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Volatility analysis of the banking sector

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1 Introduction

1.1 Task: Test on the volatility of the banking sector

The aim is to test if the volatility was higher, during the years 2009-2011, in the sector of banking, than for other sectors. Thus, we will do a statistical test for the equality of the volatility between two time series. The first time series is the sequence of the daily returns of the stock prices of a french bank. The second time series is the daily returns of a general index (CAC40 for instance). It should be taken into account that the squared returns exhibit correlations, and thus the usual statistical test for equality between the means of two i.i.d. sequences should be modified accordingly. In particular, it is asked to compute the p-value of the test result. The data of the stock prices may be found on the internet (on the yahoo site for instance)

1.2 Our Choices

The french bank that we chose for our analysis is the BNP Paribas, one of the largest European banks.
During the years 2008 and 2009, it has been the first European bank being severely hit by the crisis, obliging the bank to close and freeze 3 investment funds. This crisis also had repercussions in the following years, especially in 2010, when BNP Paribas was the most affected bank in Europe and when the European Central Bank agrees to save European banks.
The general index chosen for our analysis is the CAC40, as suggested by our exercise, that is the index made up of the largest 40 companies listed in France screened by market capitalization, trading activity, size of balance sheet, and liquidity. BNP Paribas is one of the 40 firms being part of the CAC40.

2 Volatility

Volatility is a statistical measure of the dispersion of returns for a given security or market index. In finance, is often used to measure the risk of an investment or portfolio and in most cases, the higher the volatility, the riskier the security.
There are several ways to measure volatility. The most commonly used methods are the standard deviation and the variance of the returns. The standard deviation is a measure of the dispersion of the returns around the mean, while the variance is the square of the standard deviation.
Volatility is measured by calculating the standard deviation of the annualized returns over a given period of time.
Volatility of course can change over time for several reasons. Some of the common reasons for the changes in volatility include:

- *Market conditions:* Volatility tends to be higher during market downturns or periods of uncertainty. Economic recessions, political crises, and natural disasters can all lead to increased volatility in the markets.
- *Company-specific events:* Volatility can also change as a result of company-specific events such as earnings announcements, mergers and acquisitions, and management changes.
- *Investor sentiment:* Volatility can also be affected by changes in investor sentiment. When investors are optimistic, volatility tends to be lower, and when they are pessimistic, volatility tends to be higher.
- *Volatility Clustering:* Volatility tends to cluster, meaning it tends to persist over time. When volatility is high, it will stay high for a period, and when it is low, it continues to stay low for a period.
- *Leverage effect:* Some time series exhibit leverage effect which means that negative returns are more volatile than positive returns. This can lead to asymmetry in the volatility dynamics. Volatility models such as GARCH can capture the dynamics of volatility, such as volatility clustering, and leverage effect.

2.1 How to calculate Volatility

As we have said before, there are several ways to alculate volatility of a financial time series, depending on the type of data and the specific use case. The most common method is standard deviation, that is computed as:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(R(i) - R(mean))^2}{n}}$$

where **sigma** is the standard deviation of returns, **R(i)** is the return for period i, **R(mean)** is the mean return and **n** is the number of periods.
In our case, we have to calculate the standard deviation of two returns series. To calculate the returns we implement the following formula:

$$R(t) = \frac{P(t) - P(t-1)}{P(t-1)} * 100$$

For example, if we take the data from the French bank that we have chosen, it has a closing price of $58.61 on January 5th, and a closing price of $59.11 on January 6th. Then the percent change for January 6th is:

$$R(t) = \frac{59.11 - 58.61}{58.61} * 100 = 0.85$$

Once we have computed the percent change for each day of the year, we can calculate the mean return and then use these date to compute annualized volatility.

3 Historical context

The 2008 financial crisis was the worst economic disaster since the Great Depression of 1929. The crisis led to the Great Recession, where housing prices dropped more than the price plunge during the Great Depression. Two years after the recession ended, unemployment was still above 9%.

3.1 Causes

The financial crisis was primarily caused by **deregulation in the financial industry**. That permitted banks to engage in hedge fund trading with derivatives. Banks then demanded more mortgages to support the profitable sale of these derivatives. They created interest-only loans that became affordable to subprime borrowers. In 2004, the Federal Reserve raised the fed funds rate just as the interest rates on these new mortgages reset. Housing prices started falling in 2007 as supply outpaced demand. That trapped homeowners who couldn't afford the payments, but couldn't sell their house. When the values of the derivatives crumbled, banks stopped lending to each other. That created the financial crisis that led to the Great Recession. A change in bank investing regulations allowed banks to invest customer's money in derivatives. Derivatives were created from subprime residential mortgages and demand for homes skyrocketed. When the Federal Reserve raised interest rates, subprime mortgage borrowers could no longer afford their mortgages. The supply of houses outran demand, borrowers defaulted on their mortgages, and the derivatives and all other investments tied to them lost value. The financial crisis was caused by *unscrupulous investment banking and insurance practices that passed all the risk to investors*.

Big banks had the resources to become sophisticated at the use of these complicated derivatives. The banks with the most complicated financial products made the most money. That enabled them to buy out smaller, safer banks. By 2008, many of these major banks became "**too big to fail**."

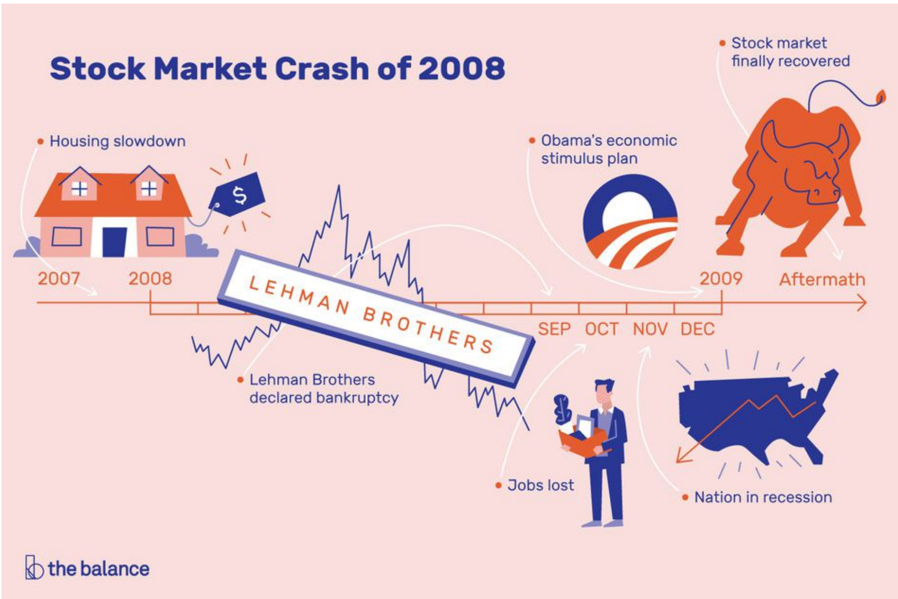

Figure 1: Timeline of Stock Market Crash

How did **securitization work?** First, hedge funds and others sold mortgage-backed securities, collateralized debt obligations, and other derivatives. A mortgage-backed security is a financial product whose price is based on the value of the mortgages that are used for collateral. Once you get a mortgage from a bank, the bank sells the loan on the secondary market. The hedge fund then bundles your mortgage with a lot of other similar mortgages. They used computer models to figure out what the bundle is worth based on several factors. These included the monthly payments, the total amount owed, the likelihood you will repay, and future home prices. The hedge fund then sells the mortgage-backed security to investors. Since the bank sold your mortgage, it can make new loans with the money it received. It may still collect your payments, but it sends them along to the hedge fund, who sends it to their investors. Of course, everyone takes a cut along the way, which is one reason they were so popular. It was basically risk-free for the bank and the hedge fund.

The investors took all the risk of default, but they didn't worry about the risk because they had insurance, called **credit default swaps**. These were sold by solid insurance companies like the American International Group. Thanks to this insurance, investors snapped up the derivatives. In time, everyone owned them, including pension funds, large banks, hedge funds, and even individual investors.

4 Solution

Time series analysis is a powerful tool for understanding and predicting patterns in data over time. It can be used to identify trends, seasonal patterns, and cyclic movements in data, and to assess whether seasonal changes are additive or multiplicative.
After choosing the French bank and the Index, thanks to the *getSymbols()* function of R, we have obtained historical financial data for the prices, selecting for both time series the closing prices for the period between the 1 January 2009 and the 31 December 2011. Financial data come from various sources such as Yahoo Finance, Google Finance, and FRED (Federal Reserve Economic Data).

After that, we calculated the returns of the two time series with the *Calculate returns* function and plotted the results that are shown in the two following graphs:

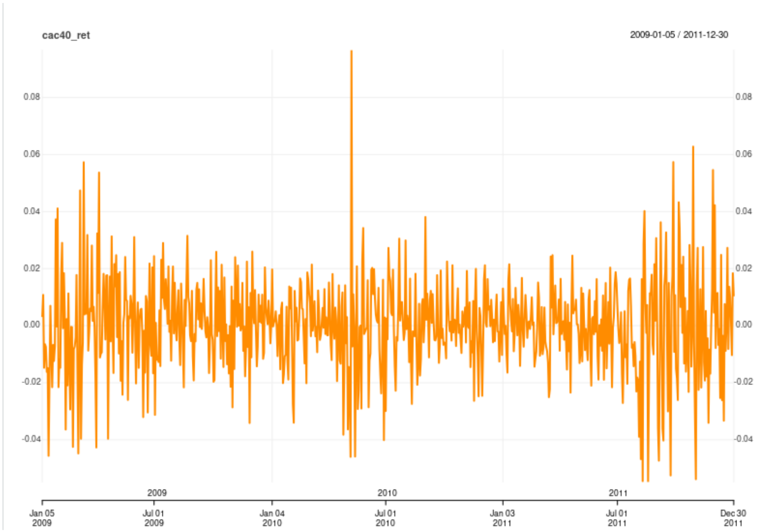

Figure 2: CAC40 time series

Figure 3: BNP times series

As we can see from the two graphs, there is a significant increase in the variability of returns over the period 2009-2011, especially in the late part of 2011 and the early part of 2009. During the crisis, volatility of returns was really high, the peak for both time series is at the end of May 2010.
Despite the huge variability of returns, we have tested whether returns are stationary or not using the Augmented Dickey-Fuller test. The result of the test shows us a very small p-value that makes us reject the null hypothesis of non-stationarity. So our returns are stationary.

Then, after having analyzed the fluctuations of the returns during the crisis period, we created the histograms of returns for the two time series and we present the results with the two following graphs:

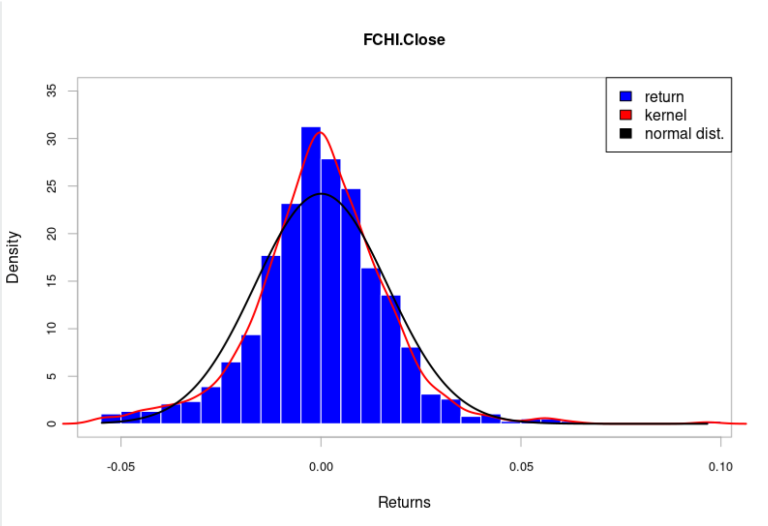

Figure 4: CAC40 distribution

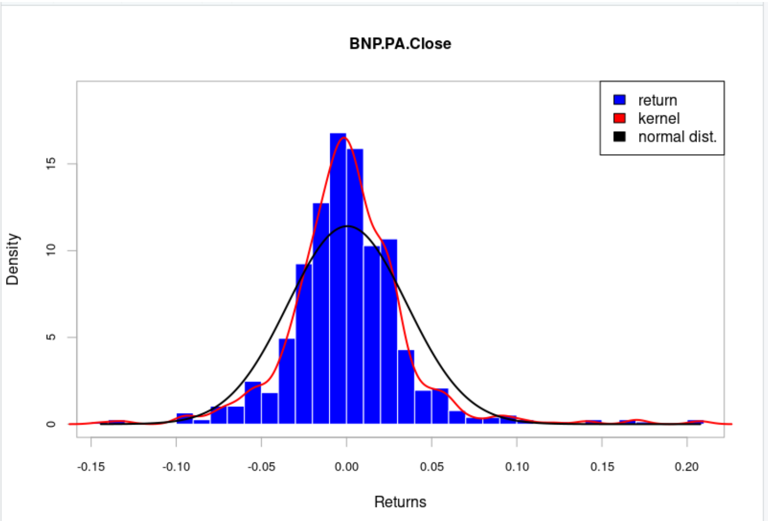

Figure 5: BNP distribution

As we can remark, neither BNP returns nor CAC40 are normally distributed. This is a crucial information for solving the exercise and to compute the equality of the two variances. The fact that returns are not normally distributed prevents us from using some statistical test available in R for the comparison of variances.
We also observe that both histograms are left-skewed.
In our code, thanks to the Shapiro test, we tested whether returns are normally distributed. For both time series, we have obtained a very small p-value, meaning that we can reject the null hypothesis of normality of returns, so our time series are not normally distributed.

4.1 Volatility Analysis

Next we can find volatility analyses performed on BNP and CAC40. From these two graphs, we can see in general a sudden increase in volatility in the years 2009- 2011, explained by the historical context of the Great Recession (also called the 2008 crisis). In particular, the volatility levels for BNP are higher than the one for the Index CAC 40. From this, we can conclude that the banking sector has been strongly hit by the financial distressed period. From figure 6, we can remark that the volatility of the CAC40 followd a decreasing path until mid of 2010, when he increased impressively. Then it mantained a lower evel until the end of 2011, when he had the second highest peak. From figure 7 for BNP instead, we can observe that the two peaks were at the beginning and at the end of the crisis. Here again we find a huge increase in mid 2010 and this reflects the path of the index.

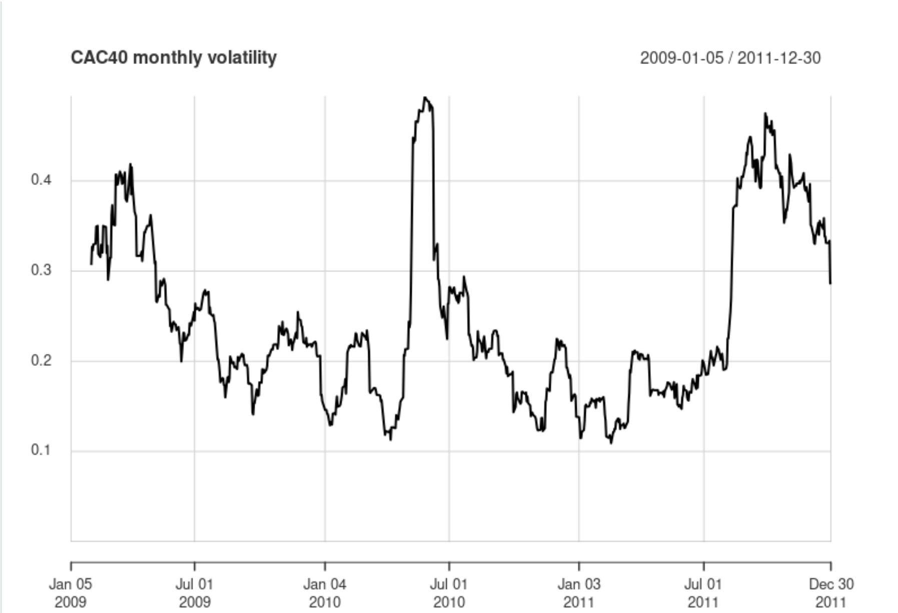

Figure 6: CAC40 monthly volatility

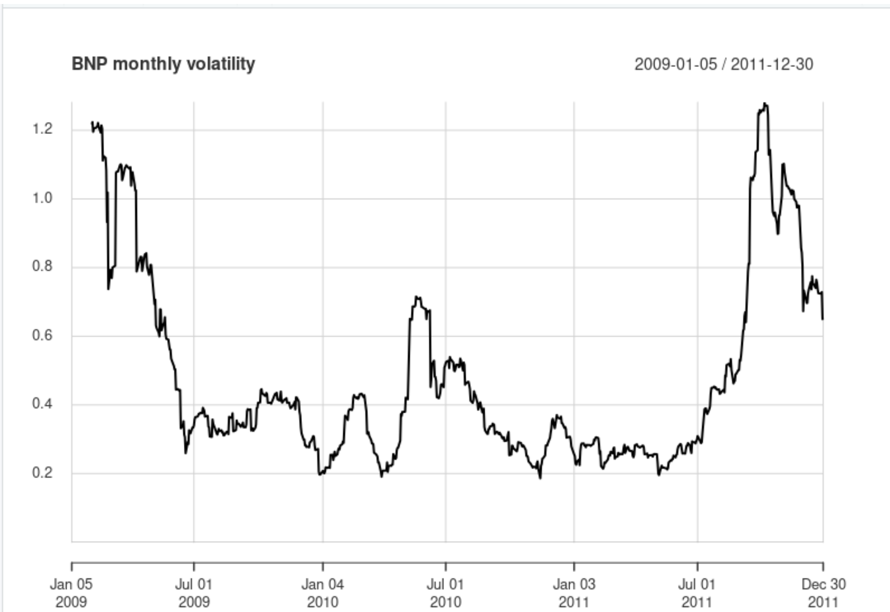

Figure 7: BNP monthly volatility

How can we justify the spikes in volatility increases in early 2009 and late 2011?
According to the **volatility paradox hypothesis**, an environment of low yields and volatility could invite excessive risk-taking by financial investors.

1. First, risk aversion tends to decline during prolonged periods of low volatility as suggested by estimates of the volatility risk premium . A lower premium amounts to investors demanding less compensation for holding risky assets. Such a fall in the price of risk changes the relative price of assets with a given risk/return trade-off and may lead to portfolio rebalancing in favour of riskier assets.

2. Second, low volatility mechanically compresses backward-looking risk measures, such as the value at risk (VaR), which shape investors' risk management decisions.

This pro-cyclical behaviour of the VaR allows investors to increase their exposure to assets which are prone to bursts of volatility for a given risk threshold. Finally, cheap funding and subdued risk measures allow investors to increase their leverage, thereby reinforcing the vulnerability of the financial sector at large.

In conclusion, by overlaying these graphs we can express that there has indeed been an increase in volatility in the banking sector (represented by BNP) but that this increase in volatility has manifested itself throughout the real economy (as we can see from the CAC 40 index).

4.2 Analysis of squared returns

After having checked the graph of the volatility, we need to test whether the two volatilities are equal or not for the time period under study. Before doing that, we have analyzed the correlation of the squared returns.
We have computed three correlation coefficients for the squared returns: the Pearson correlation coefficient, the Kendall correlation coefficient and the Spearman correlation coefficient.
All three coefficients range from -1 (perfect negative correlation) to 1 (perfect positive correlation), with 0 indicating no correlation. Pearson correlation coefficient measures the linear relationship between two variables: if the coefficient value lies between ± 0.50 and ± 1, then it is said to be a strong correlation.; Kendall correlation coefficient measures the ordinal association between two variables while Spearman correlation coefficient measures the monotonic association between two variables.

For our data, Pearson correlation coefficient is **0.62**, so our time series of squared returns are highly correlated and we have to account for this problem when testing for the equality of variances.

4.3 Comparing Variances of time series

There are several tests in R that can be used to compare the variances of two time series. Some examples include:

- *Bartlett's test:* The test is based on the chi-squared distribution and is sensitive to deviations from normality. Since our data are not normally distributed, we cannot use this test to compare the two volatilites;
- *Levene's test:* it is robust to deviations from normality and can be used when the sample sizes are not equal.
- *F-test:* It can be used to compare the variances of two or more time series if they are independently normally distributed.
- *Fligner-Killeen test:* It is based on the non-parametric rank method and is robust to deviations from normality.
- *Cochran's Q test and Brown-Forsythe test:* these tests are used to compare variances of more than two time series.

These tests cannot be used for our analysis since our data present features that are not compatible with the requirements and assumptions of these tests.
In order to deal with the squared return correlation, we decided to run a linear model regression of the squared returns on the returns of the two time series, in order to explain how the squared returns are affected by the simple returns. We used the Breusch-Pagan test on the linear model created. As a result, we have obtained a very small p-value, that leads us to reject the null hypothesis of equal volatility.
For this reason, we can affirm that the volatility of the banking sector was higher compared to the one of the other sectors, as it is shown in the figures 6 and 7. More specifically, if we look for instance at the annual volatility of the year 2009, for the CAC 40 index we have a volatility of 26% while the volatility of the BNP is 63%. The result obtained from this test confirms us that the volatility of the banking sector was higher than the volatility of the other sector during the crisis period.