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“Risk analysis in the evaluation of the international investment opportunities. Advances in modelling and forecasting volatility for risk assessment purposes”

-PhD Thesis-

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Abstract: The thesis proposes to assess the risk topic in the context of foreign investment decisions. In identifying two main risk-related concepts, I have split risks in two categories using a unique criterion: the ratio between the endogenous and exogenous content of the problem. According to it, I have built a pool of risks that the company may have entirely or partially under control (forming the endogenous part of the problem), and a pool with exogenous risks that the company cannot control at all, but can assess and build strategies for their management (forming the exogenous part of the problem).

In each category I have identified one source of risk, representing the most important of all risks belonging to the same pool. For the endogenous risks part, credit risk (in its extensive version counterparty risk) was selected. Related to this, there have been additionally discussed the topics of systemic risk and of the risk associated to the impact of the activity of the international rating agencies on the firm financing problem when a company proceeded to debt issuance.

The other half of the problem involves the risk of the sector the company activates in. I have found that the risk assessment in this category became an econometric problem of volatility forecasting for a portfolio of a number of selected returns. The discussion complicates given the following factors:

1. The scientific world has not reached yet to a consensus on the superiority of a certain model or group of models that measures volatility. As such, forecasted volatility estimates may depend on the model or methodologies to be used, type of data frequency (high or low), selection of the error statistics etc. As such, decision making as regards the opportunity of the investment becomes highly dependent on econometric choices to be made.
2. Multivariate models are computationally intensive due to the parameter estimation problem. If a large number of stocks are included in the portfolio, the number of estimations to be done would be so high that the problem would be extremely difficult to be technically undertaken.
3. Due to high correlation of stocks, the estimation problem becomes particularly imprecise and computationally difficult.

As a solution to such problems, I have justified the superiority of one autoregressive heteroskedastic model (PC-GARCH) considering not only estimation performance but also cost saving component. For this purpose, I have run an empirical exercise with a portfolio formed of seven stocks belonging to the US IT sector (Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M) in order to evidentiate advantages of this model. They may be summarized as it follows:

PC-GARCH

- Minimizes computational efforts (by transforming multivariate GARCH models into univariate ones), by reducing significantly the computational time and getting rid of any problem that may arise from complex data manipulations;
- Ensures a tight control of the amount of “noise” due to reducing the number of variables to fewer principal components. This may prove benefic since it may result in more stable correlation estimates;
- Produces volatilities and correlations for all variables in the system, including those for which direct GARCH estimation is computationally difficult.

As such, I’ve concluded that when using large portfolios formed of hundreds or thousands of stocks, for the scope of volatility (and therefore risk) forecasting, PC-GARCH is the most appropriate model to be used.

Keywords: risk, endogeneity, exogeneity, credit risk, systemic risk, counterparty risk, rating, volatility, forecasting, GARCH, PC-GARCH, principal components, autocorrelation, heteroskedasticity, orthogonality.

JEL Classifications: *C3, C53, D81.*

Contents

1. Introduction

The thesis proposes to assess the risk topic in the context of foreign investment decisions. When companies decide to go abroad, either to set up a green-field investment or to acquire a local company, they have to deal with a very broad panel of risks following such a decision. The pannel covers very abstract concepts like credit or systemic risk, to reputational, operational or political risks whose analysis requires less quantitative analysis and more qualitative one, including use of connected fields like politics, economics, or management. Risks affecting a company when going abroad may be classified in various ways, using different criteria. A rigorous study of the whole panel, given the extension of the risk concept, would require a very extensive space, beyond that of o regular doctoral thesis. Given the size limitations of the current thesis, in order to answer the research questions and in the same time maintaining the rigorousness and abstractness of a research work, I have focused the work from a very general analysis to only two aspects of risk.

In identifying such aspects, I have split risks in two categories using one unique criterium: the ratio between the endogenous and exogenous content of the problem. As such, I have built a pool of risks that the company may have under control either entirely or partially (forming the endogenous part of the problem), and a pool with exogenous risks that the company cannot control at all, but can assess and build strategies for their management (forming the exogenous part of the problem).

In each category I have identified one source of risk, representing the most important of all risks belonging to the same pool. For the endogenous risks part, credit risk (in its extensive version counterparty risk) was selected. When a company decides to invest in a foreign country, access to (local) credit is essential for developing and advancing investment projects, for keeping and expanding business in general. Business financing involves exclusively endogenous aspects, like company's profitability given by financial indicators like ROE, ROA, etc., but also exogenous aspects like the promptness with which companies involved in business relationships with the firm taken into consideration, pay their financial obligations. The financial problems of the other companies can thus transfer to our company and the speed with which this happens may determine serious difficulties until defaults. As such, the way the payment system is built and managed, and the exposure to the systemic risk may determine our company performance.

Also, if the company decides to finance itself not just by profit reinvestment or bank credits, but by debt issuance, the national or company credit ratings given by the international rating agencies may affect the cost of credit and ultimately the success of the issuance. In this context, it's assessed not only the company's performances, but also the country's economic standing and future prospects.

Thus, the problem of access to credit is partly endogenous and partly exogenous. Since it's more of financial performance, I consider (subjectively) that the endogeneity dominates and as such I have called this category of risk as endogenous.

The other half of the problem involves the risk of the sector the company activates in. Before investing, the company assesses risk by forming a pool of companies with the largest weight in the sector. For example, if our company is a French IT firm that intends to invest in US, it may want to look to the risk of a bubble of that sector (as it happened in the recent past). The success of the company is not only a matter of financial or marketing management, but also a matter of market defaults. If the US IT sector will confront with a bubble burst, no matter the company's performance, its shares will be seriously affected. As such, the assessment of the probability that such market crashes occur becomes a problem of measurement and forecasting volatility of stock returns of the selected companies. If the portfolio variance is large or if it is small but a high probability of increasing variance exists for the short future, given the fact that investors are risk averse, investment in such a market is not probably a good idea.

The opportunity of investment transforms thus into an econometric problem of volatility forecasting. The discussion complicates given more factors. The two most important are:

a) The scientific world has not reached yet to a consensus on the superiority of a certain model or group of models that measures volatility. As such, forecasted volatility estimates depend on the model used and the volatility may thus appear to be large when one model is used, whereas small with other model. There are also differences in predictions given to other factors: methodologies used, use of high or low frequency data, source of the empirical data used, selection of the error statistics etc. As such, decision making as regards the opportunity of the investment becomes highly dependent on econometric choices to be made.

b) The second source of complication comes from the fact that the company, for higher accuracy of risk assessment, will not chose to evaluate the risk of the returns of stocks of one company only, but of a portfolio formed of more companies (the relevant ones in the sector if not all of them). As such, the analysis transforms from a univariate volatility problem into a multivariate one. This complicates very much the problem given two reasons: the multivariate models that would be used must eliminate the correlations between the time series considered (for example, if the portfolio is formed by two price indexes, NASDAQ and S&P500, the model has to eliminate the correlations between historical data of S&P and past values of NASDAQ, as one jump in one price index may determine jumps in the other price index), and that multivariate problems are computationally intensive due to the parameter estimation problem. For example, the number of parameters in a multivariate GARCH increases at the rate of the square of the number of variables. As such, using n variables will necessitate estimation of $\frac{n(n+1)}{2}$ parameters; this is because each additional variable brings with it correlation terms with the other variables, and each of these correlation terms has its own parameter. The dimensionality of the problem and hence computational power requirement becomes rather large.

As a solution to both problems, I will justify the superiority of one autoregressive heteroskedastic model (PC-GARCH) considering not only estimation performance but also cost saving component. For this purpose, I will run in the last part of the thesis one empirical exercise with a portfolio formed of seven stocks belonging to the US IT sector (Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M) that will be used in order to evidentiate qualities of this model. As such, I will conclude that when using large portfolios formed of hundreds or thousands of stocks, for the scope of volatility (and therefore risk) forecasting, PC GARCH is the most appropriate model to be used.

The research questions of the thesis are:

1. Which are the most important aspects of risk when a company is going abroad?
2. How the credit risk management can be more effectively undertaken?
3. How volatility assessment can be more effectively undergone when dealing with large portfolios of stocks?

Allow me to conclude by specifying the elements that constitute the novelty of the current research.

1. The first element is represented by the integrated analysis of the credit risk, systemic risk and volatility assessment for the purpose of risk assessment in the context of foreign investment decisions.
2. The second element of novelty is the benchmarking[1] analysis of the volatility forecasting models. Although previous similar studies existed, the current one considers also more recent piece of research written for this purpose. Also, the extended literature review comprised in the form of the table represents my own review of the most important 50 papers written on the topic of the volatility model benchmarking.
3. The analysis of the forecasting volatility models from a double perspective, that of accuracy of estimation and that of the costs involved, according to which it has been concluded the superiority of PC-GARCH model represents another novel element.
4. Finally, the empirical exercise with a portfolio of seven stocks belonging to companies acting in the US IT sector is another element of novelty.

[1] Along the thesis there will be mentioned, having similar meanings, words like “benchmarking” and “ranking”. They are used to express the main objective of the study, that of comparing the models among themselves and that of highlighting the plus in performance (that is a measure of accuracy in prediction) some have against the others, putted in a specific context. The comparison will be made by measuring the errors (differences) between forecasted data and realized (“true”) data.

A. Risk analysis in the evaluation of the international investment opportunities

2. The global context of risk's increasing role

2.1 Fundamentals of risk. Risk in the context of globalization. An introduction

A financial instrument can take more forms: cash, proof of ownership of a certain equity or debt, may be as well a futures agreement, an option or simply a contract that contains the obligations and rights of the signing parts. Such financial instruments are exchanged with counterparties and traded over-the-counter. Through such transactions, they are exposed to a various panel of risks, among which credit and market risks are the most important.

The credit risk represents the risk that the other party engaged in a transaction that involves a financial instrument fails to perform in accordance to the terms and conditions of the contract, due to problems such as bankruptcy, lack of liquidity or other reasons. Credit risk is heavily present in the banking activities and dates from 1700 BC, when Code of Hamurabi was written.

In technical terms, credit risk is based on assessing the probability of default of the counterparty. Such analysis is generally undergone by credit rating agencies that grade the probability of default using a scale of risks. Since the credit risk is common to almost all business transactions and all business entities, the analysis that will later follow along this thesis as regards risks will be focused on this type of risk. Since a company, when decides to go abroad and enters in a new market, is not familiar with the capacity of local firms to meet their financial obligations, the role of assessing such capacities will rely almost exclusively on the ratings issued by the credit rating agencies. Because the lack of capacity to pay the financial debt by one company may transmit to other companies linked in a way or another with the initial one, the exposure of one economy, economic sector or company to the systemic risk should also be of interest to the new entrant on the market. For this reason, two chapters will be devoted to the systemic risk and to the credit rating agencies.

Counterparty risk is an extended type of credit risk that goes beyond the financial failure (represented by the credit risk) to include, among other things, delays in execution caused by the counterparty and the financial environment within which it operates, or unwillingness to perform, which leads to *reputational risk*. In an extended version, counterparty risk is the probability of a loss to occur due to other party's failure in not performing the transaction according to the terms of the contract, due to some adverse conditions, such as the export of hard currency (part of country risk). The source of such risk may be as well the management policy in meeting the payment deadlines, an event risk or other reasons.

Credit, counterparty and market risks denote the presence of risks of accounting loss. For example, a credit risk premium is accounted as a cost. It may be seen as a measure of financial responsibility connected to the party with which a financial instrument or any other product is traded. Credit risk originates from the fact that the products and instruments which are involved in a transaction impose not only rights, but obligations, when the counterparty risk involves additional criteria relating to financial obligations.

A certain number of critical factors limit the management's policy in its ability to cope with its contractual requirements. In the late 1990s, globalization became the most important as it turned into a basic driving force in almost any industry. By making the problem of endogeneity of financial health of a company more complex, globalization intervened in amplifying the distinction between the general counterparty risk and the specific credit risk. In other words, globalization made the list of possible factors that would affect the financial health of a company much longer. As an effect of this state of facts, especially in the narrower context of the financial industry, globalization created the premises for defining new regulations, in order to generate a new set of rules after which the larger set of interactions between companies would take place. This reversed the deregulation trend specific to the 1980-2000 period. Consequently, we can see that in the late 1990s the number of newly formed strategic alliances and partnerships (especially among financial institutions), as well of mergers, acquisitions, consolidations and restructuring schemes has strongly increased; we can also observe an intensive search to provide innovative business solutions, all in order to respond to the more complex framework that affected companies' capability to meet their obligations.

A double effect takes place as regards the trends in financial regulation: one is the extension of the span of newer regulations, that takes a global feature, examples being the 1988 Capital Accord (and its subsequent revisions), and 1996 Market Risk Amendment, but meanwhile at the national level it may be observed a deregulation that pressures incumbents to combine into new, bigger entities, while increasing the challenges posed by non-banking financial institutions. The aggressive market players approach financial institutions for money, like hedge funds that ask banks for loans and use the money to speculate with derivative instruments.

With respect to the credit risk, there may be found similarities between loans, investments and derivatives trades. Loans and investments share common criteria to diversifications, such like: counterparty, industry, interest rate, maturity, currency, country and equity. Globalization sees to it such that these criteria impact upon the setting of prudential limits, monitoring of exposure, and scenario analysis.

Globalization as well increases the complexity of client handling by banks and companies because, among other things, it underlines the need for constant innovations. Part of the effort of meeting the client requirements there is also a stream of innovation in products and services. Innovation is the ability to create business ideas as well as products and services that permit a bank or firm to differentiate itself from its competitors in a way the customer can comprehend and appreciate.

Market risks are also globalized. The internationalization of finance has increased both the size and frequency of such risks. Other market-oriented risks are country risk and equity risk. There are also operational risks involving payments, settlements, management skills and information technology.

A description of the main elements contributing to a company/bank exposure when going internationally, may be resumed as it follows.

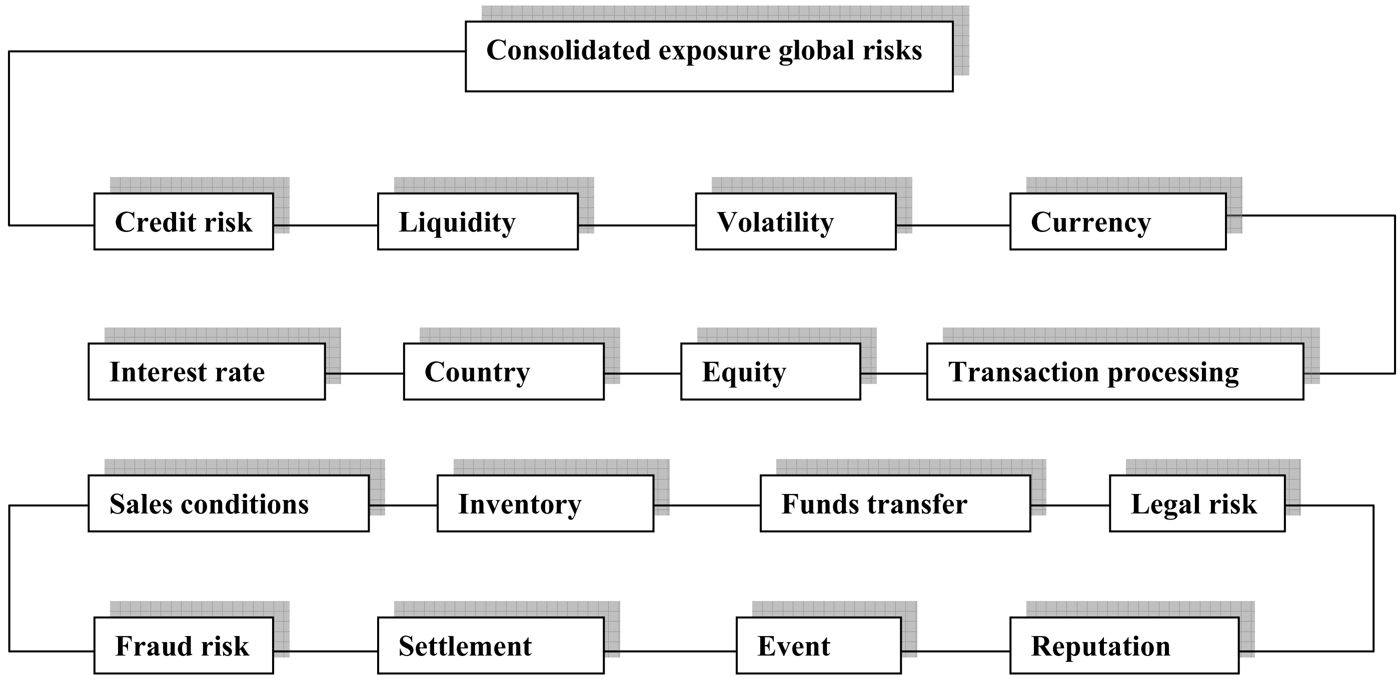


Figure 1: Examples of related risks in consolidated exposure.

Banks confront with risks not just due to the financial instruments (that contain elements of exposure) they use or due to the counterparties they deal with, but also due to the fact that they deal with maturity transformation by taking demand deposits, savings and time deposits, and issuing longer-term credit. In commercial banking the difference between deposits and loans may be a cause, in times of crisis or panic, for banking run. Any agreement may prove sour if a company which agrees to deliver cash or other financial instruments to another company subsequently fails in its obligations, or if two companies exchange financial instruments but, later on, one of them has to perform on potentially unfavorable terms because of market conditions. In the first case, credit risk is involved and in the second, market risk is involved. As well, in both transactions the counterparty risk would occur. To prove its existence, the most facile way to reveal it is to calculate the difference between the risk premium contracted at the signing of the deal, and the premium on account of most valuations of credit risk.

2.2 Evolvement of the concept of risk. Risks in the context of a secular growth of debt securities markets

Developments of the recent reality transformed the financial systems around the globe. One feature of the change is the enrichment of the considerations regarding risk. Historically, the evaluation of the creditworthiness of a borrower, that is its capacity for repaying debt when due, has been exclusively of interest only when the prospective borrower intended to lend money. Until recently, such evaluation was the responsibility of banks' credit departments only, that had a relatively small number of borrowers and sufficient resources to examine the details of the businesses of their clients.

The subsequent development of the financial markets attributed the credit analysts more complex and challenging tasks that enlarged the span of their responsibilities, requiring them now to work together with an institutional portfolio manager or sometimes together with an independent credit risk agency. Risk evaluation is not done only when borrowing money is intended, but on a constant basis. Nevertheless, the financial market developments can be resumed in three main words: "disintermediation", "securitization", and "globalization".

2.2.1 Disintermediation of bank-system lending

On a historical perspective, the most important intermediaries between savers and users of capital were the banks. Their main functions were those of collecting funds from the first ones (in terms of deposits) and then offer them (through lending) to the users of them, like companies, public institutions, governments or other producers. To this simple function, along the time, there have been added activities, like the more cost-efficient process of intermediation in the public securities markets. Thus, it may be observed a secular growth of the long term debt markets globally in terms of a steady annual rise in the number of rated bond issuers. Users of capital (in the industrial, public utility, and financial sectors) that were previously financing their activities by borrowing money from the banks only, have more and more chosen to finance their short-term capital needs by taking advantage of the commercial paper markets. Short-term instruments used for financing debt differ from the long-term debt instruments in that typical borrowing maturities for the first ones range from a few days to several months (up to a maximum of nine months in the US market), as against longer maturities of 30 years or more for bonds, debentures, and other long-term debt instruments.

The increasing use of such instruments describes the process of disintermediation. Several advantages may explain the occurrence of this process. From the borrower's point of view, sidestepping the banking system, either in the bond or commercial paper markets, may represent a substantial cost saving. Thus, the borrower will not need to pay anymore a premium for the bank's lending staff, its equity base, as well as other costs of running a bank and maintaining an adequate cushion against loss. Furthermore, the lending rates are more competitive in such open markets, because creditworthy borrowers will be able to choose the most economical ones from a wide range of domestic and international sources of capital, rather than from a few banks.

From the perspective of the fixed-income investor, lending directly to the users of capital may bring advantages, as a portion of the cost-savings realized by those borrowers may be passed on to investors in the form of marginally higher returns compared with bank deposits. Also, borrowings in the commercial paper markets are regularly more flexible than short-term borrowing.

2.2.2 Securitized borrowing and lending

Securitization complements disintermediation. As borrowers bypass the traditional banking system, they issue securities directly to investors in the public debt markets. Thus, the money they would have borrowed from banks is now borrowed by means of securities. This describes the increasing securitization of borrowings. Meanwhile, banks and other financial intermediaries have discovered ways of tapping those markets. More institutions issue now bonds, commercial papers, or other debt instruments to fund their own lending or other activities.

Moreover, banks and other non-banking financial institutions like saving banks, building societies, securities firms, mortgage originators and finance companies have increasingly packed portfolios of their own financial assets in order to trade them as tradable securities. These securitized loan pools offered banks an efficient and cost saving way of taking loans off their balance sheets, better assets/liability management and a new source of low-cost funds for further lending. Such structured financings appeared at the beginning in the form of mortgage-backed bonds offered by US federal housing agencies (like Federal Home Loan Mortgage Corporation, or Freddie Mac). By the end of the 70's, American thrifts and other mortgage lenders began to package mortgages from their own portfolios for resale as mortgage-backed securities.

This represented the first phase of securitized borrowing and lending development. The second phase was marked by the 1980's, when almost every kind of financial assets was similarly packaged for resale as structured financings. Since 1986, outstandings in the global structured finance market increased significantly, boosted partially by the success of new segments, including thriving mortgage-backed and asset-backed markets in the UK, France and Australia. But the most rapid growth was met in the 1990's when market participants continued to become more sophisticated, particularly in the area of credit risk assessment.

2.2.3 Financial market globalization

So far we have explained why the disintermediation and securitization have increasingly become global phenomena. Multinational companies, financial institutions, and sovereign nations have recognized the efficiencies of scale and the competitiveness intrinsic to the public securities markets. As a result of these, we may speak now about the globalization of the credit markets.

In domestic markets, the commercial paper and related short-term markets have generally enjoyed the earliest and fastest growth. Because of the short maturities involved, the need for a liquid secondary market was essentially eliminated, although, by the same token, commercial paper outstandings and issuers' ability to access the market could vary widely depending on the investor perceptions and credit uncertainties. In bond markets, on contrary, investors were often reluctant to purchase long-term securities unless they could be reasonably certain that, for whatever reason, they were able to sell those securities in the secondary market before their principal becomes due. Among many factors, the development of liquid secondary markets required a relatively large number of investors with differing investment views on bond issuers, along with a continuously understanding of the credit risks.

Another feature of the global view of the credit markets is represented by the different levels of development in which such markets find in different parts of the world. Due to this, the role of the independent credit rating system is being regarded now as a unique tool to helping investors in their concerns of correct evaluations of the investment opportunities, existing a unanimous opinion on their role in promoting continuous growth and stability of the debt securities markets, short and long term, domestic and international.

2.3 Opportunities and risks in the global investment framework

2.3.1 Opportunities

The two most favoring factors towards providing new opportunities of financial intermediation are the enhancement in technological level and in the market liberalization. However, ultimately, the pace and direction of growth is given by the decisions and innovations of the individual investors, issuers and market intermediaries who are in a continuous search of new avenues in order to take advantage of the improved financial technologies.

Investors have a large panel of debt instruments among which they choose to find the optimal means for maximizing the yields on the securities they buy, maximization that is also done by picking securities with currency, maturity structure, and other features that would match specific portfolio requirements. The wide range of available securities represents an important mean towards diversification against foreign exchange risk and other types of investment risks. As an example, an international portfolio can be built in such a way that it would comprise securities issued in several currencies by issuers in different countries. Such diversification would be able to offer the investor a certain degree of protection against currency losses due to swings in the exchange rates, but also would help to affect credit loss in the case of an economic downturn in one country or region.

If seen from the perspective of the borrowers, the evolvement of the debt markets in what are their dynamic and globalization, extends the range of potential funding options. The wider range of choices translates into a more robust capacity to finance in markets with low interest rates. It offers also the possibility of borrowers to sell debt in amounts, frequencies, countries, currencies and maturity structures that they would consider to best accommodate to their funding needs. An example in this regard would be a Swiss company that, in order to obtain financial resources necessary to fund a plant in Spain, may decide to issue a long-term bond in Swiss francs, which would be paid off in local earnings from the plant, thereby reducing the company's exchange risk.

The most important advantage offered by the broad-based debt markets is diversification. That means the ability of placing the investments in more portfolios around the world having as effect reducing the risk that investors' portfolios would be affected by an adverse effect. As such, the debt issuers will be able to choose from a whole range of investment choices in a global market of financing options, a flexibility which is becoming an increasingly critical element of profitability in today's more competitive global markets.

Since the benefits of diversification are quite evident, which is the credit risk associated to it? When inadequate information exists, investors may shy away from new credits, in this way limiting their investment options. If, making abstraction of credit risks, they adventure into uncertain agreements, investors risk unexpected losses – either because of market losses that reflect changing credit perceptions about the issuer or because of the occurrence of the default at the issuer. Since uncertainty keeps investors away from new and unfamiliar markets, issuers lose access to an important range of funding sources.

The vital element in this framework appears to be the credit information, that is the investors' ability to gather (along with the issuers' willingness to provide) sufficient and relevant information necessary to undergo sound credit evaluations of the new issuers in order to establish their credit worthiness and commitment to repay their debt.

2.3.2 Factors affecting the investment and credit decisions

2.3.2.1 Changing features of global issuers

Maybe the most evident development in the fast-expanding markets is the fact that credit decisions are becoming more complex. As investment horizons expand abroad, investors are introduced to issuers belonging to very different cultures, that operate in various political and regulatory environments that most of the times use different accounting systems and accounting conventions in their financial reporting, that are used to various forms and levels of corporate disclosure, that speak a different language and that may conduct business halfway around the globe in a different time zone.

This takes place concomitantly with a more advanced and efficient technology that facilitates the access to new and innovative types of debt securities bearing new and complex risk implications. The appearance of newer investment vehicles like hedges, swaps, or other derivative transactions is likewise initiating new complexities to the basic credit decisions.

In order to benefit of this diversity, investors need to allocate more and more resources to credit analysis activity to find reliable means to compare relative risks across associated to the new range of debt instruments and to the various types of cross-border debt issuers.

2.3.2.2 Impact of mark-to-market portfolio management

Alongside with higher complexity of the debt markets, we may observe their higher volatility. The classic consideration with which have been regarded bond investments was to buy and hold a security to term - often 20 to 30 years into the future. More recently, managers have shifted their attention to optimizing the value of the portfolios on a total-return basis, taking into account the income from interest payments and reinvestment, as well as the current market value of each bond in the portfolio. As a result, the value of each of the debt securities found in a portfolio had to be estimated on a continuous basis according to their current market value and quickly adjusted to any changes in credit quality that may have a direct impact on secondary market prices. The role of the credit professional thus became more time-sensitive, from evaluating the relative risk of default loss over the life of each debt instrument to monitor and forecast changes in credit-risk over time, changes assimilated to volatility.

2.3.2.3 Contractual relationship with borrowers

The advance of securitized lending has added risk to the relationship between investors and the users of capital. Historically, when confronted with liquidity problems, lenders could benefit of the help coming from the government or from other major bank lenders. They used also to take positions as key minority shareholders in the client companies, transmitting to the customers additional control over borrower behavior. Since the open-market system, such mitigations became much less frequent. As an effect, the number of investors in the company's securities became so numerous and so dispersed that it made difficult convenient negotiation when potential default became more probable. Besides that, it is increasingly impractical for lenders to be important stockholders in all companies whose debt they buy. On the other side, borrowers could once keep their lenders up to date on their current financial status by means of a few phone calls or by organizing regular meetings; more recently, treasurers of the biggest companies must find ways of communicating with hundreds up to thousands of investors in order to maintain their access to funds.

In the public markets, the borrower's relationship with its widely dispersed creditors became more transaction-oriented, that means based on legal agreements, or covenants, written specifically into each security's indenture. As a result, investors had to distribute their attention to a large span of risks linked to each agreement they established. And because borrowers lack a direct fiduciary bond with lenders, they may be more inclined to act on their own initiative without any concern for the interests of the lender.

2.3.3 Risks faced by the debt issuers

Along the higher complexity of securities markets, newer technology and freer markets affected significantly the borrowers as well. This is more obvious in the worldwide trend called privatization that is having a dual effect of proportionately decreasing the volume of higher-quality sovereign and related debt that is offered, while significantly increasing the credit risks of newly privatized companies.

2.3.3.1 The diminishing role of "risk-free" public debt

Private companies often take benefit of issuance of debt in order to cover the expenses of their operations. Even in the case of recently privatized companies, the amount of governmental financial support reduces significantly and the uncovered portion must be financed through debt issuance. In this context, the panel of government-guaranteed or government-supported instruments narrows significantly. This process is more obvious in most industrialized countries and in developing economies as well. The sovereign share of Eurobond market increased constantly since the first part of 1980s, but sovereign issuance tapered off thereafter as issuances of debt by private companies continued to raise. At the beginning of 1990s, the sovereign and supranational demand for credit boomed, backed by the increasing need for development funds in Eastern Europe and in newly-industrialized countries worldwide, but as well by needs in funding public programs and mounting budget deficits. Later on, during 2000s, more institutional investors and pension funds, initially heavily relying on investments in risk-free government debt, showed interest in investing in corporate and subnational debt also, this adding risk due to more volatile yields.

Due to the growing need for funding in the emerging markets, the span of borrowers issuing debt started to include more lower-quality sovereigns whose yields were subject to more frequent changes than the Aaa-rated credits that dominated the sovereign borrowing in the previous decades. Many mid-level up to speculative-grade sovereigns with higher funding requirements were only able to issue debt without the backing of some form of asset, like gold, oil receipts or other export earnings. This structured sovereign issuance required particular attention not only on the side of the sovereign risk but also on that of the credit structure of each careful investment offered to investors.

2.3.3.2 Substantially decrease of the role of government "safety nets"

Another feature of the global risk is that of the diminishing role of governments in the world economies. Due to privatization, unavoidably the credit risks of companies grew once the government control moved to the new private ownership. But such abandon of the public authorities' involvement has not happened only in the case of the fully-privatized companies. Once out of the business of credit providing, governments became less tempted to step in when companies with serious structural problems were heading to collapse, allowing more the market forces decide on the availability of funding resources.

Some exceptions may be considered here and the most important is that of the companies with operations considered to be of national interest. An example in this sense is that of DFC company from New Zealand, which defaulted on its international bonds and commercial papers just one year after privatization. It can be observed that, as individual companies move to private ownership and as economic sectors move to open-market systems, the risk range increases. And with it, business owners confront to new realities of competition and to new, unpredictable regulatory systems.

Such transfers of borrowing from the public to the private sector raise some additional questions regarding the sovereign risk. Thus, it is argued that as the private sector assumes a greater share of a nation's international borrowing, the credit risk of the sovereign would be lessened. As governments permit some selected borrowers to default, their own direct financial burdens will be obviously reduced. However, the risk will continue to exist, that of a sovereign be required to assume the foreign currency obligations of the failing private-sector borrowers, in order to preserve the national interest abroad. Because private sector borrowings are usually harder to be quantified than government's debt, the permanent transnational flow of private capital makes the sovereign risk assessment even more difficult.

2.3.3.3 More risk in financial institutions

The diminishing implication of the governmental authorities takes place in a context of intensified competition in the public securities markets. Along with the expansion of the debt markets, intermediaries activating in them had to reduce their spreads along time in order to allow for a scale development in terms of operations' volume and in order to expand their securities-related lines of business. In such a context, they became less interested in allocating increasing resources in terms of number of skilled people needed to deal with the risks of financial intermediation. As financial networks became more integrated and more globally competitive, banks and securities companies confronted with situations in which they had to respond to tighter international standards, like bank capital standards settled by the Bank for International Settlements. As a result, such financial institutions, from the perspective of the depositors and debtholders, as well as of those investors in securities guaranteed through letters of credit or other credit supports, became riskier investments.

The fiercer competition in financial intermediation produced effects as well in what is called structured financing markets. The strongest effects came from stronger competition among transaction participants, like underwriters, lawyers, accountants and trustees. The result of competition in other asset-backed securities markets was more obvious in the fact that investors employed more higher-risk collateral (like speculative-grade bonds and bank credits, commercial and industrial loans), but also in the structure of debt issuers (in the sense of a higher share of lower-quality issuers).

2.3.3.4 Credit cycle as an effect of a weaker financial system

Historical weakening of the financial sectors contributed to the fragility of the financial markets also, with the effect that risks of default by thinly protected borrowers were intensified. In this context, the banking systems became less capable to complete their traditional role as providers of liquidity to medium or lower-quality loans, more evident in contexts carrying higher-risk stress situations. Securities firms, once intermediating successfully the debt issuance, became less able to provide liquidity to clients searching to avoid default situations. Competition, on the other side, forced the financial intermediaries to lend to companies with high or increasing credit risk in order to generate competitive yields. Usually, the highest pressure is placed on the weakest institutions that are always looking to emphasize high-risk transactions to boost profitability. Historically, the plenty of high-yield lending means allowed for more relaxed credit standards. The underlying reasoning was that even if the prospective borrower was to encounter some difficulties, more credit was available from additional resources to help the company meet its obligations. Inevitably, such credit cycle reversed its course and the period of loose credit has been replaced by tighter credit, up to a "credit crunch". Other way said, at a certain, unpredicted stress point, the credit available may be suddenly withdrawn, creating shock waves in the financial markets and along them widespread defaults of the weaker issuers.

It is the case of the rapid changes in the availability of credit faced by the US and Eurocommercial paper markets in the 1989 and 1990. Those events allowed the financial world to question the need for committed unlimited resources of backed-up liquidity for short-term debt issuers. Over the long-term, weaker and highly-leveraged issuers proved to require special scrutiny during periods of market illiquidity. No matter of the economic cycle, the speculative-grade issuers were unable to access the short-term markets. In periods of market illiquidity they were also less likely to receive the additional external funding required for refinancing long-term debt payments. This happens more frequently with the payments grouped in time, or scheduled to increase because of variable-rate coupons or when deferred interest payments became due.

The speed with which communication of financial information takes place during our days contributes also to the market's potential fragility. This was very well evidentiated during the stock market crash of 19 October 1987. Then, the world's credit markets were hit by similar shock waves following the failure of a leveraged buy-out plan by UAL Corp in late 1989 and the collapse of junk-rated bond securities firm Drexel Burnham Lambert at the beginning of 1990s. As effects of these defaults, new issues in the US speculative-grade bond market came to a virtual standstill, and news of such credit events, due to their rapid spread, determined other bands around the world to pull back lending to high-leverage credits. The tight-credit environment was found to be responsible for the record post-WWII bond defaults in the corporate markets. For example, in 1989-1990 period, almost 150 corporate issuers defaulted on corporate debt.

2.3.3.5 Effect of proliferation of lower-quality issuers

Due to the increasing sophistication of the public securities markets (more evident in the US and Europe), the preference for higher-risk transactions from both high and low-quality issuers became more obvious. Lower-quality credit access on the debt markets tended to be facilitated during the upward phase of the credit cycle. Moreover, the existence of relevant financial technology (including appropriate debt instruments and investor's own risk management tools) could help expansion of the quality range to comprise increasing numbers of higher-risk credits. The most extreme example is the US high-yield or junk bond market, but a similar development has been evident also in the structured financing markets.

At the early stages of development of the markets, investors, unfamiliar with the new structures, typically required highly-credit-supported securities that were ranked with the best rating scores. Along with the advancement in the market confidence, investors developed preference for less highly-protected (still higher-yielding) securities. Likewise, in the majority of new bond markets where investors were typically unfamiliar with all but "name" credits, the market tended to favor higher-quality (lower-revenue) issuers. To the final stages, investors characteristically became more familiar with the credit function (usually connected to the introduction of the credit rating system and risk management tools such as portfolio diversification). As a consequence, higher-risk, higher-yield issuers became more capable to issue debt.

While observing this, it is important to remind ourselves that the probability of default on obligations increases dramatically for weaker credits, while the predictability of the credit quality decreases. As an example, in the US markets, new bond issuance by speculative-grade issuers began to dramatically increase in the early 1980's, as securities firms started actively to accept higher risk in return for higher expected returns. Meanwhile, the credit quality for US corporations decreased. The result was that downgrades of rated corporate bond issuers increased markedly during the 1980s. Ratings of some 150 to 200 issuers were decreased annually during the second half of the decade. Part of this downward trend, higher number of formerly investment-grade companies fell to speculative grade, while more upper-speculative-grade issuers declined to the lower speculative grades. The effect of both trends was that the number of issuers with junk bonds outstanding soared from 262 at the start of the decade to 873 at the end of it. In dollar terms, the amount of speculative-grade bonds outstanding grew from $23bn to $225bn.

The rise was even higher for lower speculative-grade B rating categories. This was due to the fact that the progressively-lower-rated bonds tended to have significantly higher default rates. As a general rule, as an inssuer's credit quality declined (measured by credit ratings), the risk of default rose geometrically or exponentially.

Such an abundance of low-rated companies tended to make overall default rates in the bond market highly vulnerable to financial market circumstances. Thus, the collapse of the speculative-grade bond market associated with reducing of the bank lending and other sources of credit to speculative-grade issuers, left many firms with no sources of cash to meet debt payments when earnings were low or assets could not be sold. If, even more, the economic conditions were sour, the unavoidable has been produced: the rate of defaults by corporate bond issuers rose to a 20-year high in 1989 and 1990.

Against overall higher expectations for default for lower-quality issuers, the volatility of default rates rose exponentially. Other way said, even though approximately 15% of B-rated issuers were expected to default in three years, it became more and more difficult to predict which of those issuers would default, and even less certain would be that the overall default rate would line up with the 15% historical mean in the future. This is part of the reason for which credit analysis placed higher emphasis on the weaker, thinly-protected investors. As well, more attention has been paid to the issuer's day-to-day cash flow position and to its access to external funding sources that would help it meet debt payments coming on short and medium term. The issuer's long-term fundamentals, while significantly important, would thus become less relevant to the immediate question of whether or not the issuer will have access to cash as stresses occur over the short-term.

Despite the significant sophistication of the Eurobond markets, investors are unlikely to accept highly-speculative-grade issues since they would have to manage more default risk. If, similarly, speculative-grade markets do evolve elsewhere, the importance of credit risk considerations would be expected to rise exponentially. On a lesser extent, along the progressively-lower-quality credits enter developing debt markets around the globe, the risks of default could likewise be assumed to rise.

2.3.3.6 Competitive risks in globalised markets

It has been stated above the significant contribution technology and open-markets had in raising the competitive risks for financial institutions. The effects produced in the financial sector transmitted to the non-financial one through changes in the credit quality of nearly all debt issuers inside or outside the financial sector.

An example of such effects is the 1970s development in the Japanese automotive industry, when companies acting in this industry proved increased ability in adopting and developing state-of-the-art automotive technology to produce high-quality, reasonably-priced products. Such results were backed by the early development of quality management and total quality management practices in Japan, the appearance of quality pioneers like Juran and Demming allowing for an unprecedented boost in quality levels. Cars thus manufactured were extensively shipped to foreign markets and quickly became serious competitive threats to the "Big Three" of the US automanufacturing industry. The result was that the Japanese companies prospered rapidly while the credit quality of American companies decreased. The impact was that strong that Chrysler Corp. almost defaulted on its bond debt in the early 1980s, avoiding bankruptcy only by the robust support offered by the Federal authorities.

Another example comes from the steel industry. Major established steel companies worldwide were caught off guard when more and more countries –most of them newly industrialized ones- invested in modern steel technology and tapped lower cost domestic labor to underprice and frequently outperform the already established companies in the industrialized economies. A general pattern may be observed actually in most of the manufacturing economies, from oil to aluminum, forest and farming products. At home and abroad, smaller competitors were frequently capable to use the new technologies well enough to compete efficiently with the big companies, which were in turn burdened by older manufacturing technologies and more rigid labor costs. Frequently, management teams of such large companies failed to respond adequately to the new competitive environment. Thus, the result proved to be overcapacity, intense competition for existing demand and narrowed profit margins. Such situation let a broad range of issuers unprepared for an associated across-the-board drop in commodities prices that began with the recession at the beginning of the 1980s.

The effect was a drop of the credit quality throughout the world and across the basic industries. Coupled with the competition from the public securities markets, lending exposure to countries where export revenues were heavily depending on commodities exports was a major reason for which the credit declined in the western developed economies, especially in US.

Many of the fundamental forces that intensified the competition in the 1980s, among which the most important were deregulation and technology, continued to drive business decisions in the 1990s and 2000s. Along with the market liberalization, it is by no means sure that reregulation of the non-financial markets, that is protectionism, will not serve to restrict economic competition globally. Though, the deregulatory trends in the non-financial and financial sectors seem to be very strong after the 1990s. Apart from the regulatory and political sentiments in particular nations, the fact that technology continues to progress and open up the new economic opportunities serves as a strong incentive to either contribute to the international economy or risk falling behind.

Another important question then is raised: which of the companies will prosper from being involved in an international framework? Many American and European companies pretend that they have learned their lessons, that they successfully implement now more modern and flexible management styles and production methods, attuned to hardened global competition and to an era of rapid growth and changes. However, it is the nature of competition that whatever future adjustments occur, there will be also losers, not just winners. Then, which of the debt issuers will be losers and which winners? Changing markets and growing competition bring opportunities for profit, which in turn may turn into higher capability to honor debt obligations, other way said, to better creditworthiness. Still, change and competition also bring added risks that a business strategy will fail in a new environment and ultimately lead to default on its debt payments.

No certain forecast on the probability of default can be based solely on an analysis of an issuer's current financial statistics. In an environment characterized by rapid change and fierce competition, the simple analysis of the issuer's balance sheet, its leverage and coverage ratios might not be enough. Instead, should be considered also to qualitative factors that will enhance the issuer to maintain its credit strength as unpredictable challenges are encountered in the future. Moreover, the emphasis will be granted to factors such as management quality, and its ability to respond to challenges, its financing philosophy, its business strategy, and position as regards competition in a variety of markets globally.

2.3.3.7 Risks of consolidation and complex corporate structures

Along with tougher international competition, stronger pressures may occur to what is called industry consolidation. The means of consolidation may vary from cooperative ventures between companies with the goal of sharing efforts for research and development until to outright mergers or acquisitions of competitors. Consolidation of businesses allow for a reduction in the potential for surprise or for tightened profit margins in a competitive market, thus being considered positive for the long-term credit strength of the industry, as well for its stability. However, consolidation does not offer a complete protection against any risks, sometimes proving inefficient and unstable or a drain channel of resources of one or more parties involved.

Not less important is the risk that managements may be tempted to take on unsafe levels of debt to fund acquisitions with uncertain profit potential. One example in this regard is the takeover boom in corporate in the United States in the late of 1980s. Over a five-year long period, almost 350 companies suddenly announced their intentions of taking large amounts of debt to finance acquisitions or mergers, or to cushion against being taken over by using debt financing to leverage capital structures. The immediate effect was immediate abrupt declines in the companies' credit quality and sizeable secondary market –value losses for many of the investors. Afterwards, investors suffered direct credit losses on several billions of the debt involved in high-leverage takeover activity, with more losses expected in the early 1990s.

Now it is very improbable that special events connected to high-leverage corporate takeovers will return on any scale anytime again in the future, depending as they did on an environment of low corporate interest rates coupled with an abundance of international speculative-grade credit resources. Investors became more risk-averse, and a general more conservative approach to finance now characterizes a state of facts in which large-scale takeover activities are less likely.

The international consolidation of businesses paves the way towards a more complex surviving of the corporations, with the risk implications that arise from this. One such example would be the result of an unsolicited takeover bid for the British American Tobacco Company. Although this transaction has never been completed, it caused one of the rating agencies to review the credit ratings of BAT along with those of its insurance subsidiary, Eagle Star Insurance Company Ltd, and the ratings on a $2.0bn of mortgage-backed securities which were partially guaranteed by the subsidiary; the securities were, in turn, restructured to include additional credit supports in order to ensure their ratings would be maintained.

The more complex cross-border structures make difficult to assess the actual levels of debtholder protection that is available between mother companies and their subsidiaries. Even when subsidiaries in the same group of companies take similar names, there is no insurance that their risks are the same and that special parent support agreements may be required. The tendency is that the complexity of such structures and the involved risks of assuming parity between apparently related companies are on rise.

2.3.3.8 Technological and environmental risks

In every sector of economy, the advances in technology –in particularly the use of computer technology such as artificial intelligence- decrease the traditional product development cycles and make investments in research and development more essential and more expensive. That, in turn, will tend to give the advantage to larger and more creditworthy companies that have a more facile access to economic sources of capital to fund high-cost research and development or to advanced plant or equipment that will enable them to maintain competitive. This places a stronger emphasis on the need for cooperative product development ventures and management's ability to understand how developing technology can meet real customer needs in widely dispersed markets. Meanwhile, rapid technological improvements facilitate access to market of niche competitors, which can challenge important business lines; when strategic decisions fail in reaching targets, smaller competitors may found in better positions to quickly gain field.

A faster development means also that products developed in one period are more likely to become "low margin commodities" a few years later. For example, in computer sector, low-cost merchant-supplied semiconductors and an increased preference of the customers for common operating systems and multi-vendor networking, have constantly changed the industry. The advantages of raw performance on a proprietary system are no longer probable to back growth and earnings. If taking the example of the securities industry, high-tech products such as interest-rate swaps and hedging systems, long a source of profits for many securities firms and banks, have been replicated by competing firms worldwide. The effect was that few securities companies were able to generate attractive profit margins on such non-standard derivative products, forcing them to develop ever more complex derivatives or to re-emphasize other lines to remain competitive.

Technological improvements may also bring the need to assess their environmental and health impacts. Manville Corp. may be considered as an example in this regard, the company being the only default in the US commercial paper markets during 1973 and 1988. Its default was the effect of litigation stemming from the serious health concern on the firm's products made from asbestos. At the beginning of the 1980s, there were serious concerns coming from the public as regards the environmental hazards of nuclear power plants that had a strong negative impact on the credit quality at the most significant major utilities having under construction nuclear plants, but also severe decreases in revenues for suppliers of nuclear plant technologies. Another example is represented by the coal-fired plants that were accused of causing acid rains, of serious concern for the strong adverse environmental impact. The recycling and clean-up of the environmental waste of industrial companies represented another critical risk faced by most of the industries. When companies decide to invest abroad, the environmental issue becomes even more critical. The environmental regulations may differ significantly from one country to another, so that the standard approach to deal with these in the home country may be insufficient or inappropriate when the company deals with foreign environments. Since the environmental concerns build up especially in the industrialized and in the newly-industrializing countries, and since the debates around them are still changing concepts as regards which industries are more or less polluting, it is highly probable that all companies, even those with operations currently seen as safe for the environment, may be needed to allocate in the future additional expenses for environmental and public health issues.

2.3.3.9 Risks related to the regulatory and legal environments

Although the current trend shows that regulatory barriers are generally decreasing, issues concerning the environment or public health may offer prospects for tighter regulatory controls. In the same time, we should remember that the market deregulation is not just a matter of removing current regulations. In the process of diluting regulations, other rules and procedures are defined and put in place in order to regulate the newer open environment. Along with them, management styles and business investments may become inappropriate to fit to the new environment.

Uncertainties as to future regulation make management decisions to be even more difficult and along with them the credit implications become less predictable.

In the US savings and loan crisis, as part of the trend toward deregulation, thrifts were allowed to expand their lending in order to comprise higher risk investments like real estate and junk bonds; however, federal deposit insurance on depositors' funds used for those investments was maintained, in effect subsidizing high-risk investments. Subsequently, thrifts started to fail due to their high reliance on risky operations, pressure mounted both to decrease the government's deposit insurance burden and to resolve the failed institutions in ways that reduce the political pain by shifting more of the burden of loss to creditors. The consequence was what is called "regulatory loss" to some classes of creditors, including those holding many of thrift-issued structured financings. The legal precedents established by the thrift resolutions have large implications for the banking system and its creditors. In almost each financial and nonfinancial industry may be found examples of such risks. Much of the impetus for change internationally is stemming from the broad realignment of regulations and practices as markets tend to integrate into common systems.

2.3.3.10 Political risks

Important business and credit implications stem also from important political changes in the countries companies operate in. This represents political risk. In a large sense, political risk refers to the complications businesses and governments may meet as a result of what is generally called "political decisions". According to Eurasia Group and PricewaterhouseCoopers (2006), "globalization is a process of rising acceptance of political risk in search of greater economic rewards. Economic success has bred acceptance of ever-greater political-risk exposure". Their definition of political risk is: "any political change that alters the expected outcome and value of a given economic action by changing the probability of achieving business objectives".

Politics influence how markets operate. The most unpredictable economic events are political in origin, the result of flagging political willingness or capacity to maintain a consistent and predictable economic environment. The current global investment environment may be characterized by four dominating trends that are: the interconnection of the financial markets, increased reliance on offshoring, deterioration of the national security and energy dependence. Since their presence cannot be questioned, the correct anticipation of each of them along with the risks associated requires asking the right questions on the modalities in which institutions' and leaders' preferences settle on policy choices and in turn, on economic outcomes.

Politics can make some economic decisions and management strategies look thoughtless in hindsight. The fact is more visible in countries where autocratic leaders seem to put a strong fingerprint on the governmental policy and where quantitative data is often erroneous. It is also common to the developed nations where targeted lobbying efforts may influence political decisions with strong impact on the business environment. A well managed political risk analysis may turn apparently difficult to evaluate losses, or uncertainty, into calculable risk.

Because all the business environments are impacted by political decisions in countries they operate, companies have to correctly assess the political environment into planning scenarios. The political risk may seem so shapeless and complex that managers find difficult to find a proper framework to evaluating their own exposure. As other elements of enterprise risk, political risk has systematic components that may be separated for a better understanding of the variation across different political systems.

Taking as an example the case of the East Asian Crisis in 1997-1998. Before the spread of the crisis, economic data showed few notable risks that would have announced extreme cautious in investing in Southeast and East Asia. Actually, the underlying cause of the crisis was not that much a political one as an economic one: a sudden, unexpected out-flow of funds occurred soon after the collapse of speculative bubbles throughout the region, especially in the imprudently regulated financial and real estate sectors. So, at the roots of the crisis stood no political sources. However, their influence was severe, not as much in originating crisis, but more in magnifying the effects of the crisis. Weak political institutions proved to be incapable to implement necessary policies that would have prevented risky lending, as well failed in convincing markets of their ability towards rapid implementation of credible policies in reaction to growing crisis. The effect was that the crisis took more than a year to run its virulent course, putting under threats markets like Latin America or Russia.

Business administrators were concerned about how governments across the region under crisis would respond to it. For this purpose, asking the correct questions is necessary to obtain a proper assessment of the political risk. For this specific example, they would be:

- Which governments proved to be most stable domestically or had elections approaching? Such a question would allow to identify factors of stability, as each of the two possibilities would mitigate political pressures brought on by the crisis
- Where were social tensions higher, with the resulting potential for unrest?
- Which governments are more able to come with proper policies to eliminate effects of the crisis?

A common tool to assess the political risk is what is called "scenario planning". Such tool is used by analysts to map out potential political, economic and social trajectories that would permit managers consider a range of strategic scenarios and identify critical strengths, weaknesses, risks and opportunities. However, they do not try to make forecasts on the future. Rather, they are designed as a tool to guide companies towards challenges and opportunities that would exist in the near future, by serving them as a roadmap. Key in this process is the determination of the driving forces that may propel the global affairs down a particular path. These drivers may include market factors, social trends, developments in technologies, changes in regulation. Establishing scenarios involves assessing the impact of drivers along with other certainties that are known about the future, such as population size and GDP projections. The result is a number of scenarios about the future, depending on the particular dominance of certain drivers and the available trade-offs.

3. Systemic risk and access to credit

One of the ubiquitous aspects of the contemporary financial domain is the extensive network of interconnexions that exists between companies. Although, in the economic theory, the debts of one company to another company are usually unidirectional, as obligations dependent only of the financial health of the issuing company, the accounting structure of obligations of one company is much more complex. The value of most of the companies is dependent on the payments cashed for debt reconciliation of the crediting companies. The value of these payments is thus directly proportional to the financial health of the other companies in the system. Moreover, the relationship between firms may be cyclical. The default of company A on payments done towards company B may lead to difficulties in payments company B does towards company C. The default on payments of company C may furthermore hurt the financial situation of company A.

This example illustrates a general feature of the financial system architecture which is called in the financial theory as “cyclical interdependence”. A significant part of the written papers on this topic looks to find a correction mechanism when such interdepence exists.

All markets have a self-adjustment system. The interbanking clearing payment systems were those that received a particular attention. For example, CHIPS and Fedwire in US are the most important clearing systems in the banking sectors. In Germany, EAF (Elektonische Abrechnung mit Filetransfer) fulfills such function. As regards the clearing mechanisms, one of their particularities (for example in the case of a listed options exchange), is the existence of an OPC (Options Clearing Corporation) counterparty in any transaction performed. Credit considerations do not exclude the access on these markets of low-credit counterparts. Such payment systems confront very often with defaults on payments from companies. Some examples would be I.D. Herstatt in 1974 and Bank of New York, the latter being confronted with a liquidity loss of $22.6 billion. At the system level, financial meltdowns may arise. Examples would be: the collapse of the real estate industry in Tokyo, the default and public bailout of American S&L at a cost of $500 billion, the crisis of the banking system in Venezuela in 1994, and the Long Term Capital rescue plan put in practice once the sovereign debt default in Russia. An interesting failure occurred in a clearing system strongly interconnected between its elements happened in 1982 with the al-Manakh stock-market of Kuwait. The clearing system, that was made up of around 29000 postdated checks, got bankrupt when the market crashed by 45%. The gross nominal debts of the traders in the market were at the moment of the crash almost four time the GDP of Kuwait (Elimam et al. 1997).

But regardless of the role of the architecture of the financial relationships in establishing the return-generating process for financial assets, no much attention has been granted to researching on the cyclical financial interconnections. The results of the bilateral system in clearing the nominal obligations has been mainly researched by Duffie and Huang (1996). As well, two other authors, Rochet and Tirole (1996) have investigated the incentive and regulatory impact of credits traded on the interbank market. Angelini et al. (1996) has researched the chain system of defaults by conducting an empirical analysis. In their model, the probability that a default happened at one company to trigger the default at another one was exogenously specified, without including external variables such as cash flows between companies. Elimam, Girgis si Kotob (1997) describe the procedure used in clearing intercorporate liabilities taking Kuwaiti stock market default as a benchmark. Their work is recognized as a pioneering research of the characteristics of intercompany corporate flows in those financial systems that feature cyclical interdependence clearing vectors endogenously determined.

The little attention granted to cyclical interdependence is even more evident when considering the extensive literature written for modeling the probability of default in a simple unidirectional and bilateral perspective. Actually, all has been written on term structure of interest rates doesn't take into consideration what stated above. While the usual practice is to model the valuation of a company's liabilities independently, with no endogeneity coming from the debts of the other interconnected firms, such assumption is no more valid, or at least questionable, in portfolio management theory, in corporate bond trading and in the analysis of counterparty credit risk. A more proper way to consider these is to establish and implement a simpler and more tractable model designed to correctly compute clearing vectors for interlinked financial systems.

Eisenberg and Noe (2001) developed such a model. They examined the necessary conditions imposed by the bankruptcy law, more precisely that clearing vectors (vectors of payments from nodes in the financial system to other nodes) satisfy the condition of proportional repayments of liabilities in default, limited liability of equity and total priority of debt over equity. This contributes to a better understanding of a complex financial system's modeling with cyclical obligations of the parts involved.

3.1 The concept of systemic risk

3.1.1 Definitions

One of the most averse events in the banking system is the *systemic risk*. This represents the risk or probability of breakdowns in the entire system, evidenced by comovements (or correlations) among most or all parts of the system. The presence of system risk is proved by the high correlation and clustering of bank defaults in a single country or in a certain number of countries. It is specific to the banking sector, but as well may be present in other domains of activity of the financial sector, like securities markets, where it is evidenced by synchronized reductions in prices of more securities either in one market or in more markets, in one country or across more countries. The systemic risk may be domestic or may be international.

The systemic risk represents the propagation of the financial distress of a certain economic agent towards other economic agents bound through financial transactions. The systemic risk is a serious concern especially in the industrial sectors, where the trade credit binds the producers through a chain of obligations and in the insurance industry due to the relationship companies have with the insurance and reinsurance firms. The anxiety associated to the systemic risk is, maybe, the strongest among the executives and among the supervisory institutions. The interbanking transactions, in which there are included also the interbanking loans, have substantially increased in the recent years. These include debts in the payment systems, overnight and term loans, and interest derivatives or exchange rate derivatives in the over-the-counter markets. When such interbanking loans are not collateralized or insured, the problems of one bank may be at the origin of a chain of consequences in the system, reason for which the Central Bank must intervene in order to limit the contagion process. Indeed, the general opinion in the market which comes from the side of the banking experts is that the industrialized countries adhere to a "Too-big-to-fail" strategy of protecting the uninsured depositors of large insolvent banks, whose default would spread rapidly in the financial system. Generally, authorities refuse to express publicly such position and prefer instead to mention a policy of "constructive ambiguity" when referring to intervention prospects. The interbanking transactions reduce also the transparency of the banks' balance sheets and complicate the measurement of the current liquidity of one bank and of its solvency indicators.

From the banking perspective, systemic risk refers to the risk that entering into a liquidity blockage would create a "wave" effect which propagates and leads to similar problems of other financial institutions, thus affecting stability of the whole financial system. The financial system has suffered such events in 1990 (Drezel) and 1995 (Barings). Even the recent 2008-2009 financial crisis is the effect of the same systemic risk which propagated from the United States to Europe, Asia and other emerging markets. In 1990 and 1995 the system has overcome the problems, but the risk remained a permanent concern for the regulatory institutions.

The systemic risk concept is rather ambiguous, as it usually means a different concept to different people, depending of the fields they work in. A simple search in the specialized literature may unveil three main concepts. The first one refers to a "large" shock or macroshock that produces simultaneously large adverse effects on almost each component of the economic system. In this case, systemic "refers to an event having effects on the entire banking, financial, or economic system, rather than just one or few institutions" (Bartholomew and Whalen 1995, 4). As well, Frederic Mishkin defines the system risk as "the likelihood of a sudden, usually unexpected, event that disrupts information in financial markets, making them unable to effectively channel funds to those parties with the most productive investment opportunities" (1995, 32). The way in which the effect transmission is done from the macroshock to individual units, called as well as contagion, and the selection of the units affected, remain usually unspecified. The model proposed by

Franklin Allen and Douglas Gale (1998) describes a similar process through which the macroshocks may affect the banking system.

The other two definitions concentrate more on the micro level and on the transmission mechanism from one unit to another. According to the second definition, systemic risk refers to the “probability that cumulative losses will accrue from an event that sets in motion a series of successive losses along a chain of institutions or markets comprising a system… That is, systemic risk is the risk of a chain reaction of falling interconnected dominos” (Kaufman 1995a, 47). This definition is consistent to another one given by the Federal Reserve in 2001, according to which:

In a system of payments, “systemic risk may occur if an institution participating on a private large dollar payments network were unable or unwilling to settle its net debt position. If such a settlement failure occurred, the institution’s creditors on the network might also be unable to settle their commitments. Serious repercussions could, as a result, spread to other participants in the private network, to other depository institutions not participating in the network, and to the nonfinancial economy generally.” (Board of Governors of the Federal Reserve System 2001, 2).

As well, the Bank for International Settlements (BIS) finds the systemic risk to be “the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties” (BIS 1994, 177). Such definitions highlight the relationship with causation and suggest the direct connections existing between institutions and markets. When the first domino falls, this falls on the other dominos, which causes them to fall and in turn knock down the others, provoking a “knock-on” reaction. Such an effect has been illustrated by Governor E. A. J. George of the Bank of England by saying that the chain effect occurs “through the direct financial exposures that link firms together like mountaineers, so that if one falls off the rock face others are pulled off too” (1998, 6).

In banking, this effect may happen at Bank A, if, for whatever reason, defaults on a loan, deposit or any other payment obligation towards Bank B. This may cause a loss to Bank B greater than its own capital, forcing Bank B to enter in a severe liquidity loss situation and the default on its payments to Bank C, thereby causing a loss greater than Bank C's own capital, etcetera, down to the end of chain, in a rolling over movement along the whole interconnected financial system (Crockett 1997). Especially when we speak about the national financial systems, banks are highly interconnected through interbank deposits, loans, and interest rates. As against the first definition that was considering solely macroeffects, in this case one bank is sufficient to be exposed in direct causation to the initial shock, while all others, along the channel, may remain sheltered against the shock. The default of the originating bank may set off the chain or knock-on reaction.

Smaller the capital/asset ratio, that means more leveraged the bank, more likely is that such bank be exposed to default of other banks located upstream the transmission chain and higher probability that the bank transmit its problems downstream. The feature that makes systemic risk such an alarming danger are both the lightning speed with which it occurs and transmits but as well its capacity to affect and spread over all kinds of units in the financial system, from economically solvent (innocent) companies to economically insolvent (guilty) ones, which makes it potentially difficult to protect against it.

The third definition of systemic risk emphasizes the spillover effect from an initial exogenous external shock, but does not consider the direct causation, but weaker and indirect connections. It stresses similarities in third-party risk exposures among units involved. Thus, when one party experiences adverse effects from a shock (like the default of a big financial or non financial company), this thing causes large losses and uncertainty occurs as regards the partner companies that may be also subject of adverse effects of the same shock or of a similar shock caused by the initial one. In order to minimize other potential losses, the actors in the market look more carefully to the participants in the market and investigate the degree of vulnerability to the shock. As the risk-exposure profile is more similar or identical to the company (companies) initially hit by the shock, the greater is the probability that such company (companies) encounter similar losses, and consequently higher is the probability that participants withdraw their funds out of the units under risk as soon as possible. Such a risk pattern and behavior of the market induce liquidity problems and even more fundamental solvency difficulties. Such a situation is called "common shock" or "reassessment shock" effect and illustrates the pure correlation without direct causation (or other way said, indirect causation).

Since the information as regards the causality or the magnitude of the initial shock or as regards the risk exposures of each market participant under risk is not usually available immediately or accurately and usually is offered at a certain cost, and even more, since the analysis is not done immediately and is not free, participants usually need time and resources to identify the vulnerable units and the size of any potential losses. In the banking sector, along with the worsening of the credit market, the quality of information available also deteriorates as the cost of accurate information increases and as the uncertainty increases as well. Since generally the investors have a risk aversion pattern and would rather invest in secured assets, at each sign of deterioration they flow out or transfer funds, permanently or temporarily during the period of confusion, sorting out to investment destinations previously evaluated as being safe or safer, until they complete the analysis of the size of potential losses and the units under risk. Moreover, when uncertainty and stress are considerably high, investors shift from making portfolio adjustments in prices (that are interest rates) to quantities (runs). This usually has a temporarily duration and is associated to stop from lending or borrowing at any rate. The immediate outlook is an immediate flight or run to quality, away from all units that appear to be potentially at risk, no matter if subsequent analysis would identify them ex post as having identical exposures that put them at risk of insolvency. Thus, under this perspective, the common-shock contagion seems unable to discriminate between quality and inferior economic units, potentially affecting the whole market and reflecting a general loss of confidence at all stages. Investors and creditors fail in correctly distinguishing the insolvent companies of the solvent ones. Because such runs are concurrent and widespread, it is said that the investors exhibit a herding behavior.

The run of capital exerts a strong upward pressure on the interest rates and a similar concomitant downward pressure on the prices of the securities of the affected financial institutions and markets. Any liquidity default may spillover at least temporarily to banks not directly affected by the initial shock. In this way, the initial domino piece will not fall directly on the other pieces, but the effect on the side of the other market players will be similar: they will still inspect the nearby dominos in order to check which may be subject to the same destabilizing forces that produced the fall of the initial domino pieces. The general picture, in this way, may still be a broad contagion that may spread in these sorting-out or reassessment periods.

But this state of facts may be only temporary. After the completion of the assessment periods, such flows that affect negatively solvent banks may be corrected or even reversed. During the sorting-out period, the changes in financial quantities (mentioned above to be flows) and prices (interest rates) usually overshoot their ultimate equilibrium levels due to the uncertainty discount and therefore intensify the liquidity problems, especially for more vulnerable units (Kaminsky and Schmukler 1999). More frequent the financial crises are, higher probability exists that participants in the market be more prepared and better informed, and shorter the liquidity crises are, and the size and duration of any overshooting, as previously described, is shorter.

A distinction must be made between rational and information-based risk, directly and indirectly caused systemic risk and irrational, non-information-based, random or "pure" contagious systemic risk (Aharony and Swary 1996; Kaminsky and Reinhart 1998; Kaufman 1994). The rational or informed risk-based contagion refers to situations in which investors, basically depositors, have the ability to differentiate among parties on the basis of their fundamentals. The second category contagion, that based on actions of uninformed or less-informed investors, is more worrying and seen as potentially more dangerous, due to the fact that it does not make any distinction among the companies and their degree of solvency, its impact area being thus broader and the losses it produces more difficult to be assessed. The means Central Banks have to their disposal for containing such a contagion are fewer. Since no bank is perceived to be fully secure, the effects are transmitted rapidly along the banking system and lead to the depletion of the aggregated banking reserves and, in the absence of the Central Bank intervention, to a multiple contraction in the aggregated money and credit (Davis 1995; Diamond and Dybvig 1983). According to Governor George (1998, 6) of the Bank of England, the systemic risk is generally extremely costly because of "the danger that a failure of one financial business may infect other, otherwise healthy, businesses." Thus direct, knock-on contagion may be seen as hitting with no discernment both solvent and insolvent banks along the transmission chain. The common-shock contagion systemic risk is likely to affect solvent banks immediately during the sorting-out period, although the investors will do this sorting of such banks out of the insolvent ones along the time. We may conclude that the empirical borderline between rational and irrational contagion is fuzzy and depends partially on the time horizon used.

To reduce such ambiguity, stating correctly the solvency and insolvency is required. The definition of solvent and insolvent is not always clear and precise. Solvent units are those entities with juridical form that are widely perceived as economically well behaved. In the case of banking units, solvent banks are those banks which are economically perceived as sound and not heavily leveraged. Insolvent units are those entities that are perceived as insolvent or solvent but near insolvency or excessively leveraged.

3.1.2 Dangers posed by systemic risk

The notions of the chain-reaction and common-shock in terms of the systemic risk understate speedy contagion and require actual or perceived direct or indirect correlation among the parties at risk (Kaufman 1994). Banks are tightly connected to each other by the interbank loans, deposits, interest rates, and payment-system clearings and indirectly through serving the same or similar deposits or loan markets. When they activate abroad, they constitute an important tie between the countries they operate in. Therefore, an adverse shock generating losses at one bank large enough to drive it into solvency may transmit to the other banks along the transmission chain. Adverse shocks in the financial sector seem to be transmitted more rapidly than in other sectors of activity. In the banking sector, the higher probability, strength and size of any contagious systemic risk, the larger and stronger the impact is as experienced by the bank hit by the initial shock. The conclusion is that the transmission and danger of systemic risk are expected to differ depending on the strength of the first shock and on the attributes of the banks affected initially.

When no guarantees exist, entities along the transmission chain would try to protect themselves from any negative effects coming from potential shocks. Banks, for example, might pursue in this sense increases in higher interest rates at riskier investments, or a tighter monitoring of their counterparties. Also, they might increase the standards for the accepted collateral when crediting, and might pursue to increases in capital to absorb any losses from their association with a bank already hit or from runs of their depositors. Such a structure has been modeled by Jean-Charles Rochet and Jean Tirole (1996). Like a general rule, in order to transmit an initial shock downwards the channel and to knock-down other banks, losses must exceed capital of the banks. Thus, banks with sufficient capital to absorb the transmitted losses would maintain their solvency, although seriously affected. If such a thing would occur, the domino effect would be interrupting from cascading. But then, another question rises. Which is the amount of necessary capital so that a bank would consider safe? Usually, the necessary amount of capital required to remain solvent depends on the exposure of a particular bank to other units in the system, and on the expectations regarding the size of the shocks. Both the exposure and expectations vary among banks and through time for any bank. The more leveraged the bank is to other units, the smaller is the adverse shock required to drive a bank or an institution into insolvency, and the greater the likelihood that any losses will be passed along the transmission chain. Higher the speed with which transmission is made, the more difficult is for units to develop their protection after the shock has occurred, and the more important is to them to own a corrective protection beforehand. From this point of view, the financial domain is a special case as compared to other sectors, where the transmission of adverse shocks is done with lower speed and companies have enough time to act to protect themselves after the initial shock has occurred.

In what it concerns the random contagious systemic risk, this is considered particularly dangerous and undesirable because it spreads over all types of banks, regardless their solvency. Although distinguishing solvent from insolvent banks after the crises have passed is relatively straightforward, such thing is particularly difficult to be undergone before the crisis. Ex ante information is frequently not sufficiently available, timely or reliable to help produce a correct differentiation with much confidence. Banks, often helped by the governments of countries they operate in, fail to disclose relevant information on their liquidity and solvency and, particularly when they come close to insolvency, tend to provide insufficient reserves for credit losses and to use doubtful and sometimes falsified accounting procedures to inflate the reported capital ratios.

3.1.3 The systemic risk and interbanking relations

The study of the systemic risk is tightly linked to the study of the interbanking relationships, because systemic risk appears when the lending activity between the credit institutions suffers of organic asymmetries. In other words, we cannot talk about the systemic risk and its causes if we do not grant a higher attention to the way banks work together. The assumption of all papers written on this topic is that the current system of the interbanking relationships suffers from its hybrid nature: firstly, because banks engage in an extensively decentralized mutual lending. Secondly, because government intervention, done voluntary or involuntary, destroys the very benefit of a decentralized system, like peer monitoring among banks. The consistency existing between goals and incentives may be restored in one of the following ways. If no one believes that the information each bank has or may obtain from another bank may be used in a fruitful way, or if similar information can be acquired and utilized efficiently by regulatory authorities, then there is no reason to encourage decentralized interactions between banks. Additionally, one may admit that such a reformist view of cutting the interbank linkages would maintain the current flexibility while improving banks' incentive to cross-monitor. Such a policy, to prove its efficiency, needs not just keeping banks formally accountable for their losses in the interbank transactions, but also restores the Central Bank's credible commitment for not intervening on the market in most cases of the bank distress. But such credibility in most of the cases cannot be taken for granted and must be built on a specific regulatory environment of interbank transactions.

In order to emphasize the idea that a decentralized operation of interbank lending must be associated with a peer monitoring action, let's think to the following plausible explanation of the interbank lending: a certain number of banks, due to their regional settlement, performs very well in collecting deposits, but is poor in exploiting any investment opportunities. As against those, some other banks, like money center banks, have plenty of investment opportunities, have the capability of fully taking advantage of them, and are large enough to afford large fixed costs associated with complex derivative and other high-tech financial markets. Then, it's naturally to think that the first type of banks lends to the second category. But the fact that a deposit-collecting bank (the first type) should incur a loss when the borrowing (second type) bank defaults, as it is implied by the interbank lending is not a totally valid conclusion. If the relationship established between the two banks implies a transfer of funds without any monitoring, the operation described above could be implemented in a more centralized and maybe better for prudential control, way. Thus, the bank specialized in deposit collection could pass the deposits on to the borrowing bank, while still continuing to administer them (similarly to the way a bank may continue to service mortgage loans it has securitized without recourse to other banks). The main difference with the interbank-loan organization is that the deposits made at the originating banks would become deposits of the receiving bank. In this case, if the latter defaults, losses would be borne by the deposit insurance fund, and not by the originating bank. The conclusion of this argumentation is that a plain specialization of banks into deposit-taking banks and active investment banks is not sufficient to predict the existence of decentralized interbank lending.

The interbank credit is also subject to a permanent debate in prudential context. International regulations solicit, currently, little capital for interbank lending. An interbank loan receives one fifth of the weight of an industrial loan. Because current capital requirements oblige to an eight percent ratio of equity to risk weighted assets, at an interbank loan of $1, the minimum necessary capital is of 1.6 cents. It may be argued that such a requirement of minimum capital is excessive through the perspective of the track record of interbank loan reimbursement. However, such position fails in expressing one essential issue: the track record of the loan reimbursements has been purchased at the price of government exposure. As well, it doesn't consider the bank moral hazard. Thus, in an improved system, in which banks are accountable for losses incurred from their interbank transactions, such banks would be riskier than they currently are and might be affected a higher weight in the capital adequacy requirement. It might be as well the case that formal quantitative restrictions (caps) be imposed in the interbank lending operations in order to limit the interbank linkages and dependability.

On the other hand, under a strict interbank monitoring, debtors on the interbank market(s) are certified by their peers. The beneficiaries of (medium- or long-term) interbank loans might therefore be allowed diminished capital ratios than banks that rely primarily on uninformed deposits for funds. In this way, taking advantage of better monitoring incentives, a fraction of medium and long-term interbank borrowing could conceivably be included in the borrowing bank's regulatory capital, while this enclosure would make almost no sense in the existing system. A peer monitoring approach may explain why short term loans, insured or uninsured, are regularly poor substitutes to the bank capital, as they allow lenders to get rid of any responsibility for poor monitoring by liquidating their position.

3.1.3.1 Reasons for regulating the bank capital

It is tempting to say that the banking regulation is unnecessary. "Even in the absence of such regulation, banks could administer their risks in a prudent manner and would be capable to maintain a certain level of capital proportional to the risks they are exposed to". Unfortunately, the history does not sustain such an opinion. It's unquestionable the fact that the sector's regulation has extensively played an important role in the increase of the banking capital, contributing to the banks' accountability for the risk they take.

If markets would have functioned without any governmental intervention, the banks that would have maintained low levels of capital would have found difficult to attract deposits, thus experiencing a decapitalization following a sudden run attempt of a large number of depositors occurred on short periods of time. Some governments offer certain forms of deposit insurance because they want that deponents trust banks' offered safety. However, the existence of some norms of insurance on the deposits encourages banks to reduce the capital because they should not worry anymore about the possibility of trust reductions or loss from the depositors. This is a classical example of moral hazard, through which the existence of an insurance contract may change the behavior of the insured counterparty.

From the governmental perspective, there is the risk that the existence of a deposit insurance to lead to the banking bankruptcy and to the increase of costs of the deposit insurance programs. Therefore, governments found necessary to combine deposit insurance with the minimum capital requirements that banks should apply.

3.2 The historical evidence of the systemic risk

Clusterings of bank failures are frequent along the historical observation period, but any clustering is a proof of systemic risk? The answer may be given depending of the chosen definition of systemic risk. Almost tautologically expressed, the systemic risk is observed most frequently when it should characterize a big, large shock. As stated earlier, however, such definition doesn't include any reference on the existence or transmission mechanism of contagion. Common-shock systemic risk, especially over short term, appears to be more frequent than chain-reaction systemic risk. Systemic risk, when it arises, appears to be both rational and confined primarily to "insolvent" institutions and not randomly to affect solvent banks fatally (Kaufman 2000a).

As regards the banks, more frequent in the United States and before 2008, there is little if any evidence of contagious systemic risk that caused economically solvent banks to become economically or legally insolvent, either before or after the putting in place of federal government guarantees and insurance (Kaufman 1994). The American banks have been those that have been most completely studied because of their good historical records, large number, and minimum government ownership and control. The empirical evidence shows that problems occurred at a specific bank or group of banks spread almost exclusively to banks with identical or at least similar portfolio-risk exposures, but subject to the same shock. There is little if any evidence that the default or insolvency of an individual bank leads directly to the insolvency of economically solvent banks or that bank depositors run on economically solvent banks so frequent that, when they do, they drive these banks into insolvency.

3.2.1 Potential exposure

Some studies simulated the probability of the existence of a direct causation or of a knock-on contagion in the United States, through the Federal Reserve transactions or through other interbank exposures, in the selected period February-March 1998 (according to Furfine 2003). These funds are usually uninsured and since the Depositor Preference Act of 1993, are subordinated to all domestic deposits. The research of Furfine found that if a high loss of 40 percent was assumed, well above the average bank loss rates existing even in the crises occurred in 1930s and 1980s, the failure of the largest debtor bank in the United States' Fed funds market would have caused economic insolvency of only two to six banks holding less than 1 percent of total banking assets in US. The default of smaller debtor banks would have even lesser effects. If the failure of the two largest debtor banks would occur simultaneously, fewer than ten other banks would fail as well, because all other banks would possess large enough capital to absorb the shocks and losses. If the assumed loss rate would be decreased to 5 percent, similar to the one experienced in the US Continental Illinois Bank failure in 1984, no bank would be hurt that much to approach failure.

Results have not changed that much when the total interbank exposures were simulated. The simultaneous default of the largest two debtor banks causes more than fifteen other banks with more than 3 percent of total bank assets to fail only when the loss rate exceeds 65 percent. Such a loss rate would be extremely high for large resolved banks in the United States. Even at the amplitude of the banking crises in the 1980, when regulators refrained and delayed resolving insolvencies until after significant runs by uninsured depositors effectively had stripped the banks of their best assets and had increased losses as a percent of the remaining assets, the losses at large commercial banks rarely exceeded 10 percent of the assets (Kaufman 1995b). According to Furfine (2003), at such loss rates, simulations would forecast only negligible knock-on effects. Such results overstate the damage to other banks because they assume failure only when tier 1 (especially equity capital), rather than total capital, including tier 2 (basically subordinated debt and limited loan-loss reserves), is depleted. Similar simulation studies in the Italian and Swiss financial markets indicated a relatively "small threat to financial market stability" from failure by one bank (Angelini, Maresca, and Russo 1996; Sheldon and Maurer 1998).

3.2.2 Historical experience

Chain Reactions. When the Continental Illinois Bank, at that time the seventh biggest bank in the US, with assets of more than $32 billion, has defaulted in mid-1984, it was the largest correspondent bank in the country. That means that it was the bank with the largest panel of interconnections within the system, and with the highest impact on its peers in case of an unexpected failure. Almost 2,399 banks were holding deposits at or loaned funds to this bank. Because the Federal Deposit Insurance Corporation (FDIC) fully protected all creditors when Continental got to bankruptcy, none of the 2,300 banks has suffered any losses. The question still holds: what would have happened if all creditors had not been fully protected? Could have been a disaster or a minor effect? The figures do not lead to an extremely concerning situation. Some 1,325 banks had exposure of less than $100,000 and thus were totally insured by FDIC. Although the reminder had some risk exposure, a study undergone by the House Banking Committee found that if Continental's loss were as large as sixty cents at one dollar (that suggests a recovery rate on assets of only 40 percent), which was more than ten times either the estimated loss or the actual loss as of the time of its resolution, only twenty-seven banks would have suffered losses in excess of their reported capital and thus would have become insolvent (according to the American Congress 1984). Such losses summed $137 million. Other fifty-six banks would have incurred losses equal to between 50 and 99 percent of their total capital, in an amount totaling $237 million. If the losses of Continental would have been smaller, for example ten cents at one dollar (still twice as much as the factual loss), no bank would have suffered a loss greater than 50 percent from its own capital. Banks, seemingly, acted towards their protection through limiting the uninsured exposures relative to their capital and through careful monitoring of their positions. Given the relatively small size of the loss, it is also improbable that any bank with a deposit amount of maximum $100,000 made at Continental, would have failed if those deposits were not insured, since the maintained capital was well in excess of that amount.

Spillover losses in the United States existed also when Herstatt Bank in Germany defaulted and was closed by the German authorities in 1974, often cited in the literature as evidence of the systemic risk. Herstatt risk became a generic term for any cross-border settlement risk for banking and non-banking institutions. Losses were firstly incurred by banks that had entered into foreign-exchange transactions with Herstatt, not that much due to the losses at Herstatt but more due to the fact that the exchange in payments between these banks and Herstatt was not simultaneous, given the time difference. Thus, the counterparty banks paid the mark side of the transactions towards Herstatt during the working day of the counterparty, but the German authorities closed the bank at the close of the business day in Germany before Herstatt was scheduled to make the corresponding dollar payments to the counterparty banks during their business day, primarily in New York, many hours later (Eisenbeis 1995). If the German authorities had waited until the end of the business day on the Eastern Coast of the United States, before closing the Herstatt Bank, the counterparty losses would have been much less or perhaps avoided. Instead, they would have accumulated to the depositors of Herstatt Bank and to the German bank deposit insurance fund. In this way, much of the spillover from the Herstatt Bank to other, primarily foreign, banks from these transactions represents more of a government risk than a market risk. Even in this case, no other bank failed as a result of this debacle.

Common-Shock Reassessment. Excepting fraud, clustered bank failures in the United States were caused most of the times by adverse conditions in the regional or national macroeconomies or by the asset-price bubble bursts, especially in real estate, and not by exogenous "sunspot" effects (Allen and Gale 1998; Benston and Kaufman 1995; Kaufman 1999). Banks usually fail due to their exposure to a common shock, like a depression in key sectors like agriculture, real estate or oil prices (according to Cottrell, Lawlor, and Wood 1995), not because of direct spillover from other banks, without exposure to any shock.

A study of the bank failures from 1865 to 1936, soon after the introduction of the federal deposit insurance in 1933, found that the most cited cause of default in that period was the local financial distress, and the next most cited was incompetent management. Runs or loss of public confidence were cited in less than 5 percent of all 4,449 causes listed for the 2,955 failures surveyed (according to O'Connor 1938, 90).

The negative news about a specific bank or group of banks seems to determine a process of reexamination from the side of the market participants for identifying their risk exposures. Although the dynamic of the deposits and of the shares' value of a big group of banks can be affected immediately, the sorting-out process may be initiated relatively quickly. To the extent in which such dynamics (deposit flows and stock values) of the innocent banks (those with large capital or different risk exposures) are affected adversely by a bank failure or other adverse event, they rebound within a day or two so that no lasting significant announcement effects on stock values are observed (Kaufman 1994). Likewise, a study of stock-market reaction to the disclosure of supervisory actions by bank regulators reported that the announcements can cause spillover effects to other units. However, according to Jordan, Peek and Rosengren (2000, 298), "only banks in the same region… (or) with similar exposures are affected".

The empirical evidence suggests that during the Great Contraction between 1929-1933 and during the banking crisis in Chicago in June 1932, liquidity problems and depositor runs only rarely, if ever, drove economically solvent independent banks into insolvency (Calomiris 1999; Calomiris and Mason 1997, 2000; Wicker 1996). Roughly most of the banks that failed during the Depression were small-sized banks. Although in 1930, 1931, 1932, and 1933 the annual bank failure rate was 6, 11, 8, and 28 percent, respectively, the percentage of deposits in the failed banks was only 2, 1, 2, and 12 percent of deposits in all banks. A study of this period concluded that "these failures occurred primarily because of adverse local business conditions rather than because of spillover from other failed banks outside their market areas" (Benston et al. 1986, 62). Though, as in most preceding severe U.S. banking crises, there were runs out of bank deposits and into currency, particularly by smaller depositors, so that the aggregate currency-deposit ratio rose, and aggregate bank credit and deposits decreased. Thus, contagion became rational and information based, but ignited by a common shock.

Moreover, there is no empirical evidence according to which the bank failures caused downturns in the macroeconomy. Rather, at least in the case of the United States, the direction of causation appears to be primarily from downturns in the macroeconomy and the stock market (asset price bubbles) to increases in bank failures (Benston et al. 1986; Benston and Kaufman 1995; Calomiris and Gorton

1991; Mishkin 1991). The defaults in the banking sector seem to rather exacerbate the magnitude of the downturns that caused them. The extent of adverse spillovers from the banking sector to other sectors heavily depends on the degree of leverage. Thus, the higher the leverage of business firms and households, the more vulnerable they are to losses and insolvencies from bank failures (Davis 1995; Kaufman 2000a). One reason for the small negative effects of bank failures on other units and on the macroeconomic standing overall is possibly the policy of effectively giving both insured and often uninsured depositors at failed banks immediate access to the full amount of their insured funds also the estimated recovery value of their uninsured funds. In such a way, there is no or at most just a brief loss of liquidity to depositors or to the economy (Kaufman and Seelig 2002).

In the majority of the countries, the payment of claims to both insured or uninsured depositors is done in months, if not years, after the bank is resolved as the funds are collected by the receiver. In this idea it comes the following statement of Dermine, a European banking analyst:

“The issue is not so much the fear of a domino effect where the failure of a large bank would create the failure of many smaller ones; strict analysis of counterparty exposures has reduced substantially the risk of a domino effect. The fear is rather that the need to close a bank for several months to value its illiquid assets would freeze a large part of deposits and savings, causing a significant negative effect on national consumption.”

Usually depositors fear of the loss of liquidity in bank failures as much as they fear of the loss of credit value, especially when the credit losses are absent if the deposits are wholly insured and relatively small for uninsured depositors.

In many economies, especially in the developing or transition ones, the evidence of contagious systemic risk in banking is often confounded with political risk outcomes, like crises stemming from freezing, confiscation, or devaluation of bank deposits, regardless the denomination of the currency or with evidence of defaulting on bank-held government securities by local authorities. The bank problems often stem out not from actions of the banks pursued by themselves in their banking activities, but from the governments’ use of the banks to pursue their nonbanking policies. The banking closures happened in Argentina may be taken as good examples of such government behavior. When the crises have their sources in banking activities, they almost always reflect flagrant abuses that the government allowed, if not even supported, and the government's incapacity to resolve the insolvency in a timely and efficient manner (Whitehouse 1999 uses the crisis in Russia to support this idea). Such crises can be described more accurately as "government created" rather than "bank created".

The evidence presented above strongly supports the idea that in the absence of the deposit insurances, depositors and other bank creditors take adequate protective action on their own in order to diminish sufficiently the probability of losses to themselves and of spillover to other banks. Much if not all of any externality of contagion seems to be adequately priced by the market itself and internalized. Such conclusion maintains even when it appears to exist some positive likelihood that some or all of the affected claimants may be protected partially or totally ex post de facto. The majority of the banks' shareholders use to take even stronger protective actions in the absence of regulations or other regulatory actions that project a perception of safety. In practice, private banking seems to be no less stable in an atmosphere of little government prudential regulation than with more such regulation; nor does it appear any less stable than other nonregulated industries.

3.2.3 The period before 1988

Before 1988 bank regulators in different countries tended to regulate bank capital by setting minimum levels for the ratio of capital to total assets. Though, definition of capital and the ratios considered acceptable fluctuated from one country to another. Some countries implemented their regulations more conscientiously than others. Banks competed internationally and a bank competing in a country where capital regulations were slack was considered to possess a competitive advantage over one operating in a country with a stricter capital regulatory framework. Additionally, the considerable exposures of the major international banks towards less developed countries like Mexico, Argentina or Brazil, and the accounting diversions used occasionally to manage those exposures were starting to raise questions on the adequacy of capital levels.

Another problem was that the types of transactions entered into by banks were becoming more complicated. The OTC derivatives market for products like interest rate swaps, currency swaps, and foreign exchange options was growing too fast. These contracts raised the credit risk taken by banks. For example, let's take an interest rate swap. If the counterparty in such a transaction defaults when the swap has a positive value to the bank and a negative value to the counterparty, the bank loses money. Many of these newer transactions are usually registered "off balance sheet". This means that they had no effect on the level of assets reported by a bank. Consequently, they had no effect on the amount of capital the bank required to keep. It became apparent to regulators that total assets were not any longer a good indicator of the total risks taken. Therefore, it was needed a newer, more sophisticated approach than that of the minimum levels settlement for the capital to total balance sheet assets ratio.

Such problems determined the supervisory authorities from Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States to form the Basel Committee on the Banking Supervision. They meet regularly in Basel, Switzerland, under the patronage of the Bank for International Settlements. The first important result of these meetings was a document called "International Convergence of Capital Measurement and Capital Standards", referred to also as "The 1988 BIS Accord" or as "Basel I".

3.2.4 The Basel I (BIS 1988) and Basel II Accords

The 1988 BIS Accord was the first attempt to set international risk-based standards for capital adequacy. It has been the center of numerous criticisms as being too simple and to a certain degree arbitrary. Despite those, all agreed that the Basel I Accord has been a considerable achievement. It was signed by all 12 members of the Basel Committee and paved the way to significant increases in the resources banks devoted to measuring, understanding, and managing risks.

The BIS Accord defined two minimum standards for meeting acceptable capital adequacy requirements. The first standard was identical to that existing prior to

1988 and required banks to have an assets-to-capital multiple of maximum 20. The second standard introduced what has become known as the Cooke ratio. For the majority of the banks there was no problem in satisfying the capital multiple rule. The Cooke ratio was the key regulatory requirement.

In calculating the Cooke ratio both on-balance-sheet and off-balance-sheet items are considered. They are used to calculate what is known as the bank's total risk-weight assets (also occasionally referred to as the risk-weighted amount). It is a measure of the bank's total credit exposure.

Basel II Agreement is the second agreement established in the Swiss city to establish recommendations on the banking laws and rules, starting from the decisions issued by the Basel Committee for Banking Supervision. The scope of the Basel II Agreement, initially published in June 2004, is that of creating an international standard that the banking rule agencies could use in creating legislation. Basel II comes in order to prevent any types of financial or banking risk with which banks may confront with when considering the increase of the necessary capital. The supporters of this version of the agreement assert that such an international standard would protect the international financial system against any problems that might occur following a major bank default. Basel II tries to fulfill its targets through a rigorous set of requirements as regards the risk and the capital management, set that seeks to ensure capital reserves high enough to defend the bank against any risks to which it is exposed. Generally talking, the bigger the risk the bank is exposed to, the bigger its capital should be, in order to maintain the economic solvability.

The scopes of this agreement may be synthesized in three categories:

a) Ensuring of a capital allocation according to the assumed risk
b) Separating the operational risk of the credit risk, and correct quantification of both risks
c) Reduction of the subjectivity resulted from these regulations

Basel II still left unsolved the issue of capital formal definition that differs from the accounting value in some important aspects. The definition given in Basel I remained unmodified.

Basel II uses a concept built on three pillars: (1) minimum capital requirements (addressing risk), (2) supervisory review and (3) market discipline- promotion of greater stability in the financial system. Basel I dealt with only parts of this three pillar-approach. For example, as regards the first pillar of Basel II, only one risk, that is credit risk, was dealt with in a simple manner while market risk was an afterthought. Ultimately, the operational risk was not dealt with at all.

The first pillar deals with maintenance of regulatory capital calculated for the three components of risk: credit risk, the operational risk and market risk.

The credit risk is calculated in three different ways: according to the standard procedure, Foundation IRB (Internal Rating-Based Approach) and Advanced IRB.

As regards the operational risk, there exist three different approaches: the basic indicator approach (BIA), the standardized approach (TSA) and the advanced measurement approach (AMA).

Finally, for market risk, value-at-risk (VaR) approach is the one preferred.

The second pillar deals with regulatory response to Pillar 1, allowing regulators to use improved “tools” over those available offered by Basel I. It also offers the regulatory authorities a framework for dealing with all other risks banks might face like: systemic risk, pension risk, strategic risk, reputation risk, liquidity risk and legal risk, which the Accord combines under the title of residual risk. It enforces the banks’ ability to review their own risk management system.

The third pillar obliges banks to the transparency enforcement when it’s about their own financial information. In other words increases the disclosures banks must make. This is designed in order to permit the market have a better picture of the overall risk position of the bank and to allow the counterparties of the bank to price and deal appropriately.

3.3 Prevention of the systemic risk

The systemic risk becomes a concern only in decentralized environments in which banks face credit risk in their mutual transactions. Usually, regulatory authorities dispose of a large span of tools in order to take action against the systemic risk. Traditionally, governments have implicitly insured most of the interbank claims by saving distressed banks through discount loans, facilitating the use of purchase-and-assumptions, nationalizations, etc. However, it is widely recognized that such policies do not provide proper incentives for interbank monitoring and may lead to substantial cross-subsidies from solvable banks to the economically insolvent ones by using a government-mediated mechanism. Such a concern on the moral hazard has ultimately made the politicians and representatives of the regulatory bodies to consider alternative ways of reducing the government's exposure to the banks' failures.

An alternative way of preventing the systemic risk would be to centralize banks' liquidity management. An example of putting in place such a strategy is creating a payment system in which the Central Bank acts as a counterparty in all transactions and as a guarantor for the finality of all payments. To the extent that the Central Bank bears the credit risk if the sending bank defaults, the failure cannot spread to the receiving bank through the payment system. Likewise, the American Fed Fund finances the market, acting as a global manager of liquidity; thus banks do not transact between them, but with the Central Bank (Fed, respectively). The Central Bank would thus have a better control on the interbank positions and would further prevent systemic risk from propagating over the interbank market.

Last, the bank transactions on derivative market could be protected through sufficient collateral in such a way that banks do not grant credits to each other. Whether the government is affected by a bank default in a centralized system heavily depends on the constraints set on the banks, but, in any case, centralization (like insurance) has a strong effect on the systemic risk reduction. Unsurprisingly, reformers tend to respond to the existing concerns on the systemic risk and moral hazard by promoting projects targeted to reducing interbank linkages, like tighter collateral requirements in settlement systems, qualitative reductions in the volume of the interbank lending, and restrictions on banks' participation at derivative markets.

Unfortunately, the reforms cannot be framed in an integrated conceptual framework. As previously stated, the economic theoreticians have granted the systemic risk relatively little attention. The bank literature initiated by Bryant (1980) and Diamond-Dybvig (1983) mostly concentrated on the solvency of the individual banks and left systemic risk aside for future research (actually, both banks considered a single "representative" bank). Some papers analyzed the incentive constraints imposed by the possibility open to depositors to fake liquidity needs in order to benefit from the favorable reinvestment opportunities (Helwig 1994, von Thadden 1994a, b) or to ex ante invest in profitable illiquid assets (Bhattacharya-Fulghieri 1994). The article written by Bhattacharya-Fulghieri approaches an insurance mechanism among banks facing idiosyncratic shocks. Like in Hellwig and von Thadden, private information about the realized idiosyncratic liquidity needs prevents the achievement of the optimal insurance allocation. While Bhattacharya and Fulghieri derive interbank contracting, they have no peer monitoring and thus the optimal private contract can be put in practice by a centralized liquidity management in which the Central Bank acts as counterparty in all transactions. Therefore, systemic risk cannot rise. There is also literature written on the topic of peer monitoring in LDC credit relationships, although this literature doesn't precisely study the topic of prudential regulation and that of systemic risk (for example Amendariz 1995 and Stiglitz 1990).

3.4 Managing the systemic risk

Following what discussed before, then, what is the most appropriate way to be followed by both banks and bank regulators to deal with systemic risk? The analysis clearly shows that the private-market incentives can and actually do play a major role in limiting the systemic risk and that the government should always be highly sensitive to whether its actions are either undermining or reinforcing the private mechanisms (Kaufman 1996). The governments' actions are highly important in designing and using various safety-net measures. However, the issues are not easy ones, and it is extremely useful to undertake a normative analysis in terms of the not mutually exclusive definitions of systemic risk given earlier.

3.4.1 The macroshock

If the value of an asset or currency drops abruptly and this affects a country's whole economy, banks cannot stay immune. The history has many examples in which banks proved to be particularly vulnerable because debtors failed and collateral depreciated. One example would be the banking and currency crises that hit Indonesia, Korea, Malaysia and Thailand in 1997 and Russia and Brazil in 1998. All banks will incur losses in deep recessions or when asset bubbles (especially the real estate that is mostly used in the collateralization) burst. Weaker banks will become economically insolvent and defaults may spread beyond them.

By far the most important contribution any public authority can bring to preventing macroshocks and their effects is to avoid adopting monetary and fiscal policies that produce them or to induce policies that moderate them. Such policies lie beyond the scope of this thesis. However, it would be interesting to be observed that many countries have small undiversified economies highly vulnerable to external disruptions that they have little capability to control or offset (Brock 1992). In this thesis I will make no differentiation and I will consider macroshocks from both perspectives, internal and external.

To protect themselves against such contingencies, banks make use of various risk-management techniques, including those that are designed for the maintenance of higher capital ratios to absorb unexpected losses. However, it is not an easy task to anticipate the likelihood and scale of extreme events and therefore the amount of capital that a bank, given its risk preferences, must maintain. In the majority of countries, banks do not even need to try to protect themselves against very rare events because the public authorities of the countries they live in have adopted de jure or de facto deposit insurance or other guarantee arrangements that in large part free banks from pressure exercised by depositors at risk and usually replace regulatory capital requirements for market requirements. The empirical evidence shows that failures occurred at macro level (as against to individual bank failures) usually arise more from shortcomings in government monetary, fiscal or regulatory policy than that from deficiencies in bank management. Therefore, the cost of such failures will be placed more suitably on the government's shoulders than on the bank's ones, or on the depositors' ones (Scott and Mayer 1971). However, the bank's and depositors' responses and actions to damaging government policies are likely to aggravate the risk taken, the vulnerabilities of the financial sector and the magnitude and negative effects of the macroshock (Crocckett 2000).

For example, the federal deposit insurance demonstrated efficient in preventing banks from failing in the United States' history of 2006 or before. They proved as well efficient in blocking the avenue of contagion spread – but always at a cost. The same evidence shows that the deposit insurance is associated with an increase in the costs of the initial insolvencies in two ways (Gupta and Misra 1999). First, the institutions were relieved of whatever market discipline might have been exerted by insured claimants. If the deposit insurance is underpriced, as it is not uncommon, it contributes to a moral-hazard problem in which bank management is induced to take on greater risk. Then, bank supervisors have strong incentives to delay recognition of insolvencies and payment for the losses they produce. No matter how the political regime looks like, and therefore no matter the existing of political risk, it is advantageous to postpone costs beyond one's term in office. As recognition and resolution are delayed, losses may grow rapidly. Incumbent management, if left in control, has then every reason to take high-risk (and even negative present-value) investments, and governmental liquidators have limited expertise and weak incentives to maximize profits.

The evidence on the US savings-and-loan debacle of the 1980s confirms such a scenario. Thus, in 1983, the negative net worth of the savings-and-loan industry as a whole was quantified at about $25 billion after the sharp decline in interest rates had reduced much of the earlier losses attributable to interest-rate risk (Ely 1993; Kane 1980). Yet, by 1995, at the end of the long-deferred resolution process, the cost to taxpayers has climbed to almost $160 billion, most of it attributable to losses from credit risk (FDIC 1998). Some bank runs (caused by uninsured depositors for the most of the cases) took place in the 1980s under deposit insurance, but the total losses of the institutions were of the same order of magnitude (almost 3 percent of GDP at the level of 1990) as in the Great Depression years 1930-1933 without deposit insurance and with numerous bank runs (Calomiris 1999).

The undesirable side effects of deposit insurance have generated efforts to counteract them by regulation. The Federal Deposit Insurance Corporation

Improvement Act (FDICIA) of 1991 has changed a flat-rate deposit-insurance assessment fee to a risk-related premium system to deal with the moral-hazard problem. In July 1988, The Basel Committee on Banking Supervision adopted a set of risk-based minimum-capital standards for international banks, in part to offset the substitution of government guarantees (public capital) for private capital in banks (Peltzman, 1970).

3.4.2 Failure chains

As regards the chain-reaction or direct-causation failures transmitted through interconnected institutions, there are two ways of attack. Supervisors can reduce the amount of loss in the initial failure by taking action promptly with closure rules enforcement. Private banks have also to their disposal many ways of fight, among which the most common are cautious monitoring and exposure ceilings, to protect themselves against failures by their counterparties, and it is important that regulation not undermine their incentives to do so (Rochet and Tirole 1996). Deposit insurance should not cover the interbank operations; no weaker claim for customer protection can exist than that of another institution in the same business engaging in informed and voluntary dealings. There should be no safety-net "too big to fail" policy (meaning too big to pay off in full all depositors and even other creditors at failed institutions) - a policy that eliminates entirely the need for counterparties to the largest banks to take even elementary measures to reduce their risk exposures.

In the current technological environment, the biggest volume of interbank transactions is undergone through the large-value-payments system, and is often seen as a central point of systemic risk (Corrigan, 1987). In 1999, the medium daily value of funds transferred through the Fedwire was of almost \$1.4 trillion and of government securities of almost \$700 billion, according to the Federal Reserve Board (2000). If the default of a major bank made that bank to be incapable of meeting its payment obligations in its transactions, fear of a cascade of default along the payment system might arise, thus producing what is called as "gridlock". The Fed's response was to secure payments of transfers made by a bank on Fedwire, thereby assuming the credit risk that the transfers might not be wholly collectible at the end of the day. Before 1994, the Fed offered such a guarantee of such daylight overdrafts with no charge. Thus, banks had little or no reason to pay careful attention to the financial condition of their interbank payments to counterparties, and the Fed's exposure on daylight overdrafts grew accordingly (Hancock, Wilcox and Humphrey 1996).

Starting 1994, Fed attempted to put an end to the problem by perceiving a charge (at a fairly low annualized rate of 0.36 percent) for daylight overdrafts and by setting limits on net-debit positions. Still, it funds approximately 40 percent of funds transfers by expanding daylight overdraft credit (according to McAndrews and Rajan 2000), which in 1999 ran at an average magnitude of $50 billion per minute (Zhou 2000). Once again, regulation has served to weaken banks' incentives to protect themselves. With no payment finality, banks would themselves limit their credit exposures by monitoring and rating their counterparties, charging accordingly for credit extended, limiting the size of their credit positions, and requiring collateral.

3.4.3 Common shock and reassessment failures

The other mechanism of contagion is represented by the failure or near failure of one or several institutions from losses originating elsewhere and the reassessment by depositors, creditors and shareholders of other institutions (common shock contagion). Discussions over this type of shock have focused on the question whether the reassessment of risk, in light of new information revealed by the initial failures, was rational and discriminating or panic driven and undifferentiated.

The empirical evidence indicates that depositors could successfully identify the solving banks of the unsolving ones and thus could withdraw their deposits from the nearly failed banks much sooner than the supervision authorities could do so.

The learned lesson is that banking supervision authorities should not hinder but instead enhance the disclosure of information on the financial condition of banking institutions they supervise. Bank depositors, like bank counterparties, in many situations can protect themselves if all reason to do so is not destroyed. Meanwhile, supervisors should facilitate their ability to differentiate among banks in a time of crisis or uncertainty.

In order to enhance bank transparency, supervisory institutions should permit, rather than prohibit banks to disclose the contents of their examination reports and supervisory ratings (Jones and King, 1995). The banking agencies, considering the examination and auditing reports as their own property, usually refuse to allow outside auditors to access their organization's records. In 1989, the US Congress asked such access by statute but eliminated that provision two years later in the FDICIA. The practice of mandatory secrecy, a skeptic might assert, is apparently founded either on the notion that depositor confidence should be based on ignorance or on the idea that management is always willing to disclose negative information to supervisors because they think nothing much will result from it, compared to the consequences of telling the world at large, or perhaps on the reluctance of regulators to face a market test. However, none of these propositions is reassuring.

3.5 Conclusions on systemic risk

Many regulatory actions taken in the banking system had a double effect, but still not proved to be inefficient or, even more, counterproductive. As regards the systemic risk, the exclusive concentration on the measures of deposit guarantee and on those governmental measures of protection against such risk, proved, yet well-intended, highly expensive. However, this does not minimize their role and the necessity for their implementation.

The primer scope of this chapter has been to present the sources of systemic risk, the transmission mechanisms and the protection techniques against it. The second scope was to emphasize part of the costs incurred when trying to deal with it. The most appropriate protection against the systemic risk is a strategy that would minimize the government's back-up role and that would maximize the effectiveness of private sectors as the first line of defense against the systemic risk. Yet, the governmental implication may have well meant that the benefits have outweighed the costs and that the total intervention of the public authorities should occur only as the second line of defense. Such measures include the deposit insurance measures, the buffer role assumed by the Central Bank in a centralized payment system. It is not less true the fact that, through its strategy of risk control, the regulators may have well contributed to the systemic risk as much as they retarded it. The way to go forward in terms of supervisory actions is to reduce potential counterproductive government policies and a tighter collaboration between public and private actions, in both defense lines, for a more coordinated strategy targeted to risk reduction.

4. Credit rating agencies

The international credit rating agencies play a central role in many domestic and cross-border transactions. Their main role is to evaluate the credit risk of private or public institutions that play on the international markets the role of borrowers or of issuers of fixed-income securities. The rating agencies job is to extract and make sense of the vast amounts of information available regarding an issuer or borrower, as well of its market and economic conditions at the moment of transaction, with the scope of giving the private or public investors and lenders a better understanding of the risks incurred when lending to a particular borrower or when purchasing the fixed income securities of a specific issuer. Typically, a rating represents the opinion fully assumed by a rating company, on the probability associated to a specific issuer of repaying in a period of time a certain debt or financial obligation, or all the issuer's debts generally.

Lenders, fixed-income investors, issuers and governmental regulatory authorities use the credit risks ratings issued by the credit risk rating agencies for a very large panel of purposes. Thus, corporate borrowers and issuers rely on opinions given by the rating agencies through their assessments, in order to build up the capital raise strategies. Meanwhile, the investors and lenders insist on being compensated for the uncertainty incurred when investing or lending, when they commit to take debt issuers pay for the uncertainty taken by charging higher interest rates. It's straightforward then to understand that the service the rating agencies bring to reducing uncertainty for investors represents an important contribution to the cost of capital reduction incurred by issuers. Lenders and fixed-income securities investors make use of the ratings in order to evaluate the possible risks they face when lending money or when investing in the securities of a particular issuer. As well, the institutional investors (like investing banks, hedge funds) and fiduciary ones (those independent authorities that invest on behalf of others, like managers of trust funds or pensions, sometimes insurance companies), use credit ratings for a better allocation of their investments in a diversified risk portfolio. The last but not the least, the regulatory authorities use ratings for setting capital charges for financial institutions consistent with the risks associated with the investments undergone.

4.1 The role of the credit risk rating agencies

4.1.1 The rating agencies' activity

A credit rating agency is a company that assigns credit ratings to issuers of certain types of debt obligations as well to some types of debt instruments themselves. Sometimes credit ratings are also allocated to the servicers of the underlying debt. Usually, the debt issuers (especially when it's about securities issuance) are private companies, special purpose entities, state governments or public governments, non-governmental organizations, non-profit organizations, or national governments that issue debt-like securities (most common form of such debt is bonds) that can be traded after their issuance on the primary market, on the secondary market.

Typically, a credit rating evaluates the issuer's credit worthiness (that is its ability to pay back a loan) and influences the interest rate applied to the particular security being issued. In contrast to a credit risk rating agency, a company that issues credit scores for individual credit-worthiness is generally called a credit bureau or consumer credit reporting agency.

A credit rating represents the evaluation of the probability that an issuer makes timely payments on its financial obligations. When it happens that the investors think that there is uncertainty or broad information asymmetries, they do not pursue towards investment making unless there is a corresponding compensation for the risks incurred. Such compensation (higher interest rates when it's about fixed-income securities) increases the cost of capital incurred by the securities' issuers.

Credit rating agencies offer services that solve part of the information asymmetry. They do this by examining the existing information on the issuer, but also the market in which that issuer finds in, the health of the whole economic system, the regional global circumstances that would affect the issuer and the type of the security. Since issuers may issue not one but more types of fixed-income securities (long-term and short-term instruments representing senior or subordinated debt), different securities belonging to the same issuer may have different credit risk profiles.

Summing up, the rating agencies assist investors in acquiring a more comprehensive understanding of the whole panel of risks and uncertainties they face when investing in a given debt security, contributing also to reducing the costs associated to capital raises by issuers.

In contrast to public and private credit registries (or credit bureaus) that assist investors in overcoming some information asymmetries by offering them useful information on the credit history of the issuers, the credit rating agencies usually employ additional activities like more in depth analysis of current and prospective factors that may also affect credit risk in the future. By researching and analyzing information from a host of disparate sources, the rating agencies can perform the same functions as the securities analysts. Like them, the agencies play an important role in the relationship between investors (including the institutional investors) and issuers and can contribute to the market overall understanding of the huge volume of raw data that investors will wish to assimilate to make better informed decisions. Sometimes this might prove to be difficult due to the high heterogeneity of the informational sources. Yet, as compared to the analysts, the rating agencies do not make opinions on whether a particular debt security, at a certain moment of time, should be brought, sold or kept. Nor does a credit rating provide an opinion on the value of an issuer's equity securities. Rather, the credit risk categories reflect the issuing institution's point of view on the probability that the issuer may fail on its financial obligations (when it's about an issuer rating) or default on a specific debt or fixed-income security. Additionally, the offered assessment doesn't necessarily reflect an opinion on the value of the security.

The weight the investors place on an assessment made by a credit risk rating agency has a proportional relationship with the reputation of the agency itself. Such reputation may be a function of many factors that are not necessarily directly linked to the agency's capability of accurate prediction of default rates. However, if an agency's reputation for timeliness and accuracy is about to suffer, the importance the investors give to the agency's ratings would suffer as well.

4.1.2 Types of the rating agencies

Presently there exist numerous credit rating agencies that operate in most markets around the globe. They vary significantly in size, focus and methodologies. Some specialize in the services they offer, but also focus on specific regions or sectors of economy in which they operate. Some others offer credit ratings on firms (including privately-held companies) but do not rate the credit risks of specific fixed-income securities. Sometimes, some regional agencies functioning in the emerging markets (or local affiliates of large international rating agencies) specialize on analyzing local gradations of the issuer credit risk that may otherwise be overwhelmed or obscured by the "country risk" (like the political risk, the currency-exchange risk etc.) that all issuers face on that market.

The largest three rating agencies, that are also the most important ones - Moody's, Standard & Poor's (S&P) and Fitch - operate internationally. They provide credit ratings for both corporate and sovereign issuers, and specific fixed-income securities. In contrast to many mid- or small-sized rating companies that produce revenue by offering ratings to investors on a subscription basis, Moody's, Fitch and S&P generate most of their income by charging issuers for ratings, ratings that are then provided to the public free-of-charge.

Additional to the credit rating activity, the rating companies provide supplementary business services or are themselves affiliates of larger companies that offer a broader span of activities. Such services are usually ratings assessment services where issuers present hypothetical scenarios to the agencies in order to have determined how their credit rating can be influenced by a proposed business activity. Other services may be risk management or consulting services, targeted to assist financial institutions and other firms to manage credit and operational risks. When the local agencies are simple affiliates of larger institutions, the services provided by the larger group may or may not be in a direct relationship to the credit rating business.

4.1.3 The rating process

The rating agencies may employ a variety of processes in their activity, depending on the agency's type and on the methodologies they use. Some such agencies (mostly the larger ones) rely heavily on a process in which analysts employ both quantitative and qualitative methods on whose base they produce the assessment and then report their analysis to a rating committee. Other agencies rely solely or mostly exclusively on quantitative models in which the evaluation process is more mechanical and impersonal, based on statistical analysis of an issuer's financial statements to obtain a rating. Sometimes, the process of an agency may be proprietary. It's extremely subjective to benchmark these methodologies and it cannot be stated which method is superior to other; any appraisal of the activities of the rating agencies should recognize that new developments (whether they are technological, methodological or statistical ones) in analysis making yield new and various approaches and results in the future.

Despite the different approaches employed by the rating companies in evaluating their clients, the largest agencies tend to employ similar rating procedures when instrument types are similar. The rating process itself is designed in such a way to facilitate analytical consistency and capitalize on the domain's expertise. At the basis of each process undergone by a large rating agency, is found a rating committee. Its role is usually to either initiate, withdraw or change a rating. The rating committees are generally made up of a lead analyst, managing directors or supervisors and junior analytical staff. The decisions in such a committee are taken based on a simple majority vote and represent the rating agency's own opinion as regards the probability associated to an issuer to repay in a timely manner its financial obligations.

The rating process starts with the nomination of a lead analyst in charge with the rating preparation. Its job is to first ask the information from the issuer and to dig in for other available information resources that would offer an enhanced understanding of the issuer and of the overall economic or industry specific environment. For this purpose, analysts use to arrange meetings with the senior management (or government officials when it's about a public issuance of bonds) and even visit the issuer's offices. Following such investigations, the result is materialized into a draft report and the analyst makes a recommendation with respect to the issuer and its securities. Such report is then sent to the rating committee which convenes on a credit rating.

Once the credit rating decision is taken, the analyst informs the client on it and may provide additionally a draft of the rating press release or report to allow the issuer to make a factual verification and, in the case of a public release of the report, to ensure that confidential information originally provided to the agency for the rating preparation will not be publicly disclosed. In the eventuality of a negative acceptance of the proposed rating coming from the side of the issuer, this one can request that the rating committee reconsider the rating's decision. The rating agency will decide to reconsider its decision only when the issuer presents new material information or when it indicates that the agency has relied, at the time of its analysis, on incorrect information.

After receiving the issuer's comments and after any subsequent changes will be made, the larger rating institutions will issue a press release which will summarize the rating decision and the rationale behind of it. The agency will generally continue monitoring its client or its client's securities on an ongoing, yet less intensive manner, and will continue to have periodic meetings with seniors or management representatives of the respective issuer.

4.2 Aspects of the activities of the international rating agencies

4.2.1 Users of the credit ratings

The main users of ratings are:

4.2.1.1 Bond issuers

Issuers value the credit ratings because they allow lowering the costs they pay for the capital increase. Thus, the credit ratings reassure investors on the risks they encounter when making investments in a certain bond, and also on the competence, capability and responsibility of the management. When investors are reassured, they tend to require lower returns on the investments made.

Issuers also place a great emphasis on the credit ratings as such ratings often represent an independent verification of their credit-worthiness. In the majority of cases, a large bond issuance must bear at least one rating from a well-known credit rating agency in order to ensure the success of the issuance (without it, the issuance may be undersubscribed as investors might prove reluctant to purchasing such bond, or the price offered to the investors might be too low for the purposes of the issuing company). Recent studies indicate that many institutional investors prefer that an issuance made for the purpose of debt covering have at least three ratings.

Issuers also use credit ratings in certain structured finance transactions. For example, a firm that benefits from a high credit rating and which intends to carry out a specific risky research project can establish a legally separate entity with certain assets that would own and conduct the research work. This “special purpose entity” would then assume all the research risk related to that project and issue its own debt securities to finance the research. This special purpose entity would most probably bear a low credit risk, and the issuer would not have to pay a high rate of return on the bonds issued. Such a move would have the advantage of the fact that the parent company’s credit rating would not be affected because of the legal character of the separate entity. On the other side, a company that has a low credit rating might not be able to borrow on better terms if it were to form a special purpose entity, transfer significant assets to that subsidiary and issue secured debt securities. In this way, if the venture entity is about to fail, the lenders would recourse to the assets owned by the special purpose entity. In such an eventuality, the interest rate that the special purpose entity would have to pay as part of the debt offering, would be lowered.

As before mentioned, the same issuer may have different credit ratings for different debt instruments issued. Such difference is the result of the structure of the bond, the way it has been secured, and the degree to which the bond is subordinated to other debt. Lots of large credit rating agencies provide additional “credit rating advisory services” that essentially advise a particular client on how to structure its bond offerings and on the possible special purpose entities it could create in such a way to ensure a given credit rating for a certain debt amount. However, this may constitute a source of potential conflict of interests as afterwards the credit rating agency may feel obligated to grant the issuer a given rating if this one follows closely the agency’s pieces of advice on structuring its offering. Some rating agencies avoid such conflict by refusing to rate debt offering for which its advisory services were sought.

4.2.1.2 Investors in fixed-income securities

Investors often make use of the credit ratings when assessing whether to purchase a given debt security or not. If investors conform to the opinion of a certain rating agency, they may consider the issued rating as an estimator of the risk of the investment. In such situations, credit ratings act as a proxy or as a check against investors' own research and analysis of the risks related to a particular debt security. Frequently investors seek ratings issued from more than one rating agency regarding the same issuer.

Essentially, the rating represents the fastest and most convenient mean of communicating the credit risk analysis of the agency towards the market. From the investors point of view, the central function of the ratings is relatively simple. That of offering a relative ranking of the credit default probability. The rankings granted for some bonds are used as a rapid way to determine whether the bond complies with the risk standards of the investor. Investors can thus utilize the ratings for creating "acquisition lists" that bear the same functions for the individual institutions as the regulatory requirements.

4.2.1.3 Institutional investors

The institutional investors and other buy-side companies such as collective investment schemes, pension funds and insurance companies tend to find themselves among the largest purchasers of fixed-income instruments in many jurisdictions and, in many such jurisdictions investors in fixed-income securities are almost in totality institutions. Although institutional investors often employ their own analyses and for this purpose they form their own bodies of financial analysts, they frequently rely on the assistance of the rating agencies to support or refute their own assessments.

Institutional investors may use the credit ratings in order to comply with internal investment restrictions or policies that necessitate the company to maintain certain minimum requirements as regards the credit risk levels for investments, or to identify acceptable counterparties. They may also use credit ratings to construct bond indices against which they monitor the performance of fund managers or index mutual funds.

Depending on the jurisdiction, institutional investors may also rely on credit ratings in order to comply with certain market regulatory requirements.

4.2.1.4 Equity investors

Although the credit rating agencies are not equity analysts of the shares issued by the companies (quoted or non-quoted on the Stock Exchange) and their ratings cannot substitute the equity research, equity investors often consider credit ratings in their analysis of deciding for investment in a particular type of security. The issuer default rates do not post an intrinsic direct relationship with the attractiveness of the issuer's equity securities – such that a firm that bears little risk of default on a certain fixed-income security may still be confronted with a price decline in its equity securities when the business environment external conditions turn sour. Though, equity investors can show interest in the opinions issued by the rating agencies on the likelihood of default of a specific issuer on its debts, and thus may consider such opinion in making their evaluations on the equity value.

Through the Basel II Agreement of Basel Committee for Banking Supervision, the regulatory authorities in the banking sector may allow banks to use the credit ratings offered by certain rating agencies (called in the Agreement as External Credit Assessment Institutions). In the United States, the Securities and Exchange Commission allows the investment banks and brokers to make use of the ratings of the Nationally Recognized Statistical Rating Organizations. This is meant to encourage banks and other financial institutions to not maintain as reserves more capital than needed for the protection of the institution from the liquidity default if the financial institution invests its financial resources in highly liquid and safe obligations (like the governmentally issued ones).

4.2.1.5 Broker-dealers and sell-side firms

Majority of the brokerage and other sell-side companies (like investment firms that elaborate recommendations and sell securities to clients) perform their in-house credit analysis for risk management and trading purposes. Similarly with the previously mentioned institutional investors, broker-dealers and investment advisors use the ratings issued by the credit rating agencies as a second check of their own research and recommendations. Also, bond analysts at sell-side firms may use credit ratings in their overall assessment of whether to recommend purchasing, selling or holding an issuer's fixed income securities.

The investment banks and the underwriters also use to issue opinions as regards which rating agency is more appropriate to rate a fixed-income securities offering. Such companies may also offer rating advisory services with respect to the consulting activity offered to underwriting clients along the whole rating process. In some specific markets, broker-dealers may use the credit ratings to determine optimum counterparties and set collateral levels for outstanding credit exposures.

4.2.1.6 Regulatory authorities

The financial regulatory authorities post an increasing interest towards including credit ratings for a variety of purposes. Thus, they may use a rating for setting capital requirement purposes, for elaboration of the regulatory legislation governing money market funds, pension funds and other collective investment schemes, also for regulating asset-backed securities. Basel Committee on Banking Supervision forwarded a proposal that would allow banks to use credit rankings in establishing the capital requirements existing under the new Basel Capital Accord.

4.2.1.7 Private parties

Creditors and the representatives of other businesses use credit ratings in private contracts for a large category of purposes. In financial contracts, ratings act as "rating triggers". In many secured or structured financial agreements, lenders may acceleratingly repay an outstanding loan, or receive the borrower's post collateral, if the rating of the fixed-income securities issued by the borrower fall below a certain level. Counterparties and lenders occasionally require such clauses in order to help them secure collateral and recover prospective losses in cases where a borrower faces a serious likelihood of bankruptcy or default.

Nevertheless, the ratings are used in activities performed in the real estate market and in the insurance industry.

4.2.2 Barriers at the entrance on the market

Because the rating market is dominated by the three largest credit companies (Moody's, Standard & Poor's and Fitch), some barriers may exist to market entry of new entities that intend to undergo similar activities, thus unfairly limiting competition in such industry.

To be mentioned that the rating agency market is not extensively regulated and the existing regulations do not pose high difficulties to the new market participants. The nature of the rating market makes it difficult for the new entrants to succeed. Thus, issuers search for ratings from only those rating agencies that are well known and post a good reputation among the investors for the accuracy and promptness of the rating press releases. Establishing such a reputation would take considerable time and resources. Some issuers and investors prefer to use the rating services, respectively to use the opinions of those rating agencies that the governmental regulatory agencies themselves use.

4.2.3 Ratings disclosure and publication

As previously mentioned, the largest rating agencies publicly release their rating decisions with respect to the publicly issued fixed-income securities. While the rating agencies may offer the subscribers more detailed assessments regarding methodology and reasoning behind a specific rating released, subscribers do not receive the rating decisions before the agency having them publicly released first. Instead of exclusively relying on subscriber fees, the largest rating agencies receive most of their revenues from charges received from issuers in return for the ratings released.

However, smaller size and more specialized credit rating agencies do not charge issuers for the ratings released and base their businesses on revenues acquired through subscription fees. Since the large issuers usually prefer the large and renowned rating agencies as against smaller and relatively unknown agencies (especially in the cases in which the issuer has previously received ratings from one or more larger rating companies), the smaller rating agencies use to issue unsolicited ratings as a way of building their reputations.

In some countries the ratings must be disclosed by the issuer where such ratings exist, while in other countries the disclosure is mandatory only where a rating is a regulatory requirement. Other members indicated that issuers are not required to unveil credit ratings at all, while others required disclosure only insofar as a credit rating is deemed likely to have a material impact on the price of the security or if the information is considered “material information” that a shareholder likely views as essential to taking an investment decision. But the majority of the issuers opt in for the public communication of the ratings with no regard on the regulatory requisites.

As regards the moment of the rating disclosure, the largest agencies use to publicly release the rating as soon as the rating decision has been made and only after the issuer has verified the correctness and confidentiality character of the information contained in the press release.

4.2.4 The methodology and transparency of the ratings

Because the credit rating agencies differ with respect to the size and type of specialization, the process and methodology to obtain a rating may vary significantly.

Nowadays, there are no requirements as regards the information type that must be included in the press release. Usually, the larger credit rating agencies publish the methodologies used for assessing a specific economic sector. Such rating agencies also publish default studies that describe the correlation between various types of ratings and default rates in a period. The press release that informs on a given rating usually encloses key assumptions on which that rating has been taken.

The regulatory requirements do not stipulate the commitment that the rating agencies must take in order to grant the issuers the right to review a rating prior to its publication. Their majority typically allows issuers to revise the rating and the press release associated in order to correct for any existing errors and to confirm that no non-public information is released once the press announcement is made public. Moreover, some of the rating agencies ruled the procedure that allows the issuer towards an appeal process in which it can provide reliable proofs why a rating may be incorrect or fails to take into consideration relevant factors.

Some agencies publish also names and contact details of the analysts in charge with that specific rating for allowing the public to address questions, regardless of whether or not that person has a subscription to the credit rating agency's services.

4.2.5 Conflicts of interest

There are some potential sources of conflicts of interest that may arise in the activities of the credit rating agencies. The most common are:

4.2.5.1 Issuer fees

The most common conflicts of interest reside in the fact that the larger credit rating agencies receive most of their revenue from the issuers they rate. When an agency is being paid by an issuer, that specific rating producer may be inclined to downplay the credit risk faced by the issuer in order to keep that issuer among the agency's clients. The rating agencies try to protect against such a risk by ensuring that no issuer contributes with a significant share to the agency's overall revenue. Such firms sustain that, because credit ratings from a particular firm are only valuable insofar as the firm keeps a strong reputation for independence, accuracy and thoroughness, the rating agencies will remain unwilling to risk damaging their reputations just to retain a single client. Moreover, while issuers typically prefers to use a credit rating provided by a company with reasonably lax rating standards, investors are unlikely to give these ratings much weight and the issuer would pay higher costs for the capital it is trying to raise.

The agencies claim that the compensation packages are not linked to issuer fees. This, together with the use of the rating committees, removes the probability that the rating process be flawed or inappropriately manipulated.

4.2.5.2 Access to non-public information. Insider trading

The access of the credit rating agencies to non-public information is a potential conflict of interest, as long as the staff working in such agencies may be tempted to use the information to trade securities on their own account. The largest rating agencies attempt to manage this potential conflict by implementing internal procedural safeguards in order to cushion access to non-public information and by restricting or prohibiting the agencies' staff from engaging in those financial activities (including securities trading) where a conflict of interest may arise.

4.2.5.3 Ancillary advisory services

Providing auxiliary business services may constitute a potential source of conflict of interests. As such, the decisions regarding ratings may be influenced by whether the company that follows to be rated (or whose issues follow to be rated) has an additional contract with the rating firm as regards buying advisory services from the latter one. The conflict exists no matter the purchase of such services has an impact on the ratings, since such issuers may be pressured to buy them just out of fear that by not doing so could negatively influence the rating decision (or, on the contrary, buying such services may positively impact the rating).

The rating agencies address to such concerns by

1) Not offering any additional services.
2) Settling robust information barriers and corporate "firewalls" between their employees in charge with rating assessment and the employees in charge with selling auxiliary services.

3) Not offering consulting services to companies under rating assessment.

4.2.5.4 Financial interests in rated issuers

Maintaining financial relationships between issuers and credit rating companies (by holding shares in the issuer's company or by maintaining any affiliation with the issuer) poses a potential conflict of interest as well. The internal policies of the credit agencies usually prohibit them from evaluating and rating those companies in which the agency has a financial interest or from rating affiliates of the agency.

4.3 Critics brought to the rating agencies

The rating agencies are typically subject to the following criticisms:

a) *The agencies do not downgrade promptly enough the companies that face a specific risk.* As such, Enron company's rating has stayed at investment grade up to four days before the company got bankrupt, although Enron's problems have been known to the credit rating agencies months in advance they turned to bankrupt. Studies indicated that yield spreads of corporate bonds start to expand as credit quality deteriorates but before the occurrence of any rating downgrade, thing that means that market habitually leads a downgrade and questions the informal value of a rating issued by an official credit rating agency. Such a state of facts determined financial regulators to rely less on credit ratings in their activities and encourage instead banks, insurance companies and broker-dealers to use credit spreads when calculating the portfolio risk.

b) *The large rating companies are usually criticized for maintaining too close relationships with the management of the issuers whose bonds they rate.* This raises questions as regards the independence and total autonomy they have in their assessments, leading to potential vulnerability of being mislead. A usual custom in the activity of such agencies is to meet in person with the management of the companies under assessment, and advise as regards necessary actions to be taken in order to maintain a certain rating. Moreover, since the information regarding the modification of a rating issued by a large rating agency is spread with high speed, such agencies rather than charging investors for ratings, charge debt issuers. Such a state of facts induced the rating activity to be plagued by concerns on various conflicts of interest that might affect accurate and honest assessment. The two biggest rating companies, namely Standard & Poor's and Moody's are assimilated as contributors to the globalization process that determine companies to consider how a proposed activity might affect their credit rating, usually at the expense of employees, environment, or of long-term development and research. Although such concerns have a lot of empirical background, they are not necessarily consistent: as such the big rating companies face accusations as regarding abnormal familiarity with their clients, but in the meantime they are accused of unevenly looking to the financial "bottom line" and little sensitive to adjust their analyses to the points of view expressed by the management as explanations to the reasoning staying behind their decisions.

c) *Downgrading a rating can generate a vicious cycle,* as the increase of the rate of interest for such a company would not be its only immediate effect but also worsening of the relationships with other institutions also, leading to the increase of spending and decrease in credit worthiness. Sometimes, large loans granted to companies contain a special clause that makes the loan due in full when the credit rating decreases beyond a certain threshold (that typically characterizes the entrance into "speculative" or "junk bond" categories). Such a clause is called "a rating trigger" and its scope is to ensure that the bank is able to lay claim to a weak company's assets before the company turns to bankruptcy and a receiver is appointed to divide up the claims against the company. The rating triggers may cause severe effects: thus, once the company's rating is decreased, its loans may become due in full in a very short period of time; since the affected company most probably will not be able to pay all its debt in short period of time, it is forced to go to bankruptcy following a so-called "death spiral". The default of Enron has been partly caused by the activation of such rating triggers. Since then, the rating agencies placed a smaller weight on using them, even backed significant efforts towards discouraging their use, along with the enforcement of a recent requirement of the US Securities and Exchange Commission towards full disclosure of the rating triggers' existence in the US.

d) Another accusation brought to the rating agencies is that *they act many times as oligopolists on the market.* This is a direct effect of the difficulties posed to the new entrants to enter the market, given the "reputation-based" character of this activity. Especially in the financial domain, the accent is heavily put on the agencies with a reputation widely recognized. Among all credit rating agencies, it's only Moody's that is a separate, independent, publicly held company that publicly releases its financial results without dilution by non-ratings companies.

e) The credit rating agencies are frequently blamed for making errors of judgment with regards the structured products. Such accusation specially addresses to assigning AAA ratings to structured debt, which in a large number of cases has subsequently been downgraded or even defaulted. This caused problems especially to those banks at which the minimum levels of capital depend of the structured assets' ratings they hold.

f) The rating agencies have been created in order to fill in a quasi-regulatory role but since they are first of all for-profit organizations their incentives may contradict to those of an institution with regulatory tasks. This creates conflicts of interest that have been discussed above.

g) Another criticism addresses to the fact that *many of the structured products were formed by low quality loans (rated BBB or lower) but when pooled together into CDOs (collateralized debt obligations) they were assigned AAA ratings.* Thus, the stability of a CDO was more a function of the structure given to the CDO than dependent on the strength of the compounding loans. The cash flows of a CDO are in such a way structured that the first paid are the highest ranked tranches and the last paid are the lowest quality ones. This describes the “waterfall” style and poses the threat of not having enough cash flow to pay the last tranches. Thus, although the quality of CDOs was not always as high as its ratings, the credit rating agencies only accounted for a small part of the risks, allowing for an abnormal high confidence in rating of such CDOs that had poor underlying loan qualities but rated as AAA.

4.4 Short presentation of the main credit rating agencies

4.4.1 Standard and Poor’s (S&P)

The Standard and Poor’s (S&P) is a division of McGraw-Hill Company that releases financial research and analysis with regards issued stocks and bonds. It is one of the biggest credit rating agencies, next to Moody’s and Fitch.

It is well known for some credit ratings that are widely used in the financial analysis, like S&P 500, S&P / ASX 200 (Australia), S&P / TSX (Canada), S&P / MIB (Italy) and S&P CNX Nifty (India).

The Standard and Poor’s operates as a financial services company. It offers a large variety of products and services, that ranges from credit ratings, research on bond and equity, funds ratings to risk solutions, governance services, evaluations and data services. Its advisory division, called Capital IQ, is targeted to offering information and solutions to investors, financial institutions, consulting companies and corporations. It provides technological and informational solutions, including auditable company reports, a screener merging financial and nonfinancial items, an integrated public and private capital market database and various improvement tools.

The company’s history starts in 1860, when Henry Varnum Poor published the History of Railroads and Canals in the United States. Such book attempted to realize a thorough glossary of the US railroad companies’ financial and operational statements. Subsequently, Henry Varnum and his son Henry William, established H.V. and H. W. Poor Co with which they realized updated yearly versions of such book.

The company's history scripts acknowledge 1906 year as the following important development. Then Luther Lee Blake established Standard Statistics Bureau that intended to offer financial information on non-railroad companies. The Standard & Poor's Company has been formed in 1941 through the merger between Poor's Publishing (the successor of H.V. and H.W. Poor Co) and Standard Statistics.

60 years later, in 1966, S&P was acquired by The Mc Graw-Hill Companies, in which it fulfilled the role of the Financial Services division. The ratings issued by Standard & Poor's are short and long term ratings.

4.4.1.1 Long-term ratings

The S&P uses a scale from AAA to D. Intermediate ratings are also offered at each level between AAA and CCC, like for example BBB+, BBB or BBB-. Additional perspectives offered by Standard & Poor's meant to offer more information on an issuer are of guidance type (called "credit watch") as to whether the issuer is upgraded ("positive"), downgraded ("negative") or uncertain ("neutral").

Investment grade

- AAA: granted to the issuers with the best perspectives of repaying the loan, reliable and stable. Most of the institutions that fall within this category are national governmental authorities and often local public authorities
- AA: still good quality borrowers, posing more (still moderate) risk than AAA borrowers
- A: the economic situation may influence the repayment capability
- BBB: medium class borrowers, with satisfactory capabilities at the moment but still posing a certain risk.

Non-investment grade

The bonds falling within this category are often called as "junk" bonds.

- BB: higher vulnerability to the changes in the economy
- B: the financial situation fluctuates significantly

- CCC: currently vulnerable and totally dependent on favorable economic conditions to meet the financial commitments
- CC: highly vulnerable, very speculative bonds
- C: highly vulnerable bonds, company close to bankruptcy but still continuing to pay out its financial obligations
- CI: past due on interest
- R: under supervision of regulatory authorities, poor financial situation
- SD: selectively defaulted on some of its obligations
- D: defaulted on obligations and S&P believes that the probability of further defaults is high
- NR: not rated.

4.4.1.2 Short-term credit ratings

Standard & Poor's uses a scale from A-1 to D. A rating within the A-1 category may receive a plus sign (+) that indicates the very strong commitment of the borrower to repay its financial obligations. Country risk and the currency in which the repayment is being done are also considered in the rating decision.

- A-1: it indicates a very strong commitment towards meeting the financial obligations
- A-2: vulnerable to adverse economic conditions; the capacity of financial obligations' fulfillment is considered as satisfactory
- A-3: the negative economic conditions may reduce the capacity of fulfilling the financial obligations
- B: it presents significant speculative characteristics. The obligor has at the moment capacity of repaying the loans but faces major ongoing uncertainties that could adversely affect such capacity
- C: vulnerable and highly dependable on favorable economic conditions
- D: payment default. Its obligations are due and grace period may not have expired. The rating is also used upon filing a bankruptcy petition.

4.4.1.3 Stock market indices

The Standard & Poor's also publishes a large variety of capital market indices, covering each region, level of market capitalization or investment type (for example the REIT indices and preferred stocks).

Such indices are:

- S&P 500 – which is a value weighted index containing prices of 500 largest-cap common stocks that are intensively traded in the United States.
- S&P 400 MidCap Index
- S&P SmallCap Index.

4.4.1.4 Publications

Standard & Poor's publishes on a weekly basis (48 editions in a year) a stock market analysis newsletter called The Outlook which is issued in both printed and electronic version.

4.4.1.5 Criticism

The credit rating agencies, like Standard & Poor's, have been the subject of numerous criticisms following the extensive losses suffered starting 2007 in the market of collateralized debt obligations (CDOs) which occurred despite the very high ratings granted by such agencies. For example, there were the losses valued at $340.7 millions associated to the CDOs issued by Credit Suisse Group, despite the AAA rankings granted to Standard & Poor's.

4.4.2 Fitch Ratings, Ltd.

Fitch Ratings, Ltd. is a renowned credit rating agency with two headquarters, in New York and London. It was one of the three Nationally Recognized Statistical

Rating Organizations (NRSRO) designated in 1975 by the US Securities and Exchange Commission, together with Moody's and Standard & Poor's.

The founder of the company was John Knowles Fitch on December 24, 1913 in New York, having as first name Fitch Publishing Company. In 1997, December it merged with IBCA Limited (with headquarters in London) the major stake being hold by FIMALAC, a French holding. In 2000, Fitch purchased Duff & Phelps Credit Rating Co. (based in Chicago, Illinois) and Thomson BankWatch. Though the smallest in the big three NRSROs, it frequently grew with acquisitions and positioned itself as a "tie-breaker" when S&P and Moody's had similar, but not equal, ratings in scale.

4.4.2.1 Long-term ratings

Fitch long-term ratings are set up on a scale from AAA to D. This scale has been established in 1924 by Standard & Poors. Moody's uses a similar scale but distinguishes each category in a different way. Like S&P, Fitch uses intermediate rankings between AA and CCC (like AA+, AA, AA-, A+. A, A-, BBB+, BBB, BBB- etc.).

Investment grade

- AAA: the highest quality, companies that are reliable and stable
- AA: quality companies, with some more risk than AAA
- A: economic situation can adversely impact financial prospects
- BBB: medium class firms, satisfactory at the moment.

Non-investment grade (classified as junk bonds)

- BB: more vulnerable to economic changes
- B: variable financial situation
- CCC: currently vulnerable and dependent on favorable economic conditions
- CC: high level of vulnerability, very speculative bonds
- C: highly vulnerable, close to bankruptcy, but still paying its obligations
- D: defaulted on its payment obligations, Fitch thinks that the company will generally default on most or all obligations

- NR: not publicly rated

4.4.2.2 Short-term ratings

The short term ratings of Fitch are a measure of the potential level of default within a12-month period.

- F1+: highest level of quality, indicating exceptionally strong capacity of obligor to meet its financial commitment
- F1: best quality grade, very good capacity to meet the financial commitment
- F2: good quality grade with satisfactory capacity of obligor to meet the financial obligations
- F3: fair quality grade with adequate capacity of the issuer to meet its obligations. However it indicated sensitivity to adverse economic conditions that would negatively impact such capacity
- B: speculative category, obligor has little capacity to meet its commitments; it also indicates vulnerability to short term adverse changes in financial and economic conditions
- C: high probability of default and meeting the financial commitments is dependable of favorable economic conditions
- D: the obligor is in default as it has failed on its financial commitments.

4.4.3 Moody's Corporation

Moody's Corporation is the holding company for Moody's Investors Service that realizes financial research and analysis for private or public purposes. Among its clients there are both companies and governmental institutions. It rates the credit-worthiness of borrowers using a standardized ratings scale. In the credit rating market, Moody's market share is about 40%.

The company has been established by John Moody in 1909. The biggest shareholders are now Berkshire Hathaway and Davis Selected Advisers.

4.4.3.1 Long-term ratings

Moody's long-term ratings represent estimations of the credit risk worthiness of fixed-income obligations with an original maturity of at least a year. They assess the possibility that the financial obligation will not be met. Such ratings reflect both the likelihood of default and the probability of a financial loss caused by the occurrence of a default.

Investment grade

Aaa: best quality, very low degree of risk

Aa1, Aa2, Aa3: high quality, low credit risk but bearing higher credit risk than Aaa, susceptible especially to long-term risks

A1, A2, A3: Upper-medium grade, subject to low credit risk, susceptible to impairment over the long-term

Baa1, Baa2, Baa3: moderate credit risk, medium grade obligations, protective elements may be lacking or may be characteristically unreliable.

Speculative grade (junk or high yield bonds)

Ba1, Ba2, Ba3: obligations falling within this category are considered as having a "questionable credit quality" level

B1, B2, B3: speculative category, subject to high credit risk, obligations in this category are generally of poor credit quality

Caa1, Caa2, Caa3: obligations that fall within this group are considered of poor quality, bearing high credit risk, close to default

Ca: Highly speculative obligations, usually in default on their financial commitments

C: lowest rated class of bonds, typically in default, with low potential of recovery.

Special

WR: withdrawn rating

NR: not rated

P: provisional.

4.4.3.2 Short-term taxable ratings

The short-term ratings issued for taxable securities represent opinions of the issuing agency as regards the ability of the securities' issuer to meet its short-term financial obligations. Moody's uses the following scale in order to rank different such capacities:

P-1: It defines superior ability to repay short-term debt of the obligations

P-2: Strong ability to meet short-term financial obligations

P-3: Acceptable ability to meet short-term financial obligations

NP: Issuers that do not belong to any of the previously mentioned categories.

4.4.3.3 Short-term tax-exempt ratings

As compared to the Standard & Poor's agency, Moody's has a separate rating description for short-term municipal bonds. Such rating categories largely overlap and indicate similar capacities of meeting financial short-term obligations.

4.4.3.4 Individual bank rankings

Moody's also ranks banking financial soundness. The "soundness" corresponds to the probability that the bank needs assistance from third parties.

The groups are:

A: superior intrinsic financial strength

B: strong intrinsic financial strength

C: adequate intrinsic financial strength

D: modest intrinsic financial strength, potentially requiring some outside support at times

E: very modest intrinsic financial strength, with a higher likelihood of periodic outside support

4.4.3.5 Abusive business practices

Moody's has been accused by making use in some stances of "blackmailing" potential clients. One example is the German Insurer Hannover Re that has been offered a free rating by Moody's. Although the company refused it, Moody's kept issuing free ratings but over time they were depicting a downwarding financial strength. In conditions in which Moody's still met the refusal of Hannover Re to obtain rating services from it, the German company's debt was downrated to junk, that caused Hannover Re to lose in just a few hours more than $175 million in market value.

4.5 Key regulatory aspects of the credit rating activity

Because the international rating agencies play an important role in the capital markets, their activities are of interest for a large panel of actors on such markets: investors, brokers, issuers, regulators. Especially the latter ones that have a dual interest in the rating activities of the agencies, because the rating activity may influence the market transparency and because some securities regulators use the ratings for regulatory purposes. In what it follows I will present aspects of the regulatory activity that will answer to the question why the rating agency must be under regulatory control. Such aspects may influence the authorities' decision of regulating this activity, but also may influence the shape such regulations may take.

4.5.1 The independence of the credit rating agencies and the conflicts of interest

The biggest concern from the side of the regulators as regards the credit rating agencies is to identify and address to potential conflicts of interest that may influence the rating process. Such conflicts of interest, as previously mentioned, are various, depending on the size of the agency, the jurisdiction in which it activates the sources of income etc. Everyone in the market must get familiar very well with the nature of the conflicts of interest and must put in place mechanisms by which effects of potential and actual conflicts may be eliminated or at least mitigated.

4.5.2 Issuers and the public disclosure

The credit rating agencies offer services that are meant to reducing the information asymmetry with immediate effect on lowering cost of capital for issuers. They first collect, classify and then analyze the information from a variety of sources. Most of the sources are represented by the issuer itself, reason for which the existence and transfer of accurate and relevant information on the credit worthiness of the issuer is essential to releasing relevant ratings, otherwise the market transparency would be significantly affected.

Establishing whether the quality of the existing regulations as regards the credit rating activity is done by considering the extent to which the issuer disclosure and cooperation is important for them. The rating agencies use to engage in a constant dialogue with the issuers they rate, fact that enables them to access non-public information. Despite this, the bulk of the information used for company assessment comes from information enclosed in the financial statements. Thus, the issuer's ongoing disclosure obligations become essential to undertaking the rating process. In this sense, the document that regulates these issues, "Technical Committee's Statement of Principles for Ongoing Disclosure and Material Development Reporting for Listed Entities", mentions that:

1) The listed entities have an ongoing obligation to disclose all information that would be material to an investor's investment decision; and

2) The information disclosure should be done in a timely manner and, in those circumstances in which the information involves material developments, immediate (or as soon as possible if the regulation establishes a maximum prescribed time frame).

Likewise, the appropriateness of implementing a new regulation, is considered when a threat of issuer manipulation of the rating process exists. As such, despite the fact that the issuers have an interest in maintaining the integrity and transparency of securities markets generally and the rating process in particular, some of them may manipulate the rating process in order to take advantage of immediate benefits that would result from a favorable rating issued before a transaction is done or before a larger market manipulation scheme is implemented. Therefore, regulations designed to mitigate the occurrence of such types of behavior are put in place, along with implementing credit rating agency confirmation mechanisms.

4.5.3 Ratings' public dissemination

The regulating authorities in some jurisdictions expressed their concern as regards the timing of the public disclosure of the ratings. As such, the decisions that are publicly disclosed before the close of a relevant stock exchange may influence the market volatility as it has been observed that the purchase or sales of shares immediately after a rating release is intensified, even before the investors review the implications of such a rating decision. In this sense, suggestions were made for a release of the rating decisions only after the closure of the relevant market. On the other hand, such a decision may affect the transparency and efficiency of the market functioning. Another argument against such a solution is the fact that the market, *de facto,* never closes. While the trading on a specific market may have ended for that day, trading in an inter-listed security or related security may continue in a different market, at a different time zone. In the same time, introducing a restriction that would require a rating agency release a rating only once a primary market has been closed may induce distortions in the market that would favor some investors (for example institutions that undergo large cross-border trading activities) and negatively affect others (like retail investors).

4.5.4 Preferential access to the information

Concerns exist as regards the special access to information some clients of a rating agency may have. Thus, they would take advantage of a full access to non-public information that would give them some very analytical perspectives on the market and on the competition. As well, some rating agencies allow issuers to contact their analysts to raise questions on the analysis staying behind a rating released.

Moreover, because the rating agencies differ in the business model employed, the securities regulators may take into consideration also the effects on the various types of rating agencies. The subscriptions form the primary income source for the smaller agencies and for the new entrants. Because the large rating agencies allow their analysts to take questions from the public regardless of whether or not an individual has subscribed to their services, imposing restrictions with regard to a selective access may adversely hurt the smaller rating agencies that rely on subscriptions. Similarly, large rating agencies that offer more extensive analyses to their clients may justify maintaining of a selective access based on the cost of making this information available. In this sense it can be made an analogy between the subscription service offered by the credit rating agencies and the journalistic wire services used by the newspapers, with the observation that most of the important wire service providers are subscribers of the credit rating agencies and base news stories on these agencies' subscriptions reports.

Another reason for concern is whether subscribers of the credit rating agencies receive "material information" that gives them an advantage as against the investors that rely solely on freely available public information. The way the regulators solve this area of concern starts from the way the term "material information" is understood. While some countries with selective disclosure prohibitions explicitly except the agencies from such prohibition, some others allow for it only if the agency releases the rating to the public.

4.5.5 Challenges to the new entrants

The importance the investors give to the analyses and ratings issued by the rating agencies largely depends on the reputation the respective agency has built among the investors. Such reputation comes from a history of offering accurate, relevant and timely ratings. As such, the new entrants on the rating market face some disadvantages as against the already established companies offering similar services. Such disadvantages may be defined as it follows:

The lack of a rating history. In the absence of a background with timely and accurate ratings from the new agency, the investors will be reluctant to give the same weight to the ratings of new entrants as they would give to a company that has already a solid reputation built. This happens because new entrants lack historical default rates by which investors can compare their performances as against other agencies. The consequence is that the issuers will be reluctant to establish contractual relationships with the new companies. This particularly affects the business of the new entrant because without the investor or issuer interest, the new agencies will find difficult to become self-sustaining in time. Thus, the new companies should devote lots of time and financial resources towards building reputation that would allow them later directly compete to the already established agencies.

The lack of resources and issuer access. The rating business, like many other businesses, starts with higher costs than already set up businesses. In many cases, a new rating agency has fewer resources (in terms of personnel, analytical tools, etc.) than older entrants. This particularly transforms into a significant impediment as they have to hire more staff (especially more specialized one) than their older competitors to analyze large issuers, raising thus the capital requirements. As issuers, initially, may express no interest in contracting with a new entrant for rating, the newly established agencies may start building their reputation by issuing unsolicited ratings, without the benefit of issuer cooperation and input. This may be mitigated if ongoing financial statement disclosure from the issuer would allow the new entrants draw accurate and timely conclusions regarding the financial capability of the issuer to meet its financial obligations, conclusions that would allow the recently entrant build up its reputation.

Conflicts of interest. Due to the high costs the new entrants are confronted with at the beginning of their activity, the new credit rating agencies may be vulnerable to financial pressures that, the larger agencies are immune to, given their size. In the case of a newly established agency, a single fee-paying issuer may represent a significant portion of the whole revenue of the agency, thing that creates a potential conflict of interest that may influence the agency's rating decisions as it would fear that, by granting a too small rating, it would potentially lose the issuer as its customer. Thus, given the large amount of capital and time that is necessary for a recently established rating agency to build up its reputation, realizing an affiliation to a larger firm may represent an ideal solution to overcome some of the start-up problems. However, such affiliations contain their own conflicts of interest if the financial interests of the larger company influence the rating decisions of the smaller affiliate.

4.5.6 Unsolicited ratings

The unsolicited ratings raise two separate types of problems that the regulatory authorities must control:

The unsolicited ratings and the issuer access. The unsolicited ratings are those ratings that the agencies process and issue without being formally bound by a contractual relationship with the issuer whose securities are rated. Such process that takes place behind an unsolicited rating may lack the issuer input and, given the circumstances, the access to non-public information that a solicited rating may benefit of. Therefore, the investors must know whether the ratings are solicited or unsolicited in order to decide on the opportunity to include in their decision of the inclusion of non-public information in the rating process.

Unsolicited ratings and potential abusive procedures. Some issuers accused the rating agencies of their using of unsolicited ratings. Such assertions contained also accusations that the respective agencies have either submitted bills for unsolicited ratings or have implied that the unsolicited rating could have been upgraded if the issuer would have engaged in contractual relationships with the agency.

Although unsolicited ratings may pose issues for regulators that may suggest further necessary adjustments to the existing regulations, the regulators should also take into consideration that for the new entrants, issuing unsolicited ratings is the only way to building up their reputations. Thus, blanket prohibitions on the rating activity may represent a serious barrier to new entrants; the Statement of Principles found that the best way to address this issue is the public disclosure of the issuer's financial information that may be of interest in building up a credit rating.

B. Advances in modelling and forecasting volatility for risk assessment purposes

5. Risk assessment with forecasting volatility models

5.1 Summary of the problem

The current thesis attempts to offer a guideline as regards the risk assessment of a company that proposes to invest abroad. There are many ways to assess the risk of the new environment, but, as reasoned in the introductory part, the most appropriate method is to assess the future of companies acting in the same sector. For example, if company A from France proposes to invest in the IT sector in the United States, it will try to assess the risk of the sector by evaluating the risk of the other companies already existing in the US IT sector (for example companies from B to Z). For this, the most convenient way to assess the sector's risk is to evaluate the risk of a portfolio of shares formed by stocks of all B-Z companies forming such portfolio. If we conveniently agree to represent the risk of such portfolio by its volatility, we will have then a problem in which we will have to forecast the future volatility value of a portfolio formed of the returns of selected highly inter-linked companies.

There are three problems as regards future forecasting the volatility of such a portfolio:

1. A large number of stocks included in a portfolio might make the problem of forecasting difficult to solve. In the case of hundreds or thousands of variables included, the number of estimations to be done would be so high that the problem would be extremely difficult to be technically undertaken.

2. Due to the still existing debate as regards the superiority of the volatility forecasting models, the issue of choosing one model is subjective. Which model the company should chose in order to assess the volatility if so many models coexist and the literature cannot reach a consensus as regards net superiority of one or a group of them?

3. The companies included in the portfolio might be highly inter-connected. This means that the volatility of their stock returns might be highly inter-correlated. Much of the information contained in one stock return volatility might exist in other stock return volatility. As such, the existence of multiple inter-correlation might make the estimation problem particularly imprecise, while computationally difficult.

The empirical exercise that follows is proposing to offer a critical assessment of Principal Components-GARCH (PC-GARCH) model and to offer support for the rationale behind of one idea: PC-GARCH model is the most appropriate model to use when one has to evaluate the volatility of the returns of very large groups (portfolios) of stocks, containing hundreds and even thousands of variables. The appropriateness of the model is seen through the perspective of the quality/cost fraction of volatility forecast provided by PC-GARCH when compared to any other alternative model. Although an empirical study will be enclosed to present how PC-GARCH works and to reveal the strengths of such method, the test will not be used in order to compare PC-GARCH directly with other method, for which there would have to be tested hundreds of variables for each model considered. Conclusions on PC-GARCH will stem out from the procedure itself as revealed, even as presented with only seven sets of variables. However, the conclusions of the following exposure enforce the idea that PC-GARCH reveals its superiority only when working with hundreds variables, or even thousands. Such conclusion comes by putting in balance two factors: the first one, the quality of the results, understanding by this the chosen model's ability to comprehend the relationship between the exogenous variables and the endogenous ones, by taking into account the autocorrelations and interaction effects that may exist within the data[2], and then, the second factor, the amount of computational efforts needed to obtain such results.

The previous papers written on this topic evaluated solely the benefits of using the principal component analysis in orthogonal models. Alexander (2000) described such an analysis but without any methodology offered on principal components in a GARCH model. Burn's (2005) paper offered such a methodology for PC-GARCH,

[2] The quality factor measures preciseness by comparing the forecast with the real (historical) values. A comment on the methodology used for that will follow.

but without any empirical implementation. However, none of the papers has emphasized the cost factor of the using of any such methods.

The present study addresses to two issues not fully explored previously. It attempts a benchmarking of volatility forecasting models looking also to the cost factor also, by putting in balance the amount of computational efforts needed and quality of the results, and applies, in support to the proposed solution, a method (principal component) to a multivariate GARCH, not previously empirically implemented (although described in its methodology by Burns). However, the implementation that follows includes elements of GARCH testing that have not discussed in any of such papers.

Some models need, due to their complexity and to the size of the panel of data taken into account, to estimate a too large number of parameters. In this case, the model estimation may take too long time, and the quality of the results not necessarily makes up for the length of the time when that is considerable. Sometimes, it may prove useful a trade-off between the output (represented by the quality of the results) and costs (measured by the amount of time spent to obtain such results, and other computational efforts that may exist). In other words, one could find useful to have results that weight in terms of accuracy about eighty percent, but the computational time be reduced at one third.

For the first type of factors, the one that concerns the quality of the results, I will assert the important step ahead that GARCH models make as against the more basic models. The discussion will start from ARMA models, and will be built on an approach that will justify why each refinement (that most of the time incorporates a generalization) of one model represents an improvement as compared to the previous one. Thus, I will reason why ARCH is better than ARMA and why GARCH is better than ARCH. My conclusion at this phase will be that, based on the testing with complex data manipulation, GARCH is the best model to be used. However, my analysis will go deeper and further conclusions will be stated.

5.2 Importance of volatility forecasting

5.2.1 What is volatility

In the informal context of the usual daily language, volatility is referred to as the representation of fluctuations that may be observed in the development of a process or phenomenon over a certain period of time. In the field of Economics, it is more employed to illustrate the movement of the random (unforeseen) elements of a time series, without necessarily measuring it. Actually, Economics is the first field in which the interest for volatility modeling has occurred, especially in what regards the time series.

Specifically, in the financial economics, volatility characterizes the instantaneous standard deviation of the random Wiener-driven component in a continuous-time diffusion model. Stock pricing theory uses implied volatility that specifically bears this definition. Other sources define volatility simpler, as the conditional standard deviation of the underlying asset return. Nevertheless, other financial theories refer to volatility in its larger sense, common to economics and econometrics, as against other narrow formulations that are designed to serve to specific objectives of the studies that use them. Therefore, volatility linguistics does differ across the fields, although basic meanings are kept.

Volatility forecasting in financial asset return series is the broadest volatility topic used in financial economics. Its specificity has been framed by Campbell, Lo and MacKinlay (1997) as:

"… what distinguishes financial economics is the central role that uncertainty plays in both financial theory and its empirical implementation… Indeed in the absence of uncertainty, the problems of financial economics reduce to exercises in basic microeconomics" (p. 3)

Besides uncertainty, that places each discussion in the frame of probabilities, what differentiates even more the topic of volatility in finance from that in microeconomics is its unobserved, or latent character, and its stochastic development in time. Most of the times volatility is unobserved and its metric can be evidentiated through estimation rather by direct measuring. Moreover, what further complicates the discussion, besides the existence of a significant level of uncertainty in any financial market, there is the latent character of such uncertainty. This makes the process of decision making in financial domain even more complex and difficult to be undertaken with standard models of optimizing behavior typically used in other areas of economics.

Volatility models may be formulated in discrete or continuous time, depending on the purpose the model's forecasts, on the estimates that are going to be used and, of course, on the availability of the data. The accuracy of the models increases along with the degree of correspondence of the data to the reality. And since trading and pricing of securities in today's liquid financial asset markets evolve more in a continuous form than in a discrete one, in a typical trading day, use of continuous data would improve the models predictive capacities and thus their forecasts.

However the use of continuous time modeling poses high difficulties in what regards the estimation, to which there are added problems as regards data collection for which continuous observations seldom exist. Therefore, the best approach on the financial price and return data assessment is to think of it as arising through discrete observations from an underlying continuous-time process. However, in some contexts, it will be more useful to define the underlying model directly in discrete time. There is no formal contradiction between the continuous and discrete approaches, as, in principle, it is always possible to derive the distributional implications of a price series observed only discretely from an underlying continuous-time model. Meanwhile, as previously mentioned, formulation and estimation of empirically realistic continuous-time models poses many challenges.

Though many of the discrete-time models used extensively in the empirical exercises are not formally consistent with the underlying continuous-time price processes they describe, they are much more facile to be used from an inferential perspective and therefore, still remain preferred in the empirical forecasting undertakings.

5.2.2 Why volatility forecasting is important

Although traditional research in financial economics has been concentrated on the mean of stock market returns, the more recent developments in international stock markets have increased the interest of practitioners, regulators and researchers towards the volatility of such returns. In a context of a deeper integration of the financial markets and of a higher potential systemic risk available to spread across borders, volatility forecasting activity has thus became a critical preoccupation in academia and financial markets.

More factors led to such a development and they can be summarized as they follow. First it's the frequency of financial crises that has increased along time, associated to larger magnitude of effects. The number of crashes and the size of their effects have forced all to look more carefully to the level and stationarity of volatility along time, attention being moved on development and then improvement of econometric models able to describe swings in returns' volatility. Then, it's that the larger applicability over a large panel of activities has dramatically increased the necessity of correctly formulating the variance forecasting models, so that they would prove useful no matter if applied to investment or risk management field, security valuation and pricing, or to monetary policy making. According to Poon and Granger (2008), the importance of volatility forecasting has been distinctively spotted in option pricing, due to the larger use in more recent years of derivative securities trading, in financial risk management, due to the banking sector cross-boundary globalization that has consolidated in the framework of the two Basel accords and in the monetary policies undergone by the main central banks (Fed, ECB etc) in the wake of more frequent and untypical financial crises. Volatility analysis has been found also of use in market timing decisions, portfolio selection and the provision of estimates of variance for use in asset pricing models.

Volatility modeling improves the efficiency in parameter estimation and the accuracy in interval forecast. Finally, volatility index can be a useful financial instrument in investment decision. VIX volatility index calculated by the Chicago Board of Option Exchange started to trade in futures beginning March 2006.

Andersen, Bollerslev, Christoffersen and Diebold (2005) group the possible applications of volatility forecasting in three categories. The first one represents the class of generic forecasting applications (point forecasting, interval forecasting probability forecasting including sign forecasting and density forecasting), the second group relates to financial applications (in risk management: value-at-risk and expected shortfall, covariance risk assessment: time-varying betas and conditional Sharpe ratios, asset allocations with time-varying covariances, option valuation with dynamic volatility), while the third one refers to applications outside the finance (medicine, agriculture, weather forecasting). They will be presented in what it follows.

5.2.2.1 Generic applications of volatility forecasting

The future realization of a variable can be described as

$$y_{t+1} = \mu_{t+1|t} + \sigma_{t+1|t} z_{t+1} \qquad z_{t+1} \sim i.i.d.\ F$$

In such notation, y_{t+1} represents a univariate stochastic process in discrete-time, while F stands for the zero-mean distribution. z_{t+1} represents the unit-variance innovation.

5.2.2.1.1 Applications in point forecasting

Keeping the notation from the above, we define a loss value as the difference between an ex-ante forecast, $\hat{y}_{t+1|t}$ and the ex-post realization, y_{t+1} as $L(y_{t+1}, \hat{y}_{t+1|t})$. Such a function can be exactly defined under various notations, each depending on the purpose of the forecast. In the basic form, it may take the form of an additive error, that is $e_{t+1} = y_{t+1} - \hat{y}_{t+1}$, $L(y_{t+1}, \hat{y}_{t+1|t})$ and is called the forecast error loss function.

In the case of a symmetric quadratic error loss function, it is regularly looked for the optimal point forecast that is

$$\hat{y}_{t+1} \equiv Arg\ min_{\hat{y}} E[(y_{t+1} - \hat{y})^2 | F_t] = \mu_{t+1|t}$$

From the above equation we see that volatility forecasting becomes useful only when the conditional mean depends directly on the conditional volatility. Since this is the most common occurrence in finance, as generally the expected return is a function of the volatility of the market risk factors, volatility issue takes a central role in evaluating the uncertainty of the point forecasts.

However, the role of volatility forecasts is even more straightforward when there are implied asymmetric loss function. Such a function takes usually the form

$$L(e_{t+1}) = a|e_{t+1}|I(when\ e_{t+1} > 0) + b|e_{t+1}|I(when\ e_{t+1} \leq 0)$$

a, b are strictly positive parameters and give the weights of the errors, while *I* function takes the form

$$I = \begin{cases} 0 \\ 1 \end{cases}, when\ e_{t+1} \leq 0\ \ and\ \begin{cases} 1 \\ 0 \end{cases}, when\ e_{t+1} > 0$$

Under these assumptions, the optimal forecast will take the form

$$\hat{y}_{t+1|t} = \mu_{t+1|t} + \sigma_{t+1|t}F^{-1}(a/(a+b))$$

This representation shows that the optimal forecast does not depend only of the weights' size a and b, but also by the volatility forecast. Another implication is that the optimal forecast will equal conditional mean unless the second factor disappears, that is when $F^{-1}(a/(a+b) = 0$.

Christoffersen and Diebold (1996, 1997) have also studied point forecasting under general loss functions when allowing for dynamic volatility.

5.2.2.1.2 Applications in interval forecasting

The first application of the interval forecasts was in one of the papers of Engle (1982) who has constructed interval forecasts around the conditional mean forecast of inflation. The most common version of an interval is the one in which equally probabilities are attributed to the below and upper limit of it. Under this assumption, it will take the form of

$$\hat{y}_{t+1|t} = \{\mu_{t+1|t} + \sigma_{t+1|t}F^{-1}(p/2\,),\ \ \mu_{t+1|t} + \sigma_{t+1|t}F^{-1}(1-p/2)\}$$

Under such formulation, we can observe that again, volatility forecast can seize the intervals.

Granger, White and Kamstra (1989) was among the studies that used the time-varying volatility models for finding interval forecasts.

5.2.2.1.3 Applications in probability forecasting including sign forecasting

Of interest there is if one variable falls above or below a certain level. For example, a portfolio manager might be interested if the return of one stock will be higher than that of a risk-free bond, that would make her decide to invest or not in that specific stock. Or a rating agency might be interested to find out whether the assets of one company will exceed of its liabilities. Central banks, especially those who adopted the pegged exchange rate, might be interested in checking if the exchange rate, or inflation situate within a certain target band.

In formula notation, that means that the loss function exceeds or not a certain threshold c

$$L(y_{t+1}, \hat{y}_{t+1|t}) = (I(y_{t+1} > c) - \hat{y}_{t+1|t})^2$$

The scope is to minimize the expected loss, and for doing that we set the first derivative equal to zero. It results

$$\hat{y}_{t+1|t} = E[I(y_{t+1} > c)|F_t] = P(y_{t+1} > c|F_t) = 1 - F((c - \mu_{t+1|t})/\sigma_{t+1|t})$$

We can see in the above formulation that again, volatility forecast is necessary.

The problematic of the sign occurs when c=0. The above formula takes the form

$$\hat{y}_{t+1|t} = 1 - F(-\mu_{t+1|t})/\sigma_{t+1|t})$$

Then, when the conditional mean $\mu_{t+1|t} \neq 0$, F takes a role in determining $\hat{y}_{t+1|t}$.

Christoffersen and Diebold (2003) have been among those who successfully applied volatility modeling in financial applications of probability forecasting techniques.

5.2.2.1.4 Applications in density forecasting

When the conditional density of a function is of interest, the forecast takes the form of a probability distribution function

$$\hat{y}_{t+1|t} = f_{t+1|t}(y) = f(y_{t+1|t} = y|\mu_{t+1|t}, \sigma_{t+1|t}) = F(y_{t+1} = y|F_t)$$

In this form also we can see that forecasting density includes the volatility forecasting variable also.

5.2.2.2 Financial Applications of volatility forecasting

5.2.2.2.1 Applications in risk management: Value-at-risk (VaR) and Expected shortfall (ES)

We define a portfolio of N risky assets that form a vector R_{t+1}. Each asset has its own weight in such portfolio, $w_{i,t}$forming a vector matrix, W_t . The portfolio return may be expressed then as

$$r_{w,t+1} = \sum_{i=1}^{N} w_{i,t} r_{i,t+1} \equiv W_t' R_{t+1}$$

The riskiness of the portfolio is usually expressed by referring to its VaR that is the quantile of the conditional portfolio distribution. If assuming the portfolio returns as evolving according to a univariate process, then the same equation above may be written as

$$r_{w,t+1} = \mu_{w,t+1|t} + \sigma_{w,t+1|t} z_{w,t+1} \qquad z_{w,t+1} \sim i.i.d. F_w$$

In this case, VaR takes the form

$$VaR_{t+1|t}^{p} = \mu_{w,t+1|t} + \sigma_{w,t+1|t} F_w^{-1}(p)$$

We can see, thus, that in its formulation, the forecast of the volatility is taken into consideration as a measure of the size of the probability with which the loss may occur (remember again that VaR refers solely to the loss). When the VaR is calculated using historical simulation (that is the most common way to calculate it), it is usually too large when the volatility is low and too small when volatility is high, that proves that historical simulation underestimates the risk. However, this still proves that volatility forecasting has a say in determining the riskiness of portfolios using VaR.

The Expected Shortfall (ES) risk defines the expected loss when losses are larger than VaR, under the notation

$$ES_{t+1|t}^{p} \equiv E\left[r_{w,t+1} \middle| r_{w,t+1} < VaR_{t+1|t}^{p}\right] = \mu_{w,t+1|t} + \sigma_{w,t+1|t} EF_{w}^{p}$$

When $z_{w,t}$ is i.i.d., EF_{w}^{p} that represents the multiplicative factor is constant and depends only on the shape of the distribution F_{w}. It results then that dynamics of volatility contribute to the size of the expected shortfall risk in the same manner as in the case of VaR.

$$R_{t+1} = M_{t+1|t} + \Omega_{t+1|t}^{1/2} Z_{t+1} \qquad Z_{t+1} \sim i.i.d.F$$

$$\mu_{w,t+1|t} = W_{t}^{'} M_{t+1|t}$$

$$\sigma_{w,t+1|t}^{2} = W_{t}^{'} \Omega_{t+1|t} W_{t}$$

$$r_{w,t+1} \equiv W_{t}^{'} R_{t+1} \sim N(\mu_{w,t+1|t}, \sigma_{w,t+1|t}^{2})$$

An example of works in which dynamic volatility models have been found applicable in risk management field are Christoffersen (2003) and Jorion (2000).

5.2.2.2.2 Applications in covariance Risk: Time-varying betas and conditional Sharpe ratios

Taking as assumption the absence of arbitrage opportunities, it can be proved that a stochastic factor, SDF_{t+1} may exist and may be used to price any asset i:

$$E\left[SDF_{t+1}(1 + r_{i,t+1})F_{t}\right] = 1$$

In the case of the return of a risk free asset, that pays one unit of currency, with zero risk, for next period, $1 + r_{f,t} = E[SDF_{t+1}|F_{t}]^{-1}$.

Then, the expected excess return on any risky asset will be proportional to its covariance with the stochastic factor

$$E\left[r_{i,t+1} - r_{f,t}|F_{t}\right] = -\left(1 + r_{f,t}\right) cov(SDF_{t+1}, r_{i,t+1}|F_{t})$$

Furthermore, if the stochastic discount factor is linearly related to the market return, then

$$SDF_{t+1} = a_{t} - b_{t}(1 + r_{M,t+1})$$

From $E\left[SDF_{t+1}(1+r_{M,t+1})|F_t\right]=1$ and $1+r_{f,t}=E[SDF_{t+1}|F_t]^{-1}$ results that

$a_t=(1+r_{f,t})^{-1}+b_t\mu_{M,t+1|t}$ and $b_t=\left(1+r_{f,t}\right)^{-1}(\mu_{M,t+1|t}-r_{f,t})/\sigma^2_{M,t+1|t}$, with $\mu_{M,t+1|t}\equiv E\left[r_{M,t+1}|F_t\right]$ and $\sigma^2_{M,t+1|t}\equiv Var\left[r_{M,t+1}|F_t\right]$. SDF coefficients are time-varying due to the dynamics of the market return moments and of the risk free rate.

Meantime, paralelly to the one-period CAPM model of Markowitz (1952) and Sharpe (1964), the conditional expected excess returns will verify the following equality

$$E\left[r_{i,t+1}-r_{f,t}|F_t\right]=\beta_{i,t}(\mu_{M,t+1|t}-r_{f,t})$$

Here, conditional beta is given by $\beta_{i,t}\equiv cov(r_{M,t+1},r_{i,t+1}|F_t)/\sigma^2_{M,t+1|t}$

The expected risk adjusted return, called also as conditional Sharpe ratio, is given by the following relationship

$$SR_t=\frac{E\left[r_{i,t+1}-r_{f,t}|F_t\right]}{Var\left(r_{i,t+1}|F_t\right)^{\frac{1}{2}}}=corr(r_{M,t+1},r_{i,t+1}|F_t)/\sigma_{M,t+1|t}$$

The above two relations of conditional expected excess returns and conditional Sharpe ratio shows that the expected return, absolute and risk adjusted, on various assets are influenced by the mean and volatility dynamics of the whole market return, also by the dynamics of the covariance between market and individual assets. This highlights another idea, that the forecasting of covariance is also highly important, like volatility, in the exercises of financial asset pricing.

Cochrane (2001) has developed a context in which conditional asset pricing allowing for time-varying betas is explained.

5.2.2.2.3 Applications in asset Allocation with Time-varying Covariances

Let's assume an investor who builds up a portfolio formed from N risky assets. It tries to optimize the efficiency of the portfolio by minimizing its variance when trying to obtain a certain level of portfolio return, called μ_p. Like in the precedent exercise, each asset compounding the portfolio has a weight that can be written in the matrix form W_t.

The investor's problem will be

$minW_t^{'}\Omega_{t+1|t}W_t$ subject to $W_t^{'}M_{t+1|t} = \mu_p$

We try to solve this problem by writing the first order condition:

F.O.C.:

$$W_t^* = \frac{\Omega_{t+1|t}^{-1}M_{t+1|t}}{M_{t+1|t}^{'}\Omega_{t+1|t}^{-1}M_{t+1|t}}\mu_p$$

The optimal weight oh the risk-free asset is

$$w_{f,t}^* = 1 - \sum_{i=1}^{N} w_{i,t}^*$$

The Sharpe ration of the portfolio is

$$SR_t = \mu_p / \sqrt{W_t^{*'}\Omega_{t+1|t}W_t^*}$$

Like in the CAPM pricing model discussed in the previous section, volatility and covariance dynamics have an important contribution to the asset allocation decision.

Market timing arising from time-varying Sharpe ratios has been described by Whitelaw (1997)**.**

Asset allocation by using volatility modeling techniques has been undergone in papers of Fleming, Kirby and Oestdiek (2001, 2003) (one period setting) and Wang (2004) (multi-period setting).

5.2.2.2.4 Applications in option valuation with dynamic volatility

All the previous mentioned tools may be used as instruments for analysis of basic securities with linear payoffs, like stocks, bonds, foreign exchange and futures contracts.

In the case of a European call option (in which the owner has the right, not obligation, to buy the underlying assets) at a strike date, T, at a price K. Thus, the payoff associated to the option will be a nonlinear one, whose modeling cannot be done with the instruments mentioned in previous sections.

We start from the Black-Scholes-Merton option pricing model. According to it, the returns are normally distributed, having a constant volatility σ along the possibility of a costless continuous trading and a constant risk free rate r_f.

The call price can be written as

$$c_t = BSM\left(s_t, \sigma^2, K, r_f, T\right) = s_t \Phi(d) - Kexp\left(-r_f T\right)\Phi(d - \sigma\sqrt{T})$$

s_t is the current asset price, and $d = \frac{\ln(s_t/K)+T\left(r_f+\frac{\sigma^2}{2}\right)}{\sigma\sqrt{T}}$. $\Phi(d)$ is the cumulative normal distribution function.

The constant volatility assumption produces systematic pricing errors in such a context, if comparing the estimated prices with the real (market) ones. This causes the volatility smiles that are a proof of systematic underpricing of the Black-Scholes-Merton model for in or out-of-the-money options. The deviations' directions may be explained by the existence of stochastic volatility that produces fatter tails than the normal distribution that produce the value increase in in and out-of-the-money options as against the constant volatility of the theoretical model.

Hull and White (1987) allowed for an independent stochastic volatility factor when definining the process of the underlying asset return. The integrated volatility of Hull-White model is defined as the integral spot volatility during the remaining life of an option

$$IV(T,t) = \int_t^T \sigma^2(u)du$$

where $IV(T,t) = IV(T) + IV(T-1) + \cdots + IV(t+1)$.

This is the integrated volatility in a continuous time. In a discrete time, it can be approximated as the sum of the corresponding one-period conditional variance

$$IV(T,t) \approx \sum_{\tau=t}^{T-1} \sigma^2_{\tau+1|\tau}$$

The option valuation formula in the same context is then

$$C_t = E[BSM(IV(T,t))|F_t]$$

$$C_t = E\left[BSM(\xi_{t,T}s_t, (1-\rho^2)IV(T,t))|F_t\right]$$

$$E\left[\xi_{t,T}|F_t\right] = 1$$

Volatility timing has been explored by Johannes, Polson and Stroud (2004).

Relationships between time-varying volatility and returns have been documented by Engle, Lilien and Robins (1987), French, Schwert and Stambaugh (1987), Bollerslev, Engle and Wooldridge (1988), Bollerslev, Chou and Kroner (1992), Glosten, Jagannathan and Runkle (1993).

Usage of volatility models in option valuation has been largely described in the literature. Key contributions, based on continuous time models, have been brought by Bakshi, Cao and Chen (1997), Bates (1996), Chernov and Ghysels (2000), Eraker (2004), Melino and Turnbull (1990), Pan (2002). Discrete-time applications were done by Christoffersen and Jacobs (2004) and Heston and Nandi (2000).

5.2.2.3 Volatility forecasting applications in fields outside finance

At their first formulation of the conditional heteroskedastic models, by Engle (1982), the main scope was to forecast volatility for the purpose of measuring the dynamics of inflation uncertainty. The use of this theory for financial applications came only later. Volatility modeling has been undergone in various other fields, like social sciences in general and economics in particular, medicine, and natural sciences. A short literature review of the main papers that employed volatility modeling outside finance will come in the next lines.

As mentioned, Engle has proposed the ARCH model at the beginning to serve as a tool for measuring the uncertainty regarding inflation. Further applications have been undertaken starting from Engle findings, as those belonging to Giordani and Soderlind (2003) who forecasted inflation and output or to Rich and Tracy (2004) who integrated inflation study with the labor market variables. The latter ones evidentiated an inverse relationship between desired labor contract durations and the level of inflation uncertainty.

Uncertainty measuring has been undergone also in microeconomics – Meghir and Pistaferri (2004) estimated conditional variance in income values and proved the existence at the micro level of temporal variance dynamics.

Another field that has made extensively use of the variance modeling is that of monetary economics. Lastrapes (1989) has studied the link between the volatility of the exchange rates and the monetary policy of the United States. Ruge-Murcia (2004) came with a new model of a central bank with asymmetric preferences in terms of unemployment above vs. below the natural rate. The unemployment conditional variance has been found to be positively related to the inflation rate. Tse and Yip (2003) modeled volatility for the purpose of analyzing the effect on changes in the Hong Kong currency board on inerbank market rates.

Agricultural economics also employed models to forecast volatility. Ramirez and Fadiga (2003) found evidence of asymmetric volatility patterns in the US prices of soybean, sorghum and wheat. By employing volatility spill-over related models as those developed by Engle for studying integration of the international financial markets, Ito and Lin (1990), King, Sentana and Wadhani (1994) and Buguk, Hudson and Hanson (2003) have built similar methods to acknowledge for the existence of strong price volatility spillovers in the supply-chain of the fish industry. Thus, feeding material price volatility influences the fish feed price volatility that further affects fish farm price volatility and finally the wholesale price volatility.

Barrett (1999) employs a GARCH models to document the existence of any influence from depreciations in the real exchange rates on stochastic producer prices in low-income agriculture.

Other sections of economics, like those concerning the regulatory frameworks in industries have used volatility forecasting models. Shawky, Marathe and Barret (2003) have investigated using such models, the minimum variance hedge ratios in what concerns electricity futures. The announcements on the natural gas storage have found to have an impact on intraday volatility of gas prices, according to Linn and Zhu (2004). Multivariate GARCH models have been used to simulate price paths in gas and oil, as part of a study undertaken by Battle and Barquin (2004) on the wholesale energy market.

Taylor and Buizza (2003) modeled electricity demand uncertainty using weather forecast uncertainty. Dripps and Dunsmuir (2003) used GARCH models to prove the forecastability of wind measurement variability, while Campbell and Diebold (2005) explored temperature variances in terms of seasonal volatility dynamics. Marinova and McAleer (2003) modeled volatility in terms of ecological patents.

Applications of volatility models can be found in political science also. Maestas and Preuhs (2000) proposed a model of political volatility in terms of periods of rapid and extreme changes in the political actions. Gronke and Brehm (2002) used conditional heteroskedastic models to evaluate dynamics of volatility in presidential approval ratings.

I will close this section by mentioning few studies which employed volatility models in medicine. Ewinm, Piette and Payne (2003) forecasted time varying volatility in medical net discount rates that are used in order to establish the net present value of future medical costs. Johnson, Elashoff and Harkema (2003) used heteroskedatic models to investigate the neuromuscular activation patterns in patients with spinal cord injuries. Martin-Guerrerro (2003) documented optimal EPO dosage for patients having secondary anemia by employing dynamic volatility models.

5.3 Benchmarking volatility forecasting models

Various techniques designed to obtain reliable volatility forecasts have been continuously produced in the last three decades. They range from extremely simplistic models that employ so-called “naive” (random walk) assumptions up to relatively complex conditional heteroskedastic models of the ARCH group (until GARCH and derivatives of it).

The most debated univariate volatility models are the autoregressive conditional heteroskedastic (ARCH) model compiled by Engle (1982) and the generalized ARCH (GARCH) model compiled by Bollerslev (1986). Numerous extensions of them gained importance also like the exponential GARCH (EGARCH) model of Nelson

(1991) or the conditional heteroskedastic autoregressive moving average (CHARMA) model obtained by Tsay (1987). Other models used for volatility forecasting were the random coefficient autoregressive (RCA) model of Nicholls and Quinn (1982), and the stochastic volatility (SV) models compiled by Melino and Turnbull (1990), Taylor (1994), Harvey, Ruiz and Shephard (1994), and Jacquier, Polson and Rossi (1994), etc.

Comprehensive reviews of the literature that may be examined for a broader understanding of how volatility modeling has evolved along time have been written by Bollerslev, Chou and Kroner (1992), Bera and Higgins (1993) and Bollerslev, Engle and Nelson (1994) and more recently Andersen, Bollerslev, Christoffersen and Diebold (2005). In the following paragraphs, I will make a thorough, yet dimensionally summarized, analysis of the volatility forecasting topic evolvement along the time, as it will allow the reader to understand which were the requirements the subsequent studies tried to answer to, so why later built forecasting models were, ultimately, thought to better answer the forecasting volatility problem.

Generally speaking, each model has its own strengths and weaknesses and having at hand such a large number of models, all designed to serve to the same scope, it is important to correctly distinguish between various models in order to find the one which provides the most accurate predictions.

However, a general consensus on classifying models in terms of forecast accuracy has not been reached. This is due to the fact that the literature contains contradictory evidence as regards the quality of volatility forecasts. The subjectivism arises from various sources, starting from the fact that conditional evidence is unobserved and there is no natural and intuitive way to model the conditional heteroskedasticity, so that each model will try to capture features that its author thinks to be important and, ultimately, from the fact that models with poor forecasting capacities in all empirical tests have not been yet identified.

Ranking depends on a variety of causes that may be related either to the models themselves, or to the methodology used (in-sample or out-of-sample methods), to the measurement's subject (volatility of the exchange rates or volatility of the stocks' returns), to the forecasting horizon or to the error statistic choice. For example, Brailsford and Faff (1996) found that models' performance ranking is sensitive to the choice of the error statistic, for each such statistic being identified different structures in rankings.

Maybe the most proper characterization of the literature is that of a framework of a *mixed set* of findings. However, despite of its obvious complexity and lack of homogeneity, the literature **tends** (I underline this word as the following conclusion comes from an overall view on the literature written, with no scientific, integrated study to ultimately confirm it) to widely agree that GARCH-type models generally provide superior forecasts of return volatility (in the pool of all volatility forecasting models). Brailsford and Faff (1996) were among the ones who have endorsed such a conclusion. By using four types of error statistics (I will present them in a subsequent paragraph), they investigated the out-of-sample predictive ability of eleven models (one random walk model, one historical mean model, one moving average model, one exponential smoothing model, one exponentially weighted moving average model, one simple regression model, two GJR(Glosten-Jagannathan-Runkle) asymmetric GARCH models (a GJR-GARCH(1,1) and a GJR-GARCH(3,1)) and two GARCH models (GARCH(1,1) and GARCH (3,1))) by testing them with Australian monthly data. In the measurement of performance of these models, in addition to symmetric loss functions, they employed asymmetric loss functions in order to penalize the under/over-prediction. Their conclusion was that ARCH-type models and a simple regression model provided superior forecasts of volatility, with the reserve that the choice of the forecasting models depends upon the choice of the error statistic. Akgiray (1989) also found in favor of a GARCH(1,1) model (against more traditional counterparts) empirically tested with US data. On the other side, Dimson and Marsh (1990) found evidence to be in favor of the simpler models. However, all three studies were converging in one result, that the exponential weighted moving average (EWMA) model was among the best forecasting models.

As mentioned, the present literature written on this topic contains contradictory evidence as regards the quality of the market volatility forecasts of various models. The main message of all that may be concluded is that volatility forecasting is a notoriously complicated undertaking. There is evidence that underlines the superiority of more complex models such as ARCH models (as exemplified in the previous paragraph), while there is evidence as well on the other side, underlying the superiority of more simple alternatives. This is seen as an extremely problematic fact due to the difficulty that this contradiction rises in the choosing the appropriate model in volatility forecasting in decision-making and analysis activities.

To the second category of studies, those that back the idea of superior predictive capacity of simpler models, as shortly mentioned above, it belongs the study ran by Dimson and Marsh (1990). According to them, simple models prevail in accuracy of forecasts provided, although it should be mentioned that ARCH-type models were not included in the analysis. Specifically, Dimson and Marsh compared empirically with UK data five models: a random walk model, a long-term mean model, a moving average model, an exponential smoothing model and a regression model. Their conclusion pointed to the final two of these models and along with it they called for a warning sign in the literature that the best forecasting models may not be the more complex and recent models. A similar conclusion has been advanced by Tse (1991) and Tse and Tung (1992) who, by empirically testing with Japanese and Singaporean data, found that the exponentially weighted moving average (EWMA) model produced better forecasts than ARCH models, thus questioning the superiority of the ARCH class models.

To the same group of studies it belongs the work of Hansen and Lunde (2001) who used intra-day estimated measures of volatility to compare volatility models. Their objective was to evaluate whether the evolution of volatility measures has led to better forecasts of volatility when compared to the first "species" of volatility models. For this, they compared two different time series, daily exchange rate data and stock prices. Their findings showed also that the more advanced models did not provide better forecasts than GARCH(1,1) model.

Hansen and Lunde evaluated the relative performance of the various volatility models in terms of predictive ability of realized volatility by using the tests developed by White (2000) and Hansen (2001) called as data snooping tests. Unfortunately, as pointed out by Bollerslev, Engle and Nelson (1994) and by Diebold and Lopez (1996), it's hard to say which is the best criterion to be used when comparing volatility measures. Hansen and Lunde used seven different criteria for such comparison, which included standard criteria such as mean squared error (MSE) criterion, a likelihood criterion, and the mean absolute deviation criterion which was less sensitive to extreme mispredictions, compared to the MSE.

As mentioned, they considered a benchmark model and an evaluation criterion, and tested for data snooping. This allowed them to know whether any of the competing models were significantly better than the benchmark. The benchmark models that were considered were an ARCH (1,1) and a GARCH (1,1) model. Their findings showed the superiority of all models as compared to ARCH (1,1), but GARCH (1,1) was not significantly outperformed in each stance. Although the analysis in one data set clearly indicated the existence of one superior model as compared to GARCH(1,1) when using the mean squared forecast error as a criterion, this did not hold up to other type of criteria that seemed to be more robust to outliers, such as the mean absolute deviation criterion.

Although it has long been recognized the "clustering"[3] effect of the returns' volatility, it seems that only since GARCH model has been enunciated by Bollerslev (1986) such temporal dependencies could have been formally modeled using econometric models. This boosted GARCH-class of models' empirical success, numerous papers reporting their success in modeling in-sample volatility of asset prices. However, numerous other papers have suggested the little success of standard volatility models to explain ex post squared returns (Cumby et al., 1993, Figlewski 1997, Jorion 1995, 1996), recommending the simple moving averages technique for such purpose.

Soon after, a few papers have addressed to such problem and restated the usefulness of GARCH models in providing accurate forecasts (Andersen and Bollerslev 1998, Andersen et al. 1999). They addressed to the latent character of volatility, or inherently unobserved, stochastically evolving through time. Stock volatility consists of intraday volatility and variation between days. Unlike price, which is a flow variable and can be measured instantaneously, volatility is a stock variable and therefore has to be measured over a period. This has been constantly a problem for econometricians as volatility is not observable and precisely measured, but rather estimated. Its unobservability makes difficult the forecasting performance assessment of conditional heteroskedastic models. The latent character of volatility transforms the volatility estimation and forecasting problem into a filtering problem in which the "true" volatility cannot be determined exactly, but only extracted with some degree of error. This might raise problems as the volatility given by the models must be

[3] Large/small variations in returns are followed by other large/small variations.

compared with the “true” underlying volatility. The errors then can be an effect of the model that makes the forecasts or of how the true volatility is estimated. The previous mentioned papers brought a new point of understating possible sources of such many conflicting findings as regards models’ performance ranking. They said that the failure of GARCH-class of models to provide good forecasts is not a failure of the GARCH model itself, but rather a failure to specify correctly the true volatility measure against which the forecasting performance is measured. They sustain that the standard way of using ex post daily squared returns as the measure of “true” volatility for daily forecasts is flawed as such measure comprises a large and noisy independent zero mean constant variance error term which is unrelated to the actual volatility. Andersen and Bollerslev suggest that cumulative squared-returns from intra-day data be used as an alternative way to express such “true” volatility. Such measure, called “integrated volatility” offers the opportunity of a more meaningful and accurate volatility forecast evaluation. This represents a step forward in forecasting problem as it indicates the necessity of using high frequency data in empirical estimations.

As regards the subject of the tests, it seems it existed a higher prevalence towards foreign exchange markets and individual country stock markets. Authors that tested volatilities with respect to the exchange rates were Taylor (1987), Lee (1991), West and Cho (1995), Andersen and Bollerslev (1998), Brooks and Burke (1998), Andersen, Bollerslev and Lange (1999), McKenzie (1999), Andersen, Bollerslev, Diebold and Labys (2003), Klaasen (2002), Vilasuso (2002) and Balaban (2004). A distinguished note is made by West and Cho (1995) who could not show superiority of any of the models tested.

Empirical tests have been made by using both in-sample and out-of-sample methods. The tests, generally, are made with stock market data from one country only: Australia (Brailsford and Faff, 1996, Walsh and Tsou, 1998), Japan (Tse, 1991), Germany (Bluhm and Yu, 2001), New Zealand (Yu, 2002), Sweden (Frennberg and Hannsson, 1996), Switzerland (Adjaoute, Bruand and Gibson-Asner, 1998), Turkey (Balaban, 2000), UK (Dimson and Marsh, 1990, Loudon, Watt and Yadav, 2000 and McMillan, Speight and Gwilym, 2000), US (Akgiray, 1989, Pagan and Schwert, 1990, Hamilton and Lin, 1996, Brooks, 1998). A distinguished pattern is provided by a four country-sample study undertaken by Franses and Ghijsels (1999) (Netherlands, Germany, Spain and Italy). Common to all of them is the relatively narrow range of forecasting models employed.

A more comprehensive analysis has been undergone by Balaban, Bayar and Faff (2004) who extended the evidence in a single unifying framework, analyzing a wide range of volatility forecasting methods across a broader cross-section of countries that reflected both developed and emerging markets. The procedure followed the one used by Brailsford and Faff (1996), however, their sample has been extended from one (Australia) to fifteen countries (Belgium, Canada, Denmark, Finland, Germany, Hong Kong, Italy, Japan, Malaysia, Netherlands, Philippines, Singapore, Thailand, UK and US). The number of models tested was maintained at eleven (a random walk model, a historical mean model, a moving average model, a weighted moving average model, an exponentially weighted moving average model, an exponential smoothing model, a regression model, an ARCH model, a GARCH model, a GJR-GARCH model, and an EGARCH model). The error statistics continued also to be the same as those used in Brailsford and Faff (1996): they based on a combination of symmetric error statistics (mean error, mean absolute error, the root mean squared error and the mean absolute percentage error) and asymmetric error statistics. The rationale behind using asymmetric error statistics is based on the considerable practical interest and is motivated in the context of options. Thus, in case of a call option, under-predictions (over-predictions) of volatility will induce a downward (upward) biased estimate of the call option price. Thus, it may justified the interest of the option seller (buyer) for the resulting under-estimate (over-estimate) of the price as they stand to lose money on any transaction based on such inferior volatility forecasts.

They found that, based on conventional symmetric loss functions, the exponential smoothing model provided superior forecasts of volatility. In the context of symmetric measures, the ARCH-based models generally proved to be the worst forecasters. When under-predictions were penalized more heavily, the ARCH-type group of models offered the best forecasts while the random walk the worst. Finally, when over-predictions of volatility were penalized more heavily the exponential smoothing model came as the best one while ARCH models were found again to be inferior.

One-country studies have been developed to discuss also performance of GARCH-derivated models. Although their samples are narrow, they provide interesting conclusions regarding more recent developments of GARCH. Marcucci (2005) for example has demonstrated that Markov Regime Switching GARCH (MRS-GARCH) models outperform all standard GARCH models in forecasting volatility at shorter horizons, while at longer horizons standard symmetric GARCH models fare the best.

Barucci and Renò (2002) found that by using simulated time series (based upon on the integration of the time series that would allow to naturally exploit the time structure of high frequency data by including all the observations in the volatility computation) the performance of GARCH would be further enhanced.

According to Bluhm and Yu (2001), the empirical evidence conflicts in three aspects. The first one regards to the fact that the performance of the models is sensitive to the empirical data used, to the forecasting horizon considered, to the sampling frequency and to the evaluation criteria, namely to the error statistic employed, a conclusion that has been advanced by almost all studies on this topic. The second aspect, is that due to the volatility smile, that is a typical feature of implied volatility, it is not yet clear how can be extracted the volatility from option prices (Poon an Granger, 2000). The third aspect regards the apparent contradiction between time series forecasts and option forecasts (Jorion (1995) present evidence in the favor of option forecasts while Canina and Figlewski (1993) against).

Bluhm and Yu suggest that there are two ways to forecast volatility: the first one uses historical return information only while the second one makes use of implied volatility in option prices. They compare the two such forecasting volatility approaches using data of the German stock market. The first approach concerns various univariate time series techniques while the second one concerns the implied volatility. The time series models taken into consideration under the first approach are the historical mean model, the exponentially weighted moving average model (EWMA), four ARCH-type models and a stochastic volatility (SV) model. They found that model rankings are sensitive to the error measurements and to the choice of forecast horizons, as well to the objective of the comparison. When option pricing is the main interest, SV model and implied volatility are to be used. When VaR is the objective, ARCH class of models are better performers.

The novelty of the paper belonging to Bluhm and Yu (2001) has been identified with respect to three aspects. The first one is the data origin that describes a market that, although important in international setting, has been receiving little previous attention. The second aspect is the comparison between stochastic volatility and option forecasts. Due to the involvement of two noise processes, the stochastic value model is recognized for more realistic, reliable and flexible modeling of time series than any of the ARCH models. Although Danielsson (1994), Geweke (1994) and Kim et al. (1998) have showed the better in-sample fit of the SV model the literature still seems to pay little attention to such model. The only paper that has benchmarked this model against other models, previous to Bluhm and Yu (2001), is the one belonging to Yu (1999) who, using New Zealand data, found evidence towards a better performance of SV against all other models included in the study (univariate time series models, including ARCH class). Recent research has been devoted to evaluate ARCH against option forecasts, but apparently, previous to this study, no-one has compared SV predictability as opposed to that of option models. The third source of novelty resides in the way the forecast horizons and error measurements have been selected based on the utilization of volatility forecasts in the financial industry. They use option pricing and Value-at-Risk (VaR) as the practical control to choosing forecast horizons and error statistics.

I will close the literature review section by presenting two pieces of evidence as regards the heterogeneity in ranking findings. The first one is a study undertaken by Poon and Granger (2003). They have benchmarked the models by reviewing 93 (out of which only 66 were considered relevant) published and working papers which had focused on ranking building of volatility forecasting methods. They firstly grouped the models in four groups, as it follows:

-HISVOL that accounts for historical volatility models, including random walk, historical averages of squared returns, or absolute returns, time series models based on historical volatility using moving averages, exponential weights, autoregressive models, fractionally integrated autoregressive absolute returns

-GARCH group that accounts for all derivations of ARCH, GARCH, EGARCH etc.

-ISD that accounts for option implied standard deviation, based on Black-Scholes model and different generalizations of it.

-SV that accounts for stochastic volatility models.

The final result look as it follows:

	Studies	Percentage
HISVOL > GARCH GARCH > HISVOL	22 17	56% 44%
HISVOL > ISD ISD > HISVOL	8 26	24% 76%
GARCH > ISD ISD > GARCH	1 17	6% 94%
SV > HISVOL SV > GARCH GARCH > SV ISD > SV	3 3 1 1	

Table 1. Source: Poon and Granger (2003)

The second finding is my own summary of 50 papers that I have reviewed so far for the purpose of completing the literature review. You may find it below.

Paper title	**Authors**	**Year**	**Data**	**Best performing models**	**Worst performing models**
An evaluation of volatility forecasting techniques	Brailsford, Faff	1996	Australia	GJR-GARCH(1,1), ARCH in general, Simple regression	
Conditional heteroskedasticity in time series of stock returns: evidence and forecasts	Akgiray	1989	US	GARCH(1,1), ARCH (1,1)	Historical averages, EWMA
Volatility forecasting without	Dimson, Marsh	1990	UK	Exponential smoothing model, regression model	

data-snooping					
Stock return volatility in the Tokyo Stock Exchange	Tse	1991	Japan	EWMA	ARCH
Forecasing volatility in the Singapore stock market	Tse, Tung	1992	Singapore (5 value weighted indices: SES All Share Index, SES All Finance Index, SES All Hotel Index, SES All Industrial and Commercial Index, SES All Property Index)	EWMA	Historical sample variance, GARCH(1,1)
Forecasting stock market volatility using (non-linear) GARCH models	Franses, van Dijk	1996	Germany (DAX), Netherlands (EOE), Spain (MAD), Italy (MIL), Sweden (VEC)	Q (Quadratic) GARCH, Random walk model	GJR-GARCH
Forecasting daily	Martens	2001		GARCH(1,1), ARCH (1,1)	

exchange rate volatility using intraday returns					
On measuring volatility and the GARCH forecasting performance	Barucci, Reno	2002	DM/USD, Yen/USD exchange rate returns	GARCH	
Forecasting volatilities and correlations with EGARCH models	Cumby, Figlewski, Hasbrouck	1993	US, Japan (returns on equities, long-term government bonds, dollar/yen exchange rates)	EGARCH (yet explanatory power very low)	Historical volatility
Forecasting volatility	Figlewski	1997	n/a	no method has been spotted as optimal for volatility forecasting	Implied volatility derived from option prices need not be a good proxy for the market's best forecast
Predicting volatility in the foreign exchange market	Jorion	1995	US (Chicago Mercantile Exchange closing quotes for currency futures and option on futures)	ISD (Implied Standard Deviations) from Black Scholes model; yet they are found to be biased in the sense of too variable relative to future volatiltiy	Statistical time-series models

Risk and turnover in the foreign exchange market	Jorion	1996	US (Chicago Mercantile Exchange closing quotes for currency futures and option on futures)	ISD (Implied Standard Deviations) from Black Scholes model	Statistical time-series models
Daily Volatility Forecasts: Reassessing the performance of GARCH models	McMillan, Speight	2004	17 exchange rates against USD	GARCH	
The predictive ability of several models of exchange rate volatility	West, Cho	1995	Five bilateral weekly exchange rates for the USD	could not show superiority of any models	
Answering the Skeptics: Yes, standard volatility models do provide accurate forecasts	Andersen, Bollerslev	1998	DM/USD, Yen/USD exchange rate returns	ARCH, stochastic volatility models	
Forecasting financial market	Andersen, Bollersle	1999	Foreign exchange market	SV (Standard Volatility) models	Continuous-time standard diffusion models

volatility: Sample frequency vis-a-vis forecast horizon	v, Lange		(DM/USD)		
Modeling and Forecasting Realized Volatility	Andersen, Bollerslev, Diebold, Labys	2002	DM/USD, Yen/USD exchange rate returns	VAR-RV (Long-memory Gaussian VAR for the realized logarithmic volatilities)	
Improving GARCH volatility forecasts with regime-switching GARCH	Klaasen	2002	DM/USD, GBP/USD, Yen/USD	Markov regime-switching GARCH	Single-regime GARCH
Forecasting exchange rate volatility	Vilasuso	2002	Exchange rates	Fractionally Intergated GARCH	GARCH, IGARCH
Forecasting index volatility: sampling integral and non-trading effects	Walsh, Tsou	1998	Australia (value weighted indices)	EWMA, GARCH	IEV (Improved extreme-value) method, historical volatility
Forecasting volatility: evidence from the German stock market	Bluhm, Yu	2001	Germany	stochastic volatility and implied volatility models (when option pricing is the primary interest), ARCH (when VaR is the objective)	

Forecasting volatility in the New Zealand stock market	Yu	2002	New Zealand	Stochastic volatility model, GARCH (3,2) the best within ARCH family	Regression and EWMA models
An evaluation of alternative models for predicting stock volatility: evidence from a small stock market	Frennberg	1995	Sweden (monthly stock returns)	AR(12) model, implied volatility from stock index options and lagged actual volatility	ARCH, GARCH
On the predictability of the stock market volatility: does history matter?	Adjaoute, Bruand, Gibson-Asner	1998	Switzerland (Swiss Stock Market Index)	ISD (Implied Standard Deviation)	GARCH(1,1)
An empirical analysis of alternative parametric ARCH models	Loudon, Watt, Yadav	2000	UK (FT All Share Index of the London Stock Exchange)	Parametric ARCH models (L(Linear)GARCH, M(Multiplicative)GARCH, E(Exponential)GARCH, GJR-GARCH, Non-linear asymmetric GARCH, VGARCH, TS-GARCH, Threshold GARCH)	
Forecasting UK stock market volatility	McMillan, Speight, Gwilym	2000	UK (FTA ALL Share and FTSE100 stock	All frequencies: GARCH and moving average; Monthly volatility forecasts: random walk; Weekly volatility forecasts: random	

			index)	walk, moving average recursive smoothing models; daily volatility forecasting: GARCH, moving average, exponential smoothing model	
Alternative models for conditional stock volatility	Pagan, Schwert	1989	US (stock market volatility)	Non-parametric methods, EGARCH	Hamilton, GARCH
Stock market volatility and the business cycle	Hamilton, Lin	1996	US (monthly stok returns and growth in industrial production)	They propose a new time series model able to improve stock volatility forecasting and to identify and forecast economic turning points	
Predicting stock index volatility: can market volume help?	Brooks	1998	US (NYSE aggregate volume and Dow Jones composite)	Simpler models, EGARCH	Augmenting models of volatility with measures of lagged volume, GJR-GARCH, GARCH in general
Additive Outliers, GARCH and forecasting volatility	Franses, Ghijsels	1999	Netherlands, Germany, Spain and Italy		

Forecasting stock market volatility: further international evidence	Balaban, Bayar, Faff	2004	Belgium, Canada, Denmark, Finland, Germany, Hong Kong, Italy, Japan, Malaysia, Netherlands, Philippines, Singapore, Thailand, UK and US	Exponential smoothing model (for standard symmetric loss functions and for asymmetric loss functions, when overprediction is penalized more heavily), ARCH class models (for asymmetric loss functions, underprediction penalized more heavily)	ARCH-based models (for standard symmetric loss functions and for asymmetric loss functions, when overprediction is penalized more heavily), random walk (for asymmetric loss functions, underprediction penalized more heavily)
Forecasting stock market volatility with regime-switching GARCH models	Marcucci	2005	US (S&P100)	MRS-GARCH (Markov Regime Switching GARCH) for short horizons, standard asymmetric GARCH for long horizons	GARCH for short horizons
Stock returns and volatility: empirical evidence from fourteen countries	Balaban, Bayar	2005	Belgium, Canada, Denmark, Finland, Germany, Hong Kong, Italy, Japan, Malaysia, Netherlands, Philippines	n/a	n/a

			, Singapore, Thailand, UK and US		
Multivariate GARCH with only univariate estimation	Burns	2005	n/a	PC-GARCH	
Measuring and testing the impact of news on volatility	Engle, Ng	1993	Japan	GJR-GARCH, PNP (Partially Nonparametric) ARCH	EGARCH
What good is a volatility model?	Engle, Patton	2001	US (DJIA)	GARCH	
On the relation between the expected value and the volatility of the nominal excess returns on stocks	Glosten, Jagannathan, Runkle	1993	US (returns on the CRSP value-weighted index of stocks)	GJR-GARCH	
A comparison of volatility models: Does	Hansen, Lunde	2001	DM/USD, IBM stock prices	Little evidence that GARCH (1,1) is outperformed by other models	ARCH(1)

anything beat a GARCH(1, 1)?					
Forecasting variance using stochastic volatility and GARCH	Hansson, Hordahl	2005	Swedish OMX-index returns	Stochastic volatility models	(E)GARCH
Does anything beat a GARCH(1, 1)? A comparison based on test for superior predictive ability	Hansen, Lunde	2003	US (IBM equity returns)	A-PARCH(2,2), V-GARCH with a Gaussian, generally the models that can accomodate a leverage effect	GARCH(1,1)
Forecasting the variability of stock index returns with stochastic volatility models and implied volatility	Hol, Koopman	2002	US (SP100)	In-sample: SVX(SV model with implied volatility as explanatory variable), SIV(stochastic implied volatility); Out-of-sample: SIV	In-sample: SV; Out-of-sample: SVX and SV
Forecasting the daily variability of the S&P100 stock index	Koopman, Jungbacker, Hol	2004	US (SP100)	Long memory models-Realised volatility models (ARFIMA-RV, UC-RV)	Models based on daily returns (SV, GARCH)

using historical, realised and implied volatility measurements					
Comparative performance of volatility forecasting models in Indian markets	Kumar	2006	India (stock market returns) NIFTY and Indian rupee/USD exchange rate	Stock returns: GARCH(4,1), EWMA; Forex market: GARCH(5,1)	
Forecasting China stock market volatility via GARCH models under skewed-GED distribution	Liu, Lee, Lee	2009	China (daily spot prices of Shanghai and Shenzen composite stock indices)	GARCH-SGED	GARCH-N
A forecast comparison of financial volatility models: GARCH(1,1) is not enough	Mapa	2004	Daily returns of Peso/USD exchange rate	TARCH(2,2), PARCH(2,2), EGARCH (generally models that accomodate the leverage effects)	
Stochastic volatility and	Pederzoli	2006	UK (FTSE100)	EGARCH	No straightforward preference between GARCH(1,1) and SV

GARCH: a comparison based on UK stock data					
Forecasting financial market volatility: A review	Poon, Granger	2003	Benchmarking done starting from the literature review	HISVOL (Historical Volatility), GARCH and ISD (option implied standard deviation). Among GRCH models, the best performing were models that imply volatility asymmetry such as EGARCH, GJR-GARCH, FIGARCH (Fractionally Integrated GARCH) and RSGARCH (Regime Switching GARCH), SV (stochastic volatility) models	
A multi country study of power ARCH models and national stock market returns	Brooks, Faff, McKenzie, Mitchell	2000	Australia, Canada, France, Germany, Hong Kong, Japan, New Zealand, Singapore, United Kingdom, US (Daily stock price index data) + Morgan stanley Capital International	PARCH (Power ARCH)	

Comparative forecasting performance of symmetric and asymmetric conditional volatility models of an exchange rate	Balaban	2004	Continuously compounded exchange rate returns calculated by using the average of closing bid-ask prices of USD/DM at Frankfurt Exchange	Specifically, EGARCH, GARCH; overall the standard symmetric GARCH	Specifically, GJR-GARCH; overall the standard asymmetric GARCH
Volatility forecasting for risk management	Brooks, Persand	2003	UK (FTSE All Share Total Return Index, FTA British Government Bond Index, Retuters Commodities Price Index)	In the context of statistical procedures, statistical measures preferred are GARCH(1,1). In the context of VaR estimates, the simplest models like long-term mean (historical average) or the autoregressive volatility model	Random walk, EGARCH, EWMA

Table 2. 50 paper literature review.

The whole diversity in rankings indicates the fact that researching volatility forecasting models surveyed is still far from fully exploration and volatility forecasting is still a notoriously, difficult task.

5.4 Autoregressive moving-average and conditional heteroskedastic models

5.4.1 From ARMA to ARCH model. What ARCH brings new

5.4.1.1 Modeling conditional heteroskedasticity

Volatility has some characteristics when we discuss about financial time series. The first one would be that it's not uniformly dispersed in time, it presents clustering effect, meaning that in some periods it may be overall higher or lower than in other periods. The second characteristic is its continuous evolvement in time as jumps are rarely seen. The third characteristic is that volatility does not diverge to infinity, that is, varies within some fixed range. This describes its stationary evolvement. The fourth characteristic is its leverage effect, describing a different reaction when a price largely increases or largely decreases.

Updates of the volatility forecasting models try to encompass such characteristics as the earlier models have failed to capture such features. One example would be the EGARCH model which has been developed in order to capture the asymmetry in volatility induced by large "positive" and "negative" asset returns.

Some financial time series might be serially uncorrelated, but dependent. Volatility models try to reveal such dependence in the return series of financial data.

If considering a return series as r_t, the conditional mean and variance of r_t given F_{t-1} is

$$\mu_t = E(r_t | F_{t-1}) \text{, } \sigma_t^2 = Var(r_t | F_{t-1}) = E\left[(r_t - \mu_t)^2 | F_{t-1}\right], \qquad (1)$$

where F_{t-1} stands for the information set at t-1 and σ_t is the positive root of σ_t^2. F_{t-1} usually consists of all linear functions of the past returns.

Since a serial dependence of a stock return series r_t is weak if it exists at all, the $\mu_t = E(r_t|F_{t-1})$ equation should be simple and we assume that r_t follows a simple time series model such as a stationary ARMA(p,q) model with some explanatory variables.

r_t becomes then:

$$r_t = \mu_t + a_t, \mu_t = \varphi_0 + \sum_{i=1}^{k} \beta_i x_{it} + \sum_{i=1}^{p} \varphi_i r_{t-i} - \sum_{i=1}^{q} \phi_i a_{t-i}, \tag{2}$$

where k, p, and q are non-negative integers and x_{it} are explanatory variables. a_t is called shock or innovation of an asset r_t while μ_t stands for the mean equation for r_t.

From (1) and (2) it results that

$$\sigma_t^2 = Var(r_t|F_{t-1}) = Var(a_t|F_{t-1})$$

Most of the conditional heteroskedastic models try to model σ_t^2. Actually, they differ from each other by the way in which this σ_t^2 evolves over time.

The autoregressive moving-average (ARMA) models join the concepts of AR and MA models with having as the main scope keeping the number of parameters small. Their importance in finance is given mainly for their use in explaining ARCH and GARCH models, the generalized autoregressive conditional heteroskedastic model being seen as a non-standard ARMA model for an a_t^2 series. The ARMA model has been firstly proposed by Box, Jenkins and Reinsel (1994).

An autoregressive model, in its simplest form, is a model in which one uses the statistical properties of the past behavior of a variable y_t to predict its behavior in the future. In other words, we can predict the value of the variable y_{t+1} by just taking into account the sum of the weighted values that y_t took in the previous period plus the error term ε_t.

Conditional heteroskedastic models may be grouped in two categories: one is the one in which σ_t^2 is modeled by an exact function, while the other is comprised by models that use a stochastic equation to describe σ_t^2. Examples would be GARCH model, for the first category and stochastic volatility models in the second one.

Modeling conditional heteroskedasticity means to create a dynamic equation which reproduces the evolution in time of the conditional variance of the asset return.

5.4.1.2 Testing for the ARCH effect

For simplification, we will note $a_t = r_t - \mu_t$ as the residuals of the mean equation. In the conditions of such notation, a_t^2 will be used for checking the existence of the conditional heteroskedasticity, called as well as ARCH effects.

For this purpose, there may be employed two tests. The first one is the Ljung-Box-Pierce test that applies LBPQ(m) statistics to the a_t^2 series (McLeod and Li (1983)). The null hypothesis of this test is that the first m lags of the autocorrelation function of the a_t^2 series is zero.

The other test of heteroskedasticity is the Engle test, called as well as the Lagrange multiplier test, developed by Engle (1982). The test is similar to the usual F statistic for testing $\alpha_i = 0$ where $i \in \{i, m\}$ in the linear regression

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + ... + \alpha_m a_{t-m}^2 + \varepsilon_t, t = m+1, ..., T,$$

where e_t stands for the error term, m is a preset positive integer and T stands for the sample size.

More specifically, the null hypothesis is

$$H_0 : \alpha_1 = \alpha_2 = ... = \alpha_m = 0.$$

Let $SSR_0 = \sum_{t=m+1}^{T}(a_t^2 - \overline{\omega})^2$, where $\overline{\omega} = (\frac{1}{T})\sum_{t=1}^{T} a_t^2$ is the sample mean of a_t^2 and $\mathrm{SSR}_1 = \sum_{t=m+1}^{T} \hat{e}_t^2$, where $\hat{e}_t$ is the least squares residual of the prior linear regression.

It follows then that

$$F = \frac{\frac{(SSR_0 - SSR_1)}{m}}{\frac{SSR_1}{T - 2m - 1}}$$

that is asymptotically distributed as a chi-squared distribution with m degrees of freedom under the null hypothesis.

In this case, the decision rule is:

If $F > \chi^2_m(\alpha)$ where $\chi^2_m(\alpha)$ is the upper 100(1-α)th percentile of χ^2_m, to reject the null hypothesis or if the p-value of F is less than α.

5.4.1.3 The ARCH model

The basic ideas of the ARCH model are: the shock a_t of the return of an asset is serially uncorrelated, but dependent, and the dependence of a_t can be described by a simple quadratic function of its lagged values. Specifically, ARCH(m) model is:

$$a_t = \sigma_t \varepsilon_t, \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + ... + \alpha_m a_{t-m}^2$$

where ε_t is a sequence of independent and identically distributed random variables with mean zero and variance 1, α_0>0, and $\alpha_i \geq 0$ for i>0.

In order to ensure finite unconditional variance of a_t, α_i's must satisfy some regularity conditions. In practice, ε_t is frequently assumed to follow the standard normal or a standardized Student-t distribution or a generalized error distribution.

Due to the relationship between a_t's and their lagged past values, we see that large shocks in the past $\{a_{t-1}^2\}_{i=1}^m$ generate large conditional variance σ_t^2 for the innovation a_t. Therefore, a_t tends to assume large values (in modulus). In ARCH terms, a large shock tends to be followed by another large shock. This is more obvious when clustering in asset returns is observed.

5.4.1.4 Properties of ARCH models

ARCH(1) model (with one lag) is

$$a_t = \sigma_t \varepsilon_t, \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2,$$

with α_0>0 and $\alpha_1 \geq 0$. In this case, the unconditional mean of the innovation a_t equals zero as

$$E(a_t) = E[E(a_t | F_{t-1})] = E[\sigma_t E(\varepsilon_t)] = 0.$$

Then, the unconditional variance of the innovation can be calculated as

$$Var(a_t) = E(a_t^2) = E[E(a_t^2 | F_{t-1})] = E(\alpha_0 + \alpha_1 a_{t-1}^2) = \alpha_0 + \alpha_1 E(a_{t-1}^2)$$

Since we assumed a_t as a stationary process[4], having its expectation E(a_t)=0, then Var(a_t) $= Var(a_{t-1})$=E(a_{t-1}^2). That makes that $Var(a_t)$=$\alpha_0 + \alpha_1 Var(\alpha_t)$ and $Var(a_t) = \frac{\alpha_0}{1-\alpha_1}$.

Due to the assumption of positive variation of a_t, then $\alpha_1 \in [0, 1)$.

But this is not the only constraint of α_1. Another common assumption that is done on α_1, is that its fourth moment is finite. This is assumed in order to ensure the existence of higher order moments of a_t. Thus, in the normality assumption of ε_t in the ARCH(m) model, we have

$E(a_t^4 | F_{t-1}) = 3(E(a_t^2 | F_{t-1}))^2 = 3(\alpha_0 + \alpha_1 a_{t-1}^2)^2$. Therefore, $E(a_t^4) = E\big(E(a_t^4 | F_{t-1})\big) = 3E(\alpha_0 + \alpha_1 a_{t-1}^2)^2 = 3E(\alpha_0^2 + 2\alpha_0\alpha_1 a_{t-1}^2 + \alpha_1^2 a_{t-1}^4)$.

If a_t is fourth-order stationary with $m_4 = E(a_t^4)$, then we have

$$m_4 = 3[\alpha_0^2 + 2\alpha_0\alpha_1 Var(a_t) + \alpha_1^2 m_4] = 3\alpha_0^2\left(1 + 2\frac{\alpha_1}{1-\alpha_1}\right) + 3\alpha_1^2 m_4.$$

[4] A time series $\{r_t\}$is said to be strictly stationary if the joint distribution of $(r_{t_1}, \dots, r_{t_k})$ is identical to that of $(r_{t_1+t}, \dots, r_{t_k+t})$ for all t, where k is an arbitrary positive integer and $(t_1, \dots, t_k)$ is a series of k positive integers. Other way said, strict stationarity does not vary with time. In finance, it is commonly assumed the weakly stationarity of the asset return series. A time series $\{r_t\}$ is considered to be weakly stationary when both the mean of $r_t$and r_{t-l} do not vary in time, *l* being an arbitrary integer. This is equivalent with E(r_t)=μ, where μ is a constant and Cov$(r_t, r_{t-l}) = \gamma_l$ that depends only in *l*. Graphically, weak stationarity may be observed when K observed data points fluctuate with constant variation around a fixed level.

Solving the above equation we obtain

$$m_4 = \frac{3\alpha_0^2(1+\alpha_1)}{(1-\alpha_1)(1-3\alpha_1^2)}.$$

The above formula implies two important things:

1) The first one is a further restriction on α_1. That is, since m_4, the fourth moment of a_t is positive, then $1-3\alpha_1^2 > 0$, that is $\alpha_1^2 \in \left[0, \frac{1}{3}\right)$, and
2) The unconditional kurtosis of a_t is

$$\frac{E(a_t^4)}{[Var(a_t]^2} = 3\frac{\alpha_0^2(1+\alpha_1)}{(1-\alpha_1)(1-3\alpha_1^2)} \times \frac{(1-\alpha_1)^2}{\alpha_0^2} = 3\frac{1-\alpha_1^2}{1-3\alpha_1^2} > 3$$

This means that the excess kurtosis of a_t is positive, and the tail distribution of a_t is heavier than that of a normal distribution. This is equivalent to the fact that the shock a_t of a conditional Gaussian ARCH(1) model is more likely than a Gaussian white noise series to produce "outliers". Indeed, in empirical work, the "outliers" are present more frequently in series of asset returns than that implied by an *iid* sequence of normal random variables.

These are the properties of general ARCH models and they characterize as well the general (GARCH) ARCH models, but for higher order ARCH models, formulas become more complex and difficult to be represented.

However, the $\alpha_i \geq 0$ condition can be further relaxed. Thus, this condition whose main role is to guarantee the positiveness (for all t's) of the conditional variance σ_t^2 may be rethought by rewriting the ARCH(m) model in a matrix form, as

$$a_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + A'_{m,t-1}\Omega A_{m,t-1}$$

where $A_{m,t-1}$=$(a_{t-1}, \ldots, a_{t-m})'$ and Ω is an $m \times m$ non-negative definite matrix. Under such notation, Ω must be a diagonal matrix. This is another form of ensuring positiveness of the conditional variation.

5.4.1.5 Building an ARCH model

5.4.1.5.1 Order Determination

If, when using the ACF and PACF functions a significant ARCH effect is found, PACF of a_t^2 may be employed to determine the ARCH order. The use of the PACF for this purpose may be justified as it follows:

If we look again at the conditional variance expression in the ARCH model,

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2$$

we see that for a given sample, a_t^2 is an unbiased estimate of σ_t^2. Thus, it is normal to expect that a_t^2 be linearly related to a_{t-1}^2, …, a_{t-m}^2 in a manner equivalent to that of an autoregressive model of order m. That means that for a given sample, we can look to the conditional volatility formula in an ARCH model as a simple autoregressive model. We can further observe that a single a_t^2 is not generally an efficient estimate of σ_t^2, but it may be used as an approximation that would prove informative in specifying the order *m*.

We may also define $\eta_t = a_t^2 - \sigma_t^2$. A characteristic of η_t that may be observed is that η_t is an un-correlated series with mean 0. Then, ARCH model may be re-written as

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 + \eta_t$$

which is the form of an AR(m) model for a_t^2, except that $\{\eta_t\}$ is not an iid series. Since $\{\eta_t\}$ are not identically distributed, the least squares estimates of the prior model are consistent, however, not efficient. The PACF of a_t^2 may not be effective when the sample size is small.

5.4.1.5.2 Estimation

In order to estimate ARCH, usually there are used two likelihood functions. Under the normality assumption, the ARCH(m) likelihood function is

$$f(a_{1,}\dots,a_T|\boldsymbol{\alpha}) = f(a_T|F_{T-1})f(a_{T-1}|F_{T-2})\dots f(a_{m+1}|F_m)f(a_{1,\dots,}a_m|\boldsymbol{\alpha})$$
$$= \prod_{t=m+1}^{T}\frac{1}{\sqrt{2\pi\sigma_t^2}}\exp\left(-\frac{a_t^2}{2\sigma_t^2}\right)$$

where $\alpha = (\alpha_0, \alpha_1, \dots, \alpha_m)'$ and $f(a_{1,\dots,}a_m|\boldsymbol{\alpha})$ is the joint probability density function of $a_1, a_2, \dots, a_m$. Since the exact form f is usually complicated, it is used to drop it from the prior likelihhod function, especially when the sample is large enough (and in our case, we discuss time series with 5000 observations or higher). It results the following likelihood function

$$f(a_{m+1,}\dots,a_T|\boldsymbol{\alpha}, a_1, \dots, a_m) = \prod_{t=m+1}^{T}\frac{1}{\sqrt{2\pi\sigma_t^2}}\exp\left(-\frac{a_t^2}{2\sigma_t^2}\right)$$

Maximizing the conditional likelihood function is equivalent with to maximizing its logarithm, which is easier to work with. The conditional log likelihood function is

$$l(a_{m+1,}\dots,a_T|\boldsymbol{\alpha}, a_1, \dots, a_m) = \sum_{t=m+1}^{T}\left(-\frac{1}{2}\ln(2\pi) - \frac{1}{2}\ln(\sigma_t^2) - \frac{1}{2}\frac{a_t^2}{\sigma_t^2}\right)$$

Since the first term $\ln(2\pi)$ does not consider any parameters, the log likelihood function becomes:

$$l(a_{m+1,}\dots,a_T|\boldsymbol{\alpha}, a_1, \dots, a_m) = -\sum_{t=m+1}^{T}\left(\frac{1}{2}\ln(\sigma_t^2) + \frac{1}{2}\frac{a_t^2}{\sigma_t^2}\right)$$

where $\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \dots + \alpha_m a_{t-m}^2$ can be evaluated recursively.

In some applications, it is assumed that ϵ_t follows a heavy-tailed distribution such as a standardized Student-t distribution. If we consider x_v as the Student-t distribution with v degrees of freedom, , then

$$Var(x_v) = {}^{v}/_{(v-2)}$$

for $v > 2$, and we use

$$\varepsilon_t = \frac{x_v}{\sqrt{v/(v-2)}}$$

The probability density function ε_t is then

$$f(\varepsilon_t|v) = \frac{\Gamma((v+1)/2)}{\Gamma(v/2)\sqrt{(v-2)\pi}}(1+\frac{\varepsilon_t^2}{v-2})^{-(v+1)/2}$$

Where $\Gamma(x)$ is the usual Gamma function.

If the degrees of freedom *v* of a Student-t distribution is prespecified, then the conditional log likelihood function is

$$l(a_{m+1,} \dots , a_T|\boldsymbol{\alpha}, A_m) = -\sum_{t=m+1}^{T}\left[\frac{v+1}{2}\ln\left(1+\frac{a_t^2}{(v-2)\sigma_t^2}\right)+\frac{1}{2}\ln(\sigma_t^2)\right]$$

To estimate *v* jointly with other parameters, then the log likelihood function involving degrees of freedom is

$$\begin{aligned} l(a_{m+1,} \dots , a_T|\boldsymbol{\alpha}, \boldsymbol{v}, A_m) \\ &= (T-m)[\ln(\Gamma((v+1)/2)) - \ln(\Gamma(v/2)) - 0.5\ln((v-2)\pi)] \\ &+ l(a_{m+1,} \dots , a_T|\boldsymbol{\alpha}, A_m) \end{aligned}$$

Where $l(a_{m+1,} \dots , a_T|\boldsymbol{\alpha}, A_m)$ is given above, and

$$f(x) = \frac{v exp\left(-\frac{1}{2}\left|x/\lambda|v\right)}{\lambda 2^{(1+1/v)}\Gamma(1/v)}$$

$-\infty < x < \infty$, $0 < v \leq \infty$, where Γ(.) is the gamma function and

$$\lambda = \left[2^{(-2/v)}\Gamma(1/v)/\Gamma(3/v)\right]^{1/2}$$

5.4.1.5.3 Weaknesses of ARCH models

ARCH models are simple and easy to handle, and take care of clustered errors, as well as of nonlinearities. One characteristic of ARCH models is the "random coefficients problem": the power of forecast changes from one period to another.

Among the weaknesses of the ARCH model, could be mentioned the following:

1. The model assumes the fact that both positive and negative shocks produce similar effects on volatility as it depends on the square of the previous shocks, while in the real world the price of a financial asset shows different (most often opposite) effects when affected by negative and positive shocks.
2. The ARCH model is rather restrictive. This is due to the fact that α_1^2 must find in different restricted intervals, depending of the series' moment. Thus, in an ARCH(1) model, α_1^2 must be in the $\left[0, \frac{1}{3}\right]$ interval if the series has a finite fourth moment. The constraint becomes more difficult to establish for higher order ARCH models. In the real world, such characteristic limits the ability of ARCH models with Gaussian innovations to capture excess kurtosis.
3. Another weakness of the model is that it doesn't help in understanding the source of variations of a financial time series. However, the only contribution is that it provides a mechanical method of linking the past variations to the present ones, thus depicting the time-varying conditional variance. But the causes of such behavior are not better illustrated.
4. Finally, ARCH models in most of the instances, they overpredict volatility because they respond slowly to large isolated shocks to the return series.

5.4.2 From ARCH to GARCH model. What GARCH brings new

Although the ARCH model has a basic form, one of its characteristics is that it requires many parameters to describe appropriately the volatility process of an asset return. Thus, alternative models must be further searched, one of them being the one developed by Bollerslev (1986) who proposes a useful extension known as the generalized ARCH.

As against the ARCH model, the Generalized Autoregressive Centralized Heteroskedastic Model (GARCH) has only three parameters that allow for an infinite number of squared roots to influence the current conditional variance. This feature allows GARCH be more parsimonious than ARCH model, feature that explains the wide preference for use in practice, as against ARCH.

While ARCH incorporates the feature of autocorrelation observed in return volatility of most financial assets, GARCH improves ARCH by adding a more general feature of conditional heteroskedasticity. Simple models - low values of parameters *p* and *q* in GARCH(*p,q*) - are frequently used for modeling the volatility of financial returns; these models generate good estimates with few parameters. Like everything else, however, GARCH is not a "perfect model", and thus could be improved - these improvements are observed in the form of the alphabet soup that uses GARCH as its prime ingredient: TARCH, OGARCH, M-GARCH, PC-GARCH etc.

Similar to ARCH model, the conditional variance determined through GARCH is a weighted average of past residuals. The weights decline but never reach zero. Essential to GARCH, is the fact that it permits the conditional variance to be dependent upon previous own lags.

The model can be written as it follows. Let's assume a log return series r_t and $a_t = r_t - \mu_t$ be the innovation at time *t*. We say that a_t follows a GARCH (*m,s*) model if

$a_t = \sigma_t \varepsilon_t$, $\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-1}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2$, where ε_t is a sequence of iid random variables with mean 0 and variance 1, $\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0$ and $\sum_{i=1}^{\max(m,s)} (\alpha_i + \beta_i) < 1$

(1)

Here it is understood that $\alpha_i = 0$ for i>m and $\beta_j = 0$ for *j*>*s*. The latter constraint on $\alpha_i + \beta_i$ implies that the unconditional variance of a_t is finite, whereas its conditional variance σ_t^2 evolves over time.

5.4.2.1 The GARCH model

Despite the relatively simple form of the ARCH models, they need a large number of parameters (like as the exogenous variables in a simple regression analysis) to adequately comprehend all the features of a volatility process of an asset return. To answer to this inconvenience Bollerslev (1986) proposed an extension of the model known as Generalized ARCH (GARCH) model. This may be described as it follows:

For a log return r_t series, with innovation (shock) at time t defined as $a_t = r_t - \mu_t$, it is said that a_t follows a GARCH(*m,s)* model if

$$a_t = \sigma_t \epsilon_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2$$

where ϵ_t is a sequence of iid random variables with mean 0 and variance 1. As well, $\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0$ and $\sum_{i=1}^{\max(m,s)} (\alpha_i + \beta_i) < 1$, whiles $\alpha_i = 0$ for $i > m$ and $\beta_j = 0$ for $j > s$. $\sum_{i=1}^{\max(m,s)} (\alpha_i + \beta_i) < 1$ ensures the fact that the unconditional variance of a_t is finite, while its conditional variance σ_t^2 evolves over time.

Also, ϵ_t is assumed to be standard normal or standardized Student-t distribution or generalized error distribution.

As it can be observed, a GARCH model reduces to a simple ARCH(m) model when s=0. $\alpha_i$is called as the ARCH parameter, while β_j is called as GARCH parameter.

In order to catch the strengths and weaknesses of a GARCH model, it is used to look to the simple GARCH(1,1) model. This is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

with $\alpha_1 \geq 0, \beta_1 \leq 1, (\alpha_1 + \beta_1) < 1$.

Like in a simple ARMA model, it can be seen that a large shock at moment t-1 , that is a large a_{t-1}^2, or a large σ_{t-1}^2 give rise to a large σ_t^2. That is, a large shock a_{t-1}^2tends to be followed by another shock at t, a_t^2, producing the transmission of shock or volatility clustering behavior characteristic to financial time series. This counts for the first strength of the GARCH model, its ability to model volatility clustering.

Then, if taking $1 - 2\alpha_1^2 - (\alpha_1 + \beta_1)^2 > 0$, then , taking expectations,

$$\frac{E(a_t^4)}{[E(a_t^2)]^2} = \frac{3[1 - (\alpha_1 + \beta_1)^2]}{1 - (\alpha_1 + \beta_1)^2 - 2\alpha_1^2} > 3$$

For 1-step ahead forecasts we have

$$\sigma_{h+1}^2 = \alpha_0 + \alpha_1 a_h^2 + \beta_1 \sigma_h^2$$

Where a_h and a_h^2 are known at the time index *h*. Therefore, the 1-step ahead forecast becomes

$$\sigma_h^2(1) = \alpha_0 + \alpha_1 a_h^2 + \beta_1 \sigma_h^2$$

For multistep ahead forecasts, $a_t^2 = \sigma_t^2 \epsilon_t^2$ is used and the volatility equation is written as

$$\sigma_{t+1}^2 = \alpha_0 + (\alpha_1 + \beta_1)\sigma_t^2 + \alpha_1 \sigma_t^2 (\epsilon_t^2 - 1)$$

When *t=h+1,* the equation becomes

$$\sigma_{h+2}^2 = \alpha_0 + (\alpha_1 + \beta_1)\sigma_{h+1}^2 + \alpha_1 \sigma_{h+1}^2 (\epsilon_{h+1}^2 - 1)$$

Since $E(\epsilon_{h+1}^2 - 1|F_h) = 0$, the 2-step ahead volatility forecast at the forecasting origin *h* satisfies the equation

$$\sigma_h^2(2) = \alpha_0 + (\alpha_1 + \beta_1)\sigma_h^2(1)$$

In general, we have

$$\sigma_h^2(l) = \alpha_0 + (\alpha_1 + \beta_1)\sigma_h^2(l-1), l > 1$$

This result is identical with that of an ARMA(1,1) model with AR polynomial $1 - (\alpha_1 + \beta_1)B$. By repeated substitutions in the above equation, we obtain that the *l*-step ahead forecast can be written as

$$\sigma_h^2(l) = \frac{\alpha_0[1 - (\alpha_1 + \beta_1)^{l-1}]}{1 - \alpha_1 - \beta_1} + (\alpha_1 + \beta_1)^{l-1}\sigma_h^2(1)$$

Therefore,

$$\sigma_h^2(l) \to \frac{\alpha_0}{1 - \alpha_1 - \beta_1} as\ l \to \infty$$

provided that $\alpha_1 + \beta_1 < 1$. Therefore, the multistep volatility forecast of a GARCH(1,1) converges to the unconditional variance of a_t as the forecast horizon increases to infinity provided that $Var(a_t)$ exists.

5.4.2.2 GARCH shortcomings

One of the shortcomings of GARCH is that this model takes into account only the size of the movement of the returns (magnitude), not the direction as well. Investors behave and plan their actions differently depending on whether a share moves up or down which explains why the volatility is not symmetric in the stance of the directional movements. Market declines forecast higher volatility than comparable market increases. This represents the leverage effect described by Gourieroux and Jasiak (2002). Both GARCH and ARCH have this limitation that impedes them from very accurate forecasts.

All GARCH models necessitate lots of data. Simulations (both univariate and multivariate) proved that 1000 observations is a small sample, and fewer than this does not provide any signal picked up. 5000 observations is not as well a very large sample in terms of accuracy with which parameters are estimated. GARCH models require several years of daily data in order to be trustworthy.

5.4.3 Extensions of GARCH model

5.4.3.1 The Exponential GARCH (EGARCH) Process

The GARCH process fails in explaining the "leverage effects" which are observed in the financial time series. Firstly observed by Black (1976), the leverage effects represent the tendency of variation in the prices of stocks to be negatively correlated with changes in the stock volatility. Other way said, the effect of a shock upon the volatility is asymmetric, meaning that the impacts of "good news" (positive lagged residual) and of "bad news" (negative lagged residual) are different. The Exponential GARCH (EGARCH) model of Nelson (1991) accounts for such an asymmetric response to a shock and has the following form for (1,1):

$$\log(\sigma_t^2) = \alpha_0 + \alpha_1 \left| \frac{u_{t-1}}{\sigma_{t-1}} \right| + \beta_1 \log(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sigma_{t-1}}$$

The leverage effects are represented by γ that accounts for the asymmetry of the model. The reason for considering this asymmetric effect is that it allows the volatility to react more promptly to reductions in the prices (that represent the "bad news") rather than to the corresponding increases (that stand for "good news").

The Exponential GARCH model

$$g(\epsilon_t) = \theta\epsilon_t + \gamma[|\epsilon_t| - E(|\epsilon_t|)]$$

$$E[g(\epsilon_t)] = 0$$

$$g(\epsilon_t) = \begin{cases} (\theta+\gamma)\epsilon_t - \gamma E(|\epsilon_t|)\ if\ \epsilon_t \geq 0 \\ (\theta-\gamma)\epsilon_t - \gamma E(|\epsilon_t|)\ if\ \epsilon_t < 0 \end{cases}$$

EGARCH(*m,s*):

$$a_t = \sigma_t\epsilon_t$$

$$\ln(\sigma_t^2) = \alpha_0 + \frac{1 + \beta_1 B + \cdots + \beta_S B^S}{1 - \alpha_1 B - \cdots - \alpha_m B^m} g(\epsilon_{t-1})$$

$$a_t = \sigma_t\epsilon_t$$

$$(1 - \alpha B)\ln(\sigma_t^2) = (1-\alpha)\alpha_0 + g(\epsilon_{t-1})$$

$$E(|\epsilon_t|) = \sqrt{2/\pi}$$

$$(1 - \alpha B)\ln(\sigma_t^2) = \begin{cases} \alpha_* + (\gamma+\theta)\epsilon_{t-1}\ if\ \epsilon_{t-1} \geq 0 \\ \alpha_* + (\gamma-\theta)(-\epsilon_{t-1})\ if\ \epsilon_{t-1} < 0 \end{cases}$$

where $\alpha_* = (1-\alpha)\alpha_0 - \sqrt{2/\pi}\,\gamma$

$$\sigma_t^2 = \sigma_{t-1}^{2\alpha}\exp(\alpha_*) \begin{cases} exp\left[(\gamma+\theta)\dfrac{a_{t-1}}{\sigma_{t-1}}\right]\ if\ a_{t-1} \geq 0 \\ exp\left[(\gamma-\theta)\dfrac{|a_{t-1}|}{\sigma_{t-1}}\right]\ if\ a_{t-1} < 0 \end{cases}$$

5.4.3.1.1 Forecasting using an EGARCH Model

$$\ln(\sigma_t^2) = (1-\alpha_1)\alpha_0 + \alpha_1\ln(\sigma_{t-1}^2) + g(\epsilon_{t-1})$$

$$g(\epsilon_{t-1}) = \theta\epsilon_{t-1} + \gamma(|\epsilon_{t-1}| - \sqrt{2/\pi})$$

$$\sigma_t^2 = \sigma_{t-1}^{2\alpha_1} exp[(1-\alpha_1)\alpha_0] exp[g(\epsilon_{t-1})]$$

$$g(\epsilon_{t-1}) = \theta\epsilon_{t-1} + \gamma(|\epsilon_{t-1}| - \sqrt{\frac{2}{\pi}})$$

5.4.3.2 The Threshold GARCH (TARCH) Process

EGARCH is not the only model that accounts for the asymmetric effect of the news. Threshold GARCH (TARCH) model developed by Zakoian (1994), Glosten, Jaganathan and Runkle (1993) does the same thing, but the leverage effect is expressed in a quadratic form while in the case of EGARCH it is expressed in the exponential form.

A TARCH (*p,q*) process may be specified as it follows:

$\sigma_t^2 = \omega + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{k=1}^{r} \gamma_k u_{t-k}^2 I_{t-k}^-$ where

$I_{t-k}^- =$ 1, if $u_t < 0$ and = 0 otherwise. $u_{t-i} > 0$ represents the "good news" and $u_{t-i} < 0$ represents the "bad news". They have different outcomes on the conditional variance. The impact of the news is asymmetric and the leverage effects exist when $\gamma_k \neq 0$. For $\gamma_k = 0$ (for all *k*), TARCH takes the form of a standard GARCH model.

The Threshold GARCH Model

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{s} (\alpha_i + \gamma_i N_{t-i}) a_{t-i}^2 + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2$$

$$N_{t-i} = \begin{cases} 1\ if\ a_{t-i} < 0 \\ 0\ if\ a_{t-i} \geq 0 \end{cases}$$

5.4.3.3 The Integrated GARCH (IGARCH)

$\eta_{t-i} = a_{t-i}^2 - \sigma_{t-i}^2$ for $i > 0$

$a_t = \sigma_t \epsilon_t, \sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + (1 - \beta_1) a_{t-1}^2$

$$\sigma_h^2(l) = \sigma_h^2(1) + (l - 1)\alpha_0, l \geq 1$$

$$\sigma_t^2 = (1 - \beta_1) a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 = (1 - \beta_1) a_{t-1}^2 + \beta_1 [(1 - \beta_1) a_{t-2}^2 + \beta_1 \sigma_{t-2}^2]$$
$$= (1 - \beta_1) a_{t-1}^2 + (1 - \beta_1) \beta_1 a_{t-2}^2 + \beta_1^2 \sigma_{t-2}^2$$

$$\sigma_t^2 = (1 - \beta_1)(a_{t-1}^2 + \beta_1 a_{t-2}^2 + \beta_1^2 a_{t-3}^3 + \cdots)$$

5.4.3.4 The GARCH M model

$$r_t = \mu + c\sigma_t^2 + a_t, a_t = \sigma_t \epsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

5.4.3.5 The CHARMA Model

$$r_t = \mu_t + a_t$$

$$a_t = \delta_{1t} a_{t-1} + \delta_{2t} a_{t-2} + \cdots + \delta_{mt} a_{t-m} + \eta_t$$

$$a_t = a'_{t-1} \delta_t + \eta_t$$

$$a_{t-1} = (a_{t-1}, \ldots, a_{t-1})'$$

$$\sigma_t^2 = \sigma_\eta^2 + a'_{t-1} cov(\delta_t) a_{t-1} = \sigma_\eta^2 + (a_{t-1}, \ldots, a_{t-m}) \Omega (a_{t-1}, \ldots, a_{t-m})'$$

$$\sigma_t^2 = \sigma_\eta^2 + \omega_{11} a_{t-1}^2 + 2\omega_{12} a_{t-1} a_{t-2} + \omega_{22} a_{t-2}^2$$

5.4.3.6 The Random Coefficient Autoregressive Models

$$r_t = \varphi_0 + \sum_{i=1}^{p} (\varphi_i + \delta_{it}) r_{t-i} + a_t$$

$$\mu_t = E(r_t|F_{t-i}) = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-i}$$

$$\sigma_t^2 = \sigma_a^2 + (r_{t-1}, \dots, r_{t-p}) \Omega_\delta (r_{t-1}, \dots, r_{t-p})'$$

5.4.3.7 The Stochastic Volatility Model

$$a_t = \sigma_t \epsilon_t$$

$$(1 - \alpha_1 B - \cdots - \alpha_m B^m) \ln(\sigma_t^2) = \alpha_0 + v_t$$

$$\ln \sigma_t^2 \sim N(\frac{\alpha_0}{1-\alpha_1}, \frac{\sigma_v^2}{1-\alpha_1^2}) \equiv N(\mu_{h,} \sigma_h^2)$$

5.5 Assessing the quality of the volatility forecasting techniques

A discussion regarding the quality measuring tools and methodology used for that would be needed at this point. What makes a model of better quality as against another? How quality is defined and how we measure it?

Among the evidence that highlights the superiority of more complex models (although in some points there are some consistencies in findings with the previous mentioned evidence), there is Brailsford and Faff (1995), who, by using Australian data, showed empirically that more advanced ARCH class models and a simple regression model provided superior forecasts of volatility. A second finding of them would be that the various model rankings are sensitive to the choice of error statistic, used to assess the accuracy of forecasts. Of course, when bringing into discussion the results of

Brailsford and Faff and those of Dimson and Marsh, we make a strong assumption, that the using different pools of data (Australian and UK) does not affect the quality of the models tested. This means that, if doing Brailsford and Faff analysis with UK data and Dimson and Marsh with Australian data, their conclusions would still hold.

Most of the literature expresses the quality as a measure between the actual and relative error statistics. The methodology that offers the most complete basis of argumentation and on which this paper's scale of models is based on is the one developed by Brailsford and Faff (1995). The choice for this methodology encompasses the following facts: it uses more (four) characteristics of benchmarking, it follows previous studies (Akgiray (1989), Dimson and Marsh (1990), Tse (1991) and Tse and Tung (1992)) and thus it sums up and investigates all their previously discussed models, and, the last but not least, it is straightforward and due to this, there is little space for flaws or threats. I will shortly describe this method in the few following lines of this paper.

In their (Brailsford and Faff's) paper, the quality of one model has been put in evidence by calculating four different error statistics[5] across eleven models used to forecast monthly volatility:

1) mean error (ME) statistic defined by the expression $ME = \frac{1}{90}\sum_{T=1}^{90}(\hat{\sigma}_T^2 - \sigma_T^2)$
2) mean absolute error statistic (MAE) that is a mean absolute error statistic defined by the expression $MAE = \frac{1}{90}\sum_{T=1}^{90}\left|\hat{\sigma}_T^2 - \sigma_T^2\right|$
3) root mean squared error statistic (RMSE) defined by RMSE= $\sqrt{\frac{1}{90}\sum_{T=1}^{90}(\hat{\sigma}_T^2 - \sigma_T^2)}$ and
4) mean absolute percentage error statistic (MAPE) defined by expression MAPE=$\frac{1}{90}\sum_{T=1}^{90}\left|(\hat{\sigma}_T^2 - \sigma_T^2)/\sigma_T^2\right|$

where $\hat{\sigma}_T^2$ is the raw monthly volatility series and σ_T^2 last month's observed volatility.

[5] The methodology is based on evaluating and comparing 90 monthly forecast errors generated from each model which are compared by their ME, MAE, RMSE and MAPE. These 90 errors represent the out-of-sample

They consider for testing the following models: one random walk model, one historical mean model, two moving average models, one exponential smoothing model, one exponentially weighted moving average model, one simple regression model, two standard GARCH models, and two GJR-GARCH models.

Worth to be mentioned, the methodology of Dimson and Marsh (1990) differs from the one of Brailsford and Faff (1995) by the fact that they standardize each error statistic by the value of the error statistic obtained from the random walk forecast. They chose such a methodology due to the fact that the statistics can be interpreted more easily relative to the benchmark forecast.

But Brailsford and Faff (1995) chose to express each (of the four above-mentioned) error statistic on a relative basis, where the benchmark is the value of the statistic for the worst performing model. Although usually fitting investigations on volatility models are run on the basis of full sample information, for benchmarking purposes these models need to be examined out-of-sample. This means that the authors selected an out-of-the sample of 90 observations (90 months) on which they tried to make predictions using the eleven models selected. So, for each of these eleven models, they calculated the errors made from the difference between reality and forecasts, according to the fours error statistics. For each of the eleven models, they obtained four different error statistics. Each model was benchmarked after the size of discrepancy (size of errors) between forecast and real values. They also obtained relative error statistics, by expressing the actual statistic as a ratio relative to the worst performing model (the one that had the biggest absolute error statistic) for a given error measure. They compared the actual and relative forecast error statistics for each model across the four error measures. As previously said, the **quality factor** was the difference between these actual and relative forecasts. For each statistic, the model with the biggest difference was considered to be the benchmark (as the worst performer, since the model was giving too large differences), while the model with the smallest difference was the best performing, with the highest quality. Notable to be mentioned is that for each error statistic (and model) we have (potentially) a different benchmarking model. Furthermore, the power of one test against another (by how many percentage points one model is better than another) has been calculated by the following formula:

$$\frac{(\varepsilon_i - \hat{\varepsilon}_i) - (\varepsilon_b - \hat{\varepsilon}_b)}{(\varepsilon_b - \hat{\varepsilon}_b)}$$, where

ε_i = actual forecast error statistic of the best model

$\hat{\varepsilon}_i$ = forecast error statistic of the best model

ε_b = actual forecast error statistic of the benchmark model

$\hat{\varepsilon}_b$ = relative forecast error statistic of the benchmark model

The same result (power) may be obtained by subtracting each relative error statistic from 1.

So, for each of the four error statistics, there were provided different answers as regards which model performs better. So, these statistics should be assigned different interpretations and/or different powers in assigning the best/worst model.

In this paper, the error statistics were interpreted and gave results as it follows:

a. ME gives the direction of over/underprediction. All models tested by Brailsford and Faff (1995) were found to be underpredicted with one exception (exponential smoothing model);
b. MAE statistics indicated GJR-GARCH (1,1) as the best model, with 35 percent higher accuracy than the benchmark model, which for this statistic was found to be the exponential smoothing model;
c. RMSE equally favors the historical mean and the simple regression model (23 percent more accurate than the benchmark model). To be noted that for this statistic GJR-GARCH (1,1) ranks fourth and
d. MAPE gives a relative indication of overall forecasting performance. In this case GJR-GARCH (1,1) model has been found with the best (actual) MAPE of 56.9 percent.

In summary, the ranking of each of the four forecasting models varies depending upon the choice of the error statistic, but it seems that GARCH ranks the best. This variability in rankings underlines the potential hazard of selecting the best model on the basis of an arbitrarily chosen error statistic.

However, some consistency exists among the findings of different empirical tests, although methodologies differ. Dimson and Marsh (1990) used instead of RMSE statistic, the primary error measure. Their conclusion was that the simple regression model is superior. This is relatively consistent with one result of Brailsford and Faff who found that simple regression model and RMSE equally rank among the first in terms of performance. Furthermore, Dimson and Marsh found that the superiority of the simple model is insensitive to the use of the MAE statistic, which is again consistent with Brailsford and Faff's findings. However, while Dimson and Marsh found an equivalent ranking across all models between their error statistics, Brailsford and Faff's model rankings, while similar, were not entirely robust between RMSE and MAE statistics. This inconsistency was even further exacerbated when other error statistics, like MAPE statistic, were considered.

As above mentioned, the models will be ranked according to this methodology. Accordingly, there will be assumed the superiority of more complex models (as GARCH) against simpler ones. Staring from this assumption, the paper will provide insights on PC-GARCH searching for possible areas where using principal component analysis may provide superior quality/cost ratios than simpler GARCH.

5.6 Why PC-GARCH?

GARCH splits the variance forecasts into two components - autocorrelations, or volatility in the past, and innovations, or exogenous shocks in the volatility of returns. Using GARCH(1,1) leads us immediately to ask the question: how much of the innovation is truly "exogenous" and how much is explained by "other factors" not considered in the model? To improve the model, we could begin by considering other explanatory variables that could influence the volatility of our estimate (in other words, to endogenise some of the exogeneity). However, adding explanatory variables leads us to a particular weakness of GARCH: the parameter estimation problem. Due to the correlations (usually not zero) between the variables used in the GARCH, the problem requires substantial amounts of data and computational power to come up with a reasonably robust estimate. Thus we aim to improve the volatility forecast of an asset compared to that obtained from GARCH, but using a more tractable method that handles multiple independent variables. This is accomplished using PC-GARCH.

In what it follows there will be discussed the issues with multivariate GARCH estimation, uncovered in the previous sections. We know that the number of parameters in a multivariate GARCH increases at the rate of the square of the number of variables. For example, using n variables will necessitate estimation of $\frac{n(n+1)}{2}$ parameters; this is because each additional variable brings with it correlation terms with the other variables, and each of these correlation terms has its own parameter. The dimensionality of the problem and hence computational power requirement is rather large. Further, robust parameter estimation imposes demanding data requirements. Apart from estimation problems, there are practical issues of stability for prediction: a large number of parameters as inputs to the model would frequently result in unstable estimates. Due to the inherent data-fitting nature of every statistical procedure, there may be noise in the estimation period that is captured as signals into our model.

One of the methods proposed to make the problem tractable is the PC-GARCH (another algorithm that also uses Principal Components but which is different in its implementation is called Orthogonal GARCH). In this study, a simple model will be used to illustrate the power of this method, in particular, the power of the Principal Component Analysis (PCA) used in conjunction with GARCH, that will solve the problems above-stated.

As noted earlier, the increased dimensionality of the multivariate GARCH is due to the large number of covariances between independent variables that enter the parameter space. Therefore, making these covariances zero reduces the dimension of the problem to n (or we will have to estimate only n parameters each for the GARCH and ARCH). Thus, PCA is the tool to be used to simplify the problem and make it tractable. PCA is a method of transforming original independent variables[6] into orthogonal factors[7]. Thus, using n (possibly correlated) independent variables and

[6]The term independent is not used in its mathematical sense. “Orthogonal”, “orthogonality” or “uncorrelated” are reserved for that purpose and the term “independent variables” will be used to mean the set of observed variables upon which the return volatility is expected to depend.

[7]I wish to clarify the use of the terms “variables” and “factors” in this text. “Variables” are in the sense described in the previous footnote, while “factors” and “principal components” are reserved for linear combinations of variables that are an output of the Principal Components Analysis.

applying PCA reduces the number of parameters to be estimated to $2n+1$ instead of $\frac{n(n+1)}{2}$ (a linear instead of a quadratic increase in the number of parameters to be estimated). Thus, the PCA method helps us reduce the modeling problem into n univariate GARCH models. The methodology for the analysis to be followed along the paper is the one belonging to Burns (2005). There are other, alternative, methods developed in the literature that use PCA in conjunction with GARCH; examples are Alexander (2000) and van der Weide (2002).

Briefly stating the problem in mathematical terms, we have the variable y which is dependent on k independent variables. n historical observations each of these k independent variables are arranged in a matrix $\mathbf{X}$ of dimension $n \times k$, and the n historical observations of the dependent variable are arranged in an $n \times 1$ matrix $\mathbf{Y}$. In very general terms, we wish to find the function f that maps the independent variables onto the dependent variable: $\mathbf{Y} = f(\mathbf{X})$. To summarize, the problem with finding this general function is that

(1) even a small increase in k makes the problem computationally and data intensive and

(2) some of the independent variables are correlated: they contain common information, and we wish to coalesce similar information into a single variable that represents that information and have uncorrelated independent explanatory variables.

5.7 Principal Component Analysis (PCA): a brief introduction to the method

Principal Component Analysis is an algorithm used in the Factor Analysis. Factor Analysis is a generic method given to a class of multivariate statistical methods that has as its main goal to identify the underlying structure in a data matrix. Specifically, the Factor Analysis has two primary uses: summarization and data reduction. Summarization results from describing the data with a much smaller number of variables, while reduction comes from transforming the data matrix into a score matrix, in which each column stands for a factor[8].

Principal Component Analysis is a method used for extracting the most independent sources of information in the data. From a set of *k* stationary returns it will return up to *k* orthogonal (independent) stationary variables which are called Principal Components (PCs) or variates. PCA is a classical technique to derive such uncorrelated variates. An output of the method also states how much of the total variation in the original data is explained by each PC.

Due to the high sensitivity of the results to re-scaling data, before proceeding to the analysis, the standard procedure is to normalize the data. Thus, we assume that each column in the stationary matrix has mean zero and variance one, after previously subtracted the sample mean and divided by the sample standard deviation.

We start with the matrix **X** with columns $(x_1 \quad x_2 \quad \ldots \quad x_k)$, where $\{x_i, 1 \le i \le k\}$ is such that **X'X** is a $k \times k$ symmetric matrix, having one on its diagonal. **Ω** = **X'X** is the variance-covariance matrix of the variables in **X**, and thus is positive definite. For simplicity, we consider **X** as having only one line. Each principal component will be then a combination of these columns.

$$p_m = a_{1,m}x_1 + a_{2,m}x_2 + \ldots + a_{k,m}x_k, \qquad 1 \le m \le k \qquad \textbf{(2)}$$

In matrix form, (2) can be written as $\mathbf{P_{1,m}} = \mathbf{X_{1,k}A_{k,m}}$ where $\mathbf{A}=\begin{pmatrix} a_{11} & a_{12} & \ldots & a_{1m} \\ a_{21} & a_{22} & \ldots & a_{2m} \\ \ldots & \ldots & \ldots & \ldots \\ a_{k1} & a_{k2} & \ldots & a_{km} \end{pmatrix}$.

A is called the matrix of the eigenvectors[9] of **Ω.** The weights $a_{i,m}$ for each x_i are chosen from the set of eigenvectors of the correlation matrix **Ω** such that:

---

[8] Set of common underlying dimension

[9] Here I should introduce a comment about the eigen vectors and values and their significance. An eigen vector is a vector that is scaled by a linear transformation, but not moved. It's like an arrow whose direction does not change. No matter it shrinks or stretches according to the transformation of its space, its direction does not change, pointing to the same direction. The eigen value is the scaling factor of an eigen vector. The significance of an eigen value makes sense only in the context of an eigen vector, i.e, an arrow whose length has been changed.

1) The Principal Components (PCs) are orthogonal. So, we impose the orthogonality condition to the matrix **P** of the principal components (as this is the main property of such PCs – orthogonality), and according to it, we have to find the matrix **A** of weights that fulfils this condition. In other words, we want to know who are $a_{i,m}$'s such that, their matrix, multiplied by an **X** matrix of observations, gives an orthogonal matrix.
2) The first principal component explains the maximum amount of total variation in **X,** the second component explains the maximum amount of the remaining variation, and so on.

We know from matrix algebra that if we choose the matrix **A** to be composed of orthogonal unit eigenvectors of **XX'**, then the resulting PCs are orthogonal. It means, then, the only condition such that **P** be orthogonal is that columns of **A** be orthogonal.

We next order the columns of **A** in descending order: $a_{1,m}$, $a_{2,m}$, ..., $a_{k,m}$ where $m=\{1,2,...,k\}$ (the corresponding eigenvalues). In this way, if **A**($a_{i,j}$), *i,j* = $\{1,...,k\}$ then the m^{th} column of **A**, denoted as a_m = ($a_{1,m}$, $a_{2,m}$, ..., $a_{k,m}$)' is the $(k\times 1)^{th}$ eigenvector corresponding to the eigenvalue λ_m, and the column must be ranked so that $\lambda_1>\lambda_2>...>\lambda_k>0$.

We now define a new matrix **Λ**= $\begin{pmatrix} \lambda_1 & 0 & ... & 0 \\ 0 & \lambda_2 & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \lambda_k \end{pmatrix}$ which is the diagonal matrix of the eigenvalues of **Ω**, and we note that

X'XA=AΛ, from where it results **Λ** =**A'X'XA** = **A'ΩA.** As well, we have **(XA)'XA = A'X'XA = Λ.** The above relationship then becomes

Λ = **P'P** = **A'X'XA** = **A'ΩA** **(3)**

Since **Λ** is a diagonal matrix, and it is the variance-covariance matrix of **P**, this implies that the components (columns) of **P** are uncorrelated. Since **A** is orthogonal, **A'=A^{-1}** and **P'P=Λ. A'=A^{-1}** is equivalent to **X=PA'** that is

$X_i=w_{i1}P_1+w_{i2}P_2+...+w_{ik}P_k$

where X_i and P_i denote the columns of **X** and **P** respectively. Thus each data vector is a linear combination of the principal components. The proportion of the total variation in **X** that is explained by the m^{th} principal component is λ_m/(sum of the eigenvalues).

Thus, the operation of scaling the original variables with the matrix of orthogonal unit eigenvectors **A** gives us uncorrelated components (PCs) that we could use to reduce the earlier multivariate GARCH problem to a set of univariate GARCH problems.

5.8 Methodology

As it has been said at the beginning of the discussion, the results of the paper of Brailsford and Faff (1995) will be used for the purpose of this paper and, accordingly, the superiority of GARCH type models will be assumed. But GARCH may be too costly sometimes to be used, as described earlier. For this, and at this point I will address to the second factor that supports second part's main conclusion, using Principal Component Analysis (PCA) may be an effective and at-hand solution. PCA does two things that improve the model: one is that it reduces the dimensionality of the problem, and then is that it excludes autocorrelations in the data. The only subjective point in the problem is the cut point the user has to choose. Other way said, how much of the preciseness should be sacrificed for how much time saved. This ability of choosing the output to time report gives the user of the model flexibility, allowing for tailored options according to activities and companies' specific.

The sequence of the paper started by a presentation of the main models showing what each model brought new as against the previous one; then it followed a presentation of the PC-GARCH model. That started with a discussion on the Principal Component Analysis, and on how PC-GARCH is built. After the theoretical presentation of the PC-GARCH model, an empirical application will follow from the next section. Both theoretical part and the empirical part will be developed together in order to offer a complete understanding on how PC-GARCH works. They will both contribute to the main conclusion of this chapter that will state the superiority of PC-GARCH as against any alternative models when one deals with large portfolios of data.

5.9 Experimental study

5.9.1 Data setting

Our task is to estimate the volatility of the return of a particular portfolio formed of inter-correlated stocks (Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M) using PCA in conjunction with the GARCH model. The selection of these seven stocks has been driven by the fact that PCA works best when there is a reasonable amount of correlation between the variables; there is good reason[10] to suspect that the chosen seven US stock returns would be correlated.

	ADOBE	APPLE	AUTODESK	CISCO	DELL	MICROSOFT	3M
Average daily return	0.12%	0.11%	0.08%	0.15%	0.16%	0.09%	0.03%
Daily return volatility	3.44%	3.12%	3.18%	2.95%	3.20%	2.20%	1.51%
Excess kurtosis	7. 310	4.976	20.331	5.063	4.062	5.391	4.792

Table 3: Summary statistics of Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M over the sample period. Data source: Datastream.

We are thus in a position to argue that the Microsoft, for instance, is not influenced by only its own past, but as well by the past of the other shares included in this selected portfolio. As a hypothetical example, a lot of volatility in the Microsoft returns could signal the uncertainty in the technology sector; the Adobe the next day would likely take into account[11] the uncertainty in the technology sector induced by Microsoft and extrapolate that into the uncertainty forecasts of its activity. While I limit my study to the seven stock return series mentioned above, I do not suggest that these are the only

[10] The most prominent reason being that they are influenced by the US economy even though their weighting towards sectors is different. See the discussion of the different sectoral foci of the indices which follows immediately in the text above.
[11] Through the aggregation of the trades of market participants. No particular information transmission mechanism is supposed here, only that some such mechanism holds.

shares that matter - this study is simply a means to demonstrate the power of the technique and claim that this model is “the best” in forecasting volatility of intercorrelated time series.

5.9.2 Data sample

There have been selected seven stock returns[12]: Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M beginning Feb 16th 1990 and running up to June 18th 2009. This gives us a total of 5044 return observations. As discussed earlier, the choice for these equity returns is reasoned by their high (as expected) correlations, a fact that makes their cases as ideal for applying PCA. However, the seven stocks are fundamentally different too, thing that makes interesting to isolate the effects of their composition. Let’s first familiarize ourselves with the data.

When estimating parameters of a composite conditional mean/variance model, one may confront with convergence problems. Thus, the estimation may appear to stall, or show little or no progress. To avoid these difficulties, it is recommended to perform a pre-fit analysis. The main scope of this is to mitigate against any kind of convergence problems, by choosing the most appropriate model that describes the data. In our case, the scope is to find, before performing PC-GARCH, if the data is appropriate for a GARCH-type model. This would constitute the pre-fit analysis that must precede the PC-GARCH exercise. By this, we want to establish the degree of autocorrelation in the data.

There are two steps in this **pre-fit analysis**:

A. Plotting the return series and analyzing autocorrelation function (ACF) and the partial autocorrelation function (PACF).
B. Performing preliminary tests, like Engle’s ARCH test or the Q-test.

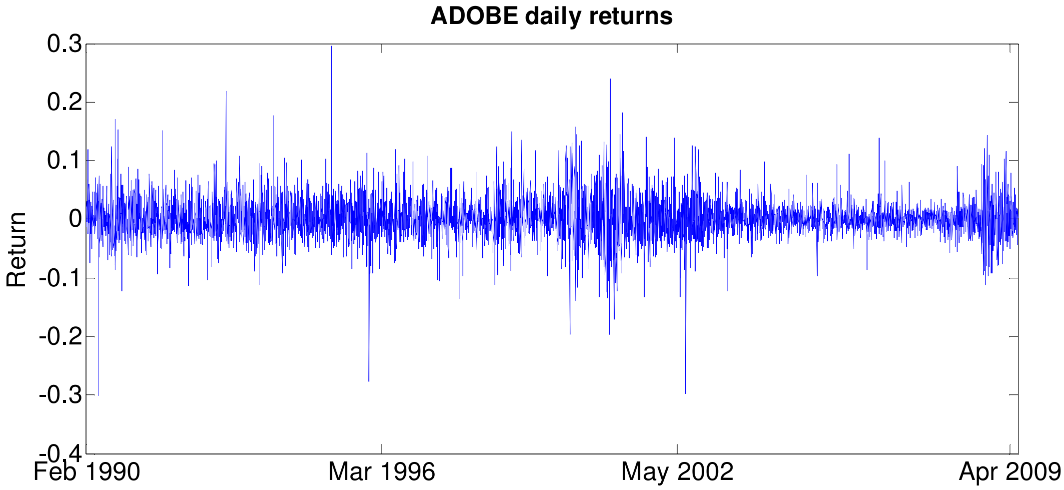
A. Plotting the return series and analyzing autocorrelation function (ACF) and the partial autocorrelation function (PACF).

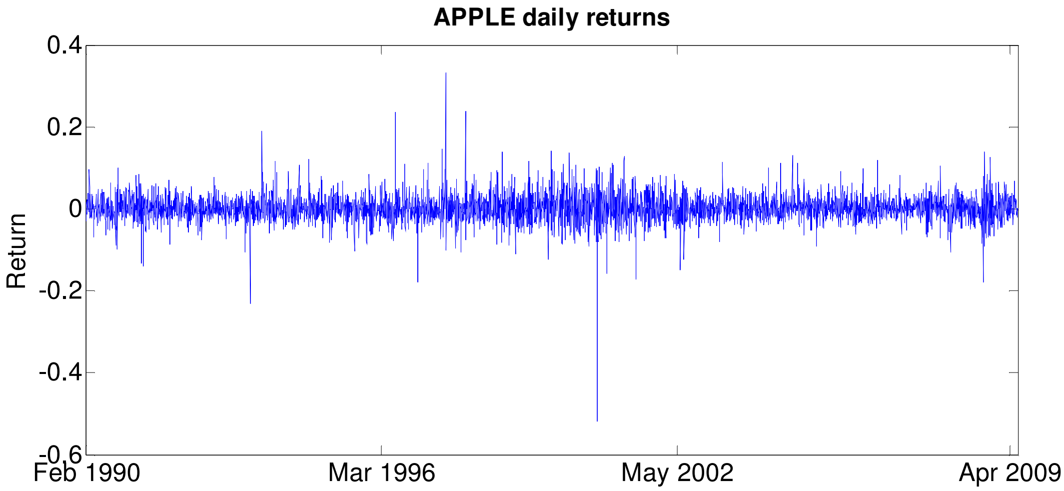
[12] Source www.datastream.com

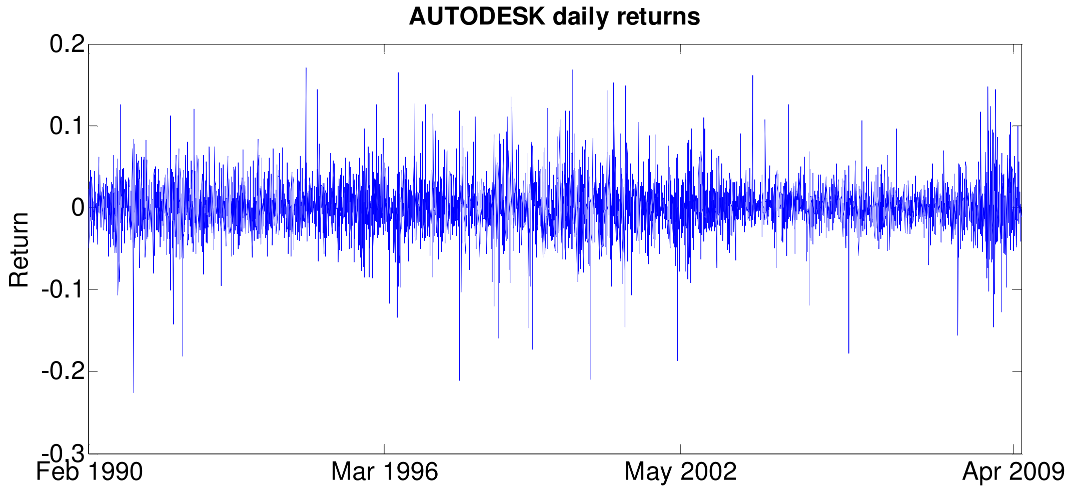
A.1. Because GARCH modeling assumes working with returns, we need to convert stock prices into stock returns.

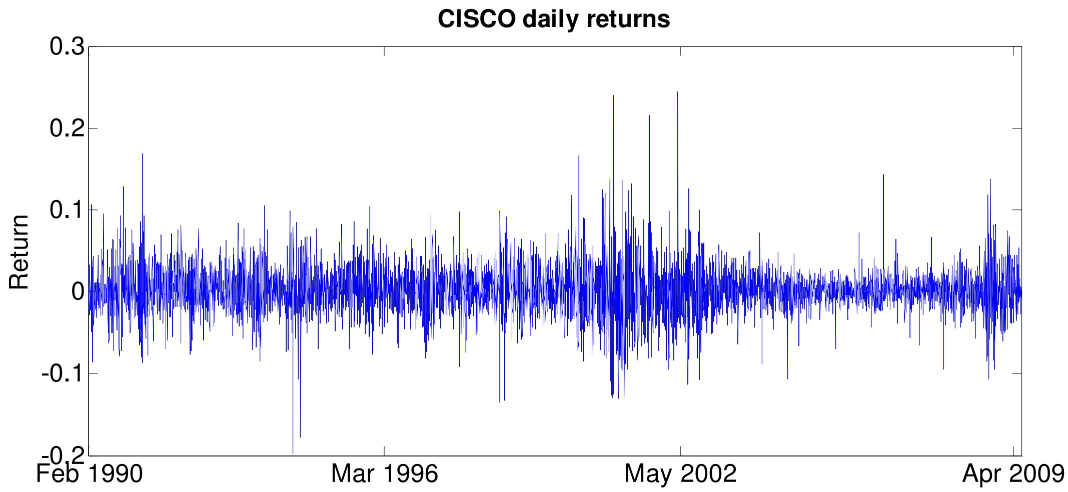
a) *price2ret* function is used to obtain the return series out of prices.

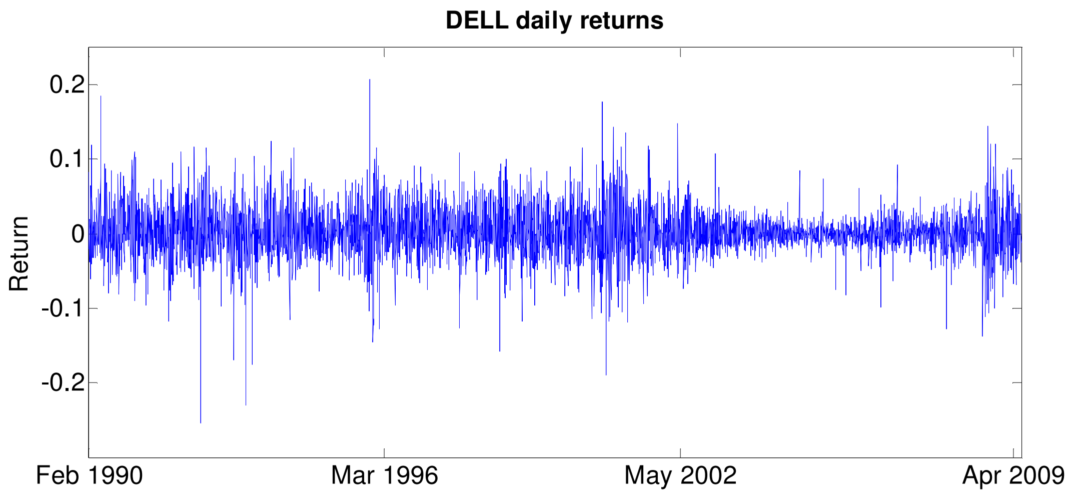
b) By using the *plot* function of Matlab, we obtain a graphical representation of these return series.

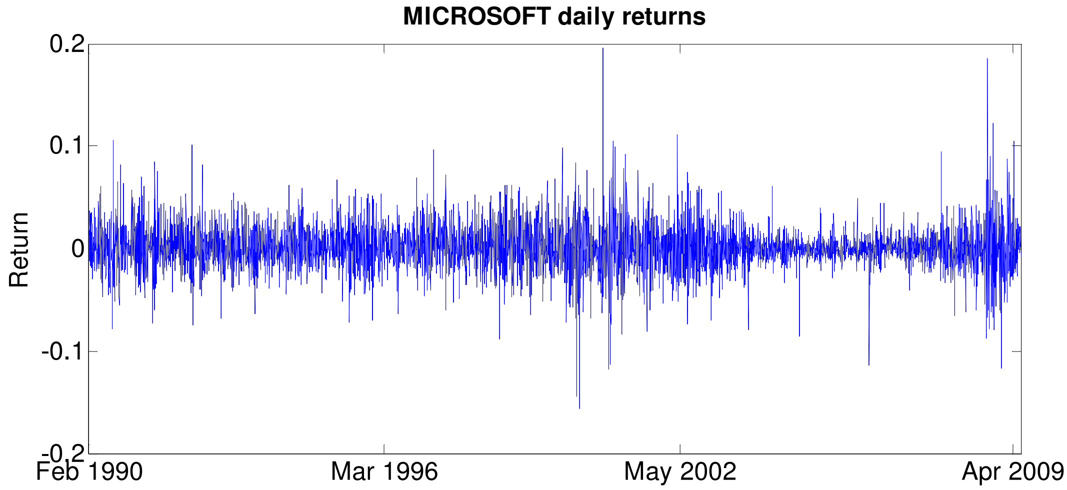


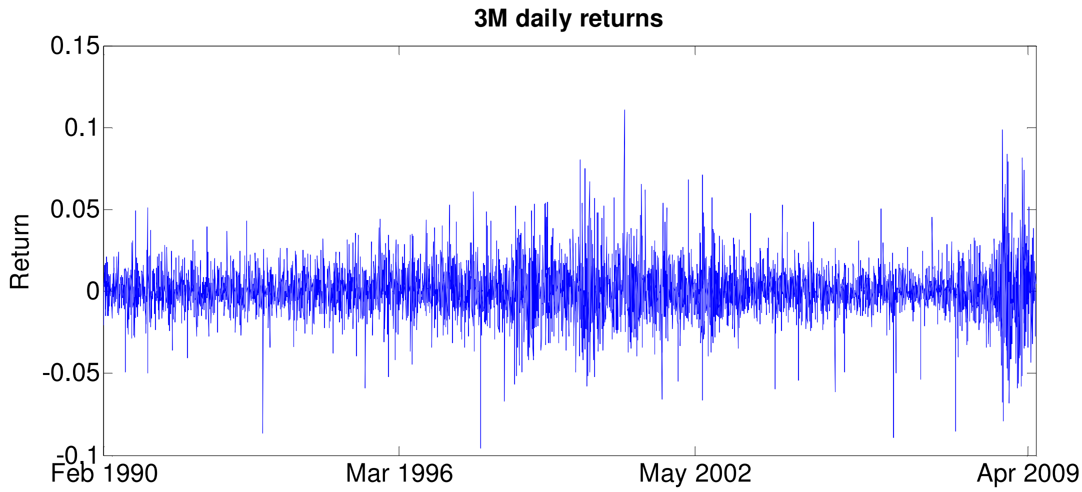



AUTODESK daily returns
Return
0.2
0.1
0
-0.1
-0.2
-0.3
Feb 1990
Mar 1996
May 2002
Apr 2009


CISCO daily returns
Return
0.3
0.2
0.1
0
-0.1
-0.2
Feb 1990
Mar 1996
May 2002
Apr 2009


DELL daily returns
Return
0.2
0.1
0
-0.1
-0.2
Feb 1990
Mar 1996
May 2002
Apr 2009

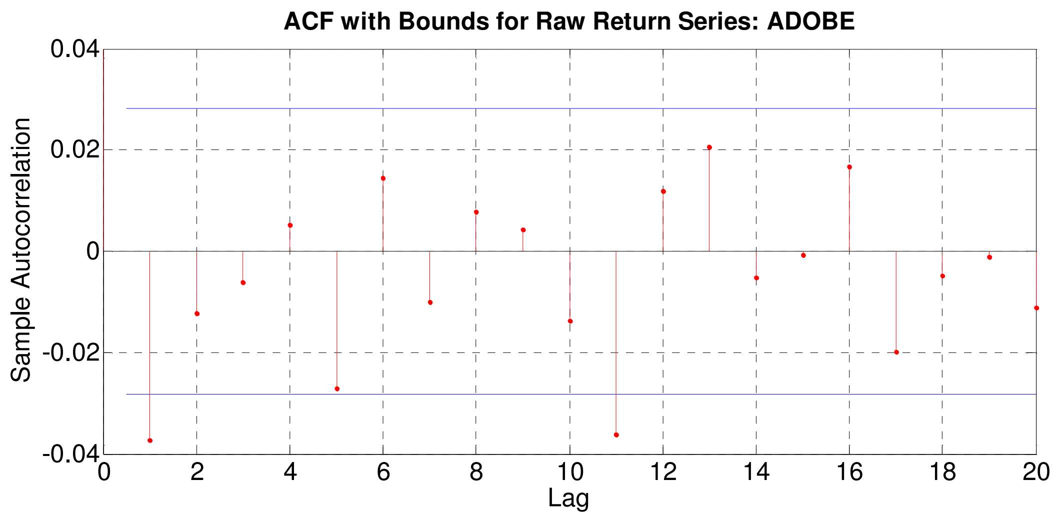


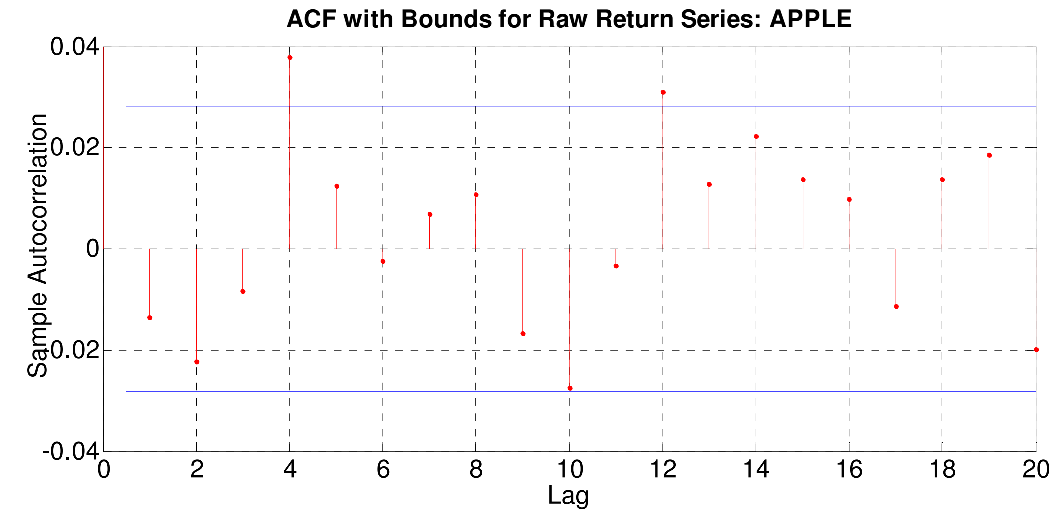


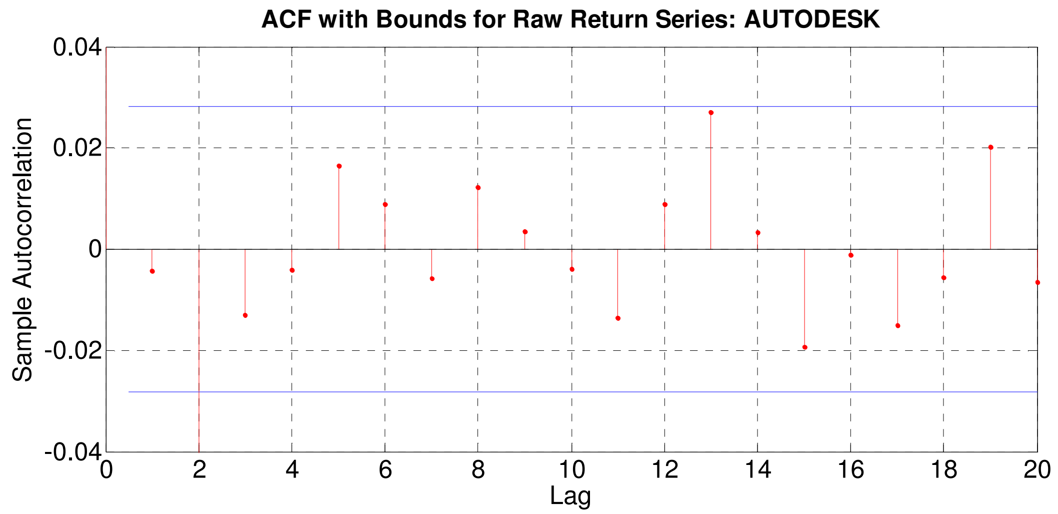
Figures 2 to 8: Daily returns of Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M over the sample period. Data source: Datastream.

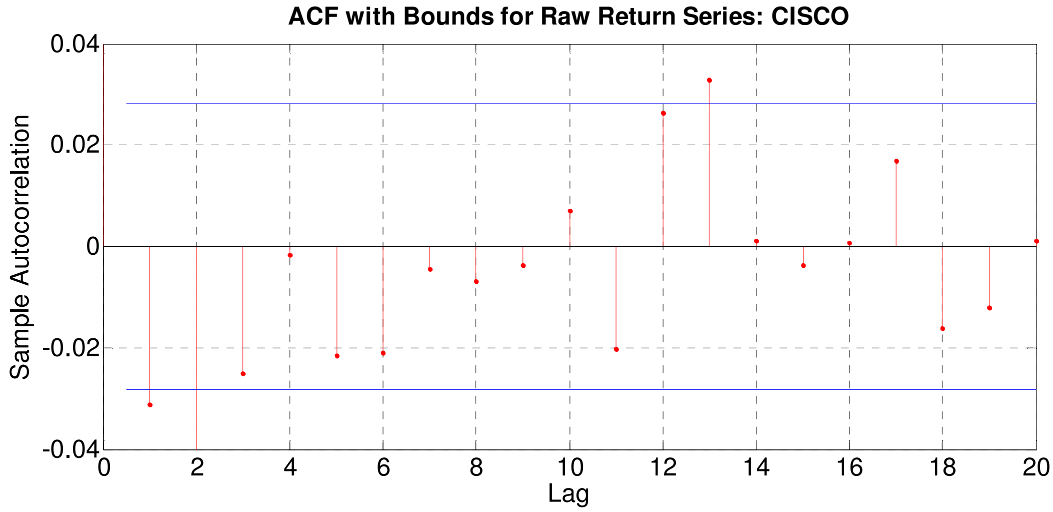
A.2. We check for correlation in the return series.

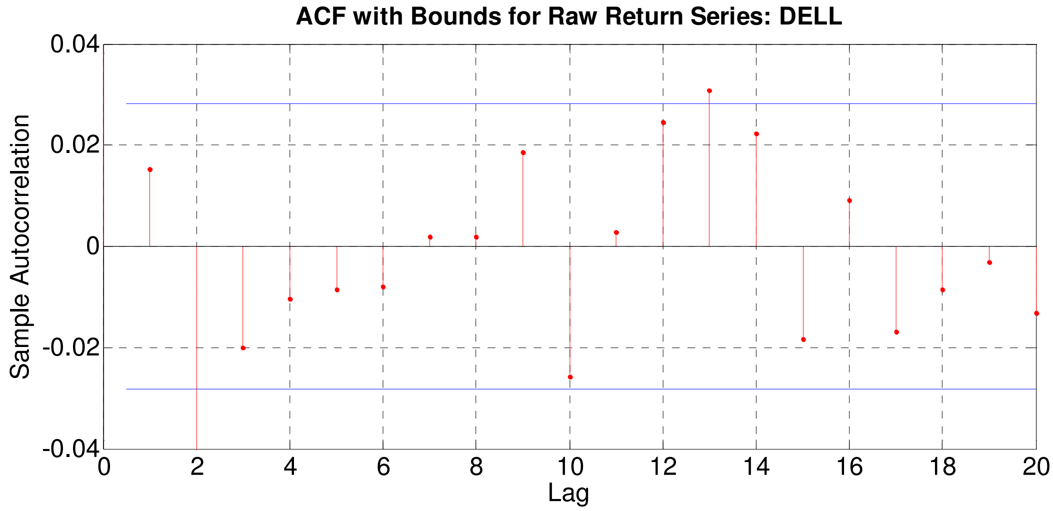
a) *autocorr* function is used to compute and display the sample ACF of the returns, along to the upper and lower standard deviation confidence bounds.

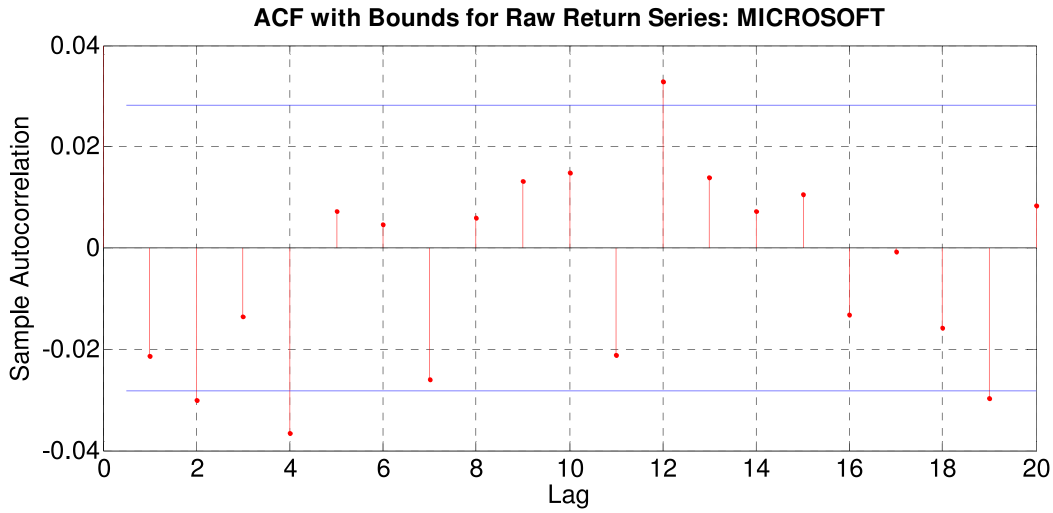

ACF with Bounds for Raw Return Series: ADOBE
Sample Autocorrelation
Lag

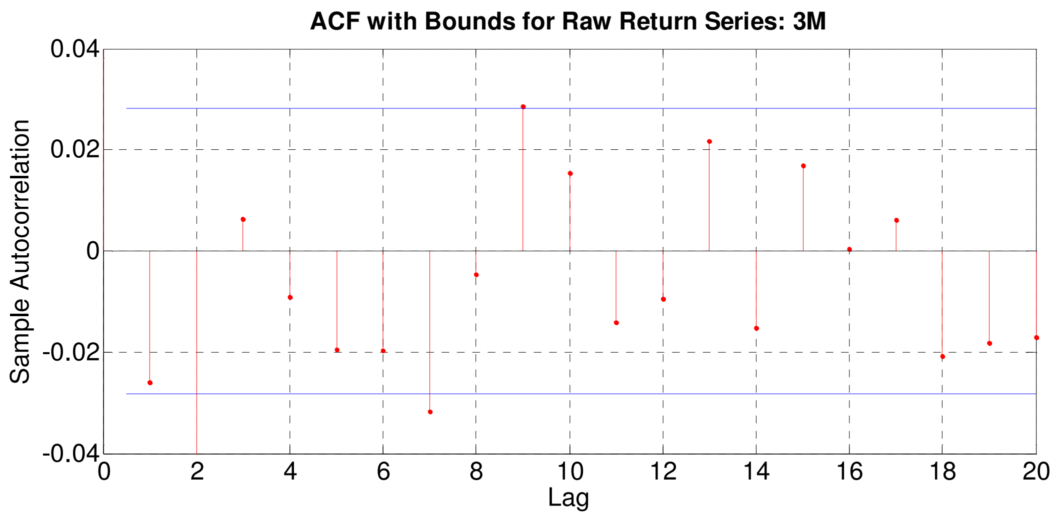

ACF with Bounds for Raw Return Series: APPLE
Sample Autocorrelation
Lag


ACF with Bounds for Raw Return Series: AUTODESK
Sample Autocorrelation
Lag


ACF with Bounds for Raw Return Series: CISCO
Sample Autocorrelation
Lag
0.04
0.02
0
-0.02
-0.04
0
2
4
6
8
10
12
14
16
18
20

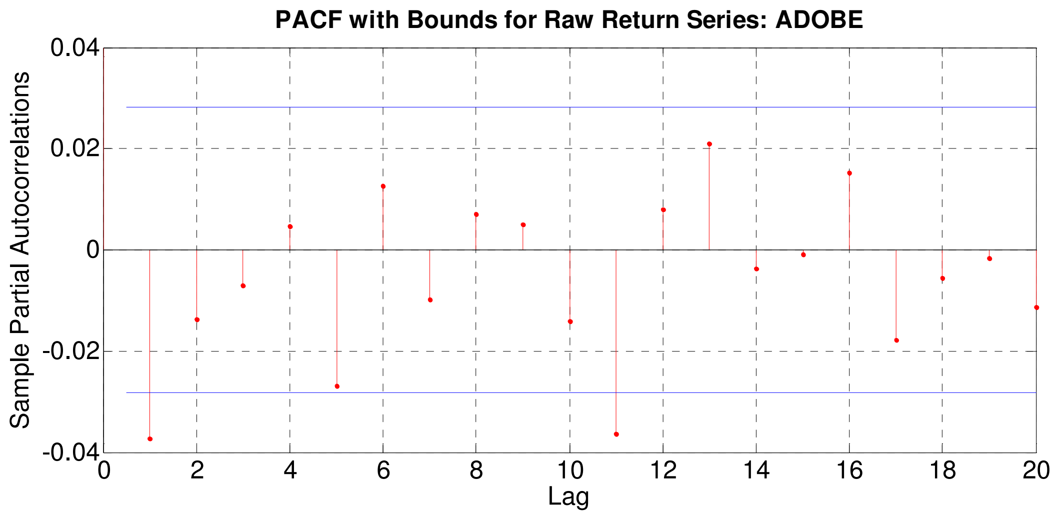

ACF with Bounds for Raw Return Series: DELL
Sample Autocorrelation
Lag
0.04
0.02
0
-0.02
-0.04
0
2
4
6
8
10
12
14
16
18
20

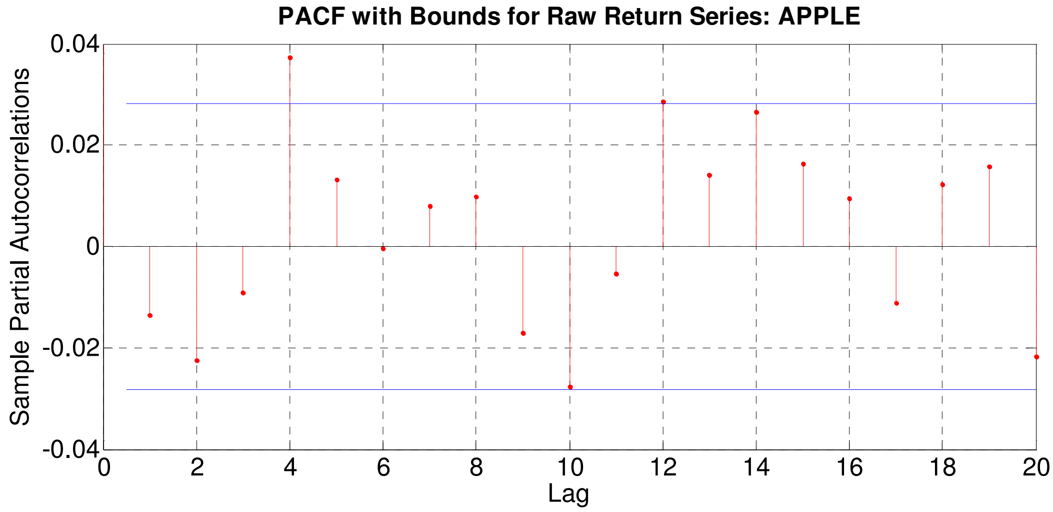

ACF with Bounds for Raw Return Series: MICROSOFT
Sample Autocorrelation
Lag
0.04
0.02
0
-0.02
-0.04
0
2
4
6
8
10
12
14
16
18
20

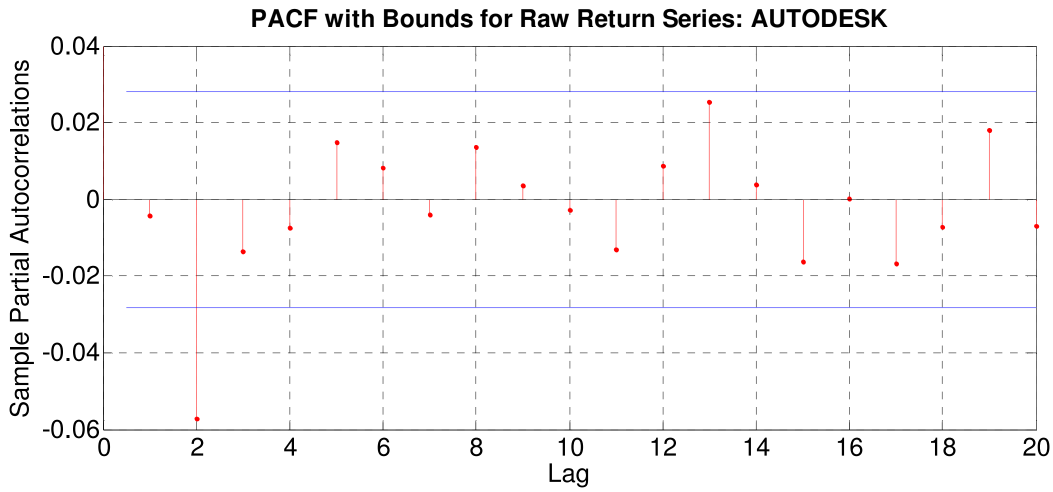


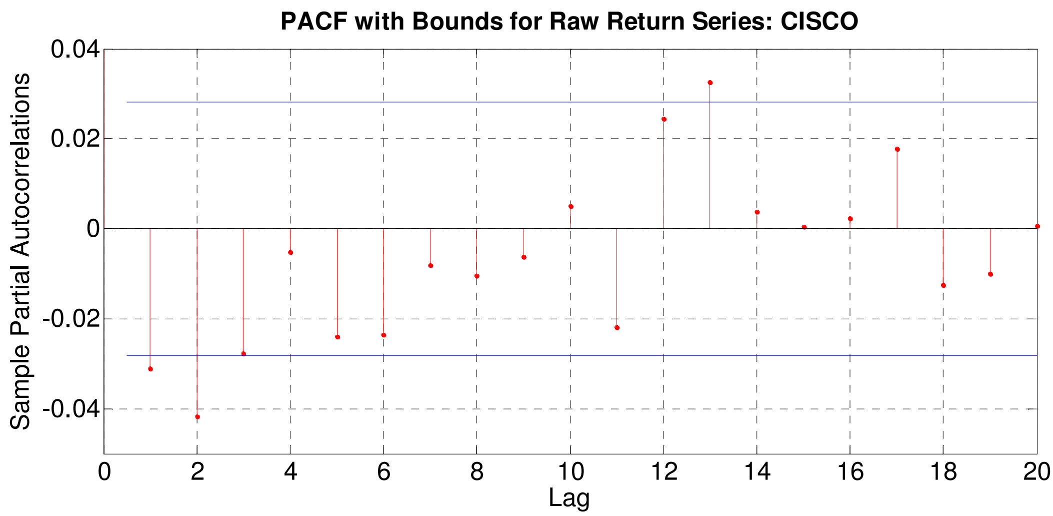
Figures 9 to 15: The autocorrelation functions of Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M daily returns over the sample period. Data source: Datastream.

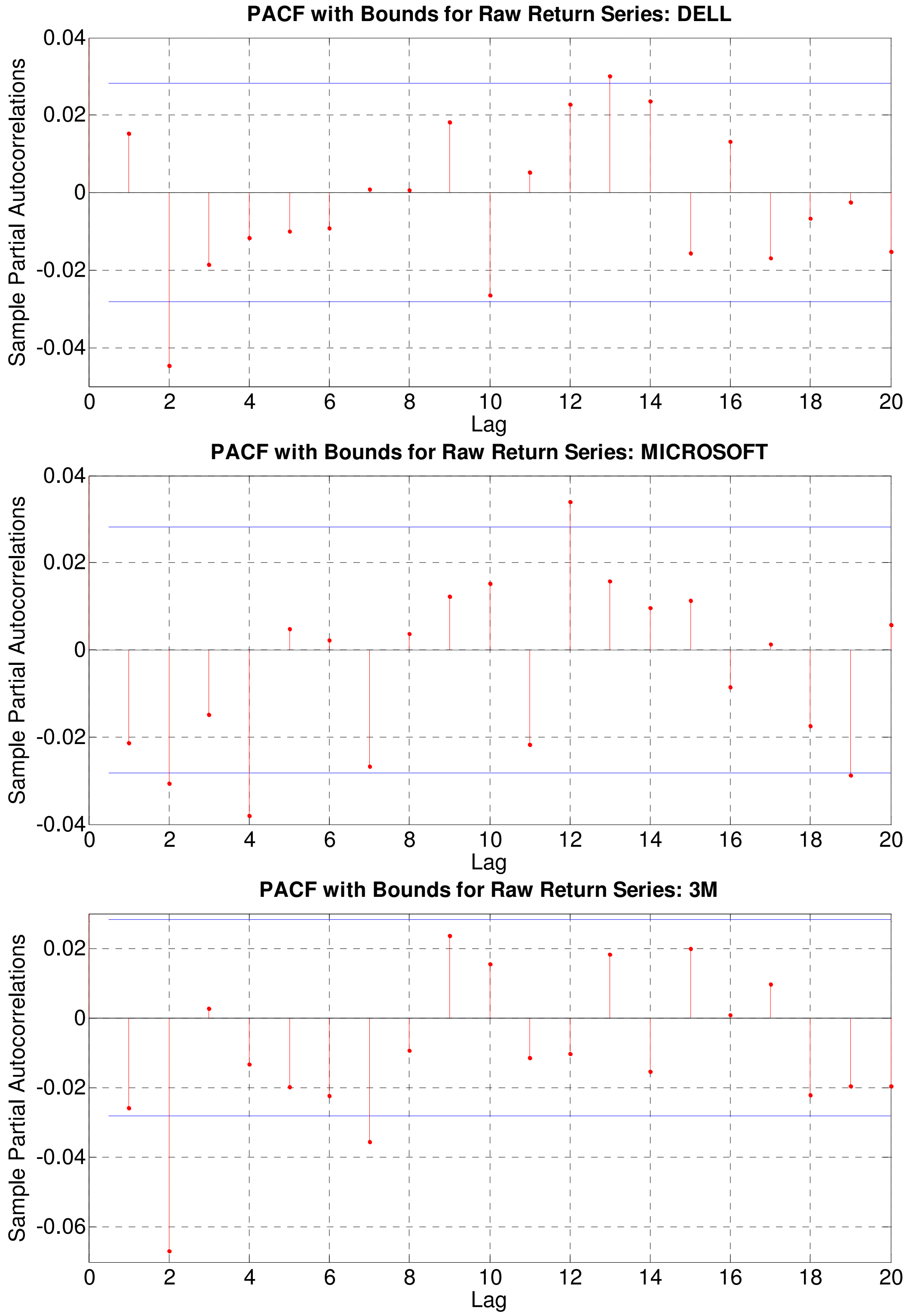
b) Similarly, I perform *parcorr* that displays the PACF with lower and upper bounds.




PACF with Bounds for Raw Return Series: APPLE
Sample Partial Autocorrelations
0.04
0.02
0
-0.02
-0.04
0
2
4
6
8
10
12
14
16
18
20
Lag


PACF with Bounds for Raw Return Series: AUTODESK
Sample Partial Autocorrelations
0.04
0.02
0
-0.02
-0.04
-0.06
0
2
4
6
8
10
12
14
16
18
20
Lag


PACF with Bounds for Raw Return Series: CISCO
Sample Partial Autocorrelations
0.04
0.02
0
-0.02
-0.04
0
2
4
6
8
10
12
14
16
18
20
Lag

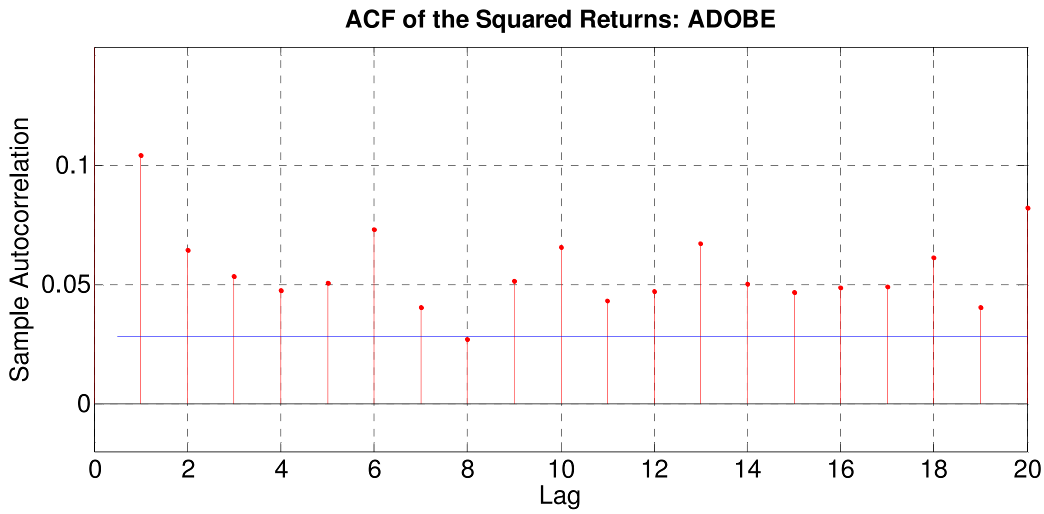


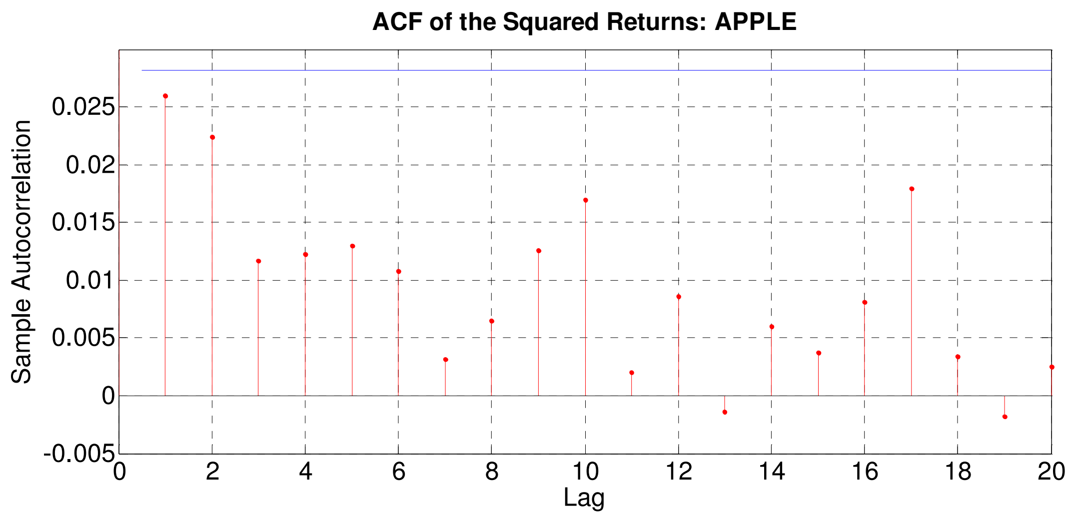
Figures 16 to 22: The partial autocorrelation functions of Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M daily returns over the sample period. Data source: Datastream.

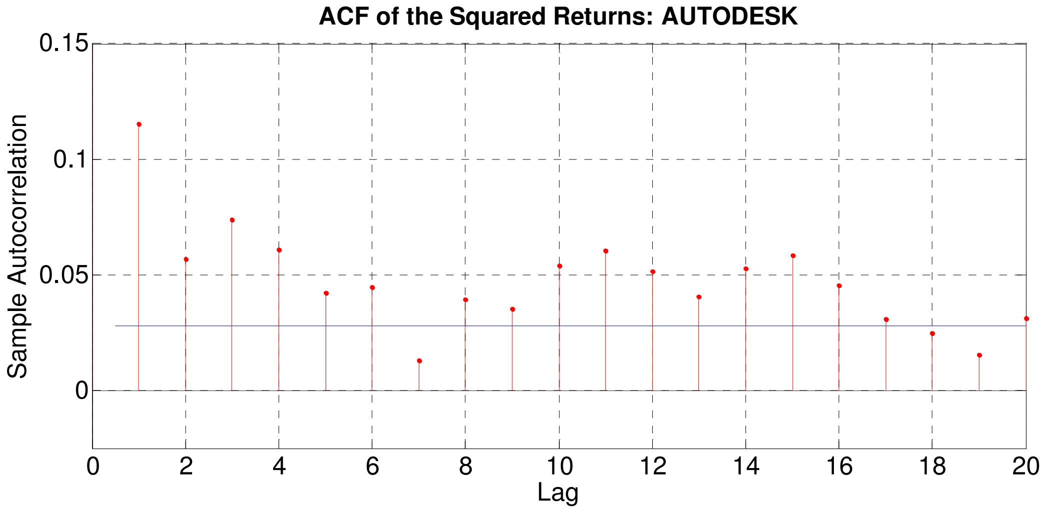
ACF and PACF graphs give some useful information on the broad characteristics of the returns. They provide indication if one needs to use any correlation structure in the conditional mean.

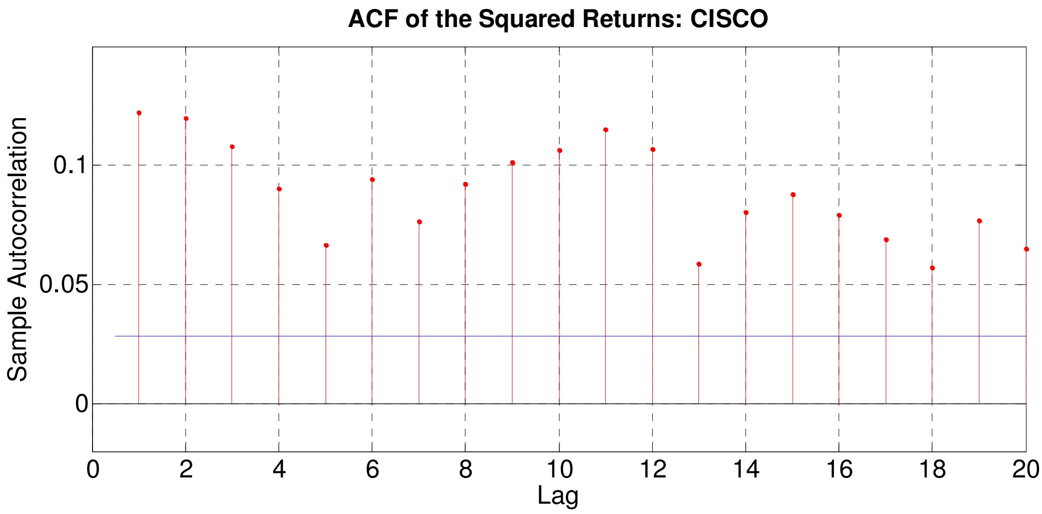
In this particular case, we can see that ACF and PACF display some autocorrelation, but much lower than in the case of the graphs of the volatility of the returns at the previous point (A.1.).

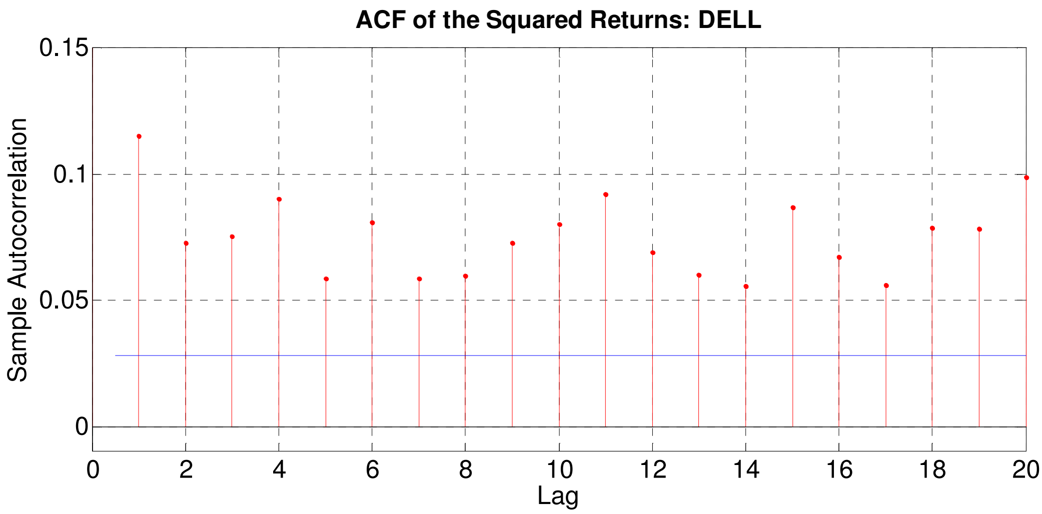
A.3. Check for correlation in the squared returns. We need this also because although ACF of the observed returns exhibits little correlation, the ACF of the squared returns may still indicate significant correlation and persistence in the second-order moments. We check for this by plotting the autocorrelation functions of the squared returns.

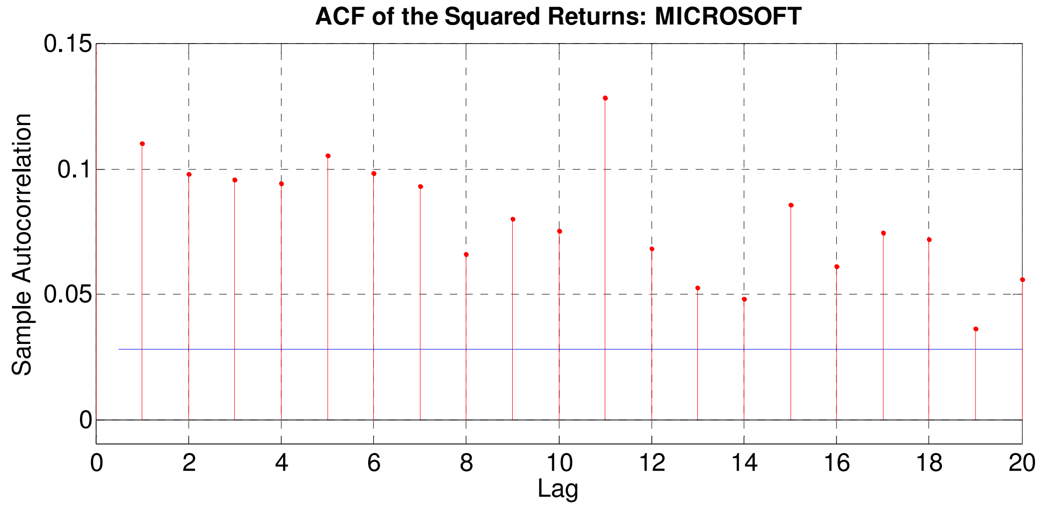


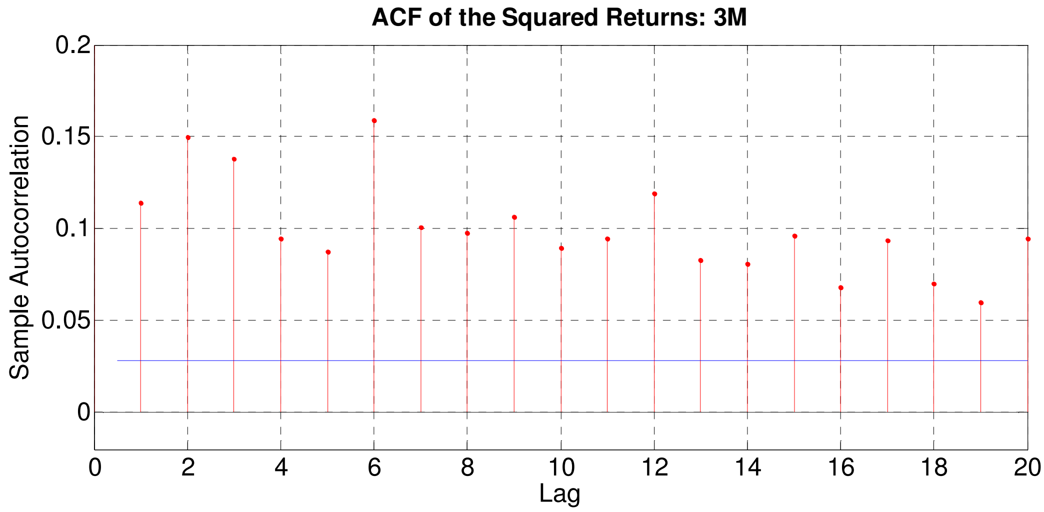



ACF of the Squared Returns: AUTODESK
Sample Autocorrelation
0.15
0.1
0.05
0
0
2
4
6
8
10
12
14
16
18
20
Lag


ACF of the Squared Returns: CISCO
Sample Autocorrelation
0.1
0.05
0
0
2
4
6
8
10
12
14
16
18
20
Lag


ACF of the Squared Returns: DELL
Sample Autocorrelation
0.15
0.1
0.05
0
0
2
4
6
8
10
12
14
16
18
20
Lag





Figures 17 to 23: The autocorrelation functions of Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M daily squared returns over the sample period. Data source: Datastream.

It can be observed that the autocorrelation has increased for all the stocks. Notice that the ACF in all graphs appears to die out slowly, showing the possibility of a variance process close to being nonstationary.

As we can see in the previous figures that reveal the case of seven daily stock returns, data shows clustered volatility, indicating possible correlations between present and previous volatilities. But this is more evident in the case of volatilities (the first group of charts) than in the case of autocorrelations between the daily returns (second and third group of charts).

In conclusion, there has been detected significant clustering in all cases, for all time series, thing that it's a good indicator of the fact that the selected stocks are an appropriate choice to reveal the usefulness of the PC-GARCH as purpose of the empirical study.

B. Performing preliminary tests, like Engle's ARCH test or the Q-test.

However, the pre-estimation analysis has not finished. Although the autocorrelation has been detected visually through the graphs, we have to quantify it. We can quantify the preceding qualitative checks for correlation using formal hypothesis checks, like Ljung-Box-Pierce Q-test and Engle's ARCH test.

By performing a Ljung-Box-Pierce Q-test, it can be verified at least approximately, the presence of any significant correlation in the raw returns when tested for up to 20 lags of the ACF at the 0.05 level of significance. The *lbqtest* function performs a lack-of-fit model misspecification, based on Q statistic. Under the null hypothesis that the model fit is adequate, the test statistic is asymptotically chi-square distributed. The rejection or acceptance of the null hypothesis is given by the decision vector H: 0 indicates the acceptance of the null hypothesis that the model fit is adequate (meaning that no serial correlation at the corresponding element of lags), 1 means rejection.

The results for LBPQ are as it follows. It can be thus checked that no significant correlation is present in the raw returns when tested for up to 20 lags of the ACF. However, since we are interested more in the how more recent data influences future variation, there will be performed both Ljung-Box-Pierce Q-test and Engle's ARCH test at 1 up to 7 lags, with by default chosen alpha of 0.05.

ADOBE- LBPQ

H	P-Value	Statistic	Critical value
1.0000	0.0080	7.0399	3.8415
1.0000	0.0202	7.8002	5.9915
1.0000	0.0463	7.9845	7.8147
0.0000	0.0872	8.1224	9.4877
1.0000	0.0372	11.8264	11.0705
1.0000	0.0449	12.8862	12.5916
0.0000	0.0629	13.4028	14.0671

APPLE – LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.3379	0.9185	3.8415
0.0000	0.1823	3.4042	5.9915
0.0000	0.2885	3.7608	7.8147
1.0000	0.0262	11.0349	9.4877
1.0000	0.0374	11.8181	11.0705
0.0000	0.0655	11.8470	12.5916
0.0000	0.0979	12.0833	14.0671

AUTODESK – LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.7643	0.0899	3.8415
1.0000	0.0002	16.6040	5.9915
1.0000	0.0006	17.4493	7.8147
1.0000	0.0015	17.5327	9.4877
1.0000	0.0020	18.9027	11.0705
1.0000	0.0037	19.2981	12.5916
1.0000	0.0068	19.4702	14.0671

CISCO – LBPSQ

H	P-Value	Statistic	Critical value
1.0000	0.0271	4.8841	3.8415
1.0000	0.0013	13.2495	5.9915
1.0000	0.0009	16.4375	7.8147
1.0000	0.0025	16.4523	9.4877
1.0000	0.0021	18.7746	11.0705
1.0000	0.0018	21.0042	12.5916
1.0000	0.0036	21.1083	14.0671

DELL – LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.2815	1.1600	3.8415
1.0000	0.0039	11.0805	5.9915
1.0000	0.0044	13.1013	7.8147
1.0000	0.0085	13.6439	9.4877
1.0000	0.0155	14.0123	11.0705
1.0000	0.0261	14.3331	12.5916
1.0000	0.0453	14.3491	14.0671

MICROSOFT - LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.1308	2.2828	3.8415
1.0000	0.0322	6.8701	5.9915
0.0000	0.0507	7.7848	7.8147
1.0000	0.0058	14.5136	9.4877
1.0000	0.0113	14.7810	11.0705
1.0000	0.0212	14.8863	12.5916
1.0000	0.0106	18.3141	14.0671

3M – LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.0657	3.3867	3.8415
1.0000	0.0000	25.4908	5.9915
1.0000	0.0000	25.6939	7.8147
1.0000	0.0000	26.1081	9.4877
1.0000	0.0000	28.0351	11.0705
1.0000	0.0000	29.9922	12.5916
1.0000	0.0000	35.0698	14.0671

Tables 2 to 8: Ljung-Box-Pierce Q-test output for heteroskedasticity. Data source: Datastream.

With the exception of Apple stocks, all tests show H=1 for most of the lags, with all parameters (where the decision vector is 1) higher than their critical values, that makes us conclude that we reject the null hypothesis. Thus, some serial correlation exists at the corresponding elements of Lags. We keep this as a reference as regards the existence of autocorrelation in the data.

Engle's test shows significant evidence in support of the GARCH effects, like heteroskedasticity. Under the null hypothesis that a time series is a random sequence of Gaussian disturbances (i.e., no ARCH effects exist), this test statistic is also asymptotically Chi-Square distributed. Like in the LBPQ case, the H vector is a Boolean decision flag. When 0, it implies the existence of no significant correlation (not rejection of the decision null hypothesis) and when 1 means that significant correlation exists (rejection of the null hypothesis). The Matlab code for it is *archtest.* The results for the Engle's test are displayed as it follows:

ADOBE – ENGLE

H	P-Value	Statistic	Critical value
1.0000	0.0000	55.7352	3.8415
1.0000	0.0000	71.1167	5.9915
1.0000	0.0000	79.9231	7.8147
1.0000	0.0000	86.2279	9.4877
1.0000	0.0000	93.5747	11.0705
1.0000	0.0000	111.3294	12.5916
1.0000	0.0000	113.2919	14.0671

APPLE – ENGLE

H	P-Value	Statistic	Critical value
1.0000	0.0001	14.986	3.8415
1.0000	0.0000	26.6524	5.9915
1.0000	0.0000	29.7582	7.8147
1.0000	0.0000	32.4745	9.4877
1.0000	0.0000	34.5962	11.0705
1.0000	0.0000	35.6367	12.5916
1.0000	0.0000	35.6941	14.0671

AUTODESK – ENGLE

H	P-Value	Statistic	Critical value
1.0000	0.0000	68.5135	3.8415
1.0000	0.0000	78.3246	5.9915
1.0000	0.0000	98.387	7.8147
1.0000	0.0000	108.127	9.4877
1.0000	0.0000	111.4049	11.0705
1.0000	0.0000	115.573	12.5916
1.0000	0.0000	115.6258	14.0671

CISCO – ENGLE

H	P-Value	Statistic	Critical value
1.0000	0.0000	61.7306	3.8415
1.0000	0.0000	102.7452	5.9915
1.0000	0.0000	133.2275	7.8147
1.0000	0.0000	157.9182	9.4877
1.0000	0.0000	188.265	11.0705
1.0000	0.0000	209.6915	12.5916
1.0000	0.0000	224.6931	14.0671

DELL – ENGLE

H	P-Value	Statistic	Critical value
1.0000	0.0000	68.6695	3.8415
1.0000	0.0000	88.7138	5.9915
1.0000	0.0000	107.6164	7.8147
1.0000	0.0000	134.4484	9.4877
1.0000	0.0000	139.7539	11.0705
1.0000	0.0000	158.5228	12.5916
1.0000	0.0000	162.9093	14.0671

MICROSOFT – ENGLE

H	P-Value	Statistic	Critical value
1.0000	0.0000	78.7403	3.8415
1.0000	0.0000	138.865	5.9915
1.0000	0.0000	175.4097	7.8147
1.0000	0.0000	192.7023	9.4877
1.0000	0.0000	197.9961	11.0705
1.0000	0.0000	217.1309	12.5916
1.0000	0.0000	225.6581	14.0671

3M - ENGLE

H	P-Value	Statistic	Critical value
1.0000	0.0000	65.8503	3.8415
1.0000	0.0000	162.344	5.9915
1.0000	0.0000	222.2332	7.8147
1.0000	0.0000	236.2768	9.4877
1.0000	0.0000	245.5152	11.0705
1.0000	0.0000	316.0154	12.5916
1.0000	0.0000	328.3765	14.0671

Tables 9 to 15: Engle's test output for heteroskedasticity. Data source: Datastream.

We can see that for all the stocks, we reject the null hypothesis, so we have significant correlation. In the case of Apple, the decision vector is now 1, although in the LBPQ test we found acceptance of the null hypothesis. Combining the two results, we can conclude that we still might have enough autocorrelation in the data that would prove useful the performing of the PC-GARCH test.

After performing Ljung-Box-Pierce and Engle tests for heteroskedasticity it can be concluded that all these series are heteroskedastic (of course, some more than others).

This indicates that the returns series for each of the seven cases may be an ideal case for PC-GARCH treatment. For the full Matlab codes used for the LBPQ and Engle tests used, please consult the appendix.

And with this, we finish the pre-estimation part of the PC-GARCH model. Before starting to perform this model, in what it follows there will be restated the problem in the specific frame of the seven stocks selected.

5.9.3 Preparing data for the PCA

The selected data consists of n = 5044 observations of returns for each of Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M. We want to find the principal components. Since each component is a linear combination of the centered variables, we must first obtain these centered variables by subtracting the mean to each x_i. So, it will be calculated the mean of each of these stock returns (thus, Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M have their mean returns over the sample period) and this will be then subtracted from x. We thus obtain $\boldsymbol{X} = \begin{pmatrix} x_1 - \bar{x}_1 \\ x_2 - \bar{x}_2 \\ x_3 - \bar{x}_3 \\ x_4 - \bar{x}_4 \\ x_5 - \bar{x}_5 \\ x_6 - \bar{x}_6 \\ x_7 - \bar{x}_7 \end{pmatrix}$, the matrix of the centered variables. To obtain the matrix of the principal components, we multiply **X** by **A** matrix, where $\boldsymbol{A} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} & a_{27} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} & a_{37} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} & a_{47} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} & a_{57} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & a_{67} \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} \end{pmatrix}$. So we call $\boldsymbol{A}_{7,7}\boldsymbol{X}_{7,1} = \boldsymbol{P}_{7,1}$. We have then $\boldsymbol{AX} = \boldsymbol{P} = \begin{pmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \\ p_5 \\ p_6 \\ p_7 \end{pmatrix}$. We want to find a matrix **A** that, when multiplied with the matrix of the centered variables **X**, gives us an orthogonal matrix **P** with which we can work (in each cell of **P** we will have a principal component that will be a linear combination between the centered variables x's and a's). If we decide to use a number of PCs less than the original number of variables, we would lose some information, but keep uncorrelated data **P** that still can explain **Y** (see Alexander (2000) for details)[13]. So, to find **P**, we must find **A** that solves **AX** = **P** and impose the orthogonality condition for **P**, that is Var(**P**) = **0**

5.9.3.1 Solving for the orthogonality

By definition, the variance-covariance matrix **P** is equal to **PP'**. Using the property that (**AB**)' = **B'A'**, we find that Var(**P**) = **PP'**= **AX**(**AX**)' = **AXX'A'**, where $\boldsymbol{X} = \begin{pmatrix} x_1 - \bar{x}_1 \\ x_2 - \bar{x}_2 \\ x_3 - \bar{x}_3 \\ x_4 - \bar{x}_4 \\ x_5 - \bar{x}_5 \\ x_6 - \bar{x}_6 \\ x_7 - \bar{x}_7 \end{pmatrix}$ and **XX'** = Var(**X**). We call **XX'** = Var(**X**) =**Ω**, from which it results that Var(**P**) = **PP'** = **A Ω A'**.

Since one of our initial problems was that some elements were correlated, we want a **P** such that it is composed of orthogonal elements. So, next, we impose the orthogonality condition on **P**. From a larger matrix of data **X**, we want to obtain the matrix **P** of smaller or equal dimension that has only uncorrelated values, each element of **P** being a linear combination of the elements of **X**.

To see the meaning of the term "uncorrelated elements of **P**", let's call $\boldsymbol{P} = \begin{pmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \\ p_5 \\ p_6 \\ p_7 \end{pmatrix}$,

then $\boldsymbol{P'} = (p_1 \quad p_2 \quad p_3 \quad p_4 \quad p_5 \quad p_6 \quad p_7)$, and

[13] As I'll explain later in this text, I do not follow this procedure for a technical reason.

$$\boldsymbol{PP'} = Var(\boldsymbol{P}) = \begin{pmatrix} p_1^2 & p_1p_2 & p_1p_3 & p_1p_4 & p_1p_5 & p_1p_6 & p_1p_7 \\ p_2p_1 & p_2^2 & p_2p_3 & p_2p_4 & p_2p_5 & p_2p_6 & p_2p_7 \\ p_3p_1 & p_3p_2 & p_3^2 & p_3p_4 & p_3p_5 & p_3p_6 & p_3p_7 \\ p_4p_1 & p_4p_2 & p_4p_3 & p_4^2 & p_4p_5 & p_4p_6 & p_4p_7 \\ p_5p_1 & p_5p_2 & p_5p_3 & p_5p_4 & p_5^2 & p_5p_6 & p_5p_7 \\ p_6p_1 & p_6p_2 & p_6p_3 & p_6p_4 & p_6p_5 & p_6^2 & p_6p_7 \\ p_7p_1 & p_7p_2 & p_7p_3 & p_7p_4 & p_7p_5 & p_7p_6 & p_7^2 \end{pmatrix}$$, which is

symmetric. For our case, p's stand for σ's. Orthogonality of **P** means that $p_i p_j = 0$, as we exclude any correlation between variances of p's. This implies that $Var(\boldsymbol{P}) = diag(p_1^2 \quad p_2^2 \quad p_3^2 \quad p_4^2 \quad p_5^2 \quad p_6^2 \quad p_7^2)$.

Thus we see that the variance-covariance matrix of a matrix of orthogonal elements is a diagonal matrix. From matrix algebra, we use the result that the matrix **A** is the matrix of orthogonal unit eigenvectors of **Ω**.

5.9.3.2 Finding the matrix of Principal Components

Let's sum up the problem: we want to use x's to explain the y's, but the x's are too many (k is too large). We chose to make k smaller so we must pick factors that explain most of the variation (or as much as possible with a k that makes the problem tractable). We are looking to find the linear relationship of x's that gives us the orthogonal p's.

In our problem, p's are the new x's, so we have to rearrange the **P** matrix (more specifically, the $\sigma^2 s$) in the descending order to see which p's are the highest. Once we rearrange it, we impose **P** = **AX** condition (where **A** is the matrix of factor loadings and **X** is the matrix as defined above). According to the matrix notation, this translates into

$$
\boldsymbol{P} = \begin{pmatrix} a_1a_2 & a_1a_2 & a_1a_3 & a_1a_4 & a_1a_5 & a_1a_6 & a_1a_7 \\ a_2a_1 & a_2a_2 & a_2a_3 & a_2a_4 & a_2a_5 & a_2a_6 & a_2a_7 \\ a_3a_1 & a_3a_2 & a_3a_3 & a_3a_4 & a_3a_5 & a_3a_6 & a_3a_7 \\ a_4a_1 & a_4a_2 & a_4a_3 & a_4a_4 & a_4a_5 & a_4a_6 & a_4a_7 \\ a_5a_1 & a_5a_2 & a_5a_3 & a_5a_4 & a_5a_5 & a_5a_6 & a_5a_7 \\ a_6a_1 & a_6a_2 & a_6a_3 & a_6a_4 & a_6a_5 & a_6a_6 & a_6a_7 \\ a_7a_1 & a_7a_2 & a_7a_3 & a_7a_4 & a_7a_5 & a_7a_6 & a_7a_7 \end{pmatrix} \begin{pmatrix} x_1 - \bar{x}_1 \\ x_2 - \bar{x}_2 \\ x_3 - \bar{x}_3 \\ x_4 - \bar{x}_4 \\ x_5 - \bar{x}_5 \\ x_6 - \bar{x}_6 \\ x_7 - \bar{x}_7 \end{pmatrix} =
$$

$$
\begin{pmatrix} \sum_{i=1}^{7} \boldsymbol{a_{1i}}(x_i - \bar{x}_i) \\ \sum_{i=1}^{7} \boldsymbol{a_{2i}}(x_i - \bar{x}_i) \\ \sum_{i=1}^{7} \boldsymbol{a_{3i}}(x_i - \bar{x}_i) \\ \sum_{i=1}^{7} \boldsymbol{a_{4i}}(x_i - \bar{x}_i) \\ \sum_{i=1}^{7} \boldsymbol{a_{5i}}(x_i - \bar{x}_i) \\ \sum_{i=1}^{7} \boldsymbol{a_{6i}}(x_i - \bar{x}_i) \\ \sum_{i=1}^{7} \boldsymbol{a_{7i}}(x_i - \bar{x}_i) \end{pmatrix}.
$$

where a_{ij}; $1 \le i, j \le 7$ represent the factor loadings. We have thus linear transformations of the *x*'s that give us *p*'s, with other words we have transformed the *x*'s in orthogonal *p*'s.

This means that

$$
p_1 = a_{11}(x_1 - \bar{x}_1) + a_{12}(x_2 - \bar{x}_2) + a_{13}(x_3 - \bar{x}_3) + a_{14}(x_4 - \bar{x}_4) + a_{15}(x_5 - \bar{x}_5) + a_{16}(x_6 - \bar{x}_6) + a_{17}(x_7 - \bar{x}_7)
$$

$$
p_2 = a_{21}(x_1 - \bar{x}_1) + a_{22}(x_2 - \bar{x}_2) + a_{23}(x_3 - \bar{x}_3) + a_{24}(x_4 - \bar{x}_4) + a_{25}(x_5 - \bar{x}_5) + a_{26}(x_6 - \bar{x}_6) + a_{27}(x_7 - \bar{x}_7)
$$

$$
p_3 = a_{31}(x_1 - \bar{x}_1) + a_{32}(x_2 - \bar{x}_2) + a_{33}(x_3 - \bar{x}_3) + a_{34}(x_4 - \bar{x}_4) + a_{35}(x_5 - \bar{x}_5) + a_{36}(x_6 - \bar{x}_6) + a_{37}(x_7 - \bar{x}_7)
$$

$$
p_4 = a_{41}(x_1 - \bar{x}_1) + a_{42}(x_2 - \bar{x}_2) + a_{43}(x_3 - \bar{x}_3) + a_{44}(x_4 - \bar{x}_4) + a_{45}(x_5 - \bar{x}_5) + a_{46}(x_6 - \bar{x}_6) + a_{47}(x_7 - \bar{x}_7)
$$

$$
p_5 = a_{51}(x_1 - \bar{x}_1) + a_{52}(x_2 - \bar{x}_2) + a_{53}(x_3 - \bar{x}_3) + a_{54}(x_4 - \bar{x}_4) + a_{55}(x_5 - \bar{x}_5) + a_{56}(x_6 - \bar{x}_6) + a_{57}(x_7 - \bar{x}_7)
$$

$$
p_6 = a_{61}(x_1 - \bar{x}_1) + a_{62}(x_2 - \bar{x}_2) + a_{63}(x_3 - \bar{x}_3) + a_{64}(x_4 - \bar{x}_4) + a_{65}(x_5 - \bar{x}_5) + a_{66}(x_6 - \bar{x}_6) + a_{67}(x_7 - \bar{x}_7)
$$

$$
p_7 = a_{71}(x_1 - \bar{x}_1) + a_{72}(x_2 - \bar{x}_2) + a_{73}(x_3 - \bar{x}_3) + a_{74}(x_4 - \bar{x}_4) + a_{75}(x_5 - \bar{x}_5) + a_{76}(x_6 - \bar{x}_6) + a_{77}(x_7 - \bar{x}_7)
$$

We know x's, but we don't know a's. What is left to do is that we have to find the a's that give us the orthogonal factors, since a's signify the weights of each of the x's. For this, because we want orthogonality, we impose the restriction that the resulting covariance matrix is just a diagonal matrix (as done before); after this, we reduce x's to p_1, p_2, …, p_7. Once we enter all x's and all y's, the software gives us the factor loadings (a's) and the eigenvalues (λ's, that are actually the $\sigma^2 s$) that come from the condition of orthogonality Var(**P**) = **0**. The eigenvectors are actually the columns of **A** (**A**= $\left(\underset{Eigenvector1}{\overset{\lambda_1}{\begin{bmatrix} \cdots \\ \cdots \\ \cdots \end{bmatrix}}} \underset{Eigenvector2}{\overset{\lambda_2}{\begin{bmatrix} \cdots \\ \cdots \\ \cdots \end{bmatrix}}} \cdots \underset{Eigenvector7}{\overset{\lambda_7}{\begin{bmatrix} \cdots \\ \cdots \\ \cdots \end{bmatrix}}} \right)$). They are orthogonal and are of unit length. After we find the factor loadings and the eigenvalues, we can pick up p's (which now are uncorrelated since we impose orthogonality condition) that show the highest variance (that is given by the eigenvalues).

We now have the orthogonal **P** whose values are a linear combination of the independent variables **X**. We now can work with **P** to make forecasts on the variations of **Y**.

5.10 PC-GARCH implementation - the algorithm

The algorithm heavily draws on the work of Burns (2005), even as I adapt this to my particular requirements. As described in detail in the earlier sections, PC-GARCH will be used to enable a tractable version of multivariate GARCH. This tractability arises from the lack of correlation among the multiple variables used, reducing the parameter set to a manageable number. In this section, there will be provided a brief overview of the algorithm, and in the next, there will be provided further details.

Firstly, there will be estimated a univariate GARCH for each of the seven price returns; this step establishes whether a multivariate GARCH is required in the first place. If the univariate GARCH models were sufficiently descriptive of the "reality", the errors from these models must be uncorrelated. Strong correlation between the errors implies the presence of a common factor that drives the seven return series simultaneously. Instead of simply using the autocorrelations of the same stock, we can exploit the autocorrelations among the various stock time series. In more intuitive terms, a correlation among the errors of the return series implies that 'there is information' in the other returns that can be used to forecast the volatility of each return series. Recall here that GARCH is a technique that splits variances into those due to ***autocorrelation*** (effects of the past) and ***innovations*** (errors, defined essentially as the difference between the predicted and the observed). Thus, a correlation between the errors implies that what the univariate GARCH model presumes to be innovations are not truly innovations, but can be explained by movements in the other stock returns.

Since our test yields that a multivariate GARCH is warranted in this scenario, our next step is to find the seven uncorrelated factors that drive the price returns. Recall from the theoretical discussion above that since we have seven variables (that are not collinear even if they are highly correlated), we are working in a seven-dimensional environment where each dimension represents the returns of a price returns. These seven dimensions are, as we have seen, highly correlated; hence not orthogonal. As stressed repeatedly, these non orthogonal but highly correlated variables result in tractability issues, and thus we want to identify orthogonal (uncorrelated) factors that we could conveniently use.

The PCA is applied on the residuals of the previous GARCH; we are trying to find seven uncorrelated sources of "errors", these "errors" being the innovations obtained from the earlier univariate GARCH. Intuitively, what we try here is to isolate the seven different factors that drive innovations. Since I am trying to find the factors that drive stock returns of the same country, we expect to find one factor whose effect on all these returns is large, and six other stock-specific factors.

An output of the principal component analysis is the matrix of coefficients. This matrix will be used to estimate the new residuals due to each PC. For reasons I shall go through in greater detail in the presentation below, I do not drop any of the principal components, but use all the seven. These new residuals are thus orthogonal to each other, and running a multivariate GARCH on them is equivalent to running seven separate univariate GARCH models. This reduction of multivariate GARCH to a set of univariate GARCH models is a key reason for the popularity of the PC-GARCH technique. The univariate GARCH models will be duly run on each of these transformed residuals. Intuitively, what was previously "unexplained" now gets "explained" based on seven orthogonal factors. But clearly, my aim has been to obtain a GARCH model of the stock return volatilities, and not the GARCH model of the transformed residuals. Thus, we need to transform these GARCH models back to the space of return volatilities. This is easy: we note that pre-multiplying by the inverse of the matrix of coefficients and post-multiplying by the matrix of coefficients gives us back our desired original variance-covariance matrix (in this case, this is a set of seven GARCH models). I shall explain this in greater detail in the section below.

5.10.1 Step one: Estimating univariate GARCH models

As discussed earlier, the first step in running a PC-GARCH algorithm is to begin with a univariate GARCH and check the necessity of adding extra variables.

	Value	T-stat
C	12.06×10^{-4}	3.21
α_0	3.06×10^{-6}	6.06
α_1	9.71×10^{-1}	524.93
β_1	2.75×10^{-2}	15.42

(a)

	Value	T-stat
C	18.09×10^{-4}	4.55
α_0	52.95×10^{-6}	10.21
α_1	8.68×10^{-1}	111.68
β_1	8.38×10^{-2}	24.92

(b)

	Value	T-stat
C	14.51×10^{-4}	3.81
α_0	62.19×10^{-6}	11.67
α_1	8.38×10^{-1}	78.92
β_1	10.24×10^{-2}	15.68

(c)

	Value	T-stat
C	19.30×10^{-4}	6.26
α_0	9.17×10^{-6}	8.07
α_1	9.20×10^{-1}	162.85
β_1	7.13×10^{-2}	14.01

(d)

	Value	T-stat
C	11.32×10^{-4}	3.30
α_0	3.59×10^{-6}	8.74
α_1	9.50×10^{-1}	352.34
β_1	4.81×10^{-2}	18.14

(e)

	Value	T-stat
C	10.01×10^{-4}	4.13
α_0	6.41×10^{-6}	13.02
α_1	9.20×10^{-1}	204.17
β_1	6.94×10^{-2}	18.24

(f)

	Value	T-stat
C	3.89×10^{-4}	2.05
α_0	2.66×10^{-6}	8.75
α_1	9.57×10^{-1}	288.22
β_1	3.08×10^{-2}	13.84

(g)

Tables 16 to 22: Summary of the GARCH(1,1) model for (a) ADOBE (b) APPLE (c) AUTODESK (d) CISCO (e) DELL (f) MICROSOFT (g) 3M. Data source: Datastream.

The rationale is rather practical - to use a parsimonious model if it is “good enough”, where the goodness of the model depends on the user's requirements. Thus, the attempt here should be to use the best possible univariate GARCH model. This means that the coordinates p and q of GARCH(p,q) must be selected in order to optimize the trade-off between the extra parameters and the extra predictive ability achieved. The selection of the variables p and q is optimized independently of the other models under consideration.

Since the aim is to illustrate the PC-GARCH approach, we simply choose a GARCH(1,1) and fit each of the daily return volatilities. The results obtained from the univariate GARCH(1,1) models are summarized in Tables 16 to 22. Recall that the GARCH(1,1) model is $y_t = C + \varepsilon_t$, $\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \beta_1 \varepsilon_{t-1}^2$.

We thus see from the Tables 16 to 22 that we can reject the null hypothesis that α_0 and α_1 are separately equal to zero (since the t-values are outside +/-1.96 interval, thus we are in the rejection region). In other words, it is appropriate to model the time series of volatility as a GARCH(1,1). We pause to consider the "visual effect" of the GARCH(1,1) decomposition; I will also contrast this with the decomposition after the PC-GARCH procedure.

5.10.2 Step two: Obtaining residuals from GARCH(1,1) and standardizing them

From the 5.10.1, it has been obtained that the GARCH(1,1) models for Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M are as it follows:

ADOBE:

$$y_t = 12.06\times10^{-4} + \varepsilon_t$$

$$\sigma_t^2 = 3.06\times10^{-6} + 0.971\sigma_{t-1}^2 + 0.028\varepsilon_{t-1}^2$$

APPLE:

$$y_t = 18.09\times10^{-4} + \varepsilon_t$$

$$\sigma_t^2 = 52.95\times10^{-6} + 0.868\sigma_{t-1}^2 + 0.084\varepsilon_{t-1}^2$$

AUTODESK:

$$y_t = 14.51\times10^{-4} + \varepsilon_t$$

$$\sigma_t^2 = 62.19\times10^{-6} + 0.838\sigma_{t-1}^2 + 0.102\varepsilon_{t-1}^2$$

CISCO:

$$y_t = 19.30\times10^{-4} + \varepsilon_t$$

$$\sigma_t^2 = 9.17\times10^{-6} + 0.920\sigma_{t-1}^2 + 0.071\varepsilon_{t-1}^2$$

DELL:

$$y_t = 11.32 \times 10^{-4} + \varepsilon_t$$

$$\sigma_t^2 = 3.59 \times 10^{-6} + 0.950\sigma_{t-1}^2 + 0.0486\varepsilon_{t-1}^2$$

MICROSOFT:

$$y_t = 10.01 \times 10^{-4} + \varepsilon_t$$

$$\sigma_t^2 = 6.41 \times 10^{-6} + 0.920\sigma_{t-1}^2 + 0.069\varepsilon_{t-1}^2$$

3M:

$$y_t = 3.89 \times 10^{-4} + \varepsilon_t$$

$$\sigma_t^2 = 2.66 \times 10^{-6} + 0.957\sigma_{t-1}^2 + 0.031\varepsilon_{t-1}^2$$

For each day (of the 5044 days of our sample), we calculate the volatility forecast and call this σ_t. We use this calculated variance forecast to obtain the standardized residuals of the daily returns for each day. In other words, we calculate $\frac{y_t - \overline{y_t}}{\sigma_t}$ as for each t we know the return y_t. Thus we now have a matrix of standardized residuals **R**. This matrix is of dimension 5044×7 (days $\times$ number of stocks). If the univariate GARCH(1,1) was an "adequate description" of "reality", we should find that the columns of **R** have zero mean (which they do by our construction), and a variance of one (which need not be true, since we use the forecast variance estimate, and not the true variance) and the covariance between the rows should be zero (meaning that there are no "common factors" outside the explanation provided by autocovariance of daily residuals).

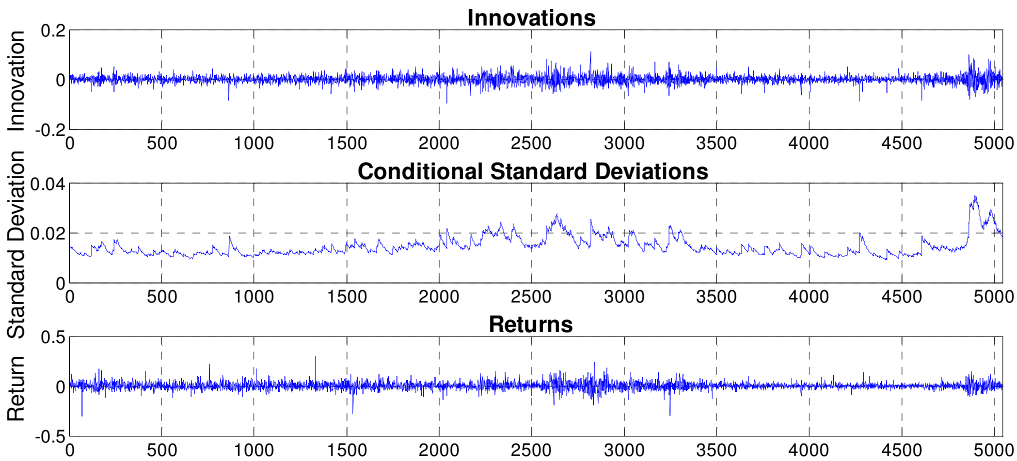
Now we are ready for our post-estimation analysis. In this part we will, first, compare the residuals, conditional standard deviations, and returns, after which we will plot and compare the correlation of the standardized innovations. Finally, we will quantify and compare the correlation of the standardized residuals.

Post-estimation analysis:

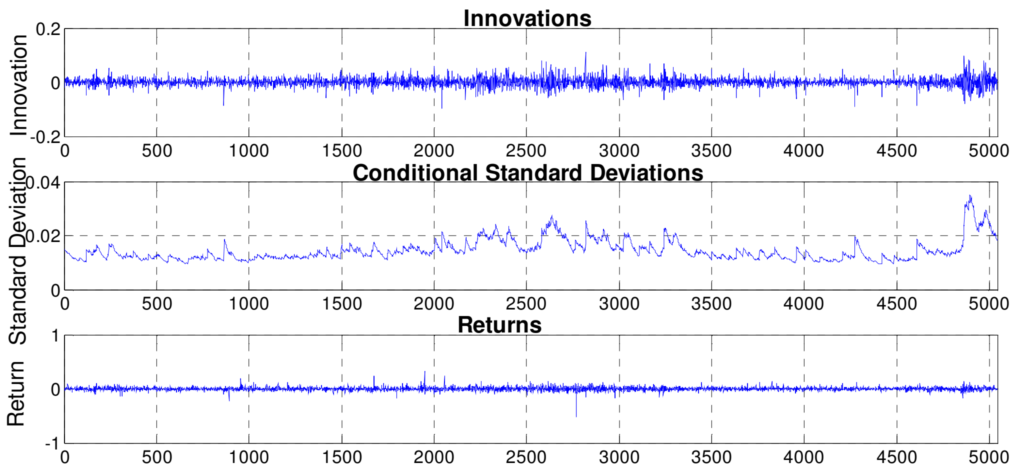
1. **Compare residuals, conditional standard deviations, and returns**. By using the Matlab function *garchplot(innovations, sigmas, nasdaqret)*, we

split the variance into variance innovations and conditional standard deviations. The GARCH test uses this step in order to investigate if the fitted innovations exhibit volatility clustering.

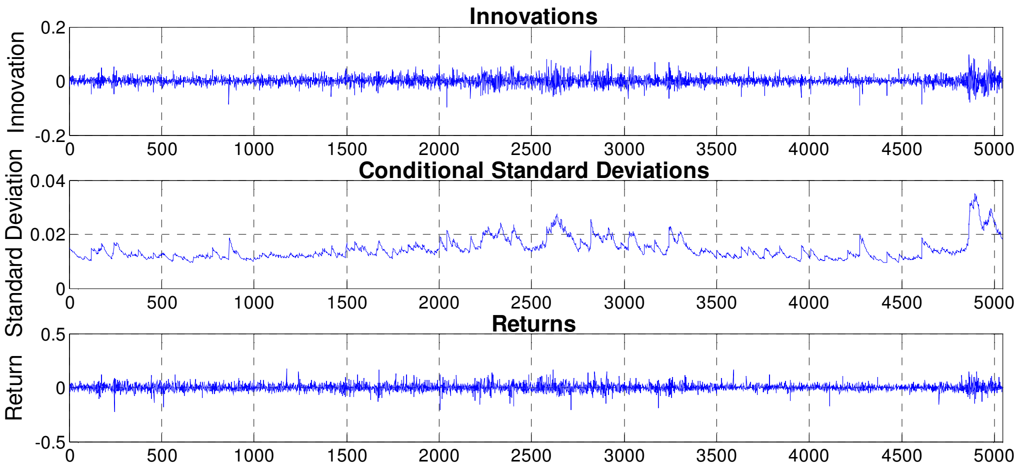
ADOBE:



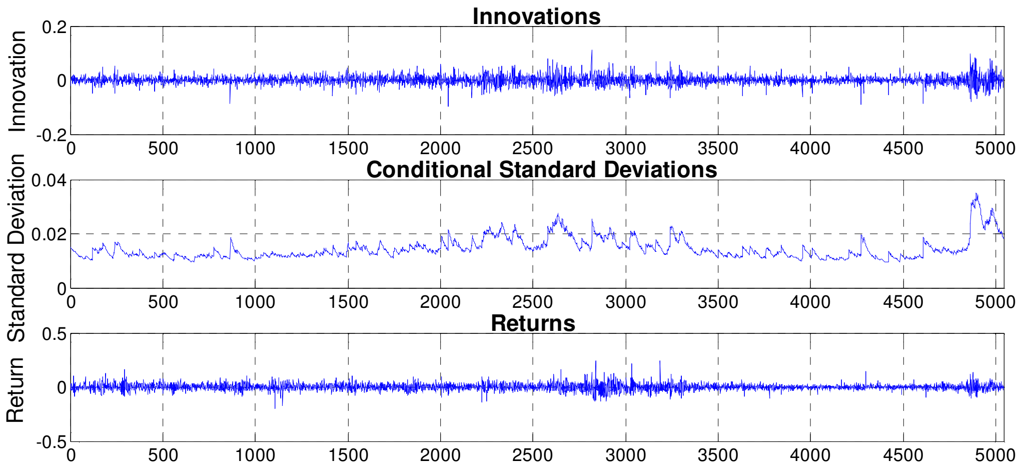
APPLE:



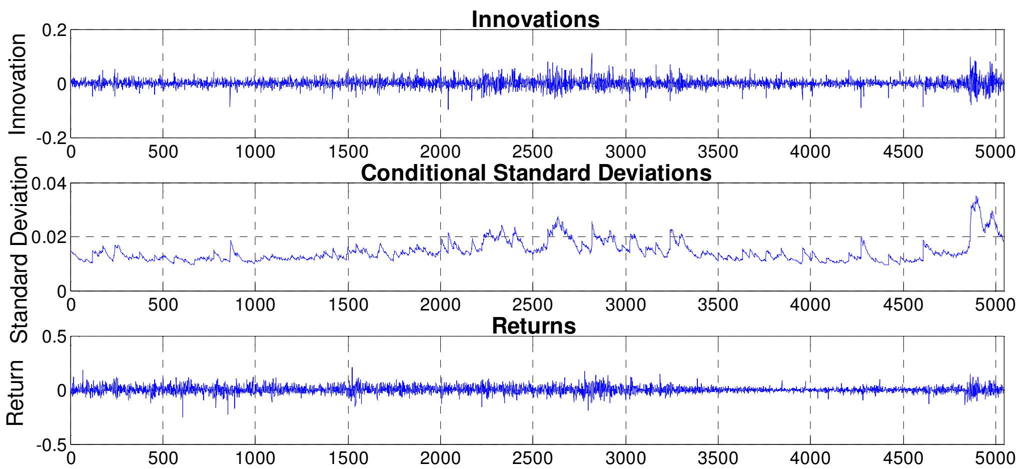
AUTODESK:



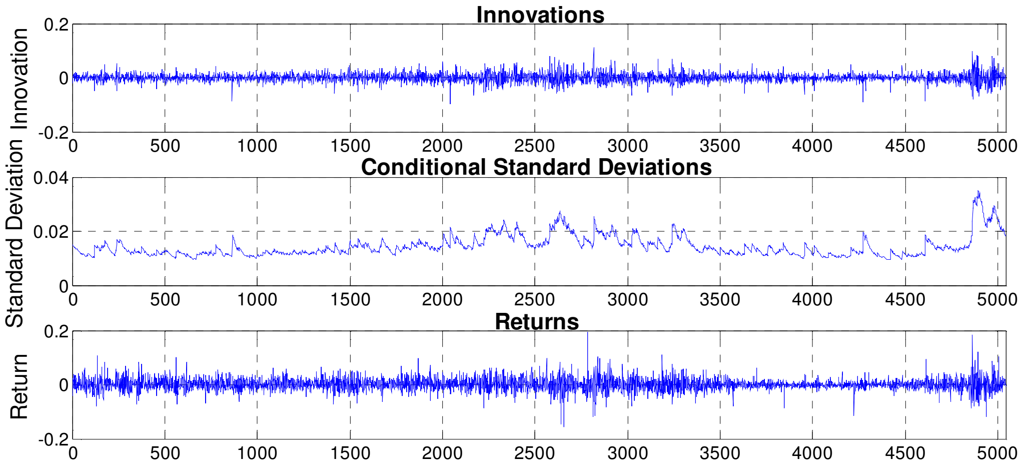
CISCO:



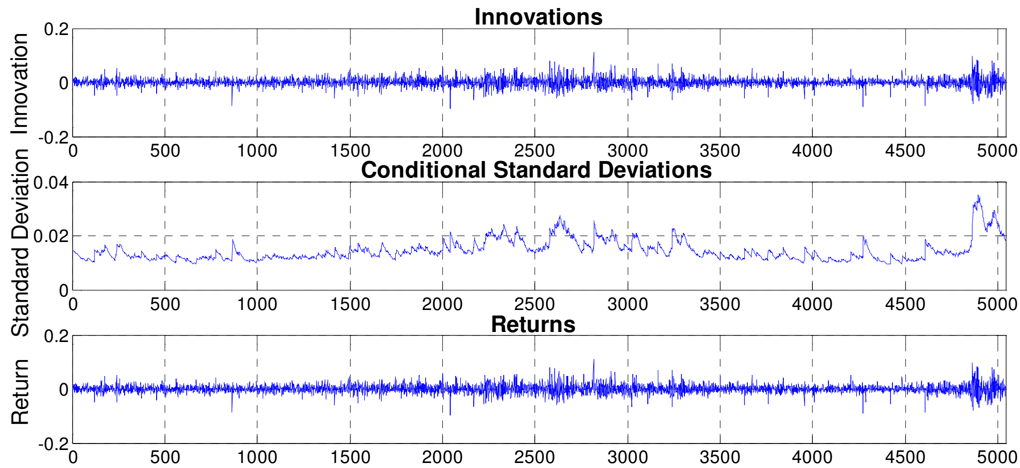
DELL:



MICROSOFT:



3M:

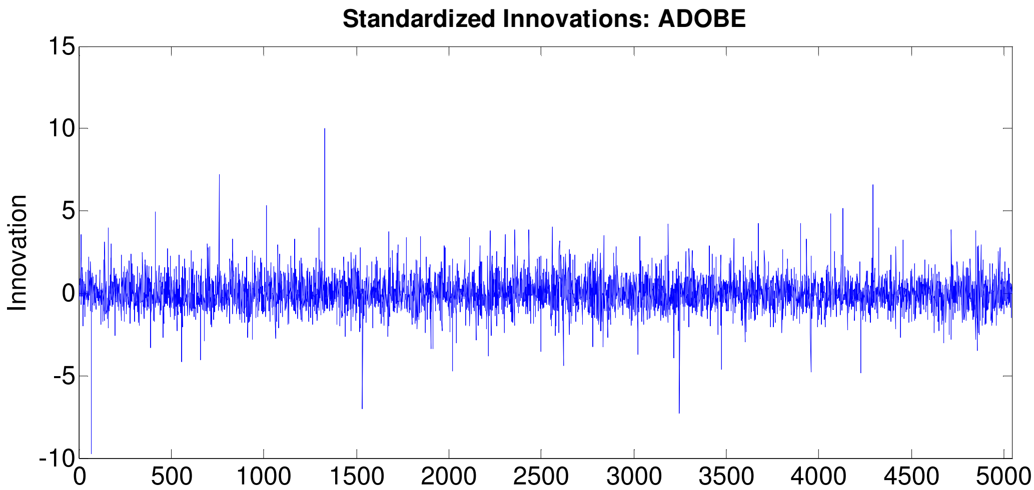


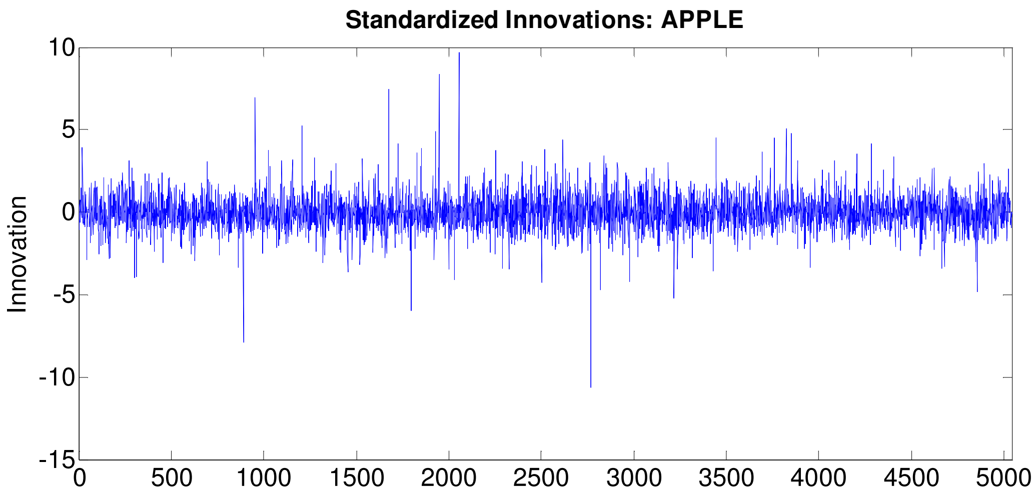
Figures 24 to 30: GARCH decomposition of Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M daily returns over the sample period. Data source: Datastream.

From the visual inspection of the graphs of each stock, we can observe volatility clustering in innovations and returns. As previously said, we want to see if the innovations of the seven price returns are uncorrelated, thing that will show us the necessity of performing a PC-GARCH. As a hint for their correlation, we see in the above graphs that innovations vary around approximately identical dates, due to probably common factors that influence all of them. As well, we can observe that, for each stock, β_1 + α_1 is very close to 1, that means it is very close to the integrated, nonstationary boundary given by the constraints stated at **(1).**

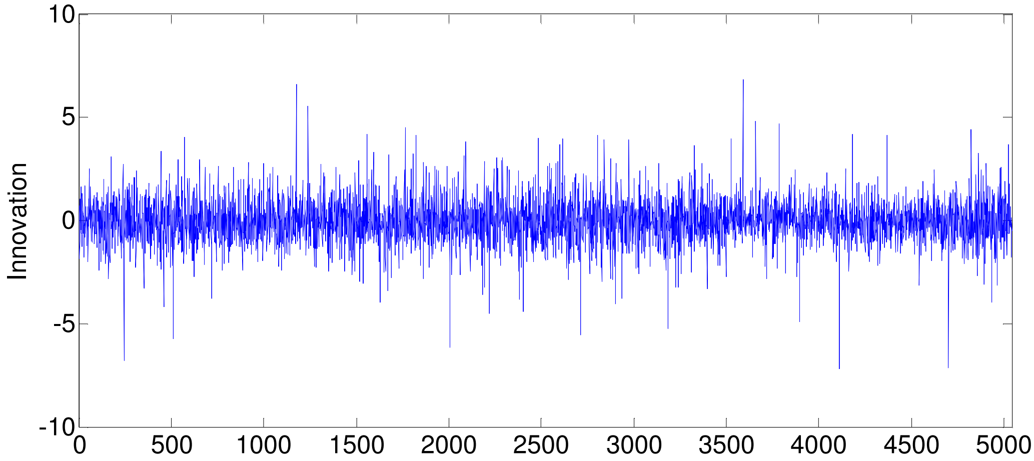
2. Plot and compare the correlation for the standardized innovations.

We saw that the previous fitted innovations display volatility clustering. But if we plot the standardized innovations (the innovations divided by their conditional standard deviation), however, they appear generally stable with little clustering.

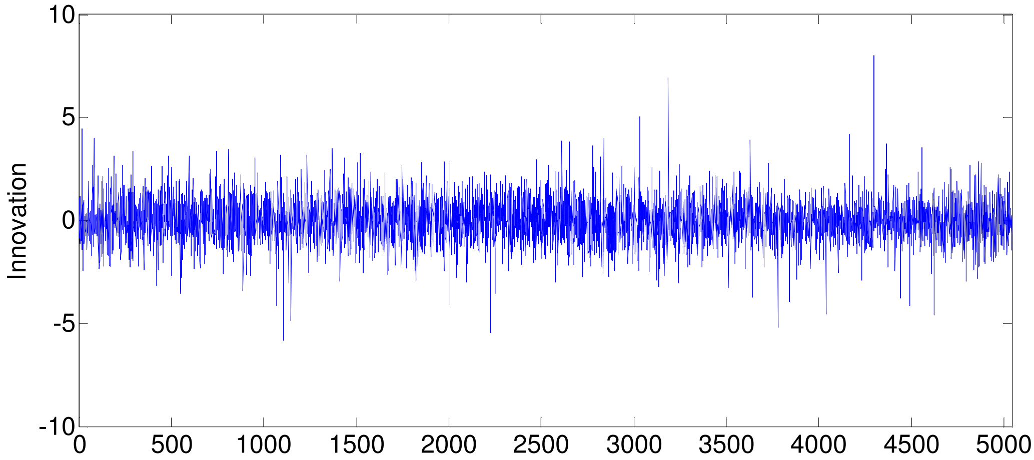




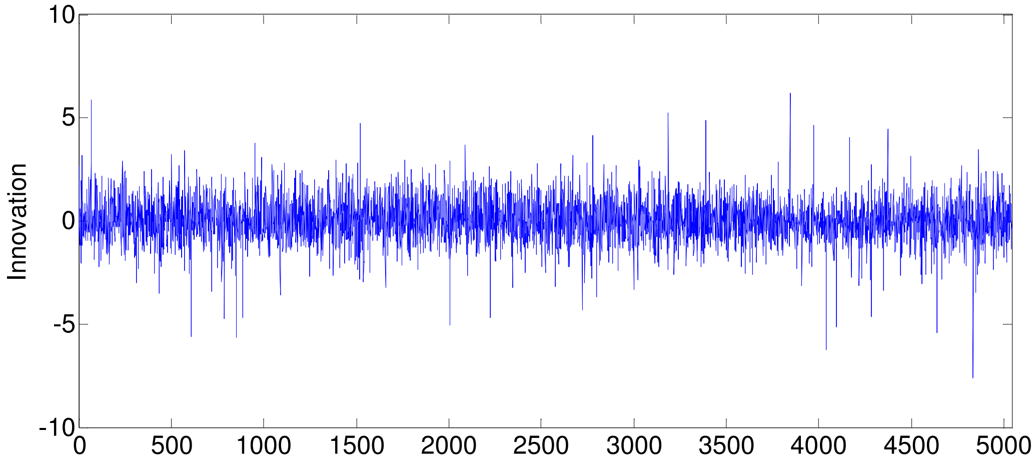
Standardized Innovations: AUTODESK

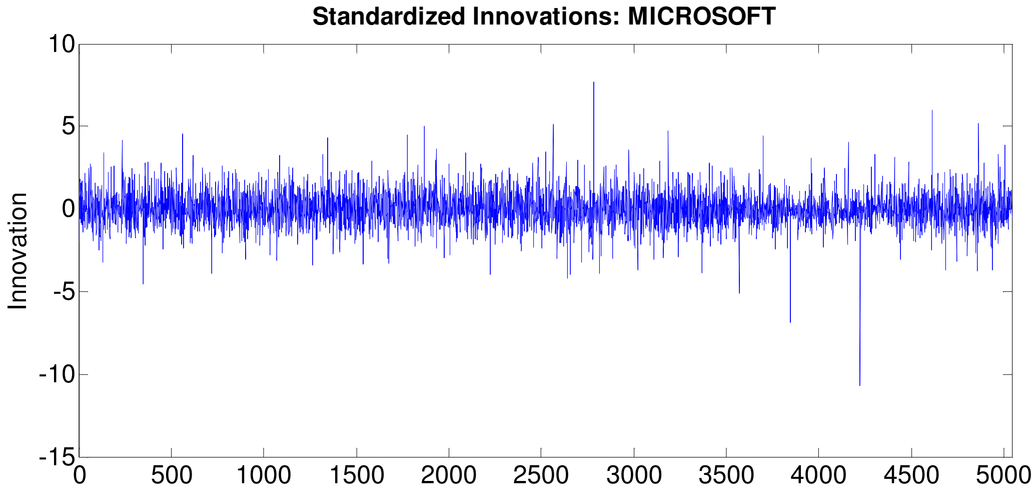


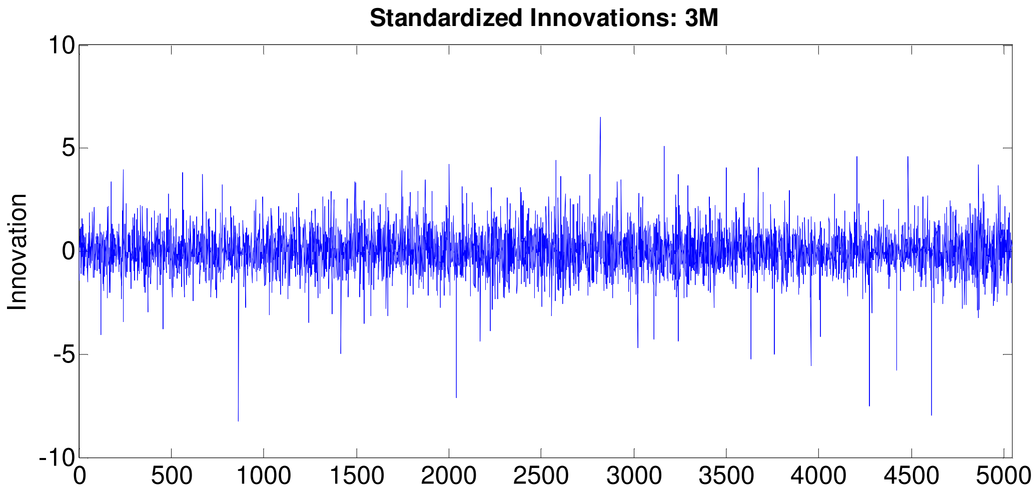
Standardized Innovations: CISCO



Standardized Innovations: DELL

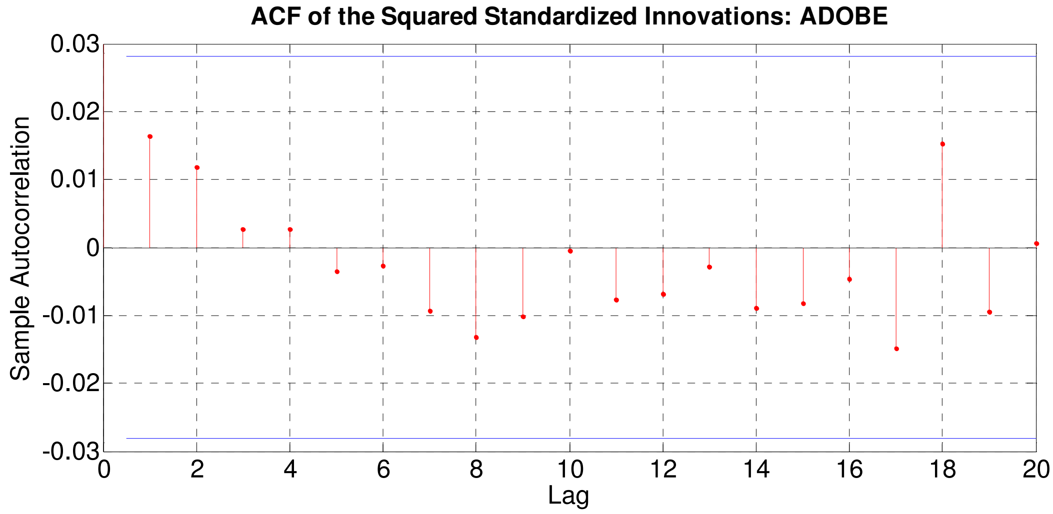


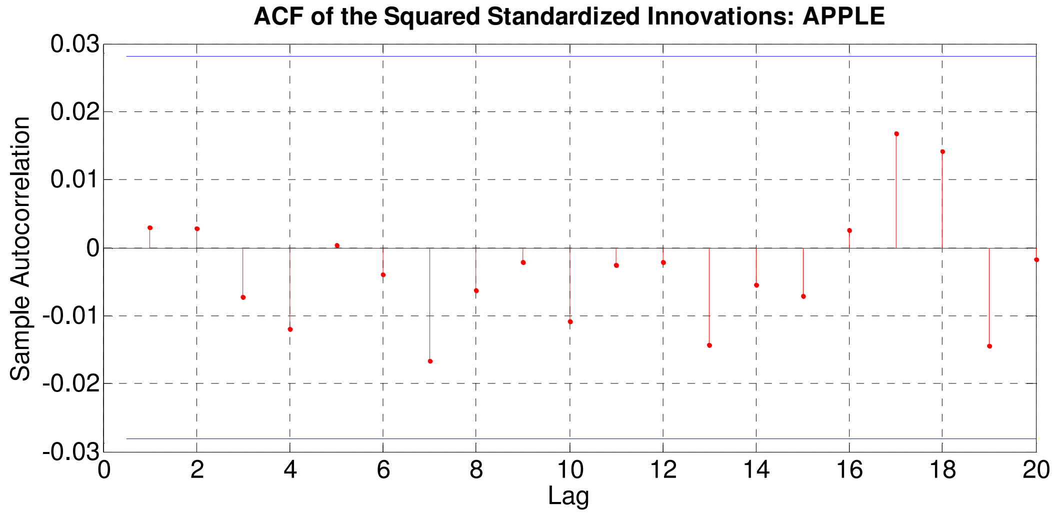


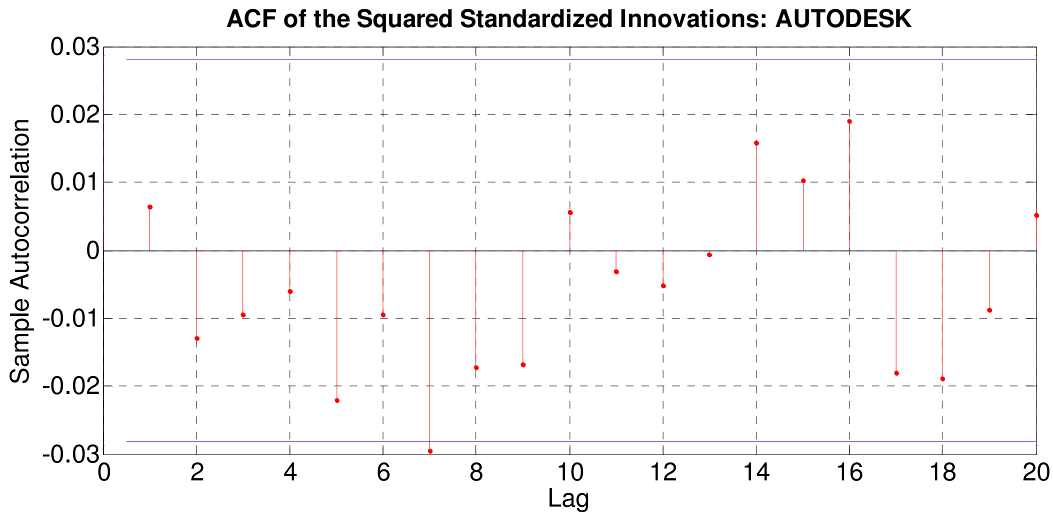


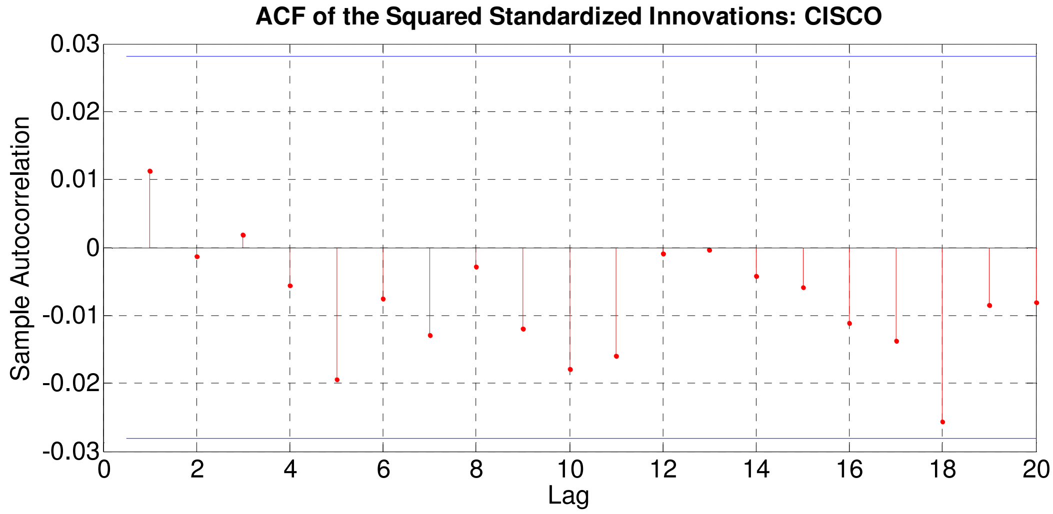
Figures 31 to 37: Standardized innovations for Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M. Data source: Datastream.

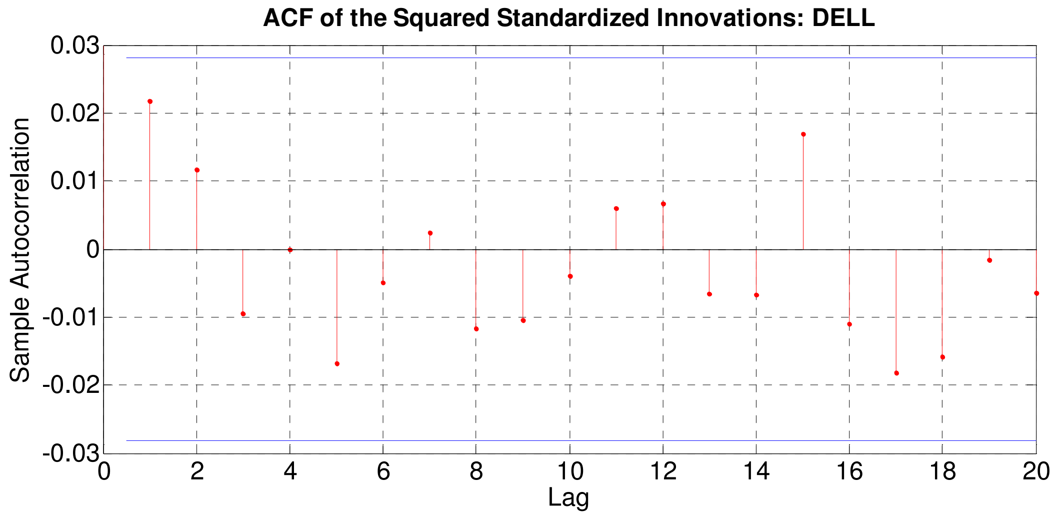
As well, if we plot the ACF of the squared standardized innovations, we will not find any further correlation.

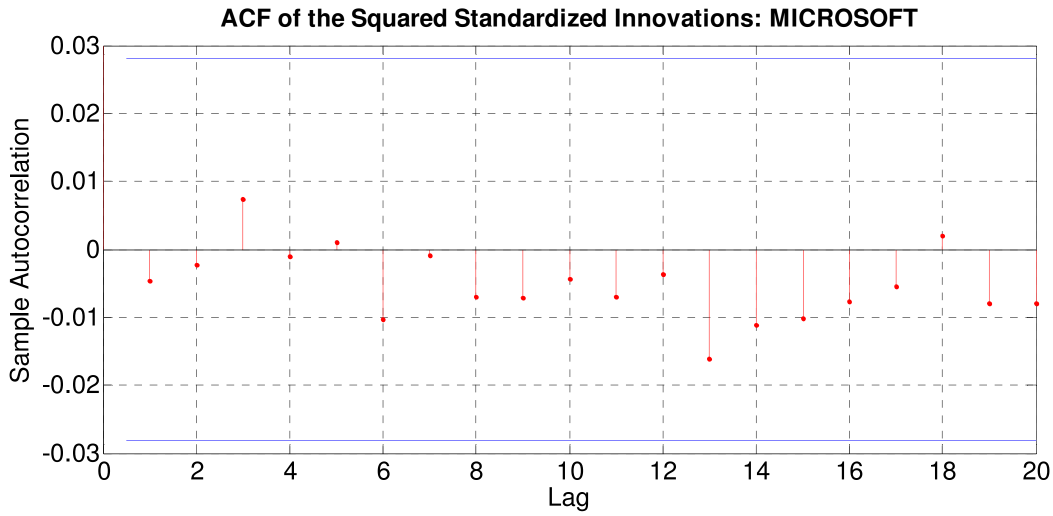

ACF of the Squared Standardized Innovations: ADOBE
Sample Autocorrelation
Lag
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
0
2
4
6
8
10
12
14
16
18
20

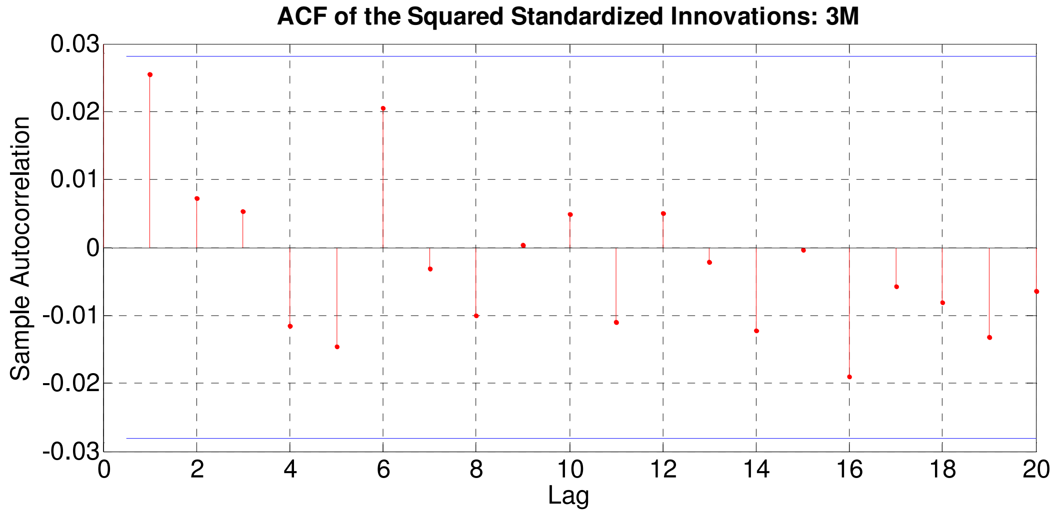

ACF of the Squared Standardized Innovations: APPLE
Sample Autocorrelation
Lag
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
0
2
4
6
8
10
12
14
16
18
20


ACF of the Squared Standardized Innovations: AUTODESK
Sample Autocorrelation
Lag
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
0
2
4
6
8
10
12
14
16
18
20


ACF of the Squared Standardized Innovations: CISCO
Sample Autocorrelation
Lag


ACF of the Squared Standardized Innovations: DELL
Sample Autocorrelation
Lag


ACF of the Squared Standardized Innovations: MICROSOFT
Sample Autocorrelation
Lag



Figures 38 to 44: The autocorrelation functions of Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M daily squared standardized innovations over the sample period. Data source: Datastream.

By observing the above ACF plots, we see no further correlation. Furthermore, if we compare the ACF of the squared standardized innovations in this figure to the ACF of the squared returns prior to the fitting the default model, we see that this GARCH model sufficiently explains the heteroskedasticity in the raw returns.

3. **Quantify and compare correlation of the standardized innovations.** At this phase, we compare the results of the Q-test and ARCH-test with the results of the same tests performed in the pre-estimation analysis. I will use this time the standardized residuals. By this action, I want to see if GARCH has treated efficiently the data.

   Q-test results:

ADOBE- LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.2463	1.3444	3.8415
0.0000	0.3593	2.0470	5.9915
0.0000	0.5552	2.0838	7.8147
0.0000	0.7135	2.1209	9.4877
0.0000	0.8234	2.1821	11.0705
0.0000	0.8985	2.2191	12.5916
0.0000	0.9147	2.6583	14.0671

APPLE – LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.8357	0.0430	3.8415
0.0000	0.9582	0.0853	5.9915
0.0000	0.9497	0.3531	7.8147
0.0000	0.8994	1.0674	9.4877
0.0000	0.9569	1.0679	11.0705
0.0000	0.9795	1.1457	12.5916
0.0000	0.9243	2.5368	14.0671

AUTODESK – LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.6470	0.2097	3.8415
0.0000	0.5927	1.0462	5.9915
0.0000	0.6835	1.4947	7.8147
0.0000	0.7951	1.6756	9.4877
0.0000	0.5298	4.1372	11.0705
0.0000	0.5982	4.5838	12.5916
0.0000	0.2536	8.9875	14.0671

CISCO – LBPSQ

H	P-Value	Statistic	Critical value
0.0000	0.4262	0.6333	3.8415
0.0000	0.7251	0.6428	5.9915
0.0000	0.8825	0.6602	7.8147
0.0000	0.9363	0.8159	9.4877
0.0000	0.7428	2.7220	11.0705
0.0000	0.8078	3.0083	12.5916
0.0000	0.7963	3.8556	14.0671

DELL – LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.1222	2.3895	3.8415
0.0000	0.2146	3.0775	5.9915
0.0000	0.3165	3.5332	7.8147
0.0000	0.4728	3.5332	9.4877
0.0000	0.4202	4.9645	11.0705
0.0000	0.5327	5.0870	12.5916
0.0000	0.6457	5.1170	14.0671

MICROSOFT – LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.7455	0.1054	3.8415
0.0000	0.9365	0.1312	5.9915
0.0000	0.9380	0.4110	7.8147
0.0000	0.9811	0.4169	9.4877
0.0000	0.9947	0.4230	11.0705
0.0000	0.9872	0.9572	12.5916
0.0000	0.9954	0.9614	14.0671

3M – LBPQ

H	P-Value	Statistic	Critical value
0.0000	0.0695	3.2956	3.8415
0.0000	0.1686	3.5610	5.9915
0.0000	0.2954	3.7027	7.8147
0.0000	0.3568	4.3821	9.4877
0.0000	0.3618	5.4653	11.0705
0.0000	0.2689	7.5997	12.5916
0.0000	0.3645	7.6497	14.0671

Tables 23-29: Ljung-Box-Pierce Q-test output for standardized residuals. Data source: Datastream.

The ARCH test results are:

ADOBE – ENGLE

H	P-Value	Statistic	Critical value
0.0000	0.9058	0.0140	3.8415
0.0000	0.9871	0.0259	5.9915
0.0000	0.9978	0.0407	7.8147
0.0000	0.9997	0.0524	9.4877
0.0000	0.9999	0.0699	11.0705
0.0000	1.0000	0.0891	12.5916
0.0000	1.0000	0.1095	14.0671

APPLE – ENGLE

H	P-Value	Statistic	Critical value
0.0000	0.9346	0.0067	3.8415
0.0000	0.9965	0.0070	5.9915
0.0000	0.9995	0.0146	7.8147
0.0000	0.9999	0.0338	9.4877
0.0000	1.0000	0.0415	11.0705
0.0000	1.0000	0.0526	12.5916
0.0000	1.0000	0.0759	14.0671

AUTODESK – ENGLE

H	P-Value	Statistic	Critical value
0.0000	0.7696	0.0858	3.8415
0.0000	0.9014	0.2076	5.9915
0.0000	0.9498	0.3530	7.8147
0.0000	0.9755	0.4793	9.4877
0.0000	0.9835	0.6895	11.0705
0.0000	0.9937	0.7365	12.5916
0.0000	0.9952	0.9742	14.0671

CISCO – ENGLE

H	P-Value	Statistic	Critical value
0.0000	0.9148	0.0114	3.8415
0.0000	0.9728	0.0551	5.9915
0.0000	0.9926	0.0934	7.8147
0.0000	0.9978	0.1342	9.4877
0.0000	0.9992	0.1954	11.0705
0.0000	0.9996	0.2684	12.5916
0.0000	0.9998	0.3512	14.0671

DELL - ENGLE

H	P-Value	Statistic	Critical value
0.0000	0.9699	0.0014	3.8415
0.0000	0.9977	0.0046	5.9915
0.0000	0.9920	0.0986	7.8147
0.0000	0.9970	0.1580	9.4877
0.0000	0.9973	0.3200	11.0705
0.0000	0.9988	0.4073	12.5916
0.0000	0.9996	0.4368	14.0671

MICROSOFT – ENGLE

H	P-Value	Statistic	Critical value
0.0000	0.9170	0.0109	3.8415
0.0000	0.9896	0.0210	5.9915
0.0000	0.9992	0.0212	7.8147
0.0000	0.9999	0.0303	9.4877
0.0000	1.0000	0.0371	11.0705
0.0000	1.0000	0.0483	12.5916
0.0000	1.0000	0.0568	14.0671

3M - ENGLE

H	P-Value	Statistic	Critical value
0.0000	0.8679	0.0277	3.8415
0.0000	0.9705	0.06	5.9915
0.0000	0.9945	0.0765	7.8147
0.0000	0.9976	0.1415	9.4877
0.0000	0.9989	0.2174	11.0705
0.0000	0.9998	0.2242	12.5916
0.0000	0.9999	0.2974	14.0671

Tables 30 to 36: Engle's test output for heteroskedasticity for standardized residuals. Data source: Datastream.

Although in the pre-estimation analysis both Q-test (with one exception) and ARCH test indicated rejection of their null hypothesis, now we find out that when using standardized innovations based on the estimated model, the same tests indicate acceptance (H=0) of the same null hypothesis. These results confirm the explanatory power of the default model and the existence of the GARCH effects.

We have GARCH effects and also correlation between innovations that disappears after treating the data. In conclusion to the post-estimation part, GARCH model is a proper model to be used to explain the variances of the seven stocks. Thus, our intuitive choice of the seven stock returns is justified, and we proceed to the next stage.

5.10.3 Third step: Principal component analysis of standardized residuals

We have seen details of the PCA method in detail above, so I shall just confine ourselves to reporting the major results here. The matrix of standardized residuals is the matrix on which we will perform PCA, because we wish to identify the common causes of what the GARCH(1,1) model leaves out as unexplained innovations.

We perform the Principal Component Analysis to the standardized innovations. The Matlab code for this operation is:

R = [adobeinnret appleinnret autodeskinnret ciscoinnret dellinnret microsoftinnret mmminnret] % stack standardized residuals into a matrix R
PC = princomp(R) % perform PCA on the matrix R
[PC,SCORE,latent,tsquare] = princomp(R)
PC
*P=R*PC; %multiply R and PC*

The PCA gives us seven mutually orthogonal linear combinations of the standardized residuals. The output will be as it follows:

	P1	P2	P3	P4	P5	P6	P7
ADOBE	0.3793	-0.0414	0.3343	-0.4477	0.6597	0.3140	0.0919
APPLE	0.3639	0.2571	-0.3263	-0.6960	-0.3840	-0.2503	0.0226
AUTODESK	0.3448	-0.0754	0.7747	0.0908	-0.5140	-0.0483	0.0211
CISCO	0.4337	0.1590	-0.0809	0.2631	0.1752	-0.1738	-0.8062

DELL	0.4022	0.2411	-0.2988	0.3107	-0.2201	0.7129	0.1938
MICROSOFT	0.4201	0.0913	-0.1025	0.3753	0.2539	-0.5454	0.5495
3M	0.2804	-0.9136	-0.2742	-0.0178	-0.0977	0.0227	-0.0338

Table 37: Matrix of principal components for Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M. Data source: Datastream.

The *latent* output gives us the eigenvalues. Accordingly, we can calculate their power, meaning the percentage of variation each explains.

PC	Eigenvalue	% of var explained
P1	2.9902	42.71%
P2	0.8372	11.96%
P3	0.7596	10.85%
P4	0.6888	9.84%
P5	0.6651	9.50%
P6	0.5578	7.97%
P7	0.5027	7.18%

Table 38: Matrix of corresponding eigenvalues and their weights. Data source: Datastream.

We see that most of the variance is explained by the first principal component, to which the change in volatility of all seven return series contributes a very similar magnitude. This concords with the initial intuition that since all seven are stock prices based in the US, there is a large common factor that moves all of them in the same direction.

We can observe that P1 (=0.3793*Adobe standardized innovation + 0.3639*Apple standardized innovation + 0.3448*Autodesk standardized innovation + 0.4337*Cisco standardized innovation + 0.4022*Dell standardized innovation + 0.4201*Microsoft standardized innovation + 0.2804*3M standardized innovation) is the first principal component that explains almost 43% of the variance of the standardized residuals. The second factor explains about 12% of the variance in standardized residuals - we note that this is positively weighted by Apple, Cisco, Dell and Microsoft, but negatively weighted by Adobe, Autodesk and 3M. The third factor explains only about 11% of the variance in the standardized residuals, and this seems to be positively driven by the Adobe and Autodesk returns while negatively driven by Apple, Cisco, Dell, Microsoft and 3M. The rest of the principal components weight less than 10% each.

Thus, we obtain, in decreasing order, seven PCs that drive the standardized excess returns - which the GARCH model earlier called innovations. We see that they are not really all innovations: that most of this innovation is driven by one major factor that drives all seven stocks together. We could now choose to, for the sake of parsimony, keep just this first PC that explains about 43% of the so-called innovations, and leave the rest out. But, a technical issue is that leaving out any of the principal components may occasionally lead to meaningless results since we would not be able to guarantee that the resulting variance covariance matrix will be positive definite (see Alexander(2000)). Since in this particular case we do not have too many variables, we can include all the factors to ensure that our results are always meaningful.

5.10.4 Fourth step: Running GARCH(1,1) on the PCs

Once again, recalling that the GARCH(1,1) model is $y_t = C + \varepsilon_t$, $\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \beta_1 \varepsilon_{t-1}^2$, we run this model on the newly obtained PCs[14]. The results obtained are summarized in Tables 39 to 45.

[14] Note that I am actually running a multivariate GARCH(1,1) model on the PCs. It is their orthogonality that makes this multivariate GARCH(1,1) equivalent to to seven univariate GARCH models.

	Value	T-stat
C	-24.08×10^{-3}	-1.02
$\boldsymbol{\alpha_0}$	8.21×10^{-3}	2.16
$\boldsymbol{\alpha_1}$	9.88×10^{-1}	364.46
$\boldsymbol{\beta_1}$	9.52×10^{-3}	5.48

(a)

	Value	T-stat
C	4.91×10^{-3}	0.40
$\boldsymbol{\alpha_0}$	4.24×10^{-1}	8.74
$\boldsymbol{\alpha_1}$	4.08×10^{-1}	6.48
$\boldsymbol{\beta_1}$	8.86×10^{-2}	7.93

(b)

	Value	T-stat
C	-13.09×10^{-3}	-1.06
$\boldsymbol{\alpha_0}$	3.15×10^{-1}	1.51
$\boldsymbol{\alpha_1}$	5.69×10^{-1}	2.03
$\boldsymbol{\beta_1}$	15.80×10^{-3}	1.73

(c)

	Value	T-stat
C	11.17×10^{-3}	0.95
$\boldsymbol{\alpha_0}$	24.53×10^{-2}	4.85
$\boldsymbol{\alpha_1}$	5.99×10^{-1}	7.82
$\boldsymbol{\beta_1}$	4.63×10^{-2}	5.27

(d)

	Value	T-stat
C	12.16×10^{-3}	1.05
$\boldsymbol{\alpha_0}$	64.34×10^{-2}	3.65
$\boldsymbol{\alpha_1}$	0.00	0.00
$\boldsymbol{\beta_1}$	3.39×10^{-2}	4.00

(e)

	Value	T-stat
C	16.95×10^{-3}	1.73
$\boldsymbol{\alpha_0}$	9.84×10^{-2}	6.77
$\boldsymbol{\alpha_1}$	7.55×10^{-1}	24.09
$\boldsymbol{\beta_1}$	7.02×10^{-2}	7.90

(f)

	Value	T-stat
C	6.79×10^{-3}	0.72
α_0	7.26×10^{-2}	8.56
α_1	7.74×10^{-1}	34.28
β_1	8.61×10^{-2}	9.82

(g)

Table 39 to 45: Summary of the GARCH(1,1) model for (a) PC1 (b) PC2 (c) PC3 (d) PC4 (e) PC5 (f) PC6 (g) PC7. Data source: Datastream.

Thus, we have a GARCH model that predicts the volatilities of the seven PCs. However, we began with the aim of obtaining volatility forecasting models for the daily return series. We shall see that this is achieved through a simple linear transformation in the next section.

5.10.5 Fifth step: Obtaining the GARCH model of the stock returns

We note that the GARCH(1,1) models that we obtained in 5.10.4 are for the principal components. For instance, $\sigma_t^2 = \alpha_0 + \alpha_1\sigma_{t-1}^2 + \beta_1\varepsilon_{t-1}^2$ gives us the volatility forecast of each PC. Notice that since these seven PCs are orthogonal to each other, we can write their variance-covariance matrix in diagonal form. In other words, recalling our discussion earlier, we re-visit equation (3) **Λ** = **P'P** = **A'X'XA** = **A'ΩA**. We now have **Λ** which consists of the volatility forecasts of the seven PCs. Using the property that **A'**=**A^{-1}**, we see that **AΛA'** = **AA'ΩAA'** = **Ω**. Thus, the simple linear transformation of premultiplying the forecasts by the matrix **A** and post-multiplying by **A'** gives us the volatility forecasts of the seven return series. The seven equations we obtain are reproduced below.

$$\sigma_t^2 = 37.66 \times 10^{-2} + \begin{pmatrix} 14.21 \times 10^{-2} \\ 0.07 \times 10^{-2} \\ 6.36 \times 10^{-2} \\ 12.01 \times 10^{-2} \\ 0 \\ 7.45 \times 10^{-2} \\ 0.65 \times 10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\sigma_{t-1}^{P_1}\right)^2 \\ \left(\sigma_{t-1}^{P_2}\right)^2 \\ \left(\sigma_{t-1}^{P_3}\right)^2 \\ \left(\sigma_{t-1}^{P_4}\right)^2 \\ \left(\sigma_{t-1}^{P_5}\right)^2 \\ \left(\sigma_{t-1}^{P_6}\right)^2 \\ \left(\sigma_{t-1}^{P_7}\right)^2 \end{pmatrix} + \begin{pmatrix} 0.14 \times 10^{-2} \\ 0.02 \times 10^{-2} \\ 0.18 \times 10^{-2} \\ 0.93 \times 10^{-2} \\ 1.47 \times 10^{-2} \\ 0.69 \times 10^{-2} \\ 0.07 \times 10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\varepsilon_{t-1}^{P_1}\right)^2 \\ \left(\varepsilon_{t-1}^{P_2}\right)^2 \\ \left(\varepsilon_{t-1}^{P_3}\right)^2 \\ \left(\varepsilon_{t-1}^{P_4}\right)^2 \\ \left(\varepsilon_{t-1}^{P_5}\right)^2 \\ \left(\varepsilon_{t-1}^{P_6}\right)^2 \\ \left(\varepsilon_{t-1}^{P_7}\right)^2 \end{pmatrix}$$

Formula 1: Multivariate PC-GARCH model for ADOBE daily return volatility.

$$\sigma_t^2 = 28.26 \times 10^{-2} + \begin{pmatrix} 13.08 \times 10^{-2} \\ 2.70 \times 10^{-2} \\ 6.06 \times 10^{-2} \\ 29.02 \times 10^{-2} \\ 0 \\ 4.73 \times 10^{-2} \\ 0.04 \times 10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\sigma_{t-1}^{P_1}\right)^2 \\ \left(\sigma_{t-1}^{P_2}\right)^2 \\ \left(\sigma_{t-1}^{P_3}\right)^2 \\ \left(\sigma_{t-1}^{P_4}\right)^2 \\ \left(\sigma_{t-1}^{P_5}\right)^2 \\ \left(\sigma_{t-1}^{P_6}\right)^2 \\ \left(\sigma_{t-1}^{P_7}\right)^2 \end{pmatrix} + \begin{pmatrix} 0.13 \times 10^{-2} \\ 0.59 \times 10^{-2} \\ 0.17 \times 10^{-2} \\ 2.24 \times 10^{-2} \\ 0.50 \times 10^{-2} \\ 0.44 \times 10^{-2} \\ 0.44 \times 10^{-4} \end{pmatrix}' \begin{pmatrix} \left(\varepsilon_{t-1}^{P_1}\right)^2 \\ \left(\varepsilon_{t-1}^{P_2}\right)^2 \\ \left(\varepsilon_{t-1}^{P_3}\right)^2 \\ \left(\varepsilon_{t-1}^{P_4}\right)^2 \\ \left(\varepsilon_{t-1}^{P_5}\right)^2 \\ \left(\varepsilon_{t-1}^{P_6}\right)^2 \\ \left(\varepsilon_{t-1}^{P_7}\right)^2 \end{pmatrix}$$

Formula 2: Multivariate PC-GARCH model for APPLE daily return volatility.

$$\sigma_t^2 = 36.49 \times 10^{-2} + \begin{pmatrix} 11.74 \times 10^{-2} \\ 0.23 \times 10^{-2} \\ 34.16 \times 10^{-2} \\ 0.49 \times 10^{-2} \\ 0 \\ 0.18 \times 10^{-2} \\ 0.03 \times 10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\sigma_{t-1}^{P_1}\right)^2 \\ \left(\sigma_{t-1}^{P_2}\right)^2 \\ \left(\sigma_{t-1}^{P_3}\right)^2 \\ \left(\sigma_{t-1}^{P_4}\right)^2 \\ \left(\sigma_{t-1}^{P_5}\right)^2 \\ \left(\sigma_{t-1}^{P_6}\right)^2 \\ \left(\sigma_{t-1}^{P_7}\right)^2 \end{pmatrix} + \begin{pmatrix} 0.11 \times 10^{-2} \\ 0.05 \times 10^{-2} \\ 0.95 \times 10^{-2} \\ 0.04 \times 10^{-2} \\ 0.90 \times 10^{-2} \\ 0.02 \times 10^{-2} \\ 0.38 \times 10^{-4} \end{pmatrix}' \begin{pmatrix} \left(\varepsilon_{t-1}^{P_1}\right)^2 \\ \left(\varepsilon_{t-1}^{P_2}\right)^2 \\ \left(\varepsilon_{t-1}^{P_3}\right)^2 \\ \left(\varepsilon_{t-1}^{P_4}\right)^2 \\ \left(\varepsilon_{t-1}^{P_5}\right)^2 \\ \left(\varepsilon_{t-1}^{P_6}\right)^2 \\ \left(\varepsilon_{t-1}^{P_7}\right)^2 \end{pmatrix}$$

Formula 3: Multivariate PC-GARCH model for AUTODESK daily return volatility.

$$\sigma_t^2 = 10.12\times10^{-2} + \begin{pmatrix} 18.58\times10^{-2} \\ 1.03\times10^{-2} \\ 0.37\times10^{-2} \\ 4.15\times10^{-2} \\ 0 \\ 2.28\times10^{-2} \\ 50.33\times10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\sigma_{t-1}^{P_1}\right)^2 \\ \left(\sigma_{t-1}^{P_2}\right)^2 \\ \left(\sigma_{t-1}^{P_3}\right)^2 \\ \left(\sigma_{t-1}^{P_4}\right)^2 \\ \left(\sigma_{t-1}^{P_5}\right)^2 \\ \left(\sigma_{t-1}^{P_6}\right)^2 \\ \left(\sigma_{t-1}^{P_7}\right)^2 \end{pmatrix} + \begin{pmatrix} 0.18\times10^{-2} \\ 0.22\times10^{-2} \\ 0.01\times10^{-2} \\ 0.32\times10^{-2} \\ 0.10\times10^{-2} \\ 0.21\times10^{-2} \\ 5.60\times10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\varepsilon_{t-1}^{P_1}\right)^2 \\ \left(\varepsilon_{t-1}^{P_2}\right)^2 \\ \left(\varepsilon_{t-1}^{P_3}\right)^2 \\ \left(\varepsilon_{t-1}^{P_4}\right)^2 \\ \left(\varepsilon_{t-1}^{P_5}\right)^2 \\ \left(\varepsilon_{t-1}^{P_6}\right)^2 \\ \left(\varepsilon_{t-1}^{P_7}\right)^2 \end{pmatrix}$$

Formula 4: Multivariate PC-GARCH model for CISCO daily return volatility

$$\sigma_t^2 = 16.17\times10^{-2} + \begin{pmatrix} 15.98\times10^{-2} \\ 2.37\times10^{-2} \\ 5.08\times10^{-2} \\ 5.78\times10^{-2} \\ 0 \\ 38.39\times10^{-2} \\ 2.91\times10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\sigma_{t-1}^{P_1}\right)^2 \\ \left(\sigma_{t-1}^{P_2}\right)^2 \\ \left(\sigma_{t-1}^{P_3}\right)^2 \\ \left(\sigma_{t-1}^{P_4}\right)^2 \\ \left(\sigma_{t-1}^{P_5}\right)^2 \\ \left(\sigma_{t-1}^{P_6}\right)^2 \\ \left(\sigma_{t-1}^{P_7}\right)^2 \end{pmatrix} + \begin{pmatrix} 0.15\times10^{-2} \\ 0.51\times10^{-2} \\ 0.14\times10^{-2} \\ 0.45\times10^{-2} \\ 0.16\times10^{-2} \\ 3.57\times10^{-2} \\ 0.32\times10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\varepsilon_{t-1}^{P_1}\right)^2 \\ \left(\varepsilon_{t-1}^{P_2}\right)^2 \\ \left(\varepsilon_{t-1}^{P_3}\right)^2 \\ \left(\varepsilon_{t-1}^{P_4}\right)^2 \\ \left(\varepsilon_{t-1}^{P_5}\right)^2 \\ \left(\varepsilon_{t-1}^{P_6}\right)^2 \\ \left(\varepsilon_{t-1}^{P_7}\right)^2 \end{pmatrix}$$

Formula 5: Multivariate PC-GARCH model for DELL daily return volatility.

$$\sigma_t^2 = 13.55\times10^{-2} + \begin{pmatrix} 17.43\times10^{-2} \\ 0.34\times10^{-2} \\ 0.60\times10^{-2} \\ 8.44\times10^{-2} \\ 0 \\ 22.47\times10^{-2} \\ 23.38\times10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\sigma_{t-1}^{P_1}\right)^2 \\ \left(\sigma_{t-1}^{P_2}\right)^2 \\ \left(\sigma_{t-1}^{P_3}\right)^2 \\ \left(\sigma_{t-1}^{P_4}\right)^2 \\ \left(\sigma_{t-1}^{P_5}\right)^2 \\ \left(\sigma_{t-1}^{P_6}\right)^2 \\ \left(\sigma_{t-1}^{P_7}\right)^2 \end{pmatrix} + \begin{pmatrix} 0.17\times10^{-2} \\ 0.07\times10^{-2} \\ 0.02\times10^{-2} \\ 0.65\times10^{-2} \\ 0.22\times10^{-2} \\ 2.09\times10^{-2} \\ 2.60\times10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\varepsilon_{t-1}^{P_1}\right)^2 \\ \left(\varepsilon_{t-1}^{P_2}\right)^2 \\ \left(\varepsilon_{t-1}^{P_3}\right)^2 \\ \left(\varepsilon_{t-1}^{P_4}\right)^2 \\ \left(\varepsilon_{t-1}^{P_5}\right)^2 \\ \left(\varepsilon_{t-1}^{P_6}\right)^2 \\ \left(\varepsilon_{t-1}^{P_7}\right)^2 \end{pmatrix}$$

Formula 6: Multivariate PC-GARCH model for MICROSOFT daily return volatility.

$$\sigma_t^2 = 38.49 \times 10^{-2} + \begin{pmatrix} 7.77 \times 10^{-2} \\ 34.09 \times 10^{-2} \\ 4.28 \times 10^{-2} \\ 0.02 \times 10^{-2} \\ 0 \\ 0.04 \times 10^{-2} \\ 0.09 \times 10^{-2} \end{pmatrix}' \begin{pmatrix} \left(\sigma_{t-1}^{P_1}\right)^2 \\ \left(\sigma_{t-1}^{P_2}\right)^2 \\ \left(\sigma_{t-1}^{P_3}\right)^2 \\ \left(\sigma_{t-1}^{P_4}\right)^2 \\ \left(\sigma_{t-1}^{P_5}\right)^2 \\ \left(\sigma_{t-1}^{P_6}\right)^2 \\ \left(\sigma_{t-1}^{P_7}\right)^2 \end{pmatrix} + \begin{pmatrix} 0.07 \times 10^{-2} \\ 7.39 \times 10^{-2} \\ 0.12 \times 10^{-2} \\ 0.15 \times 10^{-4} \\ 0.03 \times 10^{-2} \\ 0.36 \times 10^{-4} \\ 0.98 \times 10^{-4} \end{pmatrix}' \begin{pmatrix} \left(\varepsilon_{t-1}^{P_1}\right)^2 \\ \left(\varepsilon_{t-1}^{P_2}\right)^2 \\ \left(\varepsilon_{t-1}^{P_3}\right)^2 \\ \left(\varepsilon_{t-1}^{P_4}\right)^2 \\ \left(\varepsilon_{t-1}^{P_5}\right)^2 \\ \left(\varepsilon_{t-1}^{P_6}\right)^2 \\ \left(\varepsilon_{t-1}^{P_7}\right)^2 \end{pmatrix}$$

Formula 7: Multivariate PC-GARCH model for 3M daily return volatility.

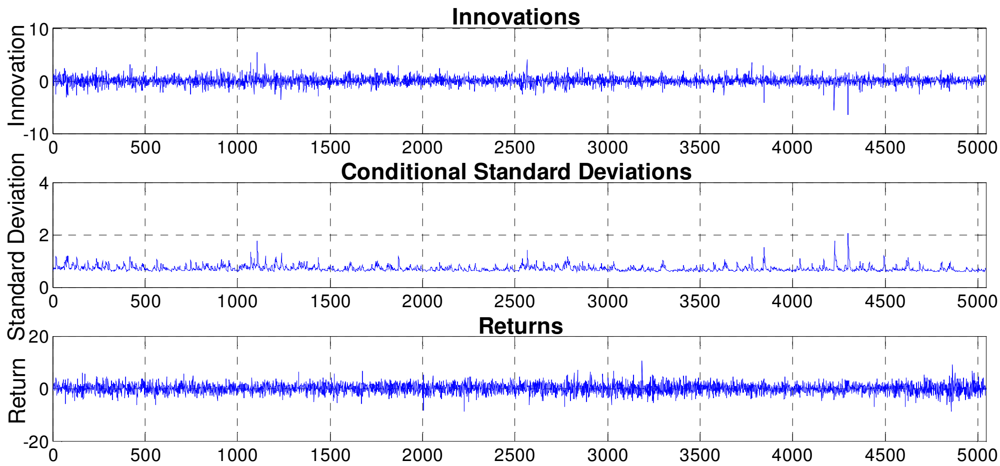
These equations are used in the following manner:

1. Use the matrix of principal components to calculate the seven PCs from the daily returns.
2. Calculate the volatility and innovation in the returns on the PCs.
3. Substitute the values calculated above in the appropriate multivariate GARCH model to obtain the volatility forecasts.

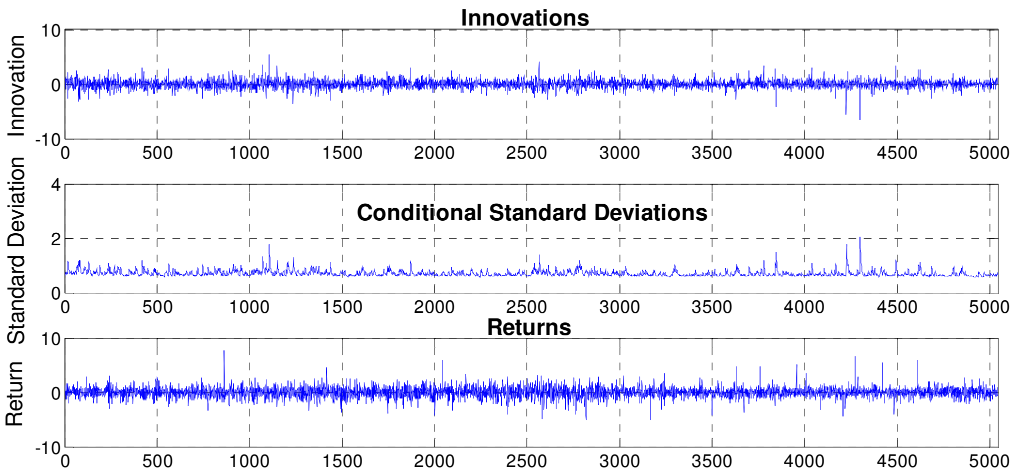
5.11 Conclusions on using PC-GARCH

We have seen that PC-GARCH is a useful way to reduce the dimensionality of the multivariate GARCH problem and to obtain robust and stable estimates using orthogonal PCs. While I have mentioned its many benefits, I would like to conclude with visual evidence of how the "innovation" claimed by the GARCH(1,1) is really not innovation. I present the decomposition of Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M volatilities after the PC-GARCH in the figures below.

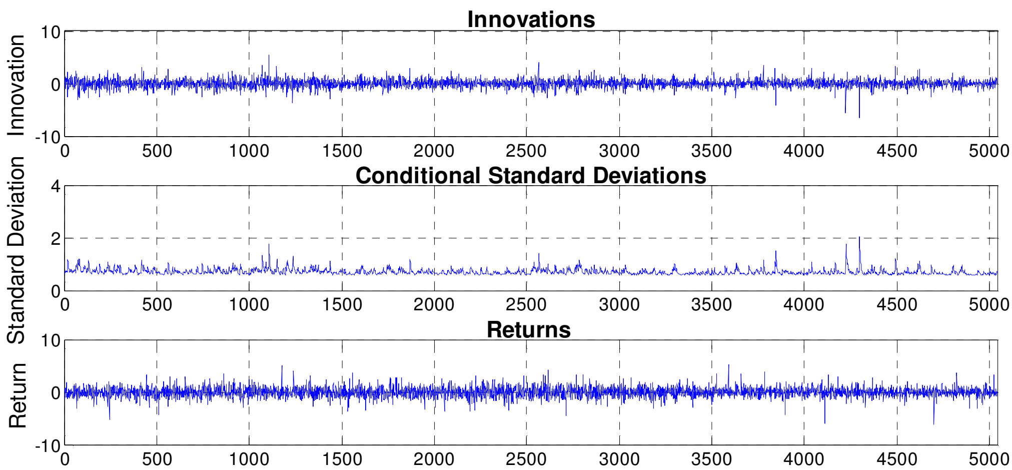
ADOBE:



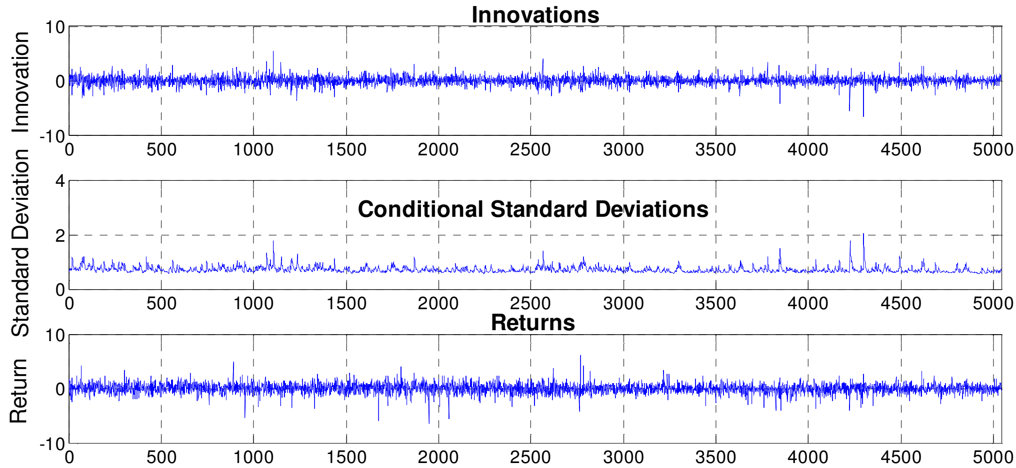
APPLE:



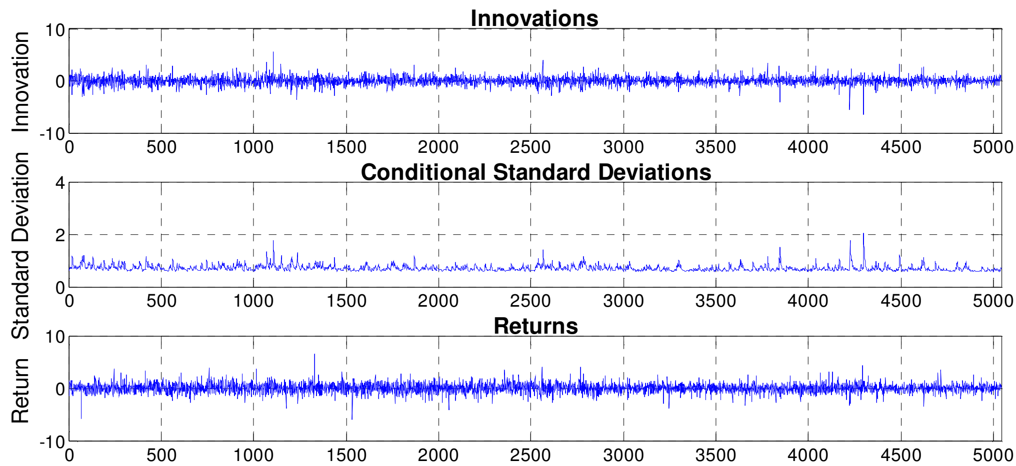
AUTODESK:



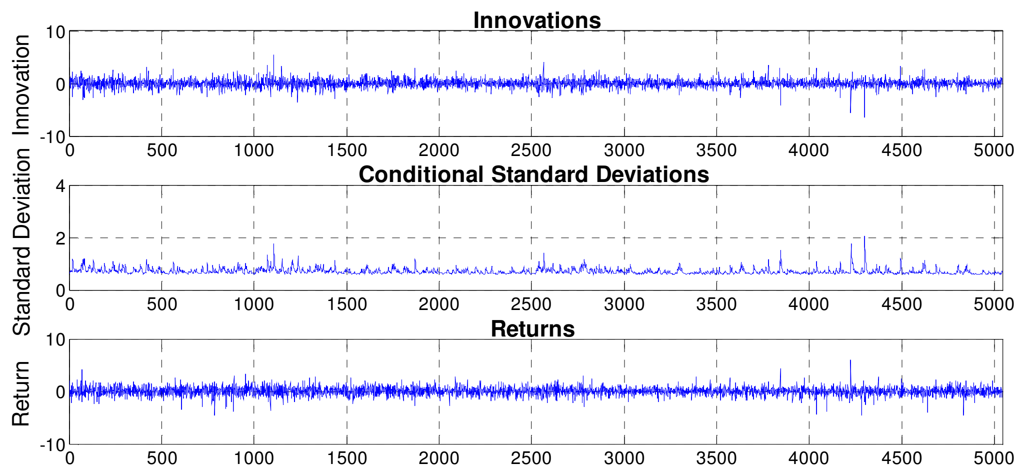
CISCO:



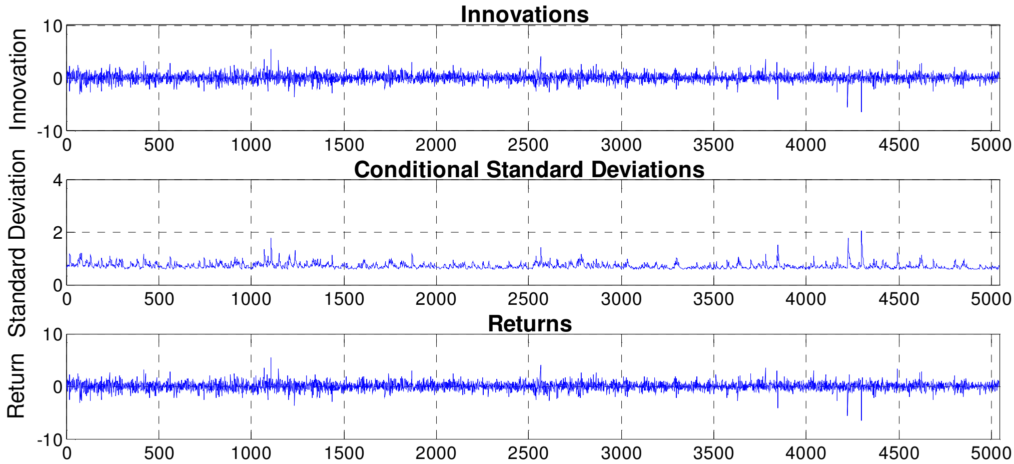
DELL:



MICROSOFT:



3M:



Figures 45 to 51: GARCH decomposition of Adobe, Apple, Autodesk, Cisco, Dell, Microsoft and 3M standardized residuals over the sample period. Data source: Datastream.

We see a marked difference between the graphs of innovations after 5.10.2 and 5.10.5. What is extremely noticeable is that volatility peaks that occurred at the same time (especially the high volatilities during 1993, 1995, 2006, 2008 and 2009) are now not considered to be "innovations", but are considered explained by the simultaneous rise in the innovations of the others. Thus, the innovations are "truly innovations" which perhaps could be explained by other factors. However, while every model can be improved, the improvement usually comes at a cost. One of the costs is that of over-fitting the model to the sample data, which makes out-of-sample model performance crucial for understanding which model to use. I leave this, as I should, in the hands of the user.

The scope of the empirical part has been to reveal the superiority of PC-GARCH in terms of quality of results/costs involved when dealing with large samples of data. It has empirically proved how can be obtained large GARCH correlation matrices by using only univariate GARCH estimation techniques on principal components of the original return series. The advantages of such method are as they follow:

- It minimizes computational efforts (by transforming multivariate GARCH models to univariate ones), by reducing significantly the computational time and getting rid of any problem that may arise from complex data manipulations;

- It ensures a tight control of the amount of “noise” due to reducing the number of variables to fewer principal components. This may prove benefic since it may result in more stable correlation estimates;
- Such method produces volatilities and correlations for all variables in the system, including those for which direct GARCH estimation is computationally difficult.

The many advantages of GARCH forecasting techniques, among them their flexibility and accuracy, place them in a unique position to fulfill many of the requirements of the practitioners, especially in the back office risk management and front office trading systems. However, this may be put at risk if a feasible method that helps at manipulating of large covariance data matrices is not as well implemented. Given the considerable difficulties in data estimation that may arise when dealing with such large GARCH covariance matrices, but as well given the need for using mean-reverting covariance forecasts in value-at-risk-models, PC-GARCH contribution is notable. Designed to capture variability of a returns sample by few orthogonal casual factors, and assigning the rest of variation to “noise” factors, the use of principal components analysis permits transformation of optimization procedures into univariate time series. This enables reduction of computational density, as the whole matrix of variances and covariances can be derived out of simple linear transformations of factor variances. Used in several real-world settings, in no case PC-GARCH has been found defective. Its superiority has been found in any cases, starting from bivariate or trivariate settings with hundreds of variables, up to multivariate ones dealing with several thousands of time series.

6. Final remarks

We have seen in the current thesis how risk can be assessed from a double perspective, from the point of view of one company that intends to invest abroad. I have thus discussed the risks with a strong endogenous component and grouped them around the main stringency for a foreign settlement, that of access to credit. I have discussed the credit risk and counterparty risk, as well how the systemic risk may affect this company, especially when the financing is done exclusively through debt issuance. When debt is issued, an important role for a successful issuance belongs to the credit rating agencies that evaluate the company's perspectives as regards capability of repayment.

Risk was also grouped into a category whose primary characteristic is that of its total exogeneity. There have been considered here the risks related to the sector perspectives, riskiness being seen as a probability of crash occurrance. It has been discussed how risky is one sector from the perspective of stock fluctuance at the stock exchange. This fluctuance has been called "volatility" and it has been assessed from the econometrical point of view. It has been suggested that the best way to assess the sector risk is to form a group of stocks belonging to relevant companies acting in the same sector, and to model and forecast the volatility of stock return of the newly created portfolio. The problem becomes complicated due to the subjectivity in the model choice, that is due to the lack of consensus from the literature side in identifying a certain model able to calculate the most reliable estimates. Additionally, since we consider a portfolio with highly inter-correlated series, a multivariate model needs to be used, fact that makes the problem even more computationally difficult. We suggested that for portfolios compounded of hundreds or even thousands of stocks, Principal Component GARCH model would be the proper model to be considered for volatility forecasting purpose.

7. Further research

Further work needs to be directed over the side of statistical properties of PC-GARCH model. As well, it would be interesting to find out comparison tests of the PC-GARCH, Orthogonal GARCH and BEKK techniques with financial data. Comparisons should represent out-of-sample predictions and follow different methodologies proposed in literature for assessing the quality of heteroskedastic volatility models. An area of future research would be as well developing empirically a test that compares with real data different heteroskedastic volatility models by measuring their quality/costs report. As such a procedure, if PC-GARCH involved, requires sets of at least hundreds of variables with at least thousands of observations, as PC-GARCH becomes obviously superior only for large pools of such sets, this endeavor is extremely cost-consuming, requiring access to extensive information and significant computational (technical) resources. Since this is a limitation of the present study, if possible the access to such resources, such study would make possible identifying and more important, quantitatively measuring the differences between such models.

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9. Appendix

*****Variable preparation. It turns the raw data into return series

```
adoberet=price2ret(adoberet)

appleret=price2ret(appleret)

autodeskret=price2ret(autodeskret)

ciscoret=price2ret(ciscoret)

dellret=price2ret(dellret)

microsoftret=price2ret(microsoftret)

mmmret=price2ret(mmmret)
```

*****Graphical representation of the return series

```
plot(adoberet)

set(gca,'XTick',[1 1600 3200 5000])

set(gca,'XTickLabel',{'Feb 1990' 'Mar 1996' 'May 2002' 'Apr 2009'})

ylabel('Return')

title('ADOBE daily returns')


plot(appleret)

set(gca,'XTick',[1 1600 3200 5000])

set(gca,'XTickLabel',{'Feb 1990' 'Mar 1996' 'May 2002' 'Apr 2009'})

ylabel('Return')

title('APPLE daily returns')
```

```
plot(autodeskret)

set(gca,'XTick',[1 1600 3200 5000])

set(gca,'XTickLabel',{'Feb 1990' 'Mar 1996' 'May 2002' 'Apr 2009'})

ylabel('Return')

title('AUTODESK daily returns')


plot(ciscoret)

set(gca,'XTick',[1 1600 3200 5000])

set(gca,'XTickLabel',{'Feb 1990' 'Mar 1996' 'May 2002' 'Apr 2009'})

ylabel('Return')

title('CISCO daily returns')


plot(dellret)

set(gca,'XTick',[1 1600 3200 5000])

set(gca,'XTickLabel',{'Feb 1990' 'Mar 1996' 'May 2002' 'Apr 2009'})

ylabel('Return')

title('DELL daily returns')


plot(microsoftret)

set(gca,'XTick',[1 1600 3200 5000])

set(gca,'XTickLabel',{'Feb 1990' 'Mar 1996' 'May 2002' 'Apr 2009'})

ylabel('Return')

title('MICROSOFT daily returns')
```

```
plot(mmmret)

set(gca,'XTick',[1 1600 3200 5000])

set(gca,'XTickLabel',{'Feb 1990' 'Mar 1996' 'May 2002' 'Apr 2009'})

ylabel('Return')

title('3M daily returns')


*****Check for correlation in the return series

autocorr(adoberet)

title('ACF with Bounds for Raw Return Series: ADOBE')


autocorr(appleret)

title('ACF with Bounds for Raw Return Series: APPLE')


autocorr(autodeskret)

title('ACF with Bounds for Raw Return Series: AUTODESK')


autocorr(ciscoret)

title('ACF with Bounds for Raw Return Series: CISCO')


autocorr(dellret)

title('ACF with Bounds for Raw Return Series: DELL')
```

```
autocorr(microsoftret)

title('ACF with Bounds for Raw Return Series: MICROSOFT')


autocorr(mmmret)

title('ACF with Bounds for Raw Return Series: 3M')


parcorr(adoberet)

title('PACF with Bounds for Raw Return Series: ADOBE')


parcorr(appleret)

title('PACF with Bounds for Raw Return Series: APPLE')


parcorr(autodeskret)

title('PACF with Bounds for Raw Return Series: AUTODESK')


parcorr(ciscoret)

title('PACF with Bounds for Raw Return Series: CISCO')


parcorr(dellret)

title('PACF with Bounds for Raw Return Series: DELL')


parcorr(microsoftret)

title('PACF with Bounds for Raw Return Series: MICROSOFT')
```

```
parcorr(mmmret)

title('PACF with Bounds for Raw Return Series: 3M')

*****Check for correlation in the squared returns returns

autocorr(adoberet.^2)

title('ACF of the Squared Returns: ADOBE')


 autocorr(appleret.^2)

title('ACF of the Squared Returns: APPLE')


autocorr(autodeskret.^2)

title('ACF of the Squared Returns: AUTODESK')


autocorr(ciscoret.^2)

title('ACF of the Squared Returns: CISCO')


autocorr(dellret.^2)

title('ACF of the Squared Returns: DELL')


autocorr(microsoftret.^2)

title('ACF of the Squared Returns: MICROSOFT')


autocorr(mmmret.^2)
```

```
title('ACF of the Squared Returns: 3M')
```

*****Performing preliminary tests: Ljung-Box-Pierce Q-test and Engel Arch test

```
[H,pValue,Stat,CriticalValue] = ...
lbqtest(adoberet-mean(adoberet),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

 [H,pValue,Stat,CriticalValue] = ...
lbqtest(appleret-mean(appleret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

 [H,pValue,Stat,CriticalValue] = ...
lbqtest(autodeskret-mean(autodeskret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

 [H,pValue,Stat,CriticalValue] = ...
lbqtest(ciscoret-mean(ciscoret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

 [H,pValue,Stat,CriticalValue] = ...
lbqtest(dellret-mean(dellret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]
```

```
[H,pValue,Stat,CriticalValue] = ...
lbqtest(microsoftret-mean(microsoftret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

[H,pValue,Stat,CriticalValue] = ...
lbqtest(mmmret-mean(mmmret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

[H,pValue,Stat,CriticalValue] = ...
archtest(adoberet-mean(adoberet),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

[H,pValue,Stat,CriticalValue] = ...
archtest(appleret-mean(appleret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

[H,pValue,Stat,CriticalValue] = ...
archtest(autodeskret-mean(autodeskret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

[H,pValue,Stat,CriticalValue] = ...
archtest(ciscoret-mean(ciscoret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]
```

```
[H,pValue,Stat,CriticalValue] = ...
archtest(dellret-mean(dellret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

[H,pValue,Stat,CriticalValue] = ...
archtest(microsoftret-mean(microsoftret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

[H,pValue,Stat,CriticalValue] = ...
archtest(mmmret-mean(mmmret),[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

*****Estimating univariate GARCH
[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(adoberet);
garchdisp(coeff,errors)

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(appleret);
garchdisp(coeff,errors)

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(autodeskret);
garchdisp(coeff,errors)
```

```
[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(ciscoret);
garchdisp(coeff,errors)

 [coeff,errors,LLF,innovations,sigmas,summary] = garchfit(dellret);
garchdisp(coeff,errors)

 [coeff,errors,LLF,innovations,sigmas,summary] = garchfit(microsoftret);
garchdisp(coeff,errors)

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(mmmret);
garchdisp(coeff,errors)

*****Compare residuals, conditional standard deviations and returns
garchplot(innovations, sigmas, adoberet)
garchplot(innovations, sigmas, appleret)
garchplot(innovations, sigmas, autodeskret)
garchplot(innovations, sigmas, ciscoret)
garchplot(innovations, sigmas, dellret)
garchplot(innovations, sigmas, microsoftret)
garchplot(innovations, sigmas, mmmret)

*****Plot and compare the correlation for the standardized innovations
[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(adoberet);
```

```
garchdisp(coeff,errors)

adobeinnret=innovations./sigmas

plot(innovations./sigmas)

ylabel('Innovation')

title('Standardized Innovations: ADOBE')


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(appleret);

garchdisp(coeff,errors)

appleinnret=innovations./sigmas

plot(innovations./sigmas)

ylabel('Innovation')

title('Standardized Innovations: APPLE')


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(autodeskret);

garchdisp(coeff,errors)

autodeskinnret=innovations./sigmas

plot(innovations./sigmas)

ylabel('Innovation')

title('Standardized Innovations: AUTODESK')


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(ciscoret);

garchdisp(coeff,errors)

ciscoinnret=innovations./sigmas
```

```
plot(innovations./sigmas)

ylabel('Innovation')

title('Standardized Innovations: CISCO')


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(dellret);

garchdisp(coeff,errors)

dellinnret=innovations./sigmas

plot(innovations./sigmas)

ylabel('Innovation')

title('Standardized Innovations: DELL')


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(microsoftret);

garchdisp(coeff,errors)

microsoftinnret=innovations./sigmas

plot(innovations./sigmas)

ylabel('Innovation')

title('Standardized Innovations: MICROSOFT')


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(mmmret);

garchdisp(coeff,errors)

mmminnret=innovations./sigmas

plot(innovations./sigmas)

ylabel('Innovation')
```

```
title('Standardized Innovations: 3M')


*****Plot the ACF of the squared standardized innovations
[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(adoberet);
garchdisp(coeff,errors)
adobeinnsquaredret=((innovations./sigmas).^2)
autocorr((innovations./sigmas).^2)
title('ACF of the Squared Standardized Innovations: ADOBE')


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(appleret);
garchdisp(coeff,errors)
appleinnsquaredret=((innovations./sigmas).^2)
autocorr((innovations./sigmas).^2)
title('ACF of the Squared Standardized Innovations: APPLE')


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(autodeskret);
garchdisp(coeff,errors)
autodeskinnsquaredret=((innovations./sigmas).^2)
autocorr((innovations./sigmas).^2)
title('ACF of the Squared Standardized Innovations: AUTODESK')


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(ciscoret);
garchdisp(coeff,errors)
```

```
ciscoinnsquaredret=((innovations./sigmas).^2)
autocorr((innovations./sigmas).^2)
title('ACF of the Squared Standardized Innovations: CISCO')

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(dellret);
garchdisp(coeff,errors)
dellinnsquaredret=((innovations./sigmas).^2)
autocorr((innovations./sigmas).^2)
title('ACF of the Squared Standardized Innovations: DELL')

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(microsoftret);
garchdisp(coeff,errors)
microsoftinnsquaredret=((innovations./sigmas).^2)
autocorr((innovations./sigmas).^2)
title('ACF of the Squared Standardized Innovations: MICROSOFT')

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(mmmret);
garchdisp(coeff,errors)
mmminnsquaredret=((innovations./sigmas).^2)
autocorr((innovations./sigmas).^2)
title('ACF of the Squared Standardized Innovations: 3M')
```

*****Quantify and compare correlation of the standardized innovations. Q-test and

ARCH test of the standardized innovations

```
[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(adoberet);
garchdisp(coeff,errors)
[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(adoberet);
garchdisp(coeff,errors)
[H, pValue,Stat,CriticalValue] = ...
lbqtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(appleret);
garchdisp(coeff,errors)
[H, pValue,Stat,CriticalValue] = ...
lbqtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(autodeskret);
garchdisp(coeff,errors)
[H, pValue,Stat,CriticalValue] = ...
lbqtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);
[H pValue Stat CriticalValue]

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(ciscoret);
```

```
garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

lbqtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(dellret);

garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

lbqtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(microsoftret);


garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

lbqtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(mmmret);

garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

lbqtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]
```

```
[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(adoberet);

garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

archtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(appleret);

garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

archtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(autodeskret);

garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

archtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(ciscoret);

garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

archtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]
```

```
[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(dellret);

garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

archtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(microsoftret);

garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

archtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(mmmret);

garchdisp(coeff,errors)

[H, pValue,Stat,CriticalValue] = ...

archtest((innovations./sigmas).^2,[1 2 3 4 5 6 7]',0.05);

[H pValue Stat CriticalValue]
```

*****Performing Principal Component Analysis of the Standardized Residuals

```
R = [adobeinnret appleinnret autodeskinnret ciscoinnret dellinnret microsoftinnret mmm2innret] % stack standardized residuals into a matrix R

PC = princomp(R) % perform PCA on the matrix R
```

```
[PC,SCORE,latent,tsquare] = princomp(R)

PC

P=R*PC; %multiply R and PC


*****Extract the columns of P

adobeinnpc=P(:,1);

appleinnpc=P(:,2);

autodeskinnpc=P(:,3);

ciscoinnpc=P(:,4);

dellinnpc=P(:,5);

microsoftinnpc=P(:,6);

mmminnpc=P(:,7)


*****Estimating a univariate GARCH model on each principal component

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(adobeinnpc);

garchdisp(coeff,errors)


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(appleinnpc);

garchdisp(coeff,errors)


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(autodeskinnpc);

garchdisp(coeff,errors)
```

```
[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(ciscoinnpc);
garchdisp(coeff,errors)


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(dellinnpc);
garchdisp(coeff,errors)


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(microsoftinnpc);
garchdisp(coeff,errors)


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(mmminnpc);
garchdisp(coeff,errors)


*****Calculate orthogonal standardized innovations
[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(adobeinnpc);
garchdisp(coeff,errors)
newadobe2inn=innovations./sigmas


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(appleinnpc);
garchdisp(coeff,errors)
newapple2inn=innovations./sigmas


[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(ciscoinnpc);
garchdisp(coeff,errors)
```

```
newcisco2inn=innovations./sigmas

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(dellinnpc);
garchdisp(coeff,errors)
newdell2inn=innovations./sigmas

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(microsoftinnpc);
garchdisp(coeff,errors)
newmicrosoft2inn=innovations./sigmas

[coeff,errors,LLF,innovations,sigmas,summary] = garchfit(mmminnpc);
garchdisp(coeff,errors)
newmmm2inn=innovations./sigmas

***** Post-estimation graphs
garchplot(innovations,sigmas,adobeinnpc)

garchplot(innovations,sigmas,appleinnpc)

garchplot(innovations,sigmas,autodeskinnpc)

garchplot(innovations,sigmas,ciscoinnpc)
```

```
garchplot(innovations,sigmas,dellinnpc)


garchplot(innovations,sigmas,microsoftinnpc)

garchplot(innovations,sigmas,mmminnpc)
```