examine if the residuals are heteroskedastic. The results of the heteroskedasticity test can be found in table(12).

Table 11. VECM normality tests (H0:Residuals are multivariate normal)

Component	Skewness	Chi-sq	df	Prob.
ResidNAS	0.03	0.10	1	0.75
ResidITCAC	0.29	13.44	1	0.00
ResidNEMAX	-0.08	0.90	1	0.34
Joint		14.44	3	0.00

Component	Kurtosis	Chi-sq	df	Prob.
ResidNAS	3.96	35.91	1	0
ResidITCAC	9.40	1612.07	1	0
ResidNEMAX	4.07	45.05	1	0
Joint		1693.03	3	0

Component	Jarque-Bera	df	Prob.
ResidNAS	36.02	2	0
ResidITCAC	1625.50	2	0
ResidNEMAX	45.95	2	0
Joint	1707.47	6	0

Table 12. VECM Residual heteroskedasticity Tests: No Cross Terms (only squares)

Joint test: Chi-sq	df	Prob.
2878.283	1056	0

Individual components:

Dependent	R-squared	F-test	Prob.	Chi-sq
$(ResidNASDAQ)^2$	0.49	4.18	0	462.30
$(ResidITCAC)^2$	0.74	12.29	0	696.75
$(ResidNEMAX)^2$	0.51	4.53	0	481.26

The joint and the individual heteroskedasticity tests show the presence of heteroskedasticity in the three indexes's residuals. This result, along with the hypothesis of dynamic correlations that we made earlier lead us to use a Dynamic Conditional Correlation multivariate GARCH model (dcc-mvgarch).

4.2.3. *DCC-MVGARCH model.* The dcc-mvgarch was introduced by Engle (2002) as a generalization of Bollerslev's (1990) multivariate GARCH with constant conditional correlation estimator. Bollerslev's MVGARCH has a variance-covariance expressed as follows:

$$H_t = D_t R D_t, \quad where \quad D_t = diag\sqrt{h_{i,t}} \tag{4.2}$$

where h_t is the conditional variance and where R is a correlation matrix containing the conditional correlations as can be directly seen from rewriting this equation as:

$$(4.3) \qquad E_{t-1}(\eta_t \eta_t') = D_t^{-1} H_t D_t^{-1} = R, \;\; since \;\; \eta_t = D_t^{-1} \epsilon_t$$

where ϵ_t is the index residuals coming from the VAR model estimated earlier, and E_{t-1} is the conditional expectation at date $t-1$ with respect to the information available till $t-1$.

The expressions for h are typically thought of as univariate GARCH models, however, these models could certainly include functions of the other variables in the system as predetermined variables or exogenous variables. A simple estimate of R is the unconditional correlation matrix of the standardized residuals.

Engle (2002) proposed an estimator called dynamic conditional correlation (dcc). The dynamic correlation model differs only in the allowing R to be time varying, and the variance-covariance matrix would be expressed as:

$$(4.4) \qquad H_t = D_t R_t D_t$$

Parameterizations of R have the same requirements that H did, except that the conditional variances must be unity (see appendix and Engle and Sheppard, 2001 for further details). The matrix R_t remains the correlation matrix. More details about the dynamic correlation estimator can be found in the appendix. Note that the dcc-mvgarch is identical in its specification to Bollerslev's multivariate GARCH with the exception of the expression of H_t above.

Table (13) below, reports the estimators[11] of the dcc-mvgarch and figure (7) shows the graphs of the dynamic conditional correlations of the three indexes residuals.

It can be seen that the estimated parameters of the MVGARCH above are almost all quite significant and the GARCH effect is quite persistent, which reflects the presence of strong heteroskedasticity found earlier in the heteroskedasticity test. Furthermore, the likelihood ratio test (LR test) strongly rejects univariate GARCH specifications for each of the series against the multivariate GARCH that we use (probability=0.001).

If we check the residuals of the dccMVGARCH for the three indexes in table 14, we can see that the residuals are follow the normal distribution and are white noises. This indicates that the residuals are properly filtered for linearities and heteroskedasticity.

[11]Note that the quasi-maximum likelihood method is used since the normality hypothesis is not met *a priori*.

TABLE 13. Trivariate GARCH estimators of the 3 indexes

	Coefficient	Std. Error	z-Statistic	Prob.
MU(1)	0.19289	1.693499	0.113901	0.91
MU(2)	-1.41066	1.0814	-1.30448	0.19
MU(3)	4.474036	1.976667	2.263424	0.02
OMEGA(1)	2.43887	1.545445	1.578103	0.11
BETA(1)	0.986281	0.00298	330.9367	0.00
ALPHA(1)	0.159726	0.016269	9.817841	0.00
OMEGA(2)	-0.28255	1.430329	-0.19754	0.84
OMEGA(4)	4.638526	1.017332	4.559503	0.00
BETA(2)	0.951596	0.008575	110.9779	0.00
ALPHA(2)	0.294954	0.026817	10.99894	0.00
OMEGA(3)	0.234706	0.897584	0.261487	0.79
OMEGA(5)	-0.02327	0.93209	-0.02496	0.98
OMEGA(6)	-0.00191	1472.742	-1.30E-06	1.00
BETA(3)	0.988205	0.00243	406.6571	0.00
ALPHA(3)	0.150763	0.015868	9.501166	0.00

TABLE 14. Residuals tests for the dccMVGARCH (star indicates the acceptance of the normality hypothesis)

	Mean	STD	Skewn.	Kurt.	Jarque-Bera(prob.)
Resid.NASD100	0.00	1.00	-0.05	2.93	0.74*
ResidITCAC	-0.11	0.99	0.16	3.02	0.10*
ResidNEMAX	0.02	0.99	-0.14	2.92	0.17*

The dynamic conditional correlation estimators represented in figure(7) have been smoothed using the Hodrick-Prescott filter. Technically, the Hodrick-Prescott (HP) filter is a two-sided linear filter that computes the smoothed series s of y by minimizing the variance of y around s, subject to a penalty that constrains the second difference of s. That is, the HP filter chooses s_t as to minimize:

$$\sum_{t=1}^{T}(y_t - s_t)^2 + \lambda \sum_{t=2}^{T-1}((s_{t+1} - s_t) - (s_t - s_{t-1}))^2 \tag{4.5}$$

The smoothed dynamic conditional correlation coefficients in figure (7) show maxima around the year 2000, the year in which the IT indexes where in a lot of turbulence. The solid lines in each graph represent the constant correlation coefficient of each couple of indexes. The fluctuation of the dcc coefficients around the constant correlations show the non-constant aspect of the correlations, even if they do not reach high levels in absolute terms. Still, their maxima around the year 2000 are quite significant and match the reality events at that time. the highest correlations are achieved by the couple NASDAQ-100 and the IT.CAC.

4.2.4. *Comparison of estimators.* In this section, several correlation estimators will be compared in terms of simple goodness of fit statistics, multivariate GARCH diagnostic tests and Value at Risk tests (Engle, 2002).

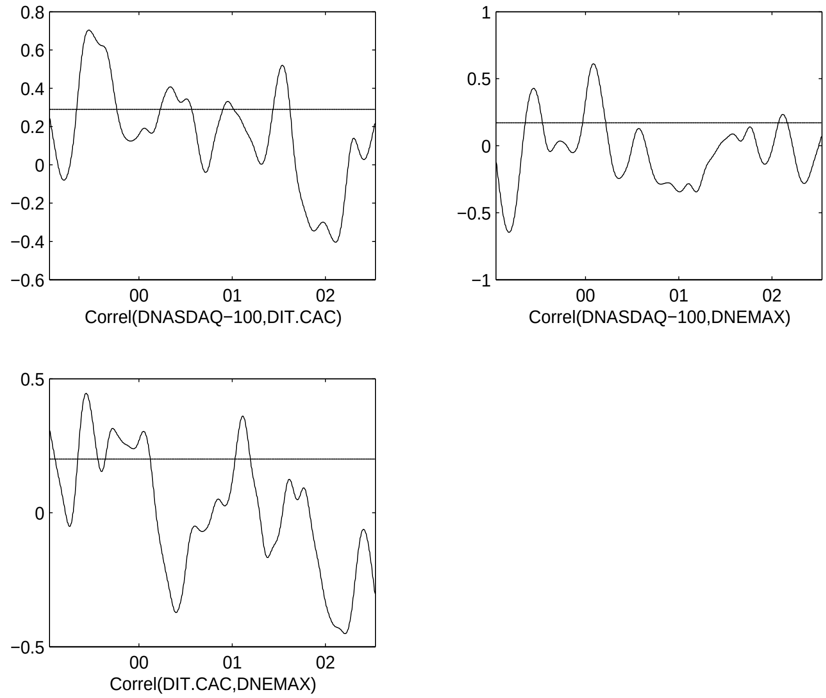


FIGURE 7. Dynamic conditional correlations for the three indexes

Five different methods are used to estimate the correlations:

- Scalar BEKK as in Engle and Kroner (1995)
- DCCLLMR as described in the appendix
- DCCLLINT as described in the appendix
- EX.06, the $RiskMetrics^{TM}$ exponential smoother as described by equation (4.8) and footnote 11 in the appendix.
- MA100 as described in footnote 10 page 13.

The first test will be a test for autocorrelation of the squared standardized residuals. For the multivariate case, the standardized residuals ν_t are defined as:

$$\nu_t = H_t^{-\frac{1}{2}} r_t \tag{4.6}$$

The test is calculated as an Fisher (F) test of the regression of the following noises: $\nu_{1,t}^2$, $\nu_{2,t}^2$ and $\nu_{3,t}^2$ on five of their squared lags and cross products, plus an intercept. The number of rejections (at 5% critical value) is the measure of each model's performance in modelling the same data. In fact, the larger is the number of rejections, the surer we get that the data are badly modelled.
A second performance test involves the usage of the value at risk (VaR). We use

this test in a bivariate context only. So, for a portfolio with ω invested in the first variable and $(1-\omega)$ in the second, under the hypothesis of normality, the VaR can be written in the following way:

$$VaR_t = 1.65\sqrt{(\omega^2 H_{ii,t} + (1-\omega)^2 H_{jj,t} + 2(\omega(1-\omega)\hat{\rho}\sqrt{H_{ii,t}H_{jj,t}})}. \tag{4.7}$$

where $i,j = 1,2,3$ with $i \neq j$ indicate the series used ($i = 1$ for the NASDAQ-100 residual, $i = 2$ for the IT.CAC residual and $i = 3$ for the NEMAX residual). We define the following variable:

$$Hit(\nu_{it}, \nu_{jt}, \theta) = Hit_{\theta t} = I(\omega * \nu_{it} + (1-\omega) * \nu_{jt} < -VaR_t) - \theta \tag{4.8}$$

where the ν represent the residuals of the examined indexes, I is an indicator function that takes the value 1 when the inequality is realized and $\theta = 0.05$.
We use the Dynamic Quantile test[12] introduced by Engle and Manganelli (2001), which is a Fisher (F) test of the hypothesis H_0 that all coefficients and the constant, in a une regression of the variable Hit_t on its past values and the actual VaR (defined by the equation 4.7), the regression equation can be written as follows:

$$Hit_t = \delta_0 + \sum_{p=1}^{p} \delta_p Hit_{t-p} + \delta_{p+1} VaR_t + u_t \tag{4.9}$$

where $p = 1, ..., 5$ and u_t is the error term of the regression. In this case, five lags of the variable Hit and the actual VaR (defined by the equation 4.7) are used. The number of rejections (at 5% critical value) represents the measure of each model's performance. The test is computed for two portfolios with $\omega = 0.5$ for the first one and $\omega = 1$ for the second (which is a hedge portfolio).

Looking at table 14, we can see that the worst model is the MA100 model with 13 rejections, next, the Scalar BEKK and the Exponential smoother with both 4 rejections, and the best models are the dynamic conditional multivariate GARCH models with only 2 rejections. These results confirm the usage of the dc-cMVGARCH model in this paper and confirm the presence of dynamic conditional correlations in the data.

[12]This test was introduced by Engle et Manganelli (2001) within a new framework of a new VaR estimator they introduce. Their new VaR estimator is called CAViaR (Conditional Value at Risk by Regression Quantiles).

Table 15. P-statistics from tests of empirical models

ARCH in sqrd RES1	SCALBEKK	DCCLLMR	DCCLLINT	EX.06	MA100
NAS&ITCAC	0.009667	0.011753	0.013318	0.007139	0
ITCAC&NEM	0.894947	0.687804	0.595367	0.010356	0
NAS&NEM	0.194241	0.54066	0.551369	0.484416	0
ARCH in sqrd RES2					
NAS&ITCAC	0.0002	0.000608	0.000883	1.23E-09	0
ITCAC&NEM	0.903956	0.927369	0.939984	0.224642	0
NAS&NEM	0.103943	0.918572	0.912164	0.473	0
ARCH in sqrd RES3					
NAS&ITCAC	0.00724	0.796626	0.777602	0.005317	0
ITCAC&NEM	0.53897	0.563765	0.635791	0.19268	0
NAS&NEM	0.033689	0.632895	0.628341	0.326404	0
Dyn.quantile test VaR1					
NAS&ITCAC	0.166294	0.297307	0.928069	0.529417	0.747822
ITCAC&NEM	0.983894	0.973408	0.922966	0.739929	0.003114
NAS&NEM	0.717617	0.561479	0.459949	0.105145	4.79E-05
Dyn.quantile test VaR1					
NAS&ITCAC	0.78702	0.85638	0.795149	0.977544	0.099688
ITCAC&NEM	0.824899	0.681015	0.505644	0.773985	0.008245
NAS&NEM	0.989572	0.980035	0.98062	0.977473	0.00486

Conclusion

In this paper, we examined the three technological indexes, the NASDAQ-100, the IT.CAC and the NEMAX on several levels. We first tested the data for linearity and cointegration and we used a VEC model to eliminate the linearity. We then used impulse-response functions and variance decomposition to check for a contagion effect following our previous paper which showed the presence of co-movement in the IT indexes (LEMAND, 2002). We find evidence of a contagion effect coming from the NASDAQ-100.

Next we used a dccMVGARCH model to model the residuals of the VEC model and to examine the presence of dynamic conditional correlation in those residuals. We find that the residuals indeed follow a dccMVGARCH and we find that this model is the best against a number of other models. We also find that the dynamic conditional correlations of the three indexes rise during turbulent periods, especially during the year 2000 IT stock price correction.

References

1. Akaike, H., 1976, "Canonical correlation analysis of time series analysis and the use of an information criterion", dans : R. K. Mehra and D. G. Lainiotis, eds, System identification : Advances and case studies (Academic Press, New York, NY).
2. Ang, A. and G. Bekaert (1998), "Regime Switches in Interest Rates," NBER Working Paper No. 6508.
3. Archer G. and Titterington D., (1995), "Parameter estimation for hidden Markov chains", Technical report, University of Glasgow, Department of Statistics.
4. Baillie, R. T. and R. P. DeGennaro, (1990), "Stock returns and volatility", Journal of Financial and Quantitative Analysis 25, 203-214.
5. Bates, D. S., (1991), "The carsh of '87 : Was it expected ? The evidence from option markets", Journal of Finance 46, 1009-1044.
6. Bera, A. K., E. Bubnys and H. Park, (1988), "Conditional heteroskedasticity in the markets model and efficient estimates of betas", Financial Review 23, 201-214.
7. Black, F., (1976), "Studies of stock market volatility changes", 1976 Proceedings of the American Statistical Association, Business and Economic Statistics Section, 177-181.
8. Bollerslev, T., (1987), "A conditionally heteroskedastic time series model for speculative prices and rates of return", Review of Economics and Statistics 69, 542-547.
9. Bollerslev, T., R. Y. Chou and K. F. Kroner, (1992), "Arch modeling in Finance : A review of the theory and empirical evidence", Journal of Econometrics, 52, 5-59.
10. Cai, J. (1994), "A Markov Model of Unconditional Variance in ARCH," Journal of Business and Economic Statistics, 12, 309-316.
11. Campbell, J. Y., A. W. Lo and A. C. MacKinlay, (1997), The Econometrics of Financial Markets, Princeton University Press.
12. Cecconi, M., G. M. Gallo and M. J. Lombardi, (2002), "GARCH-based volatility forecasts for market volatility indexes", working paper, Università degli Studi di Firenze, Dipartimento di Statistica.
13. Chaudhuri, K. and F. Klaassen (2000), "Have East Asian Stock Markets Calmed Down? Evidence from a Regime Switching Model," mimeo, University of Amsterdam.
14. Eichengreen, B., A. Rose and C. Wyplosz (1996), "Contagious Currency Crisis", Scandinavian Economic Review, 98, 4, 463-84.
15. Edwards, S. and R. Susmel, (2001), "Volatility dependence and contagion in emerging equity markets", Working paper, IASE Seminar in Buenos Aires.
16. Engle, R. (2002), "Dynamic Conditional Correlation - A Simple Class of Multivariate GARCH Models", Forthcoming, Journal of Business and Economic Statistics.
17. Engle, R. F. and T. Bollerslev (1986), "Modeling the Persistence of Conditional Variances", Econometric Reviews, 5, 1-50.
18. Engle, R. F.and C. Mustafa, (1992), "implied ARCH models from Options Prices", Journal of Econometrics, 52, 289-311.
19. Engle, R. and K. Kroner (1995), "Multivariate Simultaneous GARCH", Econometric Theory 11, 122-150.
20. Engle, R. and K. Sheppard (2001), "Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH", NBER Working Paper 8554.
21. Filardo, A.J. (1994), "Business-cycle phases and their transitional dynamics," Journal of Business and Economic Statistics, 12, 299-308.
22. Francq, C. and J.-M. Zakoian, (1999), "Linear-Representation Based Estimation of Switching-Regime GARCH Models", Institut National de la Statistique and des Etudes Economiques papier no. 9957.
23. Franses, P. H. and D. van Dijk, (2000), Non-Linear Time Series Models in Empirical Finance, Cambridge University Press.
24. Gable, J., S. van Norden and R. Vigfusson, (1995), "Analytical derivatives for Markov switching models", Working paper, Bank of Canada.
25. Glosten, L.R., R. Jagannathan, and D. Runkle (1993) On the Relation between the Expected Value and the Volatility of the Normal Excess Return on Stocks, Journal of Finance, 48, 1779-1801.
26. Gray, S.F. (1996a), "Modeling the Conditional Distribution of Interest Rates as a Regime-Switching Process", Journal of Financial Economics, 42, 27-62.

27. Gray, S. F. (1996b), "An Analysis of Conditional Regime-Switching Models", Working Paper, Fuqua School of Business, Duke University.
28. Hamilton, J. D. (1988), "Rational Expectations Econometric Analysis of Changes in Regime," Journal of Economic Dynamics and Control, 12, 385-423.
29. Hamilton, J. D. (1989), "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle", Econometrica, 57, 357-384.
30. Hamilton, J.D. and R. Susmel (1994), "Autoregressive Conditional Heteroskedasticity and Changes in Regime", Journal of Econometrics, 64, 307-333.
31. Hamilton, J. D. (1996), "Specification Testing in Markov-Switching Time Series Models," Journal of Econometrics, 70, 127-157.
32. Hamilton, J. D. and G. Lin, (1996), "Stock market volatility and the business cycle", UCSD Economics Discussion Papers, no. 96-18, University of California at San Diego, Department of Economics.
33. Hamilton, J. D., (1994), Time Series Analysis, Princeton University Press.
34. Kim, C.-J. and C. R. Nelson, (1999), State-Space Models with Regime Switching, MIT Press.
35. Klaassen, F. (2002), "Improving GARCH Volatility Forecasts with Regime-Switching GARCH," Empirical Economics, 27, 363-394
36. Krolzig, H.-M., (1997), Markov-Switching Vector Autoregressions, Springer.
37. Lamoureux, C. G. and W. D. Lastrapes, (1990), "Persistence in Variance, Structural Change, and the GARCH Model," Journal of Business and Economic Statistics, 8, 225-234.
38. Lamoureux, C. G. and W. D. Lastrapes, (1993), "Forecasting stock return variance: toward an understanding of stochastic implied volatilities", Review of Financial Studies, 5, 293, 326.
39. Masson, P. (1998), "Contagion: Monsoonal Effects, Spillovers and Jumps Between Multiple Equilibria", IMF Working Paper 98/142.
40. Mullainathan, S., "A Memory Based Model of Bounded Rationality", M.I.T. *Mimeo.*
41. Nelson, D. B. (1991) "Conditional Heteroskedasticity in Asset Returns: A New Approach," Econometrica, 59, 347–370.
42. Nelson, C. R., R. Startz and C. M. Turner, (1989), "A Markov model of heteroskedasticity, risk, and learning in the stock market", Journal of Financial Economics 25, 3-22.
43. Pagan, A.R. and G.W. Schwert (1990), "Alternative Models for Conditional Stock Volatility," Journal of Econometrics, 45, 267-290.
44. Ramchand, L. and R. Susmel (1998), "Volatility and cross correlation across major stock markets," Journal of Empirical Finance, Vol.5, 397-416.
45. Schaller, H. and S. van Norden, (1994), "Speculative behaviour, regime-switching, and stock market crashes", Working paper, Bank of Canada.
46. Schwert, G. W., (2002), "Stock volatility in the new millennium: how wacky is NASDAQ?", Journal of Monetary Economics 49, 3-26.
47. Schwert, G. W., (1989), "Why does StockMarket Volatility Change over Time?" Journal of Finance, 44, 1115-1153.
48. So, M., K. Lam and W. Li (1998), "A Stochastic Volatility Model With Markov Switching," Journal of Business and Economic Statistics, 16, 244-53.
49. Lemand, R. (2002), "The Contagion Effect Between the Volatilities of the NASDAQ-100 and the IT.CAC: A Univariate and a Bivraiate Switching Approach", M.O.R.A. working paper No 02-2002.
50. Susmel, R. (2000), "Switching Volatility in International Equity Markets," International Journal of Economics and Finance.
51. Teräasvirta, T. (1994), "Specification, Estimation, and Evaluation of Smooth Transition Autoregressive Models", Journal of The American Statistical Association, 89, 208–218.
52. Timmermann, A. (2000), "Moments of Markov Switching Models," Journal of Econometrics, 96, 75-111.
53. van Norden, S. and R. Vigfusson, (1996a), "Can regime-switching tests detect bublles?", Working paper, Bank of Canada.
54. van Norden, S. and R. Vigfusson, (1996b), "Regime-switching models: a guide to the Bank of Canada Gauss precedures", Working paper, Bank of Canada.
55. Zakoian, J.–M. (1994), "Threshold Heteroskedastic Models", Journal of Economic Dynamics and Control, 18, 931-955.

List of Figures

List of Tables

Appendix

The simplest specification for the correlation matrix is the exponential smoother which can be expressed as[13]:

$$\rho_{i,j,t} = \frac{\sum_{s=1} \lambda^s \epsilon_{i,t-s}\epsilon_{j,t-s}}{\sqrt{(\sum_{s=1}^{t-1} \lambda^s \epsilon_{i,t-s}^2)(\sum_{s=1}^{t-1} \lambda^s \epsilon_{j,t-s}^2)}} = [R_t]_{i,j} \tag{4.10}$$

which is a geometrically weighted average of standardized residuals. Clearly these equations will produce a correlation matrix at each point of time. A simple way to construct this correlation is through exponential smoothing. In this case the process followed by the

$$q_{i,j,t} = (1-\lambda)(\epsilon_{i,t-1}\epsilon_{j,t-1}) + \lambda(q_{i,j,t-1}), \quad \rho = \frac{q_{i,j,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{4.11}$$

will be integrated.

A natural alternative is suggested by the GARCH(1,1) model.

$$q_{i,j,t} = \bar{\rho}_{i,j} + \alpha(\epsilon_{i,t-1}\epsilon_{j,t-1} - \bar{\rho}_{i,j}) + \beta(q_{i,j,t-1} - \bar{\rho}_{i,j}) \tag{4.12}$$

where α and β are the GARCH(1,1) parameters. Rewriting gives:

$$q_{i,j,t} = \bar{\rho}_{i,j}(\frac{1-\alpha-\beta}{1-\beta}) + \alpha \sum_{s=1}^{\infty} \beta^s \epsilon_{i,t-s}\epsilon_{j,t-s} \tag{4.13}$$

The unconditional expectation of the cross product is $\bar{\rho}_{i,j}$ while for the variances:

$$\bar{\rho}_{i,j} = 1 \tag{4.14}$$

[13]Which is the exponential smoother used by $RiskMetrics^{TM}$ which uses declining weights based on a parameter λ, which emphasizes current data but has no fixed termination point in the past where data becomes uninformative. It lies surely in $[-1, 1]$; however there is no guidance from the data on how to choose λ. In a multivariate context, the same λ is used for all assets to ensure a positive definite correlation matrix. $RiskMetrics^{TM}$ uses the value of 0.96 for λ for all assets. In this paper, this estimator is called EX.06.

The correlation estimator

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{4.15}$$

will be positive definite as the covariance matrix, $Q_t = [q_{i,j,t}]$ is a weighted average of a positive definite and a positive semi-definite matrix. The unconditional expectation of the numerator of equation (4.13) is $\bar{\rho}_{i,j}$ and each term in the denominator has expected value one. This model is mean reverting as long as $\alpha + \beta < 1$ and when the sum is equal to one it is just the model in (4.9).

When the mean reverting formula (4.10) is used in the estimation, the resulting estimator is called DCC LL MR and DCC LL INT if the integrated formula (4.9) is used.