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Testing for Volatility Persistence Change - The effect of the Credit Crisis on the Portuguese Banks

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Abstract

In this work project I propose to study the effect of the 2008 credit crisis on the Portuguese banking system. I will analyze the volatility of stock-returns of seven representative banks in two distinct periods, before (2001-2007) and during (2008-2012) the credit crisis. The purpose is the analysis of possible persistence changes in the structure of conditional volatility after the shock caused by the spread of the crisis. I will test for nonstationarity within a stochastic volatility model, using modified unit root tests, and also in a fractional integration context, in order to detect possible changes in the memory parameter.

Keywords: Credit Crisis, Banking System, Stochastic Volatility, Fractional Integration

1. The Credit Crisis and the Banking System

The years of 2007 and 2008 marked the beginning of the most severe financial crisis since the Great Depression. Several incidents occurred due to the collapse of Lehman Brothers, the nationalization of Fanny Mae and Freddie Mac, and the difficulties suffered by the insurance company AIG, which resulted in a financial market turmoil that, ultimately, resulted in a large shock to the real economy.

The break-down of the sub-prime mortgage market caused by the housing bubble is pointed out as the main trigger of the crisis. As stated by Naudé (2009) "The anatomy of the crisis is rather simple: easy credit, bad loans, weak regulation and supervision of complex financial instruments, debt defaulting, insolvency of key financial institutions, a loss of credibility and trust, and financial panic and mass-selling of stocks and a hoarding of cash by banks and individuals".

These consecutive events created a "domino effect", boosting the contagion of all countries that were directly or indirectly exposed to US financial markets. Stock markets tumbled and a systemic crisis with global risk aversion started, with Europe in the forefront. The spread on sovereign debt increased and currency markets were under pressure, leading to the implementation of large fiscal measures that imposed enormous challenges on long-run sustainable growth. In this context, rather than to ensure price stability, financial stability has become one of the most important goals for Central Banks.

Several mechanisms were responsible for the contagion of the crisis to other countries. One of the main propagation channels was through the banking sector. In Europe, many banks had in their portfolios large amounts of assets linked to the US housing market. A new financial system inaugurated at the time to manage the real estate loans was one of the reasons for the great attraction of foreign investments to the US, and a consequent leverage of credit expansion. In this new system, loans were pooled, divided according to their degree of risk and then resold via securitization. It was expected, in this way, to increase the stability of the system by an efficient allocation of the risk.

The European banks rushed to buy these assets, which promised high rates of return, but later revealed to have a much higher probability of default than originally alleged. After all, banks ended up buying a first class ticket to join the credit crisis. “The initial contagion from the US to international financial markets quickly morphed into real sector problems and revealed the strengths of the linkages between the financial system, the housing sector, the banking sector and the credit market (Martin and Milas, 2010).”

The multiple financial tools that were implemented by the banking system over the last decade allowed for easy access to credit, which boosted and expanded markets at a worldwide level. However, the complexity of the system evolved to an “out of control” plan that turned out causing several banking crisis.

Distress in the banking sector may lead some banks to fail and others to become capital constrained, thereby resulting in the contraction of credit supply. Under the Basel Accord, banks are only able to lend if specified capital requirements on the new loans are meet. Since the crisis, the levels of the required amount of capital sustained as collateral increased significantly which in turn limited the lending scope.

The banks’ overdraft facilities and committed back-up lines for credit were created in order to protect against liquidity pressures from costumers, but Diamond and Dybvig (1983) show that this system will not work if costumers lose their confidence and decide to withdraw their funds earlier, originating “bank-runs”, or if banks do not trust each other.

A wave of bank failures can produce (as well as be caused by) a sharp and unanticipated contraction in the stock of money. Friedman and Schwartz (1963) argued that this effect was a root cause of recessions. Households and firms adjust to the contraction in the stock of money by reducing the spending and consumption, which in turn produces a decrease in output in the short-run. Repercussions in the long-run may even be verified, since investment will be restricted due to the difficulty in accessing credit, consequently reducing capital accumulation and thus productive capacity.

The management of the crisis resolution by the authorities has a big impact on the overall consequences of the shock. "A policy of forbearance by regulators could increase moral hazard and harm output over an extended period, whereas a rapid clear-out of bad loans might be expected to improve the performance of the economy over the long-run" (Hoggart *et al*., 2001).

2. Position of the Banking Sector in Portugal

Although financial regulators have implemented several measures in order to restore financial stabilization since the current crisis began, the European banking system continues to be in very weak shape. The strong decrease of banks' profitability, the sharp fall in stock market prices, the fragility of the debt issuance market and deterioration of the banks' assets have contributed to this deterioration.

In July 2010, European banks were submitted to a "stress test", a process where the European Central Bank and the central national banks of the European Union participated. It was an attempt to restore confidence in the financial system. Two distinct macroeconomic scenarios were considered when performing the test, one taken as reference based on the 2009 autumn forecasts and the other representing adverse conditions estimated by the ECB.

The main conclusion of the tests was a significant capacity of overall European banks' resistance to the shocks presented. In Portugal the exercise also did not imply a recapitalization of the Portuguese Banks. Despite the deterioration of the profitability and solvency indicators in the adverse scenario, the banks analyzed showed ability to absorb the shocks, while continuing to provide Tier 1 capital ratios above the reference level (6%), hence well above the capital requirements (Morais, 2011/12).

The Core Tier 1 is considered to be the capital ratio with higher quality and the most valued in financial markets, as an indicator of the financial health of a bank. In September 2011, the average ratio for the Portuguese banking sector was 8.5%, and 6.8% in late 2008. Since then, Portuguese banks have continued to reinforce their financial strength indices (Banco de Portugal, 2012). These levels are sufficient to keep up with European Regulation and National Regulation.

The Bank of Portugal has increased the minimum levels of Core Tier 1 requirements to 9% at the end of 2011 and to 10% in late 2012, due to the Economic and Financial Assistance Agreement, signed in the second quarter of 2011 with the International Monetary Fund, the ECB and the European Commission. The agreement included the strengthening of the requirements relative to the Portuguese banks' solvency levels, in a context of extreme adversity in relation to access to international markets for funding and widespread deterioration of the economic environment (Banco de Portugal, 2012).

The objectives settled for the Portuguese banking sector have been fulfilled through operations of capital increase, conversion of debt and repurchases of debt traded in the market. However, the major Portuguese banking groups show a negative aggregate net income in 2011. This was mainly due to impairment losses related to loan portfolios and exposure to the Greek sovereign debt, as well as the transfer of the pension retirement liabilities to the Social Security (Banco de Portugal, 2012).

3. Literature Review

When attempting to model financial relationships in the econometric framework, we have to take into account that many of them usually present a non-linear structure. As Campbell, Lo and MacKinlay (1997) state, the payoffs of options are non-linear in some of the input variables, and investors' willingness to trade off returns and risks are also non-linear. Literature also shows that some financial phenomena cannot be explained by linear time series models such as leptkurtosis, volatility clustering and leverage effects. Thus, there is strong motivation to consider the application of non-linear models in order to construct reliable representations of the variables under analysis.

Under the most popular volatility models, autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH), the tendency of volatility to occur in bursts is modeled by allowing the conditional variance of the error term, σ_t^2, to depend on the previous value of the squared error. There are several advantages in modeling the volatility across time: first, more robust inference can be applied when modeling the mean; second, it may be a useful tool for prediction. However, some difficulties arise when estimating these models, in which stands out for the ARCH model the decision of the number of lags of the squared residual required to capture all of the dependence in the conditional variance, and the fact that non-negativity constraints might be violated. The GARCH is a natural extension of the ARCH model, developed by Bollerslev (1986) and Taylor (1986). Under GARCH, shocks to variance persist according to an autoregressive moving average (ARMA) structure of the squared residuals of the process. The model tends to be in general more parsimonious than ARCH, as lagged conditional variances include much more information than lagged squared residuals, and are much less likely to breech non-negativity constraints. Nevertheless, GARCH models are still not able to account for a number of non-linear effects, such as leverage effects. Considering this characteristics of the model, several extensions have been proposed – e.g. the EGARCH is a more flexible model that does not imposes restrictions on the estimates, and also allows for leverage effects; as well as the TGARCH model which also allows for asymmetries (since in finance negative shocks may induce more volatility than positive ones), by including a dummy variable. Evidence from financial-market data suggests that the volatility of assets returns tends to follow the pattern of being time varying and highly persistent. This apparent empirical regularity has motivated Engle and Bollerslev (1986) to introduce the integrated-GARCH (I-GARCH) process, in which shocks to variance do not decay over time. Integration in variance is analogous to a unit root in the mean of a stochastic process, an example of which is a random walk (Lamoreux and Lastrapes, 1990).

Poterba and Summers (1986) showed that the extent to which stock-return volatility affects stock prices (through a time-varying risk premium) depends critically on the permanence of shocks to variance. In this context, classifying a series as stationary or non-stationary is crucial to understand the effects of shocks on the financial variables. The impact of shocks will be transitory for stationary series, while for non-stationary ones random shocks may have persistent effects.

Recently, new stochastic volatility models were proposed (see e.g. Hansen, 1995; Harvey *et al.* , 1994; Ruiz 1994) in which the variance at date t is random, although it is conditional on the information of previous periods. These models are natural discrete time analogues of the continuous time models used in modern finance theory, and may fit the data better than ARCH/GARCH models (Wright, 1999).

The stochastic volatility model represents the volatility as an autoregressive process. Interestingly, we can test for a unit root in the unobserved volatility process by testing for a unit root in the log of the squared time series (Wright 1999), which constitutes an ARMA process. Although, there is a problem that results when performing these tests, as they are composed by large negative moving average roots (Harvey *et al.*, 1994), which induce distortions and lead conventional unit root tests to have very poor size properties (Schwert, 1989); Pantula, 1991). Perron and Ng (1996), building on the work of Stock (1990, unpublished manuscript), presented modified unit root tests that have shown evidence to have better finite sample properties in tests with large MA roots.

A major theme of non-linear time series in finance and econometrics concerns the influence of instantaneous non-linear transformations on measures of memory (Robinson 2000). Recently, several papers make reference to a property common to the squares, log-squares and absolute value of asset returns. According to literature, the autocorrelation functions of these variables are best characterized by a slowly- mean hyperbolic rate of decay. This property has been found in many exchange rate and stock returns, but is not consistent with the standard ARCH/GARCH or stochastic volatility models (Wright, 2000). As attempts to model this phenomenon of the autocorrelation function in time series, long memory models have been proposed – the most accepted is the ARFIMA model, consisting of a fractional integrated ARMA model (Granger and Joyeux, 1998, and Hosking, 1981).

Ultimately, the ARFIMA framework has been applied in order to model the volatility process, with long memory models that replicate the hyperbolic rate of decay observed in the volatility time series when measured by the squared, log-squared and absolute returns. These include the long memory ARCH model in Robinson (1991), the fractionally integrated GRACH, or FIGARCH, model in Bollerslev and Mikkelsen (1996) and Baillie, Bollerslev and Mikkelsen (1996) and the fractionally integrated stochastic volatility model in Breidt, Crato and de Lima (1998).

4. The Model

4.1. Stochastic Volatility Model – Ng Perron Test Statistics

Wright (1999) proposes a stochastic volatility model which I will also consider, in order to test for persistence change in the conditional volatility of several Portuguese banks' stock returns.

The method is based on the standard autoregressive stochastic volatility (ARSV) model which specifies that $\{y_t\}_{t=1}^{T}$ is a time series of returns, such that,

$$y_{t=} \sigma_t \varepsilon_t, \tag{I}$$

where ε_t is i.i.d. with mean zero and variance 1.

Considering that:

$\log(\sigma^2) = \mu + h_t$

$a(L)h_t = \eta_t$, where η_t is i.i.d. with mean zero and variance σ_η^2, distributed independently of ε_t, $a(L) = b(L)(1 - \alpha L)$ is a *p*th-order autoregressive lag polynomial such that $b(L)$ has all roots outside the unit circle; and α is the largest autoregressive root of the volatility process.

The model further represents volatility as an autoregressive process, implying that the log of the squared time series is an ARMA process i.e. ,

$$a(L)\log(y_t^2) = a(1)\mu + \eta_t + a(L)\log(\varepsilon_t^2) \qquad \text{(II)}$$

$$a(L)\log(y_t^2) = \omega + \eta_t + a(L)\xi_t = \omega + x_t\ , \qquad \text{(III)}$$

where $\xi_t = \log(\varepsilon_t^2) - E(\log(\varepsilon_t^2))$, $\omega = a(1)\big(\mu + E(\log(\varepsilon_t^2))\big)$ and $x_t = \eta_t + a(L)\xi_t$.

Estimation of the parameters of this model is quite complex, requiring distributional assumptions for the error terms, ε_t and η_t. However, if the purpose is just to test whether $\alpha = 1$ or not, the method is simple and no distributional assumptions need to be imposed (Wright, 1999).

As indicated by Wright (1999), the time series $x_t = \eta_t + a(L)\xi_t$ is an MA(p) reduced form and $\log(y_t^2)$ is a stationary ARMA(p,p) process if $|\alpha| < 1$ and an ARIMA(p-1,1,p) if $\alpha = 1$, being α the largest autoregressive root of $\log(y_t^2)$. Thus, it is possible to test the hypothesis $\alpha = 1$ by testing for a unit root in the $\log(y_t^2)$ series.

In order to test for the presence of a unit root it is possible to use a variety of tests. However, as was already mentioned in the literature review, they are expected to have very poor size properties, since $\log(y_t^2)$ has an ARMA or ARIMA representation with a large negative moving average root.

Applying these modified unit root tests to the $\log(y_t^2)$ series, with the null hypothesis that $\alpha = 1$ against the alternative $|\alpha| < 1$, the three test statistics are:

$$MZ_\alpha = [T^{-1}(v_T - \bar{v})^2 - s^2][2T^{-2}\sum_{t=1}^{T}(v_T - \bar{v})^2]^{-1} \quad \text{(IV)}$$

$$MSB = [s^{-2}T^{-2}\sum_{t=1}^{T}(v_T - \bar{v})^2]^{1/2} \quad \text{(V)}$$

$$MZ_t = MZ_\alpha \ . \ MSB \quad \text{(VI)}$$

where $v_T = \log y^2$, $\bar{v} = T^{-1}\sum_{t=1}^{T} v_t$ and s^2 is the autoregressive spectral density estimate obtained from the autoregression

$$v_t = \alpha_0 + \alpha_1 v_{t-1} + \sum_{j=1}^{k} \alpha_j \Delta v_{t-j} + e_t \quad \text{(VII)}$$

where $k = o(T^{1/3})$.

The three tests are all one-sided and Wright (1999) describes how they manage the size property in the presence of large negative MA roots, referring that it depends on the choice of the spectral density estimator.

4.2. Long memory – Fractional Integration Model

Wright (1999) also considers the fractional integrated stochastic volatility (FISV) as a simpler version of the model proposed by Breidt *et al.* (1998). I will use this model in order to test for persistence change of the Portuguese bank's stock returns, in the fractional integration context.

The model specifies that $\{y_t\}_{t=1}^{T}$ is a time series of returns such that:

$$y_t = \sigma_t \varepsilon_t \quad \text{(VIII)}$$

where ε_t is i.i.d. with mean zero and variance 1, $\log(\sigma_t^2) = \mu + h_t$

$$(1 - L)^{d_t}(1 - \alpha L)h_t = \eta_t \quad \text{(IX)}$$

$(1-L)^{d_t}$ denotes the fractional differencing operator and η_t is i.i.d. $N\left(0, \sigma_\eta^2\right)$ and is independent of ε_t.

Martins and Rodrigues (2012) introduce the persistence change tests. The null hypothesis of the test considers that the fractional integrated parameter d_t is constant over the complete sample $(d_t = d_0)$. The alternative hypothesis considers two fractional integration parameters - d_0 corresponds to the first subsample and d_1 to the second. Within the alternative hypothesis two different results can be considered: i) a decrease in persistence $(d_0 > d_1)$; or ii) an increase in persistence $(d_0 < d_1)$. Under both alternatives the change in persistence occurs at time $[\tau^* T]$, with τ^* unknown in $[\Lambda_l, \Lambda_u] \subset (0,1)$ and $\Lambda_u = 1 - \Lambda_l$.

Considering the data generated from (IX), with $d_t = d_0$, for each fixed $\tau \in [\Lambda_l, \Lambda_u]$, Martins and Rodrigues (2012) present the following auxiliary regression:

$$x_t = \phi\,(\tau) x_{t-1}^* + e_t, \qquad t = 2, \ldots, [\tau T] \tag{X}$$

where $x_t = (1-L)^{d_t} h_t$ and $x_{t-1}^* = \sum_{j=1}^{t-1} \frac{x_{t-j}}{j}$. Changes in the memory parameter are detected by recursively estimating (X) over the complete sample. Considering the auxiliary regression (X), the OLS t-statistic for $\hat{\phi}(\tau) = 0$, which is denoted as $t_{\phi f}(\tau)$, is computed for each $\tau \in [\Lambda_l, \Lambda_u]$, i.e.,

$$t_{\phi f}(\tau) = \frac{\sum_{t=2}^{[\tau T]} x_t x_{t-1}^*}{\hat{\sigma}_e(\tau)\sqrt{\sum_{t=2}^{[\tau T]} x_{t-1}^{*2}}} \tag{XI}$$

where $\hat{\sigma}_e(\tau) = \sqrt{\frac{1}{[\tau T]-2} \sum_{t=2}^{[\tau T]} \hat{e}_t^2}$ and $\hat{e}_t$ is the least square residual of (X). The parameter Λ_l that defines the lower bond of the set of values for τ is an arbitrary value, typically 0.15 or 0.20.

Martins and Rodrigues (2012) also introduce a second auxiliary regression, representing the reverse statistic, $t_{\phi f}(\tau)$, where x_t is replaced by the time-reversed series $w_t = x_{T-t+1}$. Hence, for $(1-\tau)T$ observations it follows:

$$w_t = \phi(\tau) w_{t-1}^* + u_t, \qquad t = 2,\ldots,[\tau T], \tag{XII}$$

where $w_t = x_{T-t+1}$, $w_{t-1}^* = \sum_{j=1}^{t-1} \frac{w_{t-j}}{j} = \sum_{j=1}^{t-1} \frac{x_{T-t+j+1}}{j} = x_{T-t+2}^*$.

The t-statistic to test $\hat{\phi}(\tau) = 0$, follows:

$$t_{\phi r}(\tau) = \frac{\sum_{t=2}^{[(1-\tau)T]} w_t w_{t-1}^*}{\hat{\sigma}_u(\tau)\sqrt{\sum_{t=2}^{[(1-\tau)T]} w_{t-1}^{*2}}} = \frac{\sum_{t=2}^{[(1-\tau)T]} x_{T-t+1} x_{T-t+2}^*}{\hat{\sigma}_u(\tau)\sqrt{\sum_{t=2}^{[(1-\tau)T]} x_{T-t+2}^{*2}}} \tag{XIII}$$

where $\hat{\sigma}_u(\tau) = \sqrt{\frac{1}{[(1-\tau)T]-2} \sum_{t=2}^{[(1-\tau)T]} \hat{u}_t^2}$ and $\hat{u}_t$ is the least-squares residual of the auxiliary regression (XII).

The authors also consider for the purpose of detection of possible changes in the memory parameter, the squares of the t-statistics (XI) and (XIII), introducing the *supremum* statistics over $\tau \in [\Lambda_l, \Lambda_u]$, such that:

$$\mathcal{T}_k^2 \equiv \sup t_{\phi k}^2(\tau), \quad with\ k = f, r. \tag{XIV}$$

and for the case of the direction of the changes being unknown:

$$\mathcal{T}_{max}^2 = max\{\mathcal{T}_f^2, \mathcal{T}_r^2\}. \tag{XV}$$

5. The results

In this section I report the results of the Ng-Perron unit root and fractional integration test statistics applied to a series of Portuguese Banks' daily returns. The purpose is the analysis of persistence change in the conditional volatility after the shock caused by the spread of the crisis, in the Portuguese banking system. I will therefore analyze the persistence of volatility of the stock returns of seven representative banks in the sector, in two distinct periods, before (2001-2007) and during (2008-2012) the crisis.

The banks selected in order to perform the tests were: Banco Comercial Português (BCP), Banco Espirito Santo (BES), Banco Português de Investimento (BPI), Banco Popular Espanhol (BPE), Banco Santander Totta (SANT), Banif (BNF), and Finibanco (FNB). The daily stock prices data were obtained from Bloomberg and the stock returns were constructed as the first differences of the log daily prices. The data of the daily prices covered the years 2001-2012 (in 2012 until 1^{st} October) for all banks, with the exception of BPE, whose data was only available since February 2006.

The following figures represent the daily returns concerning each bank over the time period 2001-2012.

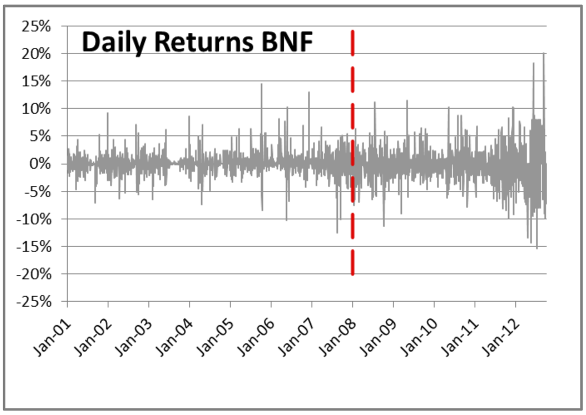

Figure I

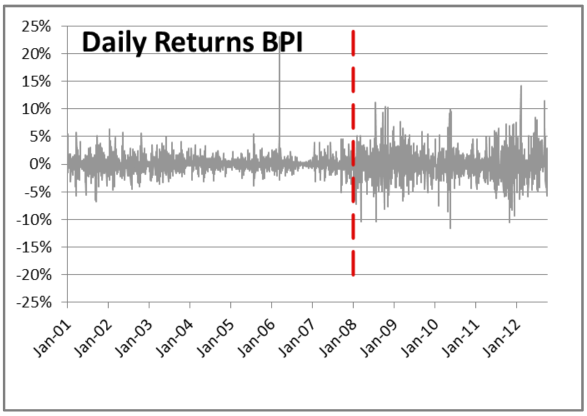

Figure II

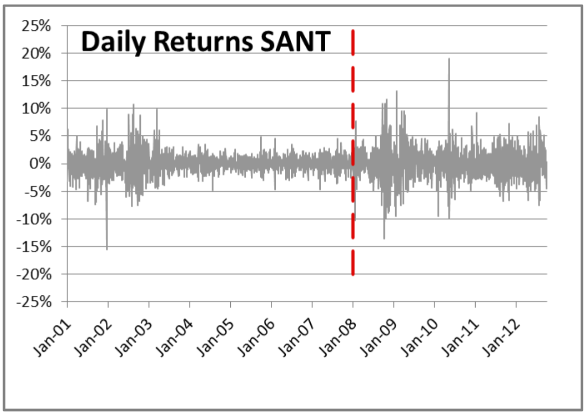

Figure III

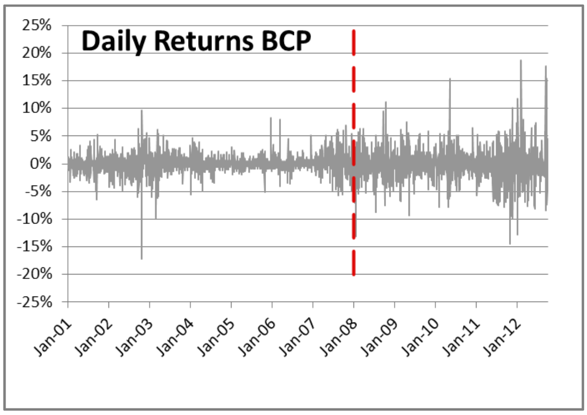

Figure IV

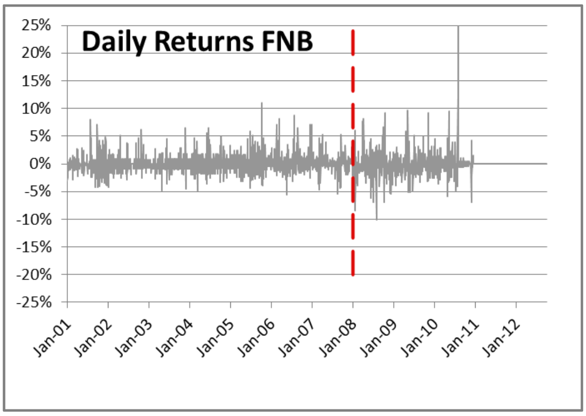

Figure V

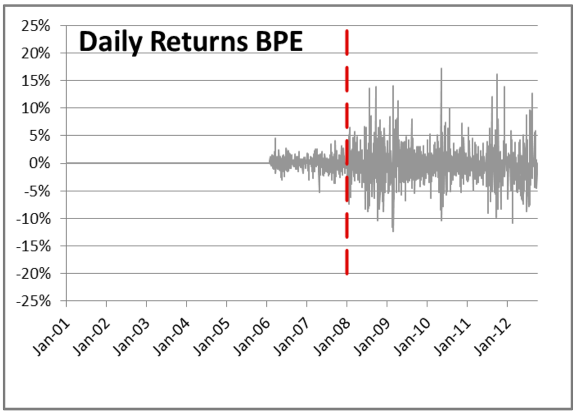

Figure VI

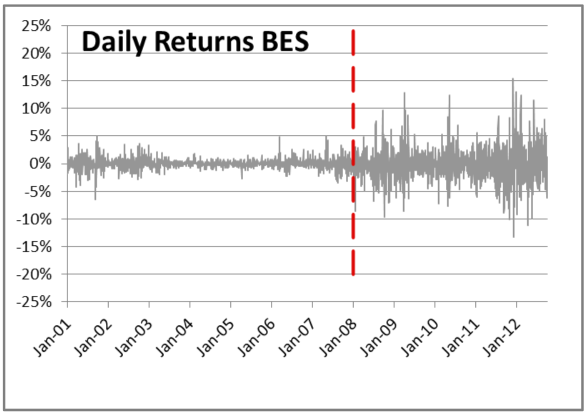

Figure VII

As one can observe, there is a significant increase in the volatility indices since 2008. In almost all figures it is possible to see a clear difference between the two periods.

5.1. Stochastic Volatility Model – Ng Perron Test Statistics

By applying the unit root tests to the $\log(y_t^2)$ series, we test for nonstationarity in the structure of the volatility since the crisis, which ultimately would be represented by a less significant degree of persistence in the stock-returns volatility series, in the 2008-2012 time period. Thus, in theory, by performing the Ng-Peron test statistics, it would be expected that the results showed higher rejections of the null hypothesis - $\log(y_t^2)$ has a unit root – in the post-crisis period, demonstrating that after the shock, past volatility values would have less impact on future ones, and so predicting risk has become more difficult.

The following tables present the results of the Ng-Perron test statistics. Three different time samples were considered, in order to make a more accurate comparison. The first table (I) refers to the pre-crisis period (2001-2007), the second table (II) to the post-crisis period (2008-2012) and the third table (III) covers the whole sample (2001-2012). The number of observations for the first sample consisted of 1825 for all banks with the exceptions of BPE bank, whose number was 502. The second sample was comprised by 1239 observations of all banks. The last sample is the sum of the first two, with the total of 3065 observations for all banks with the exception of BPE, whose value was 1742.

Table I - Ng-Perron unit root test: 2001-2007 Sample

Ng-Perron Test Statistics:	MZ_α	MZ_t	MSB
BCP	-398.876***	-14.122***	0.035***
BES	-3.503	-1.112	0.317
BNF	-47.336***	-4.833***	0.102***
BPE	-19.005***	-3.061***	0.161***
BPI	-13.763**	-2.457**	0.179**
FNB	-11.513**	-2.398**	0.208**
SANT	-13.556**	-2.544**	0.187**

Null Hypothesis: log (y^2) has a unit root
Rejection Levels: *10%; **5%; ***1%

Table II - Ng-Perron unit root test: 2007-2012 Sample

Ng-Perron Test Statistics:	MZ_α	MZ_t	MSB
BCP	-13.665**	-2.613***	0.191**
BES	-7.691*	-1.925*	0.250*
BNF	-50.067***	-4.938***	0.099***
BPE	-11.038**	-2.349**	0.212**
BPI	-491.740***	-15.677***	0.032***
FNB	-2.003	-0.844	0.421
SANT	-102.065***	-7.124***	0.070***

Null Hypothesis: log (y^2) has a unit root
Rejection Levels: *10%; **5%; ***1%

Table III - Ng-Perron unit root test: 2001-2012 Sample

Ng-Perron Test Statistics:	MZ_α	MZ_t	MSB
BCP	-58.462***	-5.344***	0.091***
BES	-10.691**	-2.311**	0.216**
BNF	-18.273***	-3.020***	0.165***
BPE	-34.004***	-4.110***	0.760***
BPI	-27.750***	-3.725***	0.134***
FNB	-5.996*	-1.602*	0.267*
SANT	-20.096***	-3.125***	0.155***

Null Hypothesis: log (y^2) has a unit root
Rejection Levels: *10%; **5%; ***1%

Comparing the three tables (I, II, III), we can observe that there are no significant differences between the results presented by the tests performed, comprising each sample of the stock-returns volatility of the seven banks. Apart from the banks BES and FNB that do not reject the null hypothesis in the first and second samples, respectively, all the other tests present fairly high rejections, regardless of the time periods considered. However, despite the results do not let us take many conclusions regarding the comparison between the different samples, they are in accordance with the results presented by Wright (1999), who applied the tests to exchange rate returns series. The author describes the results as yielding "overwhelming rejections" with strong evidence against the model of a unit root in the volatility process at all conventional significance levels, using the tests that are robust to a large MA root, which are the conclusions that globally we also obtain.

5.2. Long memory – Fractional Integration Model

In this section we test for persistence change in the memory parameter of the Banks' volatility series. Since the results of the first section were not very conclusive, by performing these tests, it is expected that the results reflect more accurately the shock caused by the crisis on the Portuguese banking sector.

Firstly two regressions were considered in order to perform the tests for each bank: the first with four lags and a second with twelve lags. Both tests had the same consistent results, so for the purpose of exposition only the results of the first regression will be presented. The tests covered the whole sample (2001-2012), with a total of 3065 observations for all banks with the exception of BPE, whose value was 1742.

Under the null hypothesis d_t is constant over time ($d_t = d_0$). When the null hypothesis is rejected, and there is evidence of a change in persistence, an estimated break point is obtained, $\hat{\tau}$, and the two respective memory parameters, one for each sub period are estimated - d_1 corresponds to the first subsample and d_2 to the second. The results are provided in the following table:

Table IV – Persistence test results: 2001-2012 Sample

	$max\{\mathcal{T}_f^2, \mathcal{T}_r^2\}$	$\hat{\tau}$	date	d_1		d_2
BCP	119.522***	0.778	2008:04	0.3803***	→	-0.1959*
BES	130.397***	0.788	2010:03	0.4259***	→	0
BNF	100.705***	0.790	2010:04	0.4209***	→	-0.1936*
BPE	71.042***	0.710	2005:09	0.3976***	→	-0.1943*
BPI	102.262***	0.775	2008:04	0.3879***	→	0
FNB	61.738***	0.798	2008:05	0.2349***	→	-0.0577*
SANT	120.071***	0.798	2008:06	0.2980**	→	-0.4582***

Null Hypothesis: $\boldsymbol{d_t}$ **is constant over the time sample** $(\boldsymbol{d_t = d_0})$
Rejection Levels: *10%; **5%; ***1%

By applying the squares of the t-statistics (as described in the second part of the model section) and considering the maximum value, $\mathcal{T}_{max}^2 = max\{\mathcal{T}_f^2, \mathcal{T}_r^2\}$, the rejection of the null hypothesis is based on specific critical values - Martins and Rodrigues (2012) present the critical values for different sample sizes, $T \in \{100, 250, 500, 750\}$, and fractional integration parameters $d_0 \in \{-0.5, 0.4, \dots, 0.5, 0.6, 0.8\}$, which were computed based on 10000 Monte Carlo replications, with $\Lambda_l = 0.2$ and $\Lambda_u = 0.8$. The values for T and d_0 considered for the tests of each Bank were: $T = 750$ (maximum level of observations) and $d_0 = 0.4$ (the values estimated for this parameter were approximately equal to 0.4 in all the seven tests). Consequently, the critical values obtained were: 6.153 for 10%, 8.720 for 5% and 10.948 for 1% significance.

As can be observed, the null hypothesis of parameter constancy is rejected for all banks. With the exception of BPE, in all the other banks, the break point occurs after 2008, which is in accordance with what was expected, since the post-crisis period considered is (2008-2012).

Within the alternative hypothesis the results show that $(d_1 > d_2)$, meaning a decrease in persistence and rejection of long memory in the volatility series. The critical values for the d_t parameter were obtained through the Normal distribution.

This result may be explained by the fact that, as previously mentioned, the Portuguese Banks passed through a process of reinforcing their financial strength indices, providing Tier 1 capital ratios above the capital requirements. This behavior might have smoothed the shock that theoretically would reflect stronger repercussions in the volatility series.

It is also important to note that the application of these persistence change tests is being performed in a new context, and that future investigation is still needed in terms of evaluating and analyzing the performance of the tests to provide the results greater robustness.

6. Conclusion

The Credit Crisis initiated in 2008 in the US market, quickly expanded in a global level, affecting with severe intensity Europe. Since the banking system was one of the main propagation channels of the crisis, in order to recover stability and confidence Banks made great efforts to reinforce their financial strengths.

The aim of this work project was to study the effect of the crisis on the Portuguese banking system. Considering the stock-returns of seven representative Banks of the sector, an analysis within an econometric framework was made. The purpose was the detection of possible persistence changes in the structure of conditional volatility after the shock caused by the spread of the crisis. Two different and complementary models were applied: a stochastic volatility model, which presented modified unit root tests that have shown evidence of having better finite sample properties in tests with large MA roots; and a fractionally integrated model in order to test for persistence change in the memory parameter of the volatility series.

The unit root tests for the first model were performed on three different sample sizes, in order to compare the periods before and after the crisis. All three tests present fairly high rejections of the null hypothesis, regardless of the time periods considered. The results obtained at this stage were in accordance with the results presented by Wright (1999) who applied the tests to exchange rate returns series.

With the objective of reaching better explanatory results, testing the memory parameter of the series showed evidence of persistence change, with a break point occurring after the shock (2008) in all the banks, excepting the BPE, what is in accordance what was expected. The tests results also indicate a decrease in persistence between each sub-period estimated by the alternative hypothesis, concluding that the processes have short-memory. This result may be explained by the fact that Portuguese Banks passed through a process of reinforcing their financial strength indices, providing Tier 1 capital ratios above the capital requirements, increasing their capacity of resistance to shocks.

References

(1) Aguiar-Conraria, L. Alexandre, F. Correia de Pinho, M. 2012. "O euro e o crescimento da economia portuguesa: uma análise contrafactual." *Instituto de Ciências Sociais de Universidade Nova de Lisboa,* 47(2)

(2) Alizadeh, S. Brandt, M. Diebold, F. 2002. "Range-Based Estimation of Stochastic Volatility Models.", *The Journal of Finance,* 57(3)

(3) Banco de Portugal. 2009. "A Economia Portuguesa no contexto da integração económica, financeira e monetária."

(4) Banco de Portugal. 2012. "Evolução da solvabilidade do sistema bancário."

(5) Berkmen, P. Gelos, G. Rennhack, R. Walsh, J. 2009. "The Global Financial Crisis: Explaining Cross-Country Differences in the Output Impact.", *IMF Working Paper,* 09/208

(6) Brooks, Chris. 2008. *Introductory Econometrics for Finance.* Cambridge: Cambridge University Press

(7) Brunnermeier, M. 2008. "Deciphering the Liquidity and Credit Crunch 2007-08", *Journal of Economic Perspectives,* 23(1): 77-100

(8) Claessens, S., Dell'Ariccia, G. Igan, D. Laeven, L. 2010. "Lessons and Policy Implications from the Global Financial Crisis.", *IMF Working Paper,* 10/44

(9) Dell'Ariccia, G. Detragiache, E. Rajan, R. 2008. "The real effect of banking crises.", *Journal of Financial Intermediation,* 89-112

(10) Furceri, D. Zdzienicka, A. 2011. "The Real Effect of Financial Crises in the European Transition Economies.", *Economics of Transition, The European Bank for Reconstruction and Development,* 19(1): 1-25

(11) Hoggarth, G. Reis, R. Saporta, V. 2001. "Cost of banking system instability: some empirical evidence.", *Bank of England Working Papers*

(12) Jacquier, E. Polson, N. Rossi, P. 1994. “Bayesian Analysis of Stochastic Volatility Models.”, *Journal of Business & Economics Statistics*, 12(4)

(13) Mallick, S. Sousa, R. 2011. “The real effects of financial stress in the Euro zone.”, *NIPE Working Papers,* 12/2001

(14) Martins, L. Rodrigues, P. 2012. “Testing for persistence change in fractionally integrated models: an application to world inflation rates”, *Preprint submitted to Computational Statistics and Data Analysis*

(15) Mishkin, F. 1992. “Anatomy of a financial crisis.”, *Journal Evolutionary Economics*, 2:115-130

(16) Morais, H. 2011/2012. “Situação da banca e a crise do sistema bancário”, *Janus,* 114-115

(17) Naudé, W. 2009. “The Financial Crisis of 2008 and the Developing Countries.”, *WIDER Discussion Paper,* 2009/01

(18) Robinson, P. 2000. “The memory of stochastic volatility models.”, *Journal of Econometrics,* 195-218

(19) Uhlig, H. 2002. “One money, but many fiscal policies in Europe: What are the consequences?”, *CEPR Discussion Papers,* 3296

(20) Wright, J. 1999. “Testing for a unit root in the volatility of Asset Returns.”, *Journal of Applied Econometrics*, 14: 309-318

(21) Wright, J. 2000. “Log-periodogram estimation of long memory volatility dependencies with conditionally heavy tailed returns”, *International Finance Discussion Papers*, 685