Transmission of banking shocks during the Greek Crisis

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SCHOOL OF SCIENCE & TECHNOLOGY
A Thesis submitted for the degree of
Master of Science (MSc) in Information and Communication Systems

OCTOBER 2012
THESSALONIKI – GREECE

1. I would like to thank my supervisor, Prof. Polimenis for help with this Thesis. All mistakes are mine, and I bear the complete responsibility of the writings in this Thesis.
Abstract

This Thesis is written under the Master degree in ICT Systems at the International Hellenic University. This dissertation tests if the Greek financial crisis has affected, the volatility of the stock of the Greek banking sector. I use five years of stock price data for three major Greek banks in order to study the evolution of volatility in the banking sector before and during the crisis. I use a GARCH methodology to study if the Greek crisis resulted in a substantial change at the level and persistence of the volatility for banking stocks. The results will show how the crisis affects the banking sector during the period of crisis.

To facilitate this analysis a single break point is used to separate two periods: the period before the crisis and the period during the crisis. This assumption of a single break is a simplistic one and is done only to simplify the statistical analysis. Due to this simplistic assumption the findings of this Thesis have limited value and should be read with caution and not as a full academic study of the evolution of the banking volatility during the Greek crisis. The choice of what date to use as the single exogenous break point is always a subjective one since there are many possible dates that one could have chosen. Since there was no clear guideline, it was decided to use the 20th of October, 2009 as the first date of the crisis period. This is because on Monday the 19th of October of 2009, it was announced that the statistical numbers and especially the government deficit figures, needed to be significantly revised upwards (announcement date, AD).

More specifically, the analysis is facilitated with the GARCH model, which forecasts and examines the volatility of returns. The banks, which will be researched, are:

- National Bank of Greece
- Alpha Bank
- Eurobank

The choice of the banks is based on their market size. The three largest banks of Greece are selected.

Moreover, the examination is separated in 2 parts:
1. The first sample period is dated from the beginning of 2007 until the 16th of October of 2009, exactly before the announcement.
2. The second sample period is between the 19th of October of 2009 and September, 2012.

The dissertation includes 7 parts. First of all, there is some introductory information about the economic crisis and how this crisis affects the banking sector. Then, a GARCH literature review follows. The third part is about the analysis on how the crisis affects the banking sector, especially, in Greece and how the banking system works during an economic crisis. After, the data, that is used for the econometric analysis, will be presented. The main section of this Thesis is the econometric analysis, where the GARCH Model will be applied. Then, the analysis of the data will be done in order to see how the banking index changed and how the speed of these changes grow or decline. Finally, I will explain how much the crisis affects the banking index, what kind of changes will be brought by the crisis and I will conclude with the economic view of the findings.
1. Introduction .................................................................................................................................. 5
   1.1 Beginning and causes of financial crisis ..................................................................................... 5-7
   1.2 Crisis in banking sector ............................................................................................................ 8-9
2. Literature review.......................................................................................................................... 11
   2.1 Introduction .............................................................................................................................. 11-12
   2.2 Econometric Methodology ........................................................................................................ 12
       2.2.1 In-sample test .................................................................................................................... 12-14
       2.2.2 Out-of-sample tests .......................................................................................................... 14-17
3. Greek banks during the crisis ........................................................................................................ 19-21
4. First look at data .......................................................................................................................... 23-26
5. Econometric analysis .................................................................................................................. 28
   5.1 Introduction .............................................................................................................................. 28
   5.2 Results of GARCH Model ......................................................................................................... 29
       5.2.1 National Bank of Greece ................................................................................................. 30-37
       5.2.2 Alpha Bank ....................................................................................................................... 38-45
       5.2.3 Eurobank .......................................................................................................................... 46-52
6. Analysing of data ......................................................................................................................... 54
   6.1 National Bank of Greece .......................................................................................................... 55-62
   6.2 Alpha Bank .............................................................................................................................. 63-70
   6.3 Eurobank .................................................................................................................................. 71-77
7. Conclusions .................................................................................................................................... 79-81
8. References ...................................................................................................................................... 83-85
9. Appendix ....................................................................................................................................... 87-88
Chapter 1

INTRODUCTION
1. Introduction

1.1 Beginning and causes of financial crisis

After 10 years or more where the economy remained stable, it is observed a period of crisis in all over the world. During this crisis world economic growth declined, and in particular the stability of the International Banking system was compromised. The main characteristic of this crisis is that the crisis does not only affect the weak economies, but it is spreading to the developed countries. The International Monetary Fund (IMF) supports that this period of financial crisis becomes worse than the crisis in the 1930's, because it affects the financial markets of advanced countries, especially in Europe, where there are emerging economies that are more sensitive than the others. The shocks channel liquidity in the inter-bank markets.

In order to overcome this situation, the central banks and the governments have decided to collaborate. The main reasons for this interplay are:

1) to enhance the stability of the economy and
2) to help markets find their “lost” confidence.

This stability can occur when the banks and the government analyze and give priority both to the internal and to the external economic environment.

The crisis began between 2007 and 2008 and the banking system in U.S. has been prodigious, when the investors lost their confidence in the securitized mortgages. As a result, it is observed a sharp drop of the capital in the financial markets. Furthermore, this crisis managed to spread in all over the world and it affected all the financial markets.

The standard process of one bank is: the cash, which a bank has, is used in order to make some investments or to loan it to the citizens. When a bank tries to invest to the process is a little bit different: the banks borrow the money at one interest rate and they are waiting to lend it in higher interest rates. In this process there are two cases:

1) The markets are growing, so the citizens return the money in time and the banks become very profitable.

2) The markets are decreasing, so the citizens can not afford the cost of the loans. They do not pay their loans in time, so the banks start to lose their cash. Moreover, the banking sector is afraid to borrow the money, which the banks have already.

The financial crisis increased, when the second case appeared.

Especially, the last 10 years in the United States, a new type of mortgage was appeared: the subprime mortgage (O'Quinn, 2008). These mortgages were given to the citizens, who had low credit scores and low incomes. Especially, they could not afford to buy a new house with their
incomes, but they could repay the mortgage in few years. A lot of people were skeptical about this project. On the one hand, if the people, who borrowed money, were considerate, this could not be so risky. On the other hand if they were not, the risk could be very enormous.

The mortgage loans had serious effects to the economy of the U.S, where low interest rates, large inflows of foreign funds and easy credit conditions were created. The results of this were:

- a housing market boom and
- a debt-financed consumption.

The home ownership rate increased from 64% in 1994 (about where it had been since 1980) to a higher percentage of 69.2% in 2004. Subprime lending was a major contributor to this increase in home ownership rates and in the overall demand for housing, which drove the prices to be higher.

Between 1997 and 2006, the price of the typical American house increased to 124%. In 2001, the national median home price ranged from 2.9 to 3.1 times median household income. This ratio rose to 4.0 in 2004, and 4.6 in 2006. Moreover the citizens decided to take second mortgages in at lower interest rates in order to spend this money in the house, which they bought with the first one. This resulted to the hoing bubble and the household debt as a percentage of annual disposable personal income was 127% at the end of 2007, vers 77% in 1990.

Furthermore, the citizens in U.S.A. were spending a lot of money without saving some and they were borrowing more. At the same time the prices of the houses were growing day – by – day. The result was that the household debt rose from $705 billion at the end of 1974 to $7.4 trillion at year 2000, and finally to $14.5 trillion in the second half of 2008. During 2008, the typical household owned 13 credit cards, with 40% of households carrying a balance, up from 6% in 1970.

When the housing bubble started, the free cash used by consumers from home equity extraction doubled from $627 billion in 2001 to $1,428 billion in 2005 as total of nearly $5 trillion dollars over the period. GDP increased from an average of 46% during the 1990s to 73% during 2008, reaching $10.5 trillion. From 2001 to 2007, U.S. the amount of mortgage debt per household rose more than 63%, from $91,500 to $149,500.

The building boom started to appear. As the credit and the prices of the houses were increasing, a lot of them remained unsold. Moreover, the prices, which were to their peak, started to decrease until the second half of 2008. Furthermore, the borrowers believed that the prices of the houses would decline, so they decided to loan more money.

Borrowers, who could not afford their new mortgages, were confident that they could refinance their loans after one or two years. But, the banks were afraid to loan more money, so this thought of refinance became more difficult to come true. The borrowers did not have enough money to pay the loans, so they were driven to a dead end.

A lot of foreclosures became at this period, because the borrowers did not have the capability to pay their loans in time. The effect for the banks was huge, because the mortgage payments declined and more and more citizens stopped to pay their loans. As it is expected, there was a very big pressure to the prices of the houses in order to start the reduction.

By September 2008, average U.S. housing prices had declined by over 20% from their mid-2006 peak. This major and unexpected decline in house prices means that many borrowers have zero or negative equity in their homes. As of March 2008, an estimated 8.8 million borrowers had negative equity in their homes, a number that is believed to have risen to 12 million by November 2008. By September 2010, 23% of all U.S. homes were worth less than the mortgage loan.

The economist, Stan Leibowitz, argued in the Wall Street Journal that although only 12% of homes had negative equity, they comprised 47% of foreclosures during the second half of 2008. He
concluded that the extent of equity in the home was the key factor in foreclosure, rather than the type of loan, credit worthiness of the borrower, or ability to pay.

Increasing foreclosure rates increases the unsold houses. The number of new homes sold in 2007 was 26.4% less than in the preceding year. By January 2008, this inventory was 9.8 times the December 2007 sales volume, the highest value of this ratio since 1981.

The inventory of the unsold houses was driven to the decrease of the prices. As prices declined, more homeowners were at risk of default or foreclosure. The house prices are expected to continue declining until this inventory declines to normal levels.

U.S. Existing Home Sales, Inventory, and Months Supply
December 2005 – June 2009

Graph 1. Home sales - Inventory

This crisis has been tested by a lot of researches and institutions. Some of them said that the factor is bringing the crisis either the absence of an adequate regulation framework in the U.S. Markets (Batrancea L. et. al); or the lack of quality of the accounting and financial regimes which failed to transmit the real risk behind financial assets and obligations (Huian M, 2010); or the sharp and unexpected fall of confidence level on behalf of the investors that brought the drastic creditors’ run and crash of financial system (Ignat I, Ifrim M, 2010); or the increase of the global debt burden in a macro as well as micro level, which could not be supported any more by the existing levels of production and were not exactly generated wealth what brought insolvency (Smrcka L, 2010). But whatever may be the root of the crisis the fact remains that this crisis resembled a real tsunami encompassing almost every country in the world (Nistor I, Ulici M, 2009). If we were to put it in the words of a report of 2008 from Goldman Sachs Investment Bank “This crisis has become the new bird flu, which has infected absolutely everything”. 
1.2 Crisis in banking sector

When the financial crisis affects not only the economy in one country, but it is appeared as failures to the banks, for example in Latin America, Scandinavia, Southeast Asia, or Japan in the 1990s, the cost of resolving the crisis and recapitalizing the banks can be huge. After the Indonesian banking crisis of 1997–1998, for example, recapitalizing the banking system cost tax-payers around $77 billion—58 percent of Indonesia’s average GDP in 1998–2001. The Indonesian Banking Restructuring Agency, tried to retrieve the banking system, is expected to recover only about $2 billion from the sale of banks under its control. An expensive banking failure in dollar terms is the one that began in Japan in the early 1990s. By 1998, nonperforming loans were estimated at $725 billion (18 percent of Japan’s GDP). The Obuchi Plan announced the same year provided $500 billion (12 percent of GDP) in public funds for loan losses, bank recapitalizations, and depositor protection. This figure shows the cost of banking crisis as a percentage of GDP and it does not include the cost of keeping so-called zombie borrowers—companies that continue to exist only because their banks extend further credit—in business. On the other hand, they do not necessarily include funds recovered in later years.

Graph 2. Countries with banking Crisis

The costs of reducing may seem large, but they often pale in comparison to the long-term effects of systemic banking crises. The resources committed to resolving a crisis are diverted from productive uses, economic reforms and stabilization programs. During the financial crisis the economy suffers from higher interest rates, lower growth, and higher unemployment. Every citizen is affected by the declining living standards brought on by large banking crises, the public should
understand the factors that weaken a banking system and make it susceptible to systemic crises.

The crisis are affected by two cases:

1) the risk, which a bank may take

2) the performance of the manager

In a period of financial crisis, the market is at very low levels, so that the resources of the banks can not be used as they are and the banks are driven to the failure. In this case, one of the major factors is how the manager can handle it. At the case of poor banks, the managers must be less risky and they must do standard movements in order to save the banks. On the other hand, the managers in rich banks must handle the resources in the right way and they must not be so risky, especially, when a country follows the financial crisis.
Chapter 2

LITERATURE REVIEW
2. Literature review

2.1 Introduction

One of the most powerful tools, which forecasts the volatility of the shocks, is the GARCH model. This model can be applied to a lot of areas both in finance and economics. Especially, the GARCH model is used to 3 areas: risk management, portfolio management and the pricing of derivative securities. Moreover, the volatility of assets return changes with fast rhythms, the canonical generalized autoregressive conditional heteroskedastic (GARCH) model of Engle (1982) and Bollerslev (1986), especially the GARCH(1,1) model, is the most popular volatility forecasting model. The GARCH model allows to forecast the future volatility using the current shocks to asset returns. This results are given by an autoregressive-type process.

Despite the fact that the GARCH model is used to forecast the volatility during a period, the structural breaks, which may be appeared, do not be exercised by the researchers. They assume that the model remains stable, while looking for the changes of the volatility. The truth is that in an a period of financial crisis the markets, and especially the banks, does not remain stable and there are a lot of structural breaks in the unconditional variance of assets return, which must be assumed in order to find the right volatility and how it changes during a particular period, such as before, at the time which the crisis is appeared and during this period.

Moreover, in order to forecast the volatility with GARCH models, the periodic breaks in the unconditional variance of asset returns must implicate. Some researches by Diebold (1986), Hendry (1986), and Lamoureux and Lastrapes (1990), as well as more recent ones by Mikosch and Stàricà (2004) and Hillebrand (2005), shows that failing to account for structural breaks in the unconditional volatility of asset returns can lead to sizable upward biases in the degree of persistence in estimated GARCH models. Moreover, the volatility can not be researched correct, if there are no structural breaks, because the results will be underestimated or overestimated. So, fitted GARCH processes used for forecasting asset return volatility are insistent and often same as the integrated GARCH (IGARCH) model of Engle and Bollerslev (1986). The failure to account for structural breaks in the unconditional variance of asset returns may lead to fitting GARCH models that are persistent, which can create effects on volatility forecasts. Moreover, fitted GARCH models that neglect structural breaks can fail to track change in the unconditional variance and the produce forecasts that systematically under- or over- estimate volatility on average for long stretches. In summary, structural breaks have important implications for forecasting the volatility of asset returns.

Despite the facts that structural breaks are very important in order to investigate the volatility of the shocks and there are a lot of applications for GARCH models, there are no handful of tests for structural breaks that have been implemented. Examples of these tests include Lundbergh and Terasvirta (2002), who develop a number of specification tests, including a test for parameter constancy against a threshold-GARCH alternative (which is related to structural break tests), unfortunately there were no empirical applications in their paper.

Another relevant paper is Malik (2003), who develops a test based on the iterated cumulated sums of squares algorithm and analyzes five exchange rates from January 1990 to September 2000 and he finds a number of structural breaks in the data. The ICCS algorithm works by identifying breaks in the volatility of time series, and assumes that the volatility between two break points is constant. Malik finds a number of breaks in the different exchange rate series that were analyzed. In
particular, after determining the break points by this ICSS algorithm, Malik fits a dummy variable to allow the unconditional volatility to be different between these break dates. Malik’s test requires constant volatility between break dates. Secondly, the dummy variables are endogenously determined and subject to estimation error. This will influence the standard errors of the parameters. A key finding in Malik is that accounting for these breaks reduces the estimated persistence of volatility shocks. This inference would depend on the estimated break dates. The paper does not test if the dummy variables are different from zero, which would suggest the existence of structural breaks, but again failure to account for estimation error would preclude the standard hypothesis testing procedures.

The investigation of the structural breaks in GARCH(1,1) models of exchange rate volatility can be done by using both in-sample and out-of-sample tests. In the in-sample tests, a modified version of the Inclán and Tiao (1994) iterated cumulative sum of squares (ICSS) algorithm is implied and it allows for dependent processes. In order to test for structural breaks in the unconditional variance of daily returns in exchange rates, the algorithm is implied. Inspection of the estimated GARCH(1,1) processes across the sub-samples defined by the structural breaks often reveals sharp differences in parameter estimates, and the GARCH(1,1) models fitted to the different sub-samples are sometimes considerably less persistent than models fitted to the entire sample.

2.2 Econometric Methodology

2.2.1 In-Sample Test

Let $e_t = 100 \log(E_t / E_{t-1})$, where $E_t$ is the nominal exchange rate at the end of period $t$, so that $e_t$ is the percent return for the exchange rate from period $t-1$ to period $t$. Following West and Cho (1995), we treat the unconditional and conditional mean of $e_t$ as zero. Suppose that $e_t$ is observed for $t = 1, \ldots, T$ and are interested in testing whether the unconditional variance of $e_t$ is constant over the available sample. A constant unconditional variance implies a stable GARCH process governing conditional volatility, while a structural break in the unconditional variance implies a structural break in the GARCH process as well. Inclán and Tiao (1994) develop a cumulative sum of squares statistic to test the null hypothesis of a constant unconditional variance against the alternative hypothesis of a break in the unconditional variance. The Inclán and Tiao (1994) statistic is given by

$$IT = \sup (T/2)^{0.5} Dk,$$

where $D = (C / C) - (k/T)$ and $C_k = \sum_{t=1}^{k} e_t^2$ for $k = 1, \ldots, T$. The value of $k$ that maximizes $(T/2)^{0.5} D k$ is the estimate of the break date. When $e_t$ is distributed iid $N(0, \sigma^2)$, Inclán and Tiao
(1994) show that the asymptotic distribution of the $IT$ statistic is given by $\sup | W^* (r) |$, where $W^*(r)=W(r)-rW(1)$ is a Brownian bridge and $W(r)$ is standard Brownian motion.

As demonstrated in Monte Carlo simulations in de Pooter and van Dijk (2004) and Sansó et al. (2004), the $IT$ statistic can be plagued by substantial size distortions when $e_t$ is not distributed iid $N (0, \sigma^2)$. This will be the case when $e_t$ follows a GARCH process. Kokoszka and Leip (2000), Kim et al. (2000), and Sansó et al. (2004) suggest applying a nonparametric adjustment to the $IT$ statistic that allows $e_t$ to obey a wide class of dependent processes, including GARCH processes. Following de Pooter and Sansó et al. (2004), a nonparametric adjustment is used, based on the Bartlett kernel. The adjusted $IT$ statistic can be expressed as

$$ AIT = \sup | T^{-0.5} G_k | , \hspace{1cm} (2) $$

where

$$ G_k = \hat{\lambda}^{-0.5} \left[ C_k - \left( k/T \right) C_T \right] , \hspace{1cm} \hat{\lambda} = \hat{\gamma}_0 + \sum_{i=1}^m \left[ 1 - i (m+1)^{-1} \right] \hat{\gamma}_1 , \hspace{1cm} \hat{\gamma}_1 = T^{-1} \sum_{t=T+1}^T \left( \epsilon_t^2 - \hat{\sigma}^2 \right) \left( \epsilon_{t-1}^2 - \hat{\sigma}^2 \right) $$

$$ \hat{\sigma}^2 = T^{-1} C_T $$

and the lag truncation parameter $m$ is selected using the procedure in Newey and West (1994). Under general conditions, the asymptotic distribution of $AIT$ is also given by $\sup | W^* (r) |$.

Critical values for the $AIT$ statistic can be generated via simulation and are provided in, for example, Sansó et al. (2004). In Monte Carlo simulations, de Pooter and van Dijk (2004) and Sansó et al. (2004) find that the $AIT$ statistic has good size properties for a variety of dependent processes, including GARCH processes.

Inclán and Tiao (1994) develop an iterated cumulative sum of squares (ICSS) algorithm based on the $IT$ statistic to test for multiple breaks in the unconditional variance; see Steps 0-3 in Inclán and Tiao (1994, p. 916). Alternatively, the ICSS algorithm can be based on the $AIT$ statistic in order to avoid the size distortions that plague the $IT$ statistic when $e_t$ follows a GARCH process. The ICSS algorithm based on the $AIT$ statistic begins by testing for a structural break over the entire sample, $t=1,...,T$, using the $AIT$ statistic. If the $AIT$ statistic is not significant, the data does not support a structural break in the variance of $e_t$. If the $AIT$ statistic detects a significant break at, say, $t=T_i$, then the algorithm applies $t_i$ the $AIT$ statistic to test for a break over each of the two sub-samples defined by the break at $t=T_i$, ($t=1,...,T$; $t=T+1,...,T$). If neither of the $AIT$ statistics is significant for the sub-samples, the data supports a single break in the variance over the entire sample. If either of the $AIT$ statistics is significant over the two sub-samples, then the algorithm tests for breaks in the new sub-samples defined by any significant $AIT$ statistic. The algorithm proceeds in this manner until the $AIT$ statistic is insignificant for all of the sub-samples defined by any significant breaks.

Andreou and Ghysels (2002), de Pooter and van Dijk (2004), and Sansó et al. (2004) find that the ICSS algorithm based on the $AIT$ statistic generally performs well in extensive Monte Carlo simulations with respect to detecting the correct number of unconditional variance breaks for a variety of GARCH processes. In empirical applications using stock returns in emerging markets, de Pooter and van Dijk (2004) and Sansó et al. (2004) show that the standard ICSS algorithm based on the $IT$ statistic detects an implausibly large number of variance breaks, while the ICSS algorithm based on the $AIT$ statistic selects more reasonable estimates of the number of breaks. If a significant evidence of at least one structural break is detected, then GARCH(1,1) models over the different regimes defined by the significant structural breaks are estimated.

The canonical GARCH(1,1) model for $e_t$ with mean zero (conditional and unconditional) takes the form,

$$ e_t = h^{0.5} \epsilon_t , \hspace{1cm} (3) $$
\[ h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1}, \quad (4) \]

where \( e_t \) is iid with mean zero and unit variance. In order to ensure that the conditional variance, \( h_t \), is positive, \( \omega > 0 \) and \( \alpha, \beta \geq 0 \) are required. The GARCH(1,1) process specified in equations (3) and (4) is stationary if \( \alpha + \beta < 1 \); when \( \alpha + \beta = 1 \), the integrated GARCH(1,1) (IGARCH(1,1)) model of Engle and Bollerslev (1986) is appeared. For a stationary GARCH(1,1) process, the unconditional variance for \( e_t \) is given by \( \omega / (1 - \alpha - \beta) \). Note that when \( \alpha = 0 \) in equation (4), \( \beta \) is unidentified (and set to zero), so that \( h_t = \omega \) and \( e_t \), is characterized by conditional homoskedasticity. The GARCH(1,1) process is typically estimated using quasi maximum likelihood estimation (QMLE), where the likelihood function corresponding to \( e_t \sim N(0,1) \) is ed and the restrictions \( \omega > 0 \) and \( \alpha, \beta \geq 0 \) are imposed. The QMLE parameter estimates are consistent and asymptotically normal; see, for example, Jensen and Rahbek (2004).

### 2.2.2 Out-of-Sample Tests

An out-of-sample forecasts of volatility is compared and it generated by two benchmark forecasting models and four competing forecasting models. The first benchmark model is a GARCH(1,1) model estimated using an expanding window (“GARCH(1,1) expanding window” model). More specifically, we divide the sample for a given exchange rate return series into in-sample and out-of-sample portions, where the in-sample portion spans the first \( R \) observations and the out-of-sample portion the last \( P \) observations. In order to generate the first out-of-sample forecast at the one-period horizon, we estimate the GARCH(1,1) model given by equations (3) and (4) ing QMLE and data from the first observation through observation \( R \). The initial forecast is given by:

\[
\hat{h}_{R}^\exp = \hat{\omega}^\exp R + \hat{\alpha}^\exp R \cdot \exp e_{R-1}^2 + \hat{\beta}^\exp R \cdot \exp \hat{h}_{R-1}^\exp,
\]

where \( \hat{\omega}_R^\exp, \hat{\alpha}_R^\exp, \) and \( \hat{\beta}_R^\exp \) are the estimates of \( \omega, \alpha, \) and \( \beta, \) respectively, in equation (4) and it is the estimate of \( \hat{h}_R^\exp \) obtained using data from the first observation through observation \( R \). Then the estimation window will be expanded by one observation in order to form a forecast for period \( R + 2 \), \( \hat{h}_{R+2}^\exp \). The end of the available out-of-sample period, leaving with a series of \( P \) out-of-sample forecasts is:

\[
\{ [\hat{h}_{(R+1)}^\exp]_{R=R+1}^{T} \}.
\]

The GARCH(1,1) expanding window model is a natural benchmark model that is appropriate for forecasting when the data are generated by a stable GARCH(1,1) process.

The second benchmark model is the RiskMetrics model based on an expanding window, a popular model often included in studies of out-of-sample volatility forecasting performance. The RiskMetrics model is a restricted version of the GARCH(1,1) model in equation (4), with \( \omega = 0, \beta = 0.94, \) and \( \alpha + \beta = 1 \), so that the conditional volatility process is assumed to be an IGARCH(1,1) process. Note that the RiskMetrics model does not involve the estimation of any parameters, making it easy to implement. The forecasts for the RiskMetrics model by:

\[
\{ [\hat{h}_{(R+1)}^\exp]_{R=R+1}^{T} | h_{(R-1),RM} \}.
\]

In addition to its popularity, recent results in Hillebrand (2005) make the RiskMetrics model a relevant benchmark. Hillebrand (2005) shows that under fairly general conditions, if structural breaks in a GARCH(1,1) process are neglected, the estimates of \( \omega \) and \( \alpha + \beta \) in equation (4) go to zero and one, respectively. The popular RiskMetrics model specification is what we would expect when structural breaks in volatility are important but neglected.

The four competing forecasting models all make adjustments to the estimation window in order to account for potential changes in the unconditional variance of exchange rate returns. The first competing model is a GARCH(1,1) model estimated using a rolling window with size equal to one-
half of the length of the in-sample period ("GARCH(1,1) 0.50 rolling window" model). The forecasts are formed as described above, with the exception that the GARCH(1,1) forecasting model is estimated using a rolling window with size equal to one-half of the length of the in-sample period; that is, the first forecast uses estimates of equation (4) based on observations 0.5$R$ through $R$ , the second forecast estimates based on observations 0.5$R$ +1 through $R$ +1, and so on. The forecasts for the GARCH(1,1) 0.50 rolling window model is denoted by $h_{\hat{t} \mid (t-1) \cdot \text{ROLL}(0.5)}^T_{\mid t=R+1}$. A rolling window with size equal to one-half of the length of the in-sample period is longer rolling window that represents a compromise between having a relatively long estimationwindow to accurately estimate the parameters of the GARCH(1,1) process and not relying too extensively on data from separate regimes. A GARCH(1,1) model estimated using a shorter rolling window with size equal to one-quarter of the length of the in-sample period (the second competing model; “GARCH(1,1) 0.25 rolling window” model), so that the first forecast uses estimates based on observations 0.75$R$ through observation $R$ . By using a shorter estimation window, this forecasting model has fewer observations available for estimating the parameters of the GARCH(1,1) process, but it runs a lower risk of using data from different regimes. We denote the forecasts generated by the GARCH(1,1) 0.25 rolling window model by:

$$\left[ h_{\hat{t} \mid (t-1) \cdot \text{ROLL}(0.25)}^T_{\mid t=R+1} \right]$$

The third competing model is a GARCH(1,1) model estimated using a window whose size is determined by applying the modified ICSS algorithm to an expanding window (“GARCH(1,1) with breaks” model). Firstly, the modified ICSS algorithm is applied to observations one through $R$ . Suppose that significant evidence of one or more structural breaks according to the ICSS algorithm is found and that the final break is estimated to occur at time $T_B$ . A GARCH(1,1) model uses observations $T_B +1$ through $R$ to form an estimate of $h_{R+1}$ . If there is no significant evidence of a structural break according to the ICSS algorithm, a GARCH(1,1) model uses observations one through $R$ to form an estimate of $h_{R+1}$ . To compute the second out-of-sample forecast, the modified ICSS algorithm is applied to observations one through $R +1$ and proceed as described above. Continuing in this manner through the end of the available out-of-sample period, a series of forecasts are generated corresponding to the GARCH(1,1) with breaks model, $\{ h_{t \mid t-1}, \text{BREAKS} \}_T=T_{g+1}$ . A potential drawback to this forecasting model is that a relatively short sample will be available for estimating the GARCH(1,1) parameters when a break is detected relatively closing to the forecast date.

The final forecasting model is the simple moving average model used in Stărică et al. (2005). It uses the average of the squared returns over the previous 250 days to form the volatility forecast for day $t$: $h_{\hat{t} \mid (t-1) \cdot \text{MA}(250)} = (1/250) \sum_{i=1}^{250} e_t^{2}$. This model assumes there are no GARCH dynamics present in the volatility process and allows the unconditional variance to change steadily over time. Stărică et al. (2005) find that this model often outperforms a GARCH(1,1) model at longer horizons when forecasting daily stock return volatility in industrialized countries.

In order to compare forecasts across models, two loss functions are considered. The first is an aggregated version of the familiar MSFE metric. The conventional MSFE at horizon $s$ for model $i$ is given by:

$$\text{MSFE} = \frac{1}{T} \sum_{i=1}^{T} \left( \epsilon_t^2 - h_{\hat{t} \mid (t-s,i)}^2 \right)^2$$

A difficulty in assessing the predictive accuracy of models of conditional volatility using equation (5) is that $h_t$ is not directly observed, and a proxy is used. In equation (5), following much of the literature, squared returns serve as a proxy for the latent volatility, $h_t$ . Awartani and Corradi (2004) and Hansen and Lunde (2004a) show that $\text{MSFE}$ produces a consistent empirical ranking of
forecasting models when squared returns serve as a proxy for the latent volatility. Patton (2005) also shows that MSFE is an appropriate loss function when using squared returns as a volatility proxy, while a number of other popular loss functions, such as absolute error, are inappropriate. Even though MSFE produces a consistent ranking of models when using squared returns as a proxy for $h_t$, as emphasized by Andersen and Bollerslev (1998), squared returns still tend to be a very noisy proxy for latent volatility. In order to reduce some of the idiosyncratic noise in the day-to-day movements in squared returns, Granger and Stărică (2005) and Stărică et al. (2005) are followes and an aggregate MSFE criterion is used:

$$MSFE = [P - (s - 1)]^{-1} \sum_{t=R+s}^{T} (e_i^2 - h_{(t-s,i)})^2$$  \hspace{1cm} (6)$$

where

$$e_i = \sum_{j=1}^{s} e_{(t-(j-1))}^2$$ and $$h_{(t-s,i)} = \sum_{j=1}^{s} h_{(t-(j-1)(t-s,i)}$$

Aggregating helps to reduce the idiosyncratic noise in squared returns at horizons beyond one period and provides a more informative metric for comparing volatility forecast accuracy.

The second loss function is the González-Rivera et al. (2004) VaR loss function. Let $VaR_{0.05,t,i}$ be the forecast of the 0.05 quantile of the cumulative distribution function for the cumulative return,

$$\tilde{e}_i = \sum_{j=1}^{s} e_{(t-(j-1))}$$

generated by model $i$ and formed at time $t - s$. We follow González-Rivera et al. (2004) and evaluate the forecasting models with respect to VaR using the following mean loss function:

$$MVaR = [P - (s - 1)]^{-1} \sum_{t=R+s}^{T} (0.05 - d_{i}) (\tilde{e}_i - VaR_{0.05,t,i})$$  \hspace{1cm} (7)$$

where

$$d_{i} = 1(\tilde{e}_i < VaR_{0.05,t,i})$$

and $1(\cdot)$ is the indicator function that takes on a value of unity when the argument is satisfied. This asymmetric loss function penalizes more severely observations for which

$$\tilde{e}_i = VaR_{0.05,t,i}, < 0$$

The $MVaR$ criterion has the advantage that it does not require observations of the latent volatility, $h_t$. It is also well-motivated, as VaR is an important risk management tool. The following simulation procedure is used in order to generate $VaR_{0.05,t,i}$ at horizon $s$. A given model $i$ produces the sequence of point forecasts for the latent volatility, $h_{(t-(j-1)(t-s,i)}$, for $j = 1, ..., s$ at time $t - s$. Assuming $\epsilon_r \sim N(0,1)$, a sequence of returns is simulated, $\{e_{t}^{*},_{(t-(j-1))}^{j-1}, \}$, ing equations (3) and (4) and compute the simulated cumulative return,

$$\tilde{e}_i = \sum_{j=1}^{s} e_{(t-(j-1))}.$$
\[ \bar{f}_{t,j} = \left[ P - (s-1) \right]^{-1} \sum_{t=R-s}^{T} f_{t,t,j}. \]

The White (2000) statistic is given by

\[ V_t = \max_{i=1,\ldots,n} \left[ P - (s-1) \right]^{0.5} \left( f_{[i,1,\ldots]} - f_{(i)} \right) \tag{8} \]

where \( l \) is the number of competing models. The null hypothesis is that none of the competing models has superior predictive ability in terms of expected loss over the benchmark model, whereas the one-sided (upper-tail) alternative hypothesis is that at least one of the competing models has superior predictive ability over the benchmark model. Following White (2000), a \( p \)-value corresponding to \( V_t \) is generated using the stationary bootstrap of Politis and Romano (1994). The White (2000) reality check with the GARCH(1,1) expanding window is performed and RiskMetrics models serving in turn as the benchmark model. The reality check allows to test whether any of our four methods of accommodating structural breaks in the unconditional variance of exchange rate returns improves real-time volatility forecasting performance relative to a benchmark model based on the assumption of a stable GARCH(1,1) process. The reality check helps to control for data mining when considering a multiple number of competing models. This is important in these applications, as a variety of ways to accommodate potential structural breaks is considered when forming out-of-sample forecasts. The Hansen (2005) studentized version of the \( V_t \) statistic is computed by \( T_{SPA}^{\text{std}} \), where the corresponding \( p \)-value uses the stationary bootstrap of Politis and Romano (1994). The Hansen (2005) version of the White (2000) reality check is designed to be a more powerful test of superior predictive ability. A word of caution is in order with respect to the use of the White (2000) and Hansen (2005) statistics and the stationary bootstrap. Recent research shows that making inferences concerning relative predictive accuracy across forecasting models can be tricky and depends on a number of factors, such as the size of the in-sample period relative to the out-of-sample period (\( P/R \)), type of estimation window used (expanding, rolling, or fixed), and whether the models being compared are nested or non-nested. We recognize that it is not necessarily the case that all of the required technical conditions for the strict validity of the stationary bootstrap are satisfied in our applications, and we report bootstrapped \( p \)-values for the White (2000) \( V_t \) and Hansen (2005) \( T_{SPA}^{\text{std}} \) statistics as a rough guide to assessing statistical significance.
Chapter 3

GREEK BANKS DURING THE CRISIS
3. Greek banks during the crisis

By mid – 2008 the financial crisis not only increased public debt figures in weak economies, but it started to affect the development regions. The crisis, which started from U.S. mortgage loans spread to the European countries. At this point, the governments of eurozone try to stabilize the debt crisis. *ECB Quarterly Euro Area accounts* (research between 1999 and 2010) concluded to some interesting points. First, there are periods during which private debt increased in the eurozone whereas there are other periods that private debt has been reduced with a great speed. Second, during periods of economic booms, private debt has risen. Third, for the whole period the increase in private debt was greater than the percentage increase of public debt. Fourth, during the 2005-2007 economic boom, there is an average annual increase in private debt of the eurozone countries of approximately 35% of GDP. In contrast during the years of economic recession 2008-2009, private debt slows down and public debt growth accelerates (De Grauwe 2010a).

The overall picture from these accounts is that private debt increased more than public over the whole period. When the crisis started in October 2008 the governments tried to save the problematic banks. Furthermore, they followed monetary policies in order to grow the demand and to make sure that the economies will not drop down sharply. These large stimulus programs are expected to increase the total public sector debt of the world developed economies over 100% of the GDP in 2011 (Organization for Economic Cooperation and Development - OECD 2010). The debt crisis has important implications for the eurozone raising questions about it’s viability and about the future of the euro as a common currency (Adrian Blundell-Wingall and Patrick Slovic 2010; International Monetary Fund - IMF 2010). The debt crisis in the eurozone is still unfolding since (i) Ireland is the second country (Greece was the first one) requesting financial support from the rescue mechanism set out by EU/IMF and (ii) spreads on the 10-year government bond yields of Portugal and Spain have been increased sharply. Part of this increase in interest rate spreads can be attributed to speculation, but the problem appeared to the public finances of these countries. Especially, gross debt/GDP ratio increased across all EMU economies over the period 2007-2010 but not in a symmetric way; it was increased by 62.3% in Ireland, by 38.2% in Greece and by 36.3% in Spain. These were the largest increases of the gross debt/GDP ratio in the eurozone. For this reason, the government of EMU countries gave a lot of money to the banks in order to reduce the stability. An important question at this stage is whether the overall debt level for eurozone countries is stainable. It seems that this issue is not crucial one since the total government debt for the eurozone countries is 86% of GDP. Grammatikos and Vermeulen (2010) argue that one needs to decompose total debt into three components in order to evaluate the issue of debt stainability. These components are: the primary balance, which is fully controlled by the government; the interest and growth contributions, which are not directly controlled by the government since it largely depends of expenses made by the government in the past as well as on the current economic situation; and the stock-flow adjustments, which are not considered to be direct expenses but can be rather considered as investments that lead to the increase of government’s assets. The last component is of crucial importance when we take into consideration the bank bailouts put forward by several governments. However, this part of the public debt may be similar to a group of countries it is the fast increase in the primary deficit due to the high speed of contraction that can lead to a serious debt crisis because of its permanent nature. Greece, Portugal, Ireland and Spain are the countries with the largest primary balance and interest and growth contributions. Furthermore, Stephen G. Cecchetti, M. S. Mohan- ti, and Fabrizio Zampolli (2010) look into the prospects and implications of the future evolution in public debt. They argue that the most worrying aspect of the future development on
public debt is that most of the future budget deficits (and the public debt) are structural rather than cyclical in nature.

One of the main features of the Greek banking system is its rapidly increasing exposure to the emerging market economies of SEE, dating from the mid 1990s. This development has been driven by several factors. First, after the liberalization of the Greek banking system in the mid 1990s, many new products appeared in the money market making the access of households and firms to credit much easier and cheaper. At the same time, banking competition was enhanced resulting in an improvement in the services provided both with respect to quality and price. Further, banking intermediation measured as the ratio of private lending to output grew quickly. Second, given the number of the Greek banks relative to the size of the domestic money market, the possibility to exploit further economies of scale and scope was deemed to be extremely limited. Therefore, many Greek banks first proceeded to consolidation via mergers and acquisitions, strongly supported by the privatization policies of the governments and, second, extended their presence in the Balkan Peninsula where private bank lending was still at very low levels.

The banking system’s vulnerability has increased during the financial crisis, with more non-performing loans (12.8% by the end of second quarter of 2011). There are created a lot of deposit losses for the Greek banking system, because citizens of Greece were afraid a possible Greek exit from the Eurozone. An abrupt Greek exit from the Eurozone will result in de-stabilization of the Banking System of the country. But, the things change and the greek government agreed to a haircut for private bondholders will take a further toll on the banking system, with Greek banks holding EUR 50 billion of Greek sovereign debt. That said, the second bailout package includes EUR 30 billion to recapitalize Greek banks and support the banking system.

Especially, a lot of Greek people transfer money abroad or to buy bonds, shares or other assets. The banking system has lost about a third of its total deposits over the past two years, some of this as people run down savings. There are worrying indications that this trickle of deposits has started to swell in recent days.

Reliable figures will not officially be released for weeks, but bankers say that as much as €1.2 billion flowed out. “Most of the hard money has already left,” says one. “Now we are seeing a flare-up of withdrawals from small depositors who don't know what to make of what is said on the evening news.”

But the deposit runs to spread to other vulnerable eurozone countries such as Portugal or Spain. “The typical thing with a bank run is it trickles and then it floods,” says one banker. “The real concern is that you could have the dam breaking, first in Greece, but then elsewhere.” Citizens in other countries seem to be leaving their deposits where they are. But big companies are sweeping money out of peripheral banks and countries. In Britain some local-government bodies are reportedly moving their deposits from Santander's British bank, even though it is locally capitalized and supervised.

Moreover, the authorities could do much to restore confidence by quickly injecting into Greek banks some €48 billion in new capital that has been earmarked by the European Financial Stability Facility for this very purpose. The European Central Bank (ECB), which stopped conducting some monetary-policy operations with some Greek banks because they were not yet recapitalized, could also do more to reassure depositors by showing that abundant liquidity is on hand. That is a gamble, however: showing depositors that the cash is there if they want might encourage the outflow, not stanch it.

The most terrible thing for Greek banking sector is the exit of eurozone. “Leaving the euro is a nightmare,” says one Greek banker. “It's not like Argentina where there already was a currency.
Here the economy would instantly revert to barter.” Yet the risks of an exit stretch well beyond Aegean shores.

The direct financial costs of a Greek exit to the country's creditors are more manageable than they were, but they are still large. By far the biggest losers of any Greek exit would be European taxpayers. The Greek central bank owes about €100 billion to the other central banks that are members of the euro. If Greece were to default on that debt Germany alone would probably take a hit of about €30 billion. The ECB would take losses on the €56 billion of Greek government bonds it (and other central banks) have bought on the secondary market. Euro-zone members and the International Monetary Fund would also be on the hook if Greece repudiated its bail-out loans. Europe's disbursed bail-out funds total €161 billion, including some collateral temporarily set aside to protect the ECB against losses; the IMF has lent €22 billion.

The next point of financial contagion would be banks' direct exposures to Greece. Even after writing down the value of their Greek government bonds, and swapping them for less valuable ones, European banks and other investors still hold a nominal €55 billion-worth of Greek government debt that might then have to be written down further, according to Berenberg Bank.

The sovereign is not the only debtor in Greece. The Bank for International Settlements reckons that international banks were still owed $69 billion by Greek companies and households at the end of 2011. Most at risk is France (with a total exposure to households and companies of about $37 billion) followed by banks in Britain (almost $8 billion) and Germany (almost $6 billion).
Chapter 4

FIRST LOOK AT DATA
4. First look at data

At this section, the data, which will be used in order to examine how the volatility stocks behaved before and during the crisis, is presented. This data represents stock prices of three banks in Greece. The choice of the banks was done by their size, which they have to the financial market. The three banks, which will be studied are: Eurobank, National Bank of Greece and Alpha bank. The shares are dated between 2007 and 2012. To facilitate the analysis a single break point is used to separate two periods: the period before the crisis and the period during the crisis. The date that is used as the start of the crisis period is the 20th of October, 2009, because on Monday the 19th of October of 2009, it was announced that the statistical numbers and especially the government deficit figures, needed to be significantly revised upwards (announcement date, AD).

Especially, for every bank, the histogram and the technical analysis are presented. The first look at the data shows that the closing prices of the shares follow a sharp decline after the summer of 2007 and it continues throughout the sample period.

Graph 3. Historical graph of National Bank of Greece (ETE)
Graph 4. Technical analysis of shares of National Bank of Greece ( ETE )

Graph 5. Historical graph of Alpha Bank ( ΑΛΦΑ )
Graph 6. Technical analysis of shares of Alpha Bank ( ΑΛΦΑ )

Graph 7. Historical graph of Eurobank ( ΕΥΡΩΒ )
The overall picture of the graphs shows that the shares were moved at the same motive for the three banks. In 2007, the shares started from 24 for both Eurobank and National Bank of Greece and from 22 for Alpha bank. Before the sample period, there is a sharp decline of the price of the shares, at the end of 2007 with the peak to be in the middle of 2007, which held stable for a few months. By mid 2008, the financial crisis started to affect Greece and the shares followed a vertical plummet until 2009. During 2010, there is a small growth of the shares, but at the end of the same years the prices reduced again. And, finally, in 2012, the shares take the lowest prices that are observed in the last 5 years, where this research takes place.
Chapter 5

ECONOMETRIC ANALYSIS
5. Econometric analysis

5.1 Introduction

The historical graphs of the shares shows that there is a sharp decline of banking stock that started around summer of 2007 and reached the worst point sometime in early 2009. On Monday, the 19th of October 2009, the Greek Government announced that the statistical numbers and especially the government deficit figures, needed to be significantly revised upwards (announcement date, AD).

At this section, stock return volatility will be examined. The model, which is used in order to describe the volatility of the stock, is the GARCH model. This research will be done for the 3 biggest banks of Greece: Eurobank, Alpha Bank and National Bank of Greece. There are 2 sample periods for every bank. The one sample period starts at the 1st of January, 2007 and it ends at the 18th of October, 2009. The second one is referred to the shares from the 20th of October, 2009 until the September of 2012.

The aim of this break is to observe how the stock return volatility has changed during these years and how the crisis affects one of the major sectors in Greece, the banks.

5.2 Results of GARCH Model
5.2.1 National Bank of Greece

Sample period 2007 - 2009

A Estimate

The table below describes the statistical results for National Bank of Greece before the hypothetical break point. The sample period starts on the 2nd of January, 2007 and it ends a few days before the 19th of October, 2009. This table describes the volatility, which was appeared during this period.

First of all, the observations, which are made, are 694. Moreover, in order to simulate realization from GARCH, a pre sample conditional variance is needed in order to initialize the variance equation. In this case the parameter is 0.7. As this table describes, the convergence achieved after 101 iterations. The equation that was used is:

\[ GARCH = C(2) + C(3) \times RESID(-1)^2 + C(4) \times GARCH(-1) \]

The table describes, how the stock return was moved. Especially, the coefficient of variance on both the lagged squared residuals and lagged conditional variance equation has low prices. This means that they are not highly statistically persistent. Moreover, the sum of the lagged squared residuals and lagged conditional variance equation is very far from the unity and they have negative value. This percentage shows that the stock of the conditional variance are not persistent. Furthermore, the small sum of these coefficients means that there is a positive or large negative return on equity and the future forecasts of the variance will be low during this period. The variance of “C” (intercept term) is very small, the “ARCH” parameter is about 0.029 and the “GARCH” parameter is approximately -0.04.

Moreover, the unconditional average volatility is given as:

\[ h = C(2) / (1 - C(3) - C(4)) \]

The unconditional volatility in this sample period, as is shown by the table below, is:

\[ h = 0.03 / (1 - 0.52 - (0.04)) = 5.8 \% \]

The persistence of volatility is given by the sum: \( C(3) + C(4) = 0.52 + (-0.04) = 0.48 \) or 48%.

<table>
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<td>-0.172261</td>
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<table>
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<th>z-Statistic</th>
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<td>0.068006</td>
<td>7.586603</td>
<td>0.0000</td>
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<tr>
<td>GARCH(-1)</td>
<td>-0.041142</td>
<td>0.010044</td>
<td>-4.095998</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 1. Estimate GARCH Model, National Bank of Greece from 2 / 1 / 2007 to 16/10 / 2009
The graph below shows the forecast, which done using GARCH model. As it is observed, the prices are presented to have low volatility. The Table 1. shows that there will be low volatility in the stock returns and the graph proves this estimates. The prices follow a stable trend. The value reaches almost 4.5. Furthermore, the second graph shows that the stock returns are positive at the beginning and then it remains stable. The prices begin from 0.0455 and they are almost 0.0055 until 2009.

GARCH graphs

Conditional Standard Deviation

The conditional standard deviation is referred to the periods, where the volatility of the assets is appeared. At this plot, there are periods, which are characterized by standard levels of volatility. The graph shows that there is only one period of high volatility. First of all, there is a stable period of volatility in the stock returns, which starts from the first quarter of 2007 and it lasts until the end of the same year. The level of volatility is moved from 2 to 4. From the first quarter of 2008 until the first half of 2009, there is a period with high return on equity. This means that the prices of the shares start to grow, where the highest point is more than 0.85 and the lowest one is 0.2. After this, there is a decrease, which remains stable until the third quarter of 2009. Finally, at the first days of the final quarter of 2009, it is observed a high volatility to these certain dates of the sample period.

**Conditional Variance**

The graph of conditional variance shows how the volatility was moved from the beginning of 2007 until the 16th of October, 2009. First of all, the graph shows that the volatility of the stock returns is very low until the end of the fourth quarter of 2007 and it does not reach more than 0.15. After this, there is a sharp increase that presents high volatility from the beginning of 2008 until the end of the same year (with the highest value to be more than 0.7 and lowest one is near to 0.03). After this observation, the volatility of the return of assets is in a very low level (same values with 2007). At the end, it grows and it reaches about 0.3.

Sample period 2009 – 2012

Estimate

The second sample period is about the volatility of the stock return from the 20th of October 2009 until the 12th September of 2012. The aim of this separation is to examine how the volatility of the stock returns has envolved after the hypothetical beginning of the crisis until today. The observations will be done as before and the data will be researched in same way.

The size of these observations are bigger than before and they are 728. At this sample, the convergence achieved after 41 iterations. The parameter of the presample variance is 0.7 and the equation, which is used, is:

\[ \text{GARCH} = C(2) + C(3) \times \text{RESID}(-1)^2 + C(4) \times \text{GARCH}(-1). \]

The table below shows the movement of the stock returns. Moreover, at this stage only statistical elements are presented. As it is observed, the coefficient of variance on both the lagged squared residuals and lagged conditional variance equation has low prices. The result of this is that they are not highly statistically persistent. Furthermore, the sum of the lagged squared residuals and lagged conditional variance equation is a little bit far from unity. The value, which is proved this, is 0.33 and it shows that the stocks, when the conditional variance is examined, are not persistent. Moreover, the small sum of the coefficients shows that the return on equity will not have large or negative values and in some cases, it may be stable. Moreover, the forecast will be small during this period. At the end, we can see the variance of “C”, which is very low (0.014), the “GARCH” parameter is 0.33 and the parameter of “ARCH” is about 0.237.

The unconditional variance at this sample period is:

\[ h = \frac{C(2)}{1 - C(3) - C(4)} = \frac{0.03}{1 - 0.24 - 0.34} = 7.14\% \]

The persistence of volatility is given by the sum \( C(3) + C(4) = 0.24 + 0.34 = 58\% \).

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<td>1.405254</td>
<td>0.1599</td>
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<th>Std. Error</th>
<th>z-Statistic</th>
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<tbody>
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<td>7.164202</td>
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<td>RESID(-1)^2</td>
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<td>GARCH(-1)</td>
<td>0.335984</td>
<td>0.085953</td>
<td>3.908927</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

Table 2. Estimate GARCH Model, National Bank of Greece from 20/10/2009 to 12/09/2012
This table forecasts the volatility of the stock returns, using the GARCH model. The first graph shows how the volatility will move in general and the second one shows which will be the trend of the value of the stock returns. As it is observed, from the output graph, the volatility will not have a lot of fluctuations. The first plot starts from a value, which is a little bit greater than 0.40 or smaller than -0.40 and after this there is a horizontal line, which means that the volatility of the stock returns will not reach high values. The same motive is for the second one. It starts from about 0.050 and it presents a stability at 0.075.

Graph 12. Forecast with GARCH Model, National Bank of Greece from 20/10/2009 to 12/09/2012
GARCH graphs

Conditional standard deviation

The graph of conditional standard deviation shows the periods, where there is low or high level of volatility of the stock returns. The values are moving, which it is shown to the vertical axis, between 0.2 and 0.9 and the horizontal one is about the periods. The point of this sample period is that there are not a lot fluctuations and this is proved by this graph. There are only 9 times, where the variance is above the average (0.45). The most notable times that are observed to the below periods are:

1. Near to the end of 2009, where the values are about 0.5.
2. At the beginning of 2010, there is low volatility to the stock returns. The same, as above, is shown before the middle of 2010
3. After the first half of 2010 until the first half of 2011 there are a lot of variances, where the highest levels of volatility are appeared. As it is observed, after the first half of 2010 there is the highest value (0.85) and there are 5 values greater than 0.6. Also, at this period there are the smallest values, which are almost 0.22.
4. Finally, there are fluctuations during 2012, but they are in low levels.

**Conditional variance**

The conditional variance shows the movement of volatility for the sample period, which is dated between the 20th of October of 2009 until the 12th September of 2012. The same motive as before (Graph 13) is observed. The volatility is presented to the same periods, but the values are different:

- For the upper points it is moved between 0.4 and 0.68 (after the second half of 2010).
- At the lower one, the values are moved between between 0.05 and 0.1.

5.2.2 Alpha Bank

Sample period 2007 - 2009

Estimate

The table below shows the estimation of the sample period, which is dated between the 2nd of January, 2007 and a few days before the 19th of October, 2009. The results are presented from the statistical view and they show how the volatility will be during the examination of this sample period.

The table shows that the observations are 695. Furthermore, in order to simulate realization from GARCH, a pre sample conditional variance is needed in order to initialize the variance equation. The value of the parameter is 0.7. As this table describes, the convergence achieved after 8 iterations. The equation that was used is:

\[ \text{GARCH} = C(2) + C(3) \times \text{RESID}(-1)^2 + C(4) \times \text{GARCH}(-1) \]

Especially, the coefficient of variance on both the lagged squared residuals and lagged conditional variance equation has high prices. This means that they are highly statistically persistent. Moreover, the sum of the lagged squared residuals and lagged conditional variance equation is very close to unity and it is approximately 0.88. This means that the stocks of the conditional variance are highly persistent. Furthermore, the large sum of these coefficients means that there is a large positive or large negative return on equity and the future forecast of the variance will be high during this period. The variance of “C” is very small, the “ARCH” parameter is about 0.12 and the “GARCH” parameter is approximately 0.88.

At this sample period the unconditional variance is: \( h = \frac{C(2)}{1 - C(3) - C(4)} = 0.7\% \).

The persistence of volatility is the sum of \( C(3) + C(4) = 0.12 + 0.87 = 99\% \).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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</thead>
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<table>
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<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<td>GARCH(-1)</td>
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<td>0.021474</td>
<td>40.92360</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Table 3. Estimate GARCH Model, AlphaBank from 3/1/2007 to 16/10/2009
**Forecast**

The graph below shows if there will be a volatility to the stock returns. As it is observed, the first plot shows a rising or a decreasing trend. This means that there will be large volatility to the sample period as it describes before to Table 3. To the second plot, the values are increased during the period, where this examination takes place. The values of the plot start from 0.01 and they end to 0.12. The rising is very sharply, so I expect high volatility in the assets.

**Graph 15. Forecast GARCH Model, Alpha Bank from 3/1/2007 to 16/10/2009**
GARCH graphs

Conditional Standard Deviation

The plot below shows the chronical periods, where there is high level of volatility. These periods are:

- At the third quarter of 2007 (0.04).
- At the first quarter of 2008 (0.04).
- At the third quarter of 2008 (more than 0.045).
- At the fourth quarter 2008 (At this point the highest level of volatility of the stock returns are presented, which reaches the value of 0.075).
- During all the period of 2009, where the values are ranging between 0.03 and 0.06.

The conditional variance of the stock returns is presented in the graph below. It shows the movement of volatility of these returns. As observed, the graph 18 has a lot of similarities with the graph of the conditional standard deviation (graph 17). The only difference is that the values appear to have an increase trend from the beginning of the sample period until the end of 2008, where the highest value is more than 0.005. After this period, there is a sharp decline to the values with the lowest point to be less than 0.001.

Graph 17. Conditional Variance GARCH Model, Alpha Bank from 3/1/2007 to 16/10/2009
**Sample period 2009 – 2012**

**Estimate**

The sample period, which is used in order to examine the volatility of the stocks, is put between the 20\textsuperscript{th} of October, 2009 and the 12\textsuperscript{th} of September, 2012. The statistical results, which are presented to this table, show the volatility of the stock returns for these particular dates.

As it is observed, the number of observations is 727. Furthermore, a pre sample conditional variance is needed in order to initialize the variance equation. The value of the parameter is 0.7. As this table describes, the convergence achieved after 16 iterations. The equation that was ed is:

\[ \text{GARCH} = C(2) + C(3)\text{RESID}(-1)^2 + C(4)\text{GARCH}(-1) \]

Especially, the coefficient of variance on both the lagged squared residuals and lagged conditional variance equation has high prices. This means that they are highly statistically persistent. Moreover, the sum of the lagged squared residuals and lagged conditional variance equation is very close to unity and it is approximately 0.92. This means that the shocks are very highly persistent. Furthermore, the large sum of these coefficients means that there is a very large positive or very large negative return on equity and it shows that the future forecasts of the variance will be high during this period. The variance of “C“ is negative, the “ARCH” parameter is about 0.068 and the “GARCH“ parameter is approximately 0.92.

The conditional average variance is: \[ h = \frac{4.88E-05}{1 - 0.068 - 0.92} = 0.04 \% \]

The persistence of volatility is: \[ 0.92 + 0.068 = 98.8\% \]

![Table 4. Estimate GARCH Model, Alpha Bank from 20 / 10 / 2009 to 12 / 09 / 2012](image_url)
One of the components of GARCH Model is that it gives the opportunity to forecast what will happen to the further examination of the sample period. These plots show how the volatility of the stocks will budge during the dates. Especially, the first graph shows that there will not be a lot fluctuations, because it has a very little increasing or decreasing trend, which is between 0.05 and approximately 0.12. The second one shows a sharply rise until the beginning of 2010 and then the values remain almost stable.

Graph 18. Forecast with GARCH Model, Alpha Bank from 20 / 10 / 2009 to 12 / 09 / 2012
As it is explained before, the conditional standard deviation is referred to the periods, where low or high level of volatility of the stock returns, is observed. The values, which is presented to the vertical axis, is between 0.2 and 0.14 and the horizontal one shows the dates. At the case of Alpha Bank, the high level of volatility is between the third quarter of 2011 and the third quarter of 2012. The highest value of the stock returns is observed at the beginning of 2012, where is almost 0.14. In contrast, the rest of the periods show a stability with little variations, which are moved between 0.03 and 0.06.

Graph 19. Conditional Standard Deviation, Alpha Bank from 20 / 10 / 2009 to 12 / 09 / 2012
The conditional variance shows the volatility for the sample period, which is dated between the 20th of October of 2009 until the 12th September of 2012, and the graph shows the same motive as before. The volatility is presented to the same periods, but the values are different:

- For the upper points it is moved between 0.012 until 0.019. (third quarter of 2011 until before the end of the sample period)
- The lower one is moved between between 0.01 and 0.06. (end of sample period)
5.2.3 Eurobank

Sample period 2007 – 2009

Estimate

As it is described before to the other banks, the table shows the statistical results, which are presented after the use of GARCH Model. The sample period is referred to the Eurobank and it starts on the 2nd of January, 2007 and it ends a few days before the 19th of October, 2009.

First of all, the observations, which are made, are 694. Moreover, in order to simulate realization from GARCH, a pre sample conditional variance is needed. In this case the parameter is 0.7. As this table describes, the convergence achieved after 18 iterations. The equation that was ed is:

\[
GARCH = C(2) + C(3) * RESID(-1)^2 + C(4) * GARCH(-1)
\]

The table describes the volatility of the stock returns. Especially, the coefficient of variance on both the lagged squared residuals and lagged conditional variance equation does not have high prices. This means that they are not statistically persistent. Moreover, the sum of the lagged squared residuals and lagged conditional variance equation is not closing to unity and they are approximately 0.23. This percentage shows that the stocks to the conditional variance are not highly persistent. Furthermore, the large sum of these coefficients means that there will not be appeared a lot of large positive or large negative return on equity. The variance of “C” is very small, the “ARCH” parameter is about 0.91 and the “GARCH” parameter is approximately 0.23.

Unconditional average volatility:

\[
h = 0.01 - (1 - 0.92 - 0.23) = -6.7 \%
\]

Persistence of volatility is: 115%.

Table 5. Estimate GARCH Model, Eurobank from 06 / 01 / 2007 to 12 / 10 / 2009
Forecast

These plots show how the volatility will be moved during this period. The first graph shows the forecast, where the prices are presented not to have high levels of volatility. As the Table 5. described there will be large or low return on equity at 2009 and the graph proves this estimation. The prices follow an increasing trend with the highest value to teach $6E+40$ and the lowest one is near to zero. Furthermore, the second graph shows that the stock returns follows a positive trend and it rises until 2009. The prices begin from 0 and until 2009 they reach the value of $7E+40$.

Graph 21. Forecast GARCH Model, Eurobank from 2/1/2007 to 16/10/2009
GARCH graphs

Conditional standard deviation

This plot shows which periods are characterized by high levels of volatility at the end of the sample period. First of all, there is a stable period of volatility in the stock returns, which starts from the first quarter of 2007 and it ends to 2007. The higher periods of volatilities are:

- At the 1\textsuperscript{st} quarter of 2008, where the highest level of volatility is appeared and it is almost 1.2, and it continues to the second half of the same year.
- At the 3\textsuperscript{rd} quarter of 2008
- At the 4\textsuperscript{th} quarter of 2008.
- All the days of 2009, which are examined.

Graph 22. Conditional Standard Deviation, Eurobank from 2 /1 / 2007 to 16 / 10 / 2009
**Conditional variance**

The conditional variance graph shows that the volatility presents a stability from the start of 2007 until the 16th of October, 2009. First of all, the graph shows that the volatility of the stock returns remains stable at 2007. After this, the rest of the observations are presented to have high levels of volatility. Especially, at the beginning of 2008, the values have the highest volatility and they are between 1.2 and approximately 1.4. As the months pass, there are a lot of fluctuations, but in lower levels as before. At the second and third half of 2009, there are a lot of low values and after this the volatility begins to grow.

Graph 23. Conditional Variance, Eurobank from 2/1/2007 to 16/10/2009
\textbullet \textbf{Sample period 2009 -2012}

\textbf{Estimate}

The second sample period is dated from the 20\textsuperscript{th} of October 2009 until the 12\textsuperscript{th} September of 2012. The observations will be done as before and we will research the data in the same way.

The size of these observations are a little bit bigger than before. Especially, they are 727. At this sample period, the convergence achieved after 12 iterations. The parameter of the presample variance is 0.7 and the equation, which is ed, is:

\[ GARCH = C(2) + C(3)\times RESID(-1)^2 + C(4)\times GARCH(-1). \]

The table below shows the movement of the return on equity. As it is observed, the coefficient of variance on both the lagged squared residuals and lagged conditional variance equation has high prices and they have high values. The result of this is that they are highly statistically persistent. Furthermore, the sum of the lagged squared residuals and lagged conditional variance equation is a closing to unity (the value is 0.81). This shows that the shocks, when I examine for conditional variance, are highly persistent. Moreover, the small sum of the coefficients tells that the return of equity will have large or negative values. The forecast will be large during this period. At the end, we can see the variance of “C”, which is negative (-0.0025), the “GARCH” parameter is almost 0.81 and the parameter of “ARCH” is about 0.136.

Unconditional average variance : \( 0.0002 / (1 - 0.13 \times 0.81) = 0.33 \% \)

Persistence of volatility = 94 %

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.002890</td>
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Variance Equation

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<th></th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
<td>C</td>
<td>0.000205</td>
<td>4.70E-05</td>
<td>4.355380</td>
<td>0.0000</td>
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<td>RESID(-1)^2</td>
<td>0.135579</td>
<td>0.024289</td>
<td>5.581966</td>
<td>0.0000</td>
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<tr>
<td>GARCH(-1)</td>
<td>0.816116</td>
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<td>0.0000</td>
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Table 6. Estimate GARCH Model, Eurobank from 20 /10 /2009 to 12 /09/ 2012
A Forecast

These plots forecast the volatility of the stock returns using the GARCH model. The first graph shows the movement of the volatility and the second one shows which will be the trend of the value of the stock returns. The first graph starts from a small period of rising, which means that there will be some fluctuations to the next graphs. Then, a period of stability is presented and this value is near to 0.13. The same movement is observed to the second graph.

Graph 24. Forecast GARCH Model, Eurobank from 20 /10 /2009 to 12 /09 /2012
\textbf{GARCH graphs}

\textbf{Conditional Standard Deviation}

This graph is referred to the conditional standard deviation and shows the periods, where there is low or high level of volatility. The values are moving, which are shown to the vertical axis, between 0.02 and 0.14 and the horizontal one is about the periods. The most notable times that are observed to the below periods are:

\begin{itemize}
  \item From the beginning of the sample period until the second quarter of 2011, the period is not characterized by high volatility. There is a stability to the values, which is moved between 0.04 and 0.07.
  \item At the third quarter of the same year, there is a big variance, where it reaches more than 0.12.
  \item At the fourth quarter of 2011, there is a fluctuation, which is near to 0.12, but after this there is a sharp drop to 0.05.
  \item At the first quarter of 2012, it is observed the highest volatility (0.14).
  \item Finally, the rest sample period moves to the same motive, but at the third quarter of 2012 it drops again to almost 0.05.
\end{itemize}

Graph 25. Conditional Standard Deviation, Eurobank from 20/10/2009 to 12/09/2012
**Conditional Variance**

The conditional variance shows the movement of the volatility of the sample period. The most important points to this graph are:

1. The period which is not characterized by volatility and it remains stable is from the beginning of the sample period until the middle of the third quarter of 2011.
2. At the rest of the third quarter of the same year, there is a big variance, where it reaches 0.16.
3. At the first quarter of 2012, it is observed the highest volatility (approximately 0.20).
4. At the end of the sample period, there is a drop until it reaches almost 0.02.

Graph 26. conditional variance, Eurobank from 20/10/2009 to 12/09/2012
Chapter 6

ANALYZING OF DATA
6. Analyzing of data

National Bank of Greece

Sample period 2007 – 2009

3) Residuals

This graph shows the residuals, the actual prices and the fitted values. The two lines, which present the actual prices and the residuals, are at the same motive. As it is shown, the period before the crisis is characterized by high volatility, as it is described to table 1. While, the volatility of the stock is low until the end of 2007, where the lowest value reaches – 0.5 and the highest one is less than 0.05, the volatility of stock returns is growing after this period. One important point is appeared from the beginning of 2008 until the end of the same year, where there are the highest fluctuations and they are moved between – 0.7 and more than 1. The rest months follows the same motive, but they do not have very huge variances. At the end of this plot, the volatility of the stock returns is moved to low levels and it takes some of the smallest values of the sample period.

Graph 27. Residual, Actual prices, Fitted prices of GARCH Model, National Bank of Greece from 2 / 1 / 2007 to 16 / 10 / 2009
As it is described before, all the values of the stock follow an increasing trend. This graph shows this trend and the variance of the residuals presents high volatility. The residuals do not remain stable and they reach a lot of values. The upper case, which is at the beginning of 2008, reaches 1.2. On the other hand, the lowest value is almost – 0.8.

Standardized Residual Graph

The plot shows the variance of the standardized residuals. The values of the residuals vary in all over the sample period and there are not remain stable. The most important points are:

- Some of them are moving near to 0, but no one reaches it.
- The lowest variance is near to –4.
- The highest variance is about 6, which is observed at the end of 2008.

Graph 29. Standardized Residual of GARCH Model, National Bank of Greece from 2/1/2007 to 16/10/2009
The histogram controls the normality of the volatility of the stock returns. One sample period follows a normal distribution if kurtosis is greater than 3. This histogram shows that the standardized residuals follow normal distribution from two results:

- Kurtosis is about ten and this greater than 3.
- The histogram, as it is presented, follows a normal distribution.

The most values are moving between 1 and -1. Moreover, the rest of the them, which are on the right side, reaches values between 1 and 4. On the left side, there are only few values between 1 and 6 and there are no standardized residuals from 4 to 5.5.

Graph 30. Histogram, National Bank of Greece from 2 / 1 / 2007 to 16/10 / 2009
- Sample period 2009 – 2012

Residuals

The follow graph shows where the fitted value and the volatility of both the residuals and the actual values are. The two lines follow the same trend. These lines show that the volatility has a lot of fluctuations during all this period. At the beginning the values are moved to low levels and they are between 0.1 and 0.8. Moreover, at this point some of the prices are almost to zero, but they never reach it.

On the other hand, after the second half of 2010, the variances become higher than before until the end of the sample period. The highest value is between 1.6 and – 1.2. The rest of them are at the same motive, but the volatility is not to high levels. One point, which must be referred, is at the end of the sample period, where there is a lot of volatility on the stock returns. But at this case, the volatility has small values.

This plot shows which the variance, that are presented during the period after the announcement of the crisis, is. For one more time, it is observed a period where the fluctuations are to high levels. Especially, there are 8 points, where the variance moves between 0.1 and 0.3. The period, which this phenomenon is observed, is after the second half of 2009 until the second half of 2012.

While there are only 5 points, where there is a positive fluctuation, the negative values are shown to be at 15 points. But these points do not reach the value of – 0.3 and they are moving between -0.1 and – 0.2, which is the lowest value.
This plot presents the variance of the standardized residuals. As it is expected, the variance of the values does not remain stable for one more time. The vertical axis is referred to the values of the standardized residuals. These values are moving between – 0.4 and 1.6. The highest values of this variance is observed to 6 points, where they are between 1.2 and approximately 1.6. In contrast, the negative values present lower variance, because they are between 0 and – 1.2. There are 11 points, where the values are between -0.8 and about – 1.1. The rest of them are moving between 0.5 and – 0.4, without reaching the zero value.

Graph 33. Standardized Residuals of GARCH Model, National Bank of Greece from 20 / 10 / 2009 to 12 / 09 / 2012
The histogram shows if the sample period follows a normal distribution or not. The Kurtosis, which is the basic metric for the normal distribution, is greater than 3 (approximately 6.8), and the graph shows that the sample period is characterized by normality. The range is between -4 and 6 and the most values are moved between – 1.5 and 1.5.
6.2 Alpha Bank

Sample period 2007 – 2009

Resids

At this point, the volatility of the residuals, before the announcement of the economic crisis, is examined. The residuals and the actual values follow the same trend. The prices remain almost stable until the middle of 2007. At the third quarter of 2007, there is a sharp fluctuation to volatility, in which the range is between –0.05 and 0.10. Moreover, before the middle of 2008, the volatility is to low levels. The lines do not remain stable across the fitted. There are 3 points, which are above 0.10 and below –0.05.

Graph 35. Residual, Actual prices, Fitted prices of GARCH Model, Alpha Bank from 2/1/2007 to 16/10/2009
Residual Graph

This plot describes the volatility of the residuals, where the sample period is dated between the beginning of 2007 and the 16th of October of 2009. Especially, the variance of the residuals presents high volatility. The most important points are:

1. The first fluctuation is at the second half of 2007, where the upper point is at 0.09 and the lower one is at – 0.05.
2. Secondly, the same fluctuation, as before, is presented at the beginning of 2008.
3. Thirdly, there is a continuous variance from 2008 until the end of the sample period with the peak to be between 0.12 and – 0.12.

Graph 36. Residuals of GARCH Model, Alpha Bank from 2 / 1 / 2007 to 16 / 10 / 2009
The variance of the standardized residual graph is very high. There is not a point, where this variance remains stable. The fluctuations are observed to all the sample period. All the values of the standardized residuals have various levels and it changes as the time passes. The upper value is about 3.8 and the lower one reaches – 3.8. The volatility of the variance of the standardized residuals is very high and it never stops growing or decreasing!

Graph 37. Standardized Residuals of GARCH Model, Alpha Bank from 2 / 1 / 2007 to 16 / 10 / 2009
The graph shows that the values of the standardized residuals follow a normal distribution. This is shown by the value of the Kurtosis (it is greater than 3). The Table 3 presents this distribution and it is proved to this histogram. The range of the histogram is between -4 and 4. The most values are between – 1.5 and 1.75. The upper level, which is to the vertical axis, is 85.

Graph 38. Histogram, Alpha Bank from 2/1/2007 to 16/10/2009

Table 3: Standardized Residuals

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<tr>
<th>Sample 1/03/2007 to 10/16/2009</th>
<th>Observations 695</th>
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<td>Median</td>
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</tr>
<tr>
<td>Probability</td>
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</tr>
</tbody>
</table>
Sample period 2009 -2012

Resids

The follow graph shows where the fitted value and the volatility of both residuals and actual values are moved. The two lines follow the same trend. There is a big period, where the volatility of the stock returns has very few fluctuations, where the highest value is put closing to 0.1 and the lowest one is closing to – 0.1. These values are observed until the start of 2011.

On the other hand, after this small volatility, the things change. After the beginning of 2011 until the second half of 2012, there is a period, where the values take the highest ( almost 0.3 ) and the lowest value ( -0.2 ). The volatility does not stop here and there are 4 points, where the graph reaches the values between approximately – 0.2 and 0.25.

Graph 39. Residuals of GARCH Model, Alpha Bank from 20 / 10 / 2009 to 12 / 09 / 2012
This plot presents the variance of the residuals from 20 / 10 / 2009 to 12 / 09 / 2012. The results are as they are expected to be. At this period, the variance of the residuals does not be presented to have a lot of variances until the end of the third quarter of 2011. Moreover, there are 7 quarters to the sample period, where the variance moves between 0 and 0.12. This period starts from the beginning of the sample period and it ends to the second quarter of 2011.

After this period, the volatility of the stocks starts to vary. It reaches the value of 0.3, where it is observed the positive values, and -0.2 for the negative ones. During this period, the variance does not stop growing or declining until the end of the sample period.

Graph 40. Residuals of GARCH Model, Alpha Bank from 20 / 10 / 2009 to 12 / 09 / 2012
As it is expected to this plot, the variance of the values does not remain stable. The highest volatility is at the second quarter of 2011. These values are moving between – 4 and 6. The highest positive value of this variance is at the third quarter of 2011 and the highest negative one is appeared to the second half of 2012. Moreover, it is observed 3 points, where the values are above 4 and approximately less than – 2.5. Moreover, there are 19 points to this graph, which are around to -2 and 10 of them have prices more than 2.
**Histogram – normality**

At this sample period the standardized residuals follow a normal distribution. The Kurtosis, which is the basic metric for the normal distribution, is greater than 3 (approximately 4.6), and the graph shows that the residuals are characterized by normality. The range is between -3 and 5 and the most of the standardized residuals are moved between – 1.5 and 1.5.

---

**Graph 42. Histogram, Alpha Bank from 20 / 10 / 2009 to 12 / 09 / 2012**
6.3 Eurobank

Sample period 2007 – 2009

Residuals

This graph presents two lines, where the actual values and the residuals, have the same direction. As it is shown, the period before the crisis is characterized by high volatility, as the statistical values at table 5 describes. While, the volatility of the stock returns is very low until the fourth quarter of 2007, after this period the volatility of stock returns is increasing day – by - day. The most evaluated point is appeared at the first and at the second quarter of 2009, where there are 4 points that take the value of 1. Then it drops to -0.08. The rest months of this period seem to have a lot of fluctuations, especially at the end of the sample period.

Graph 43. Residuals of GARCH Model, Eurobank from 2 / 1 / 2007 to 16 / 10 / 2009
Residual Graph

This graph shows the volatility of the variance of the residuals, which follows an increasing trend and they present to have high volatility. At the beginning, the residuals remain stable, but after that the values are presented to have a lot of variances. The upper case, which is at the first and at the second quarter of 2008, reaches almost the value of 1.2 at 4 points. On the other hand, the lower case is almost – 0.08.
To the observation below, the variance of residuals is presented. At this stage, the variance of standardized residuals is estimated. The plot shows that this period is characterized by high levels of volatility. The most important points are:

1. At the beginning, there is a period, which is characterized by stability.
2. The lowest variance is near to – 8.
3. The highest variance is about 8.

Graph 45. Standardized Residuals of GARCH Model, Eurobank from 2 / 1 / 2007 to 16 / 10 / 2009
**Histogram – normality**

The standardized residuals follow a normal distribution. This is observed from both histogram, which presents a normal distribution and the value of Kurtosis (greater than 3). Almost all values are moving between 0.5 and -1. Moreover, the rest of the values are between –8 and 8.

![Histogram](image)

**Graph 46. Histogram, Eurobank from 02/01/2007 to 16/10/2009**
Sample period 2009 - 2012

▲ Resids

The follow graph shows the fitted value and the volatility of both the residuals and the actual values. The fluctuations of the lines follow the same motive. There is a big period, where the volatility of the stocks presents a lot of fluctuations.

Especially, after the third quarter of 2011, there are the highest volatilities both to the residuals and to the actual values. The values take the biggest price at the beginning of the half of 2011 (almost 0.28), and at these dates they are the lowest value, too. At the end of the period, the variances are very few and the volatility takes very low levels (approximately – 0.2).

Graph 47. Residuals, Eurobank from 20 / 10 / 2009 to 12 / 09 / 2012
Residual Graph

This plot shows that there is a period where the variance of the residuals does not remain stable, after the announcement of the crisis. Especially, there is not a period of stability and there are a lot of important variances.

After the third quarter of 2011, there are the highest variations. The most important points to this plot are:
- There are 8 points, where the variation is above 0.2.
- There are 6 points, where the fluctuation is near to –0.2.

Graph 48. Residuals, Eurobank from 20/10/2009 to 12/09/2012
This plot presents the variance of the standardized residuals. As it is expected, the variance of the values is moving to high levels. The values of the standardized residuals are between –2 and 2. The highest values of this variance are observed to 6 points, where the values are between 3 and approximately 5. In contrast, the negative values are between 0 and –3, with 10 points to be between -2 and about –3.5. The rest of them are moving between 0, 1 and -1.

Graph 49. Standardized Residuals, Eurobank from 20 / 10 / 2009 to 12 / 09 / 2012
The histogram shows that the standardized residuals follow a normal distribution. This is proved by both the number of the Kurtosis, which is greater than 3 (approximately 5) and the graph, which shows that the standardized residuals are characterized by normality. The range is between -3 and 5 and the standardized residuals are moved between –1.5 and 1.5 and the most of them have negative values.
Chapter 7

CONCLUSIONS
7. Conclusions

In order to abut to the conclusions, the overall picture of the results must be examined. As it is shown from all the tables and the graphs, there are a lot of similarities between the three major banks of Greece. Especially, at the beginning of 2007 the prices of the shares continued to grow to arrive at their peak during the beginning of 2008. This peak took place until the beginning of 2008. But, during 2008 the values started to decline with fast rhythms, because the International crisis propagates to Greece. During early 2009, it seems that Greek economy would emerge from the International crisis without large exposure to the losses. At this point, the closing prices were increased with stable trend. But in late 2009, it became clear that Greek economy was in trouble and the International crisis affects the Greek banking sector. The closing prices started to decline sharply until the end of the sample period. The historical graph and the technical analysis show that the closing prices take the lowest values during 2012.

The historical graph shows that both Alpha bank and National Bank of Greece begin with 22 euros and Eurobank starts with 24 euros at the beginning of 2007. The peaks were: 35 euros for National Bank of Greece, 24 euros for Alpha Bank and 26 euros for Eurobank. But, sometime on 2008, the prices decreased very sharply and they were: 10 euros for both the shares of Alpha Bank and Eurobank and 10 euros for National Bank of Greece. The difference between these prices was very big and it affects the stock returns for every bank.

Before the analysis, where the GARCH Model is performed, the dates are seperated in two sample periods: the period before the crisis and the period during the crisis. For this separation a single break is used in order to simplify the statistical analysis. Moreover, it was decided to use the 20th of October, 2009 as the first date of the crisis period. This is because on Monday the 19th of October of 2009, it was announced that the statistical numbers and especially the government deficit figures, needed to be significantly revised upwards. So, the first sample period starts from the beginning of 2007 until the 16th of October of 2009 and the second one is dated between the 20th of October of 2009 and September of 2012.

After, the decision of the use of the break point, the GARCH Model is implied in order to observe how the volatility is moved before and during the crisis. First of all, the first sample period of National Bank of Greece is examined. During 2007, volatility was generally low as indicated by low GARCH estimated figures. Then, a sharp jump to volatility takes place in the beginning of 2008. It appears that this time is threat of the highest uncertainty for banking institutions are to the unknown exposure and magnitude at International banking crisis.

During 2008 and 2009, banking volatility attains much higher levels than the low 2007 volatility numbers, but also follows a generally declining path from its peak early 2008 values.

In the second sample period of National Bank of Greece, the volatility remains stable with low fluctuations. But, the volatility seems to peak around the summer 2010 period, when Greek officially enters the bailout program. After this observation, the volatility starts to decline sharply until the first months of 2011. Before the second quarter of 2011 and at the beginning of 2012, the volatility has higher levels than before.

Then, the case of Alpha Bank follows. The first sample period shows that at the beginning of 2007 until the third quarter of 2008, the volatility remains stable to low levels. But, between the middle of the third quarter of 2008 and the beginning of the fourth quarter of 2009 the volatility is observed to have the highest levels and this point is the peak of this sample period. After this, there
is, there is a sharp decline to the volatility of the stocks. At the middle of the first quarter of 2009, there is a small growth to the volatility, but a downward trend is appeared until the end of this sample period.

At the second sample period (AD) for Alpha Bank, the volatility is moved to low and stable levels until the third quarter of 2011. Before the middle of the third quarter of 2011, there is a sharp increase to the levels of the volatility. At the beginning of the third quarter of 2011, there is a sharp decline to the volatility, but after this a sharp growth is observed. Between the fourth quarter of 2011 and the beginning of 2012, the volatility is shown to have very low levels. But, after the beginning of 2012, there is a peak to the levels of the volatility and this shows that the International crisis affects Alpha Bank. After this, the volatility follows a declining trend until the end of the sample, where the volatility moves to low levels.

Furthermore, the volatility for the shares of Eurobank, when the first sample period is examined, remains stable for almost one year (from the beginning of 2007 until approximately the end of this year. Exactly, at the end of 2007, the volatility of the stocks is moved to the highest levels and it seems that the International crisis affects Eurobank, too. After the second half of 2008 there is a sharp decrease and it continues until the third half of 2008. But, at the beginning of the third quarter of 2008, there is a decline to the levels of volatility, but after this, the volatility starts to grow until the middle of the fourth quarter of 2008. Then, the levels of volatility continues to decline, but at the end of the first sample period there are high levels of volatility.

The final observation is about the second sample period of Eurobank (AD). From the beginning of the second period until the third quarter of 2011, the volatility is moved to stable levels. But, during the middle of the fourth quarter of 2011, there is a sharp decline to the levels of volatility. This picture does not remain stable and at the beginning of 2012, there is a peak to the levels of volatility. Until the end of the second sample period the volatility of the stocks follows a downward trend.

The results, which are described above, are examined by the type:

\[ r_{t+1} = \ln(S_{t+1}) - \ln(S_t) \]

where \( r_{t+1} \) the stock returns.

In order to find these stock returns, I take away the LN of the closing prices of the shares at a certain time \( t \) from the LN of the closing prices of the shares, which are to the next time \( t+1 \). The results are as they are expected to be, because as the prices of the shares started to decrease or to increase, the volatility changed and it had a lot of variances.

As we analyzed before, the crisis affects the banking sector a lot. The banks saw the assets to move downwards day-by-day. The banking sector was one of the main sectors, where the financial crisis affects a lot. Especially, Greece suffered after the announcement of the crisis and the banking sector needs the support of the International Monetary Fund in order to survive. The most money of the loans from the European Union are spent to the Greek banks.

But, there are a lot of effects of the crisis in the banks. First of all, the people are afraid and they have a negative attitude to them. After the financial crisis, the Greek citizens feel unsecured every day and they can not trust the banks any more. They do not have money in order to pay their loans and the banks started to be driven to confiscation of their homes. So, more and more Greek people decides to transfer their money to another banks abroad. For this case, big role played the fear of a lot of citizens that a bankruptcy may appear and they took their money from the banks.
On the other hand, the banks are afraid to loan money to the citizens, because it is not sure that they can afford the loan installments. Moreover, one certain case of this situation is that the risks of the banks are growing during a financial crisis. There is not only the fear from the side of the Greek citizens, but from the side of the banks, too. Finally, the banks do not have cash in order to give loans to citizens or to do some investments in order to win again the trust of the people and to stop loan money from the International Monetary Fund.

A lot of citizens ask the economists when this crisis will end. No one can answer to this question with accuracy. Or they can not forecast when this situation will start to become better. The people suffer and the most of them are indignant. From the economic view, every curve, which decrease every day, sometime will follow an increasing trend. We do not know where this fall will go. The only thing that we can do is to think positive.
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**Sites**


**Books**

9. Appendix

Tables

Table 1. Estimate GARCH Model, National Bank of Greece from 2 / 1 / 2007 to 16/10 / 2009.....30
Table 2. Estimate GARCH Model, National Bank of Greece from 20 /10 / 2009 to 12/ 09 / 2012.34
Table 3. Estimate GARCH Model, Alphabank from 3 / 1 / 2007 to 16/10 / 2009.......................38
Table 4. Estimate GARCH Model, Alpha Bank from 20 / 10 / 2009 to 12 / 09 / 2012............... 42
Table 5. Estimate GARCH Model, Eurobank from 06 / 01 / 2007 to 12 / 10 / 2009.................. 46
Table 6. Estimate GARCH Model, Eurobank from 20 /10 / 2009 to 12 / 09 / 2012.............50
Graphs

Graph 1. Home sales – Inventory..................................................................................................8
Graph 2. Countries with banking Crisis..............................................................................................9
Graph 3. Historical graph of National Bank of Greece( ETE ).........................................................24
Graph 4. Technical analysis of shares of National Bank of Greece( ETE )......................................25
Graph 5. Historical graph of Alpha Bank ( ΑΛΦΑ ).........................................................................25
Graph 6. Technical analysis of shares of Alpha Bank ( ΑΛΦΑ )......................................................26
Graph 7. Historical graph of Eurobank( ΕΥΡΩΒ )............................................................................26
Graph 8. Technical analysis of shares of Eurobank( ΕΥΡΩΒ )..........................................................27
Graph 12. Forecast with GARCH Model, National Bank of Greece from 20/10/2009 to 12/09/2012....................................................................................................................................................35
Graph 13. Conditional standard deviation, National Bank of Greece from 20/10/2009 to 12/09/2012....................................................................................................................................................36
Graph 16. Conditional Variance GARCH Model, Alpha Bank from 3/1/2007 to 16/10/2009....41
Graph 17. Conditional Variance GARCH Model, Alpha Bank from 3/1/2007 to 16/10/2009....41
Graph 18. Forecast with GARCH Model, Alpha Bank from 20/10/2009 to 12/09/2012........43
Graph 19. Conditional Standard Deviation, Alpha Bank from 20/10/2009 to 12/09/2012.........44
Graph 20. Conditional Variance, Alpha Bank from 20/10/2009 to 12/09/2012.........................45
Graph 21. Forecast GARCH Model, Eurobank from 2/1/2007 to 16/10/2009.............................47
Graph 22. Conditional Standard Deviation, Eurobank from 2/1/2007 to 16/10/2009.................48
Graph 23. Conditional Variance, Eurobank from 2/1/2007 to 16/10/2009.................................49
Graph 24. Forecast GARCH Model, Eurobank from 20/10/2009 to 12/09/2012.......................51
Graph 25. Conditional Standard Deviation, Eurobank from 20/10/2009 to 12/09/2012........52
Graph 26. Conditional variance, Eurobank from 20/10/2009 to 12/09/2012............................53
Graph 27. Residual, Actual prices, Fitted prices of GARCH Model, National Bank of Greece from 2/1/2007 to 16/10/2009.................................................................................................................55
Graph 28. Residuals of GARCH Model, National Bank of Greece from 2/1/2007 to 16/10/2009....................................................................................................................................................56
Graph 29. Standardized Residual of GARCH Model, National Bank of Greece from 2/1/2007 to 16/10/2009....................................................................................................................................................57
Graph 30. Histogram, National Bank of Greece from 2/1/2007 to 16/10/2009.............................58
Graph 32. Residuals of GARCH Model, National Bank of Greece from 20/10/2009 to 12/09/2009....................................................................................................................................................60
Graph 33. Standardized Residuals of GARCH Model, National Bank of Greece from 20/10/2009 to 12/09/2012....................................................................................................................................................61
Graph 34. Histogram, National Bank of Greece from 20/10/2009 to 12/09/2012

Graph 35. Residual, Actual prices, Fitted prices of GARCH Model, Alpha Bank from 2/1/2007 to 16/10/2009

Graph 36. Residuals of GARCH Model, Alpha Bank from 2/1/2007 to 16/10/2009

Graph 37. Standardized Residuals of GARCH Model, Alpha Bank from 2/1/2007 to 16/10/2009

Graph 38. Histogram, Alpha Bank from 2/1/2007 to 16/10/2009

Graph 39. Residuals of GARCH Model, Alpha Bank from 20/10/2009 to 12/09/2012

Graph 40. Residuals of GARCH Model, Alpha Bank from 20/10/2009 to 12/09/2012

Graph 41. Standardized Residuals of GARCH Model, Alpha Bank from 20/10/2009 to 12/09/2012

Graph 42. Histogram, Alpha Bank from 20/10/2009 to 12/09/2012

Graph 43. Residuals of GARCH Model, Eurobank from 2/1/2007 to 16/10/2009

Graph 44. Residuals of GARCH Model, Eurobank from 2/1/2007 to 16/10/2009

Graph 45. Standardized Residuals of GARCH Model, Eurobank from 2/1/2007 to 16/10/2009

Graph 46. Histogram, Eurobank from 02/01/2007 to 16/10/2009

Graph 47. Residuals, Eurobank from 20/10/2009 to 12/09/2012

Graph 48. Residuals, Eurobank from 20/10/2009 to 12/09/2012

Graph 49. Standardized Residuals, Eurobank from 20/10/2009 to 12/09/2012

Graph 50. Histogram, Eurobank from 20/10/2009 to 12/09/2012