Universidade do Minho

Documentos de Trabalho

Working Paper Series

"Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI"

Vítor Castro

NIPE WP 11/ 2012

NÚCLEO DE INVESTIGAÇÃO EM POLÍTICAS ECONÓMICAS

UNIVERSIDADE DO MINHO

“Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI”

Vítor Castro

NIPE* WP 11/ 2012

URL:
http://www.eeg.uminho.pt/economia/nipe

Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI

Vítor Castro[*]

University of Coimbra and NIPE, Portugal

Abstract

In this paper, we analyse the link between the macroeconomic developments and the banking credit risk in a particular group of countries – Greece, Ireland, Portugal, Spain and Italy (GIPSI) – recently affected by unfavourable economic and financial conditions and to which, on this matter, the literature has not given a particular attention yet.

Employing dynamic panel data approaches to these five countries over the period 1997q1-2011q3, we conclude that the banking credit risk is significantly affected by the macroeconomic environment: the credit risk increases when GDP growth and the share price indices decrease and rises when the unemployment rate, interest rate, and credit growth increase; it is also positively affected by an appreciation of the real exchange rate; moreover, we observe a substantial increase in the credit risk during the recent financial crisis period. Several robustness tests with different estimators have also confirmed these results.

Keywords: Credit risk; Macroeconomic factors; Banking system; GIPSI; Panel data.

JEL classification: C23; G21; F41.

[*] V. Castro: Faculty of Economics, University of Coimbra, Avenida Dias da Silva 165, 3004-512 Coimbra, Portugal; Economic Policies Research Unit (NIPE), University of Minho, Campus de Gualtar, 4710-057, Braga, Portugal. Tel.: +351 239 790543; Fax: +351 239 790514; E-mail: vcastro@fe.uc.pt

1. Introduction

The recent financial crisis has called the attention to the consequences that banking crises can have on the economy (Agnello and Sousa, 2011; Agnello et al., 2011). At the same time, it has also stimulated some economists to look again at the factors that may trigger a banking crisis (De Grauwe, 2008; Laeven and Valencia, 2008, 2010). Macroeconomic factors are considered to play an important role on this matter (Demirguç-Kunt and Detragiache, 1998; Llewellyn, 2002). More specifically, adverse economic conditions, where growth is low or negative, with high levels of unemployment, high interest rates and high inflation, are favourable to banking crises (Demirguç-Kunt and Detragiache, 1998). Llewellyn (2002) also notices that in any banking crisis there is an interaction between economic, financial and structural weaknesses. Moreover, most of the banking crisis is preceded by changes in the economic environment that move the economy from a growth cycle to a recession.

A banking crisis may also arise because, in first place, banks can be struggling with liquidity and/or insolvency problems caused by the increase of bad or nonperforming loans in their balance sheets. This also means that before looking at the causes of banking crisis, we must give attention to the conditionings of the banking credit risk. Several studies have focused their attention on this matter and have concluded that the macroeconomic environment is the most important factor in the determination of the credit risk.[1]

In this paper, we intend to understand this link between the macroeconomic developments and the credit risk in a particular group of countries (Greece, Ireland, Portugal, Spain and Italy – henceforth, GIPSI) recently affected by unfavourable economic and financial conditions and to which the literature has not given a particular attention yet on this matter. The unfavourable conditions that they are facing (recession and unemployment), the

[1] See, for example, Salas and Saurina (2002), Jimenez and Saurina (2006), Quagliariello (2006), Jakubík (2007), Aver (2008), Bohachova (2008), Bonfim (2009), Kattai (2010), Festic et al. (2011), Nkuzu (2011) and Louzis et al. (2012), among others.

high levels of public deficits and debts that they present and the difficulties that they have felt in borrowing money to finance their economies were critical in our decision of choosing them for this analysis. This deterioration of the economic environment may increase the risk of credit default in these countries. Therefore, it becomes pertinent to study how macroeconomic variables are affecting the credit risk in this more vulnerable group of countries and the respective policy implications. As the risk of default is highly influenced by the way families and companies are affected by the economic environment, we believe that some macroeconomic factors will take a substantial part in the explanation of the credit risk.

Employing a proper dynamic panel data approach, that relies on the Arellano-Bond estimator, over this particular group of countries spanning the period from the first quarter of 1997 to the third quarter of 2011, we conclude that the credit risk in these five countries is significantly affected by the macroeconomic environment. In particular, the credit risk increases when GDP growth and the share price indices decrease, and rises when the unemployment rate, interest rate, and credit growth increase. It is also positively affected with an appreciation of the real exchange rate. Moreover, we observe a substantial increase in the credit risk during the recent financial crisis period. Several robustness tests with different estimators have also confirmed these results.

In terms of policy implications, this means that structural measures and programmes that can be implemented to promote external competitiveness, to increase productivity, to reduce external and public debt and to support growth and employment in these countries are fundamental to stabilize their economies.

This article is organized as follows. Section 2 reviews the existing literature on the determinants of the credit risk. Section 3 describes the data and the hypotheses to test. The econometric model is explained in section 4. The empirical results are presented and discussed in Section 5. Section 6 concludes emphasizing the main findings of this article.

2. Review of the literature

There are several empirical studies that analyse the influence of macroeconomic and specific banking sector factors on the credit risk or nonperforming loans. In general, the credit risk is defined as the risk of a loan not being (partially or totally) paid to the lender. The analysis of the credit risk is essential because it can provide signs of alarm when the financial sector becomes more vulnerable to shocks. This can help the regulatory authorities to take measures to prevent a possible crisis (Agnello and Sousa, 2011; Agnello et al., 2011). According to Heffernan (2005), the analysis of the credit risk is also important because many banks' bankruptcies are related to the huge ratio of nonperforming loans to the total loans.

In the literature, we find an important distinction between the kind of factors that can affect banking credit risk: factors influencing the systematic credit risk; and factors influencing the unsystematic credit risk.[2] The factors influencing the systematic credit risk are: (i) macroeconomic factors like the employment rate, growth in gross domestic product, stock index, inflation rate, and exchange rate movements; (ii) changes in economic policies like changes in monetary and tax policies, economic legislation changes, as well as import restrictions and export stimulation; (iii) and political changes or changes in the goals of leading political parties. All these variables can have an important influence on the likelihood of borrowers paying their debts, but as changes in economic policies and political changes are difficult to examine, the literature has mainly focused on the macroeconomic factors.

The factors influencing the unsystematic credit risk are specific factors: (i) to the individuals like their individual personality, financial solvency and capital, credit insurance; (ii) and to the companies like management, financial position, sources of funds and financial reporting, their ability to pay the loan and specific factors of the industry sector. Industry specific factors may include the structure and economic successfulness of the industry, maturity of the industry and its stability.

[2] See, for example, Ahmad and Casu et al. (2006), Ariff (2007), Aver (2008), Saunders and Cornett (2008).

A great deal of studies looks at the macroeconomic factors that affect the credit risk. In particular, Salas and Saurina (2002), Jimenez and Saurina (2006), Jakubík (2007), Aver (2008), Bohachova (2008), Bonfim (2009), Kattai (2010) and Nkuzu (2011), among others, concentrate their research essentially on the influence of macroeconomic variables over the credit risk growth and stress that those variables should be included into the analysis since they have considerable influence on the changes of credit risk.

Aver (2008) shows that the credit risk of the Slovenian banking loan portfolio depends especially on the economic environment (employment and unemployment), long-term interest rates and on the value of the stock exchange index. Kattai (2010) and Fainstein and Novikov (2011) reach the same conclusion in a study for three Baltic States (Estonia, Latvia and Lithuania) banking systems. Their results highlight the importance of economic growth and interest rates as the most influential factor behind the soundness of the banking system.[3] Salas and Saurina (2002) and Jakubík (2007), in studies for the Spanish and Czech banking sectors respectively, also point out the GDP growth and changes in the interest rates as the main macroeconomic factors affecting the credit risk.

In the same line, Bohachova (2008) concludes that the business cycle plays an important role in the evolution of the credit risk: in OECD countries, banks tend to hold higher capital ratios during business cycle highs; in non-OECD countries, periods of higher economic growth are associated with lower capital ratios (procyclical behavior). Thus, banks accumulate risks more rapidly in economically good times and some of these risks materialize as asset quality deteriorates during subsequent recessions. Nkuzu (2011) also analyses this issue for a sample of 26 advanced economies over the period 1998-2009 using single-equation panel regressions and a panel vector autoregressive model and confirms the adverse link between macroeconomic developments and nonperforming loans.

[3] Contrary to Kattai (2010), Fainstein and Novikov (2011) also notice that the rapid growth of indebtedness has been crucial to the growth of non-performing loans.

The implications of macroeconomic factors on credit default are also explored in this literature. Ali and Daly (2010) employ a logit model over Australian and US data for the period 1995-2009 and find that the level of economic activity, interest rates and total debt provide meaningful indicators for aggregate default.[4] They also notice that the US economy is more vulnerable to adverse macroeconomic shocks than the Australian economy.

In a close line of research, Pesola (2005) analyses the macroeconomic determinants of banking sector distresses over a panel of some industrial countries for the period 1980-2002 using OLS and SUR estimators. According to his results, high customer indebtedness combined with adverse macroeconomic surprise shocks to income and real interest rates contributed to the distress in banking sector.

In particular, Pesola (2005), Jimenez and Saurina (2006), Bohachova (2008) and Bonfim (2009) conclude that the result of wrong decisions of financing will become apparent only during the period of recession of the economy and this will cause the growth of non-performing loans and loan losses.

Other authors like, for example, Quagliariello (2006), Festic et al. (2011) and Louzis et al. (2012) combine the systematic and unsystematic credit risk factors. Quagliariello (2006) uses a large panel of Italian banks over the period 1985-2002 to analyse the movements of loan loss provisions and new bad debts over the business cycle using both static fixed-effects and dynamic models. His results confirm that banks' loan loss provisions and new bad debts are affected by the evolution of the business cycle but several bank-level indicators also play an important role in explaining the changes in the evolution of banks' riskiness.

In a dynamic panel data analysis for nine Greek banks over the period 2003-2009, Louzis et al. (2012) finds that not only the real GDP growth rate, the unemployment rate and the lending rates have a strong effect on the level of nonperforming loans, but also some bank-specific variables such as performance and efficiency indicators possess additional

[4] Similar results are also found for Turkey by Cifter et al. (2009).

explanatory power. Considering a panel of five new EU member states (Bulgaria, Romania, Estonia, Latvia, Lithuania), Festic et al. (2011) also show that the mix of slowdown in economic activity, growth of credit and available finance and lack of supervision are harmful to banking performance and deteriorate nonperforming loans dynamics.

The unsystematic credit risk factors are under the attention of a few studies. Zribi and Boujelbène (2011) provide an analysis for Tunisia estimating a panel model controlling for random effects for ten commercial banks over the period 1995-2008. Despite they look at some macroeconomic factors, they take especially into account the impact of several microeconomic variables on credit risk. Their results show that the main determinants of bank credit risk in Tunisia are ownership structure, prudential regulation of capital, profitability.

Jimenes and Saurina (2004) and Ahmad and Ariff (2007) also focus their analysis on the unsystematic factors. While Jimenes and Saurina (2004) analyse the determinants of the probability of default of bank loans in several Spanish credit institutions, Ahmad and Ariff (2007) look at their impact on the credit risk using micro data from commercial banks of some emerging and developed economies. They emphasize that regulatory capital and management quality are critical to credit risk. The role of collateral, type of lender, bank-borrower relationship, the characteristics of the borrower and of the loan are also under the scope of Jimenes and Saurina's (2004) study. They find that collateralised loans have a higher probability of default, loans granted by savings banks are riskier and that a close bank-borrower relationship increases the willingness for banks taking more risk.

This survey of the literature shows that, among the studies on banking credit risk determinants, the vast majority of them consider the macroeconomic environment as the most important factor in the determination of the credit risk. Moreover, we also observe that they are mostly based on a single country analysis. Some provide a multi-country comparative analysis, but few use adequate dynamic panel data techniques. Louzis et al. (2012) make such analysis but at the bank level for a single country (Greece).

In this paper, we intend to extend the empirical analysis to a panel of countries – that share common characteristics – using a proper dynamic panel data approach. As we are providing an analysis at a macro-level, the macroeconomic variables assume a very important role here. Thus, we try to understand the link between the macroeconomic developments and the credit risk in the GIPSI, which have been highly affected by unfavourable economic and financial conditions and to which, on this matter, no study has given special attention yet. As the risk of default is highly influenced by the way families and companies are affected by the economic environment, macroeconomic factors will take a substantial part in the explanation of the credit risk in this study.

3. Data and hypotheses to test

The dataset consists of a panel of five European countries (the GIPSI) spanning the period from the first quarter of 1997 to the third quarter of 2011.The difficult economic conditions that these countries are facing (recession and unemployment), the high levels of public deficits and debts that they present and the problems that they have felt in borrowing money to finance their economies were critical in our decision of choosing them for this analysis. This unfavourable economic environment may increase the risk of credit default in these more vulnerable countries. Therefore, it becomes pertinent to study how macroeconomic variables are affecting that risk and the respective policy implications.

The time period considered starts around the moment in which those countries took part in the European Economic and Monetary Union, with the Euro as a common currency. This time-constrain is mainly due to the available data for the credit risk variable provided by the central banks of each country.

The credit risk is measured as the ratio between the (aggregate) banks' nonperforming loans in their balance sheets and the total gross loans. This represents the dependent variable that will be used in our model. This variable is modeled at the macroeconomic level from the consolidated balance sheet of each country's banking sector. In Figure 1, we can observe the evolution of the credit risk in those five countries.[5]

[Insert Figure 1 around here]

This picture shows a significant decline in the credit risk ratio from 1997 until 2008, especially in Greece and Italy. Nevertheless, this trend was inverted in 2008 with the spreading of the financial crisis that started in the US, in the year before, and that affected most of the developed economies. In particular, Greece and Ireland faced an exponential growth in the ratio of nonperforming loans, which can be seen as a sign of their fragile budgetary and banking conditions that were exposed by the financial crisis. This may have also been one additional factor that forced them to ask for financial help to the IMF, European Union and to the European Central Bank in 2010. Portugal was also forced to ask for financial support in 2011, but the increase in the ratio was not so huge. In this case, the big issue is more on the side of the public accounts. Even though so far Spain and Italy have not asked for financial support, the problem with the nonperforming loans in these countries is becoming serious and may put in danger the banking system if no effective measures are taken.

To provide some insights on how these particular countries can adjust their macroeconomic policies in order to avoid an increase in the nonperforming loans, we provide here an analysis to identify the main macroeconomic determinants of the credit risk. Several macroeconomic conditionings are considered in this study. We start by considering two variables to control for the economic environment: the growth rate of real gross domestic product (*GDP*) and the unemployment rate (*UR*).

[5] Due to the unavailability of data for some earlier years in some countries, the sample is not balanced. Moreover, as the available data for the ratio of nonperforming loans for Ireland are annual, we employed a linear interpolation to generate quarterly series. As the annual series present a smooth evolution over time, this interpolation technique is considered reasonable and suitable to generate those quarterly data. The same technique was used to create quarterly data (from the available annual data) for the period 2000-2004 for Greece.

The economic environment is fundamental to explain the behaviour of the credit risk. The expansion phase of the economy is usually characterized by a relatively low rate of nonperforming loans, as both consumers and firms face a sufficient stream of income and revenues to service their debts. However, as the booming period continues, credit is extended to lower-quality debtors and subsequently, when the recession phase sets in, nonperforming loans tend to increase.

The unemployment rate may provide additional information regarding the impact of economic conditions. An increase in the unemployment rate should influence negatively the cash flow streams of households and increase the debt burden. With regards to firms, increases in unemployment may signal a decrease in production as a consequence of a drop in effective demand. This may lead to a decrease in revenues and a fragile debt condition.

Empirical studies have confirmed this link between the phase of the cycle and credit risk/defaults in some countries at several disaggregated levels.[6] Therefore, we expect that a decrease in the growth rate of GDP or an increase in the unemployment rate will lead to an increase in the banking credit risk.

The interest rate is another important conditioning of the credit risk because it affects the debt burden. This means that the effect of the interest rate on the credit risk is expected to be positive. In fact, the increase in the debt burden caused by rising interest rates will lead to a higher rate of nonperforming loans (Aver, 2008; Nkusu, 2011; Louzis et al., 2012).[7] To control for this effect, we use the long-term interest rate (*IR_lt*), the real interest rate (*RIR*) and the spread between the long and short-term interest rates (*IR_spd*).

Another factor that can influence the credit risk is the overall credit growth (*Cred_gr*). It transmits information on general conditions in the credit market and reflects how easy it is

---

[6] See, among others, Salas and Saurina (2002), Jakubík (2007), Quagliarello (2007), Aver (2008), Bohachova (2008), Bonfim (2009), Cifter et al. (2009), Kattai (2010), Nkuzu, (2011) and Louzis et al. (2012).

[7] See also Bohachova (2008) on how higher interest rates can exacerbate problems of adverse selection and moral hazard.

to get access to credit and roll over earlier contracts, if necessary, in order to avoid default (Kattai, 2010). We conjecture that higher levels of credit growth may increase the propensity for more defaults in the future because that increase might reflect that more risky loans are approved. Hence, this will contribute to an increasing rate of nonperforming loans in the future. The private indebtedness (*Indebtness*), measured as the ratio of total gross loans to GDP, is also considered in our analysis. High debt burdens make debtors more vulnerable to adverse shocks affecting their wealth or income, which raises the chances that they would run into debt servicing problems. (Pesola, 2005; Kattai, 2010; Fainstein and Novikov, 2011; Nkusu, 2011). Therefore, the expected sign for this variable is the same as for the overall credit growth. Additionally – and to separate the private from the public "effects" – we consider the public debt (*PubDebt*) in some regressions. As the confidence of investors in a country decreases when public debt increases, the interest rates will tend to rise, which will affect the credit risk positively.

The growth rate of the share price indices (*Shares_ygr*) gives an indication of the general financial conditions of the most important companies in the market (Bonfim, 2006; Aver, 2008). An increase in the stock prices reflects an improvement in those conditions and may contribute to a reduction in the credit defaults. As a result, we expect that a good stock market performance will contribute to reduce the credit risk.

The real effective exchange rate (*REER*), with reference to the 27 EU members, is also included in the equation to control for external competitiveness. An increase in this variable means an appreciation of the local currency, making the goods and services produced in that country relatively more expensive. This weakens the competitiveness of export-oriented firms and affects adversely their ability to service their debt (Fofack, 2005; Nkusu, 2011). Hence, the impact of *REER* on the ratio of nonperforming loans is expected to be positive. Additionally, we also consider the effect of the terms of trade (*TermsTrade*) on the credit risk. Shifts in the terms of trade also affect bank's risks by influencing the profitability of borrowers. A drop in the terms of trade occurs when imports become more expensive relative to exports, eroding the purchasing power in a country (Bohachova, 2008). Therefore, falling terms of trade are expected to increase banks' credit risk.

Inflation is another variable to be considered, but its impact is not clear. Higher inflation can make debt servicing easier by reducing the real value of outstanding loans. However, it can also weaken borrowers' ability to service debt by reducing their real income. Therefore, the relationship between inflation and credit risk can be positive or negative.

A last variable to be included in the model is dummy variable to control for the financial crises period (*FinCrisis*): it takes value 1 from the fourth quarter of 2008 onwards, and 0 otherwise. The financial crises arose in the US in September 2007 and quickly spread out to the rest of the world. It started to affect the European economy (and the GIPSI, in particular) with more intensity in the end of 2008. Due to the consequent deterioration of the economic activity, borrowers feel more difficulties to pay their debts, therefore, increasing the rate of nonperforming loans. Hence, we expect a positive and significant sign for the coefficient on this dummy.

A complete description of all variables employed in this study and the expected signs for the respective coefficients can be found in Annex in Table A.1. Descriptive statistics for all variables used in this study are reported in Table A.2.[8] Additionally, we also test for the presence of unit roots in all the series employed in this study. The tests used to proceed with such task are the Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS) and Fisher-ADF tests. The results are also presented in Annex in Table A.4 and show that almost all the series are stationary at a 5% significance level, with the exception of the unemployment rate and indebtedness that are only stationary in differences. Hence, we can carry on with the empirical analysis using these stationary variables in the econometric model.

[8] Se also Table A.3 for correlations between all the variables used in this study.

4. Econometric model

According to the literature in panel data studies, a dynamic approach should be adopted in order to account for the time persistence in the credit risk structure.[9] Therefore, the model to be estimated is given by:

$$CredRisk_{it} = \alpha + \sum_{j=1}^{J} \gamma_j CredRisk_{it-j} + \mathbf{x}_{it}^{'}\boldsymbol{\beta} + \eta_i + \varepsilon_{it} \qquad (1)$$

where the subscripts i=1,…,N and t=1,…,T denote the cross sectional and time dimension of the panel, respectively; $\mathbf{x}_{it}$ is a k×1 vector of explanatory variables, $\boldsymbol{\beta}$ is a k×1, vector of coefficients, η_i are the unobserved country-specific effects and ε_{it} is the error term.

We will start our analysis by considering some traditional panel data estimators: pooled-OLS, fixed-effects (FE) and random effects (RE). These are used as a very simple starting point to our empirical exploration of the data. However, as noticed for example by Baltagi (2008), the OLS estimator is biased and inconsistent even if ε_{it} are not serially correlated. The random effects estimator is also biased in a dynamic panel data model. Nevertheless, as T gets large, the fixed effects estimator becomes consistent. As the time dimension in our sample is relatively large, the bias from the correlation between the lagged dependent variable and the country-specific effects might be small and this estimator could be a reasonable choice for our analysis. The problem is that Judson and Owen (1999) notice that even for T=30 the bias can be as much as 20% of the true value of the coefficient of interest.

These problems can be addressed by first-differencing equation (1):

$$\Delta CredRisk_{it} = \sum_{j=1}^{J} \gamma_j \Delta CredRisk_{it-j} + \Delta\mathbf{x}_{it}^{'}\boldsymbol{\beta} + \Delta\varepsilon_{it} \qquad (2)$$

[9] See, among others, Salas and Saurina (2002), Quagliarello (2007), Athanasoglou et al. (2008) and Merkl and Stolz (2009) and Louzis et al. (2012). In fact, some lags of the dependent variable have to be included in our analysis to account for that persistence. Only those that are statistically significant are included.

Thus, the country-specific effects are eliminated and instrumental variable estimators such as those proposed by Anderson and Hsiao (1981) and Arellano and Bond (1991) can be used in its estimation. These two estimators produce consistent estimates, but the Arellano-Bond (AB) generalized method of the moments (GMM) estimator is more efficient. Hence, we will solve the problems described above by employing it in this study. Lags of order j+1 and more of the dependent variable (and lags of the regressors) can be used to satisfy the respective moment conditions:[10]

$$E[CredRisk_{it-s}\ \Delta\varepsilon_{it}] = 0 \quad \text{and} \quad E[\mathbf{x}_{it-s}\ \Delta\varepsilon_{it}] = 0 \tag{3}$$

for $t = j+2,...,T$ and $s \geq j+1$.

These orthogonality restrictions are the basis of the one-step GMM estimation which, under the assumption of independent and homoscedastic residuals, produces consistent parameter estimates. Following the Arellano-Bond methodology, the differences of the strictly exogenous regressors are instrumented with themselves and the dependent and predetermined/endogenous variables are instrumented with their lagged levels. This procedure requires that no second-order autocorrelation is present in the differenced equation. In fact, while the presence of first-order autocorrelation in the error terms does not imply inconsistency of the estimates, the presence of second-order autocorrelation generates inconsistent estimates (Arellano and Bond, 1991).[11]

The validity of the instruments used in the moment conditions is also crucial for the consistency of the GMM estimates. Hence, we test the overall validity of the instruments using the Sargan specification test proposed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundel and Bond (1998).[12]

---

[10] For further details, see Arellano and Bond (1991) and Baltagi (2008, p.149-155).

[11] The assumption that the errors, (ε_{it}) are serially uncorrelated can be assessed by testing for the hypothesis that the differenced errors ($\Delta\varepsilon_{it}$) are not second order autocorrelated. Rejection of the null of no second order autocorrelation of $\Delta\varepsilon_{it}$ implies serial correlation for ε_{it} and thus inconsistency of the GMM estimates.

[12] Under the null of valid moment conditions, the Sargan test statistic is asymptotically distributed as chi-square.

Arellano and Bond (1991) proposed another variant of the GMM estimator, namely the two-step estimator, which utilizes the estimated residuals in order to construct a consistent variance-covariance matrix of the moment conditions. Although the two-step estimator is asymptotically more efficient than the one-step estimator and relaxes the assumption of homoscedasticity, the efficiency gains are not that important even in the case of heteroscedastic errors.[13] This result is supported by Judson and Owen (1999), who showed empirically that the one-step estimator outperforms the two-step estimator. Moreover, the two-step estimator imposes a bias in standard errors due to its dependence relatively to estimated residuals from the one-step estimator (Windmeijer, 2005), which may lead to unreliable asymptotic statistical inference (Bond, 2002; Bond and Windmeijeir, 2002). Arellano and Bond (1991) and Blundell and Bond (1998) notice that this issue should be taken into account especially when the cross section dimension is relatively small, which is precisely the case our sample.

5. Empirical results

We start our empirical analysis emphasizing the impact of the economic environment on the credit risk. Next we consider the impact of other relevant macroeconomic variables. Additionally, we also provide a sensitivity analysis and some robustness checks.

5.1. Macroeconomic conditionings

Despite the problems mentioned above regarding the traditional panel data estimators in a dynamic framework, we present first the results from a pooled-OLS, fixed-effects (FE) and random effects (RE). Those results are reported in Table 1 (columns 1-6) and Table 2 (columns 1-4). The Arellano-Bond (AB) estimator is then employed to overcome the bias and inconsistency of the OLS estimation methods (Table 1, columns 7-8; Table 2, columns 5-8).

[13] See Arellano and Bond (1991), Blundel and Bond (1998) and Blundell et al. (2000).

[Insert Table 1 around here]

[Insert Table 2 around here]

To begin with, two lags of the dependent variable are included in the set of regressors to capture the effect of possible omitted explanatory variables and the persistence of the credit risk. The results indicate that there is indeed persistence in the adjustment to the long-run equilibrium. When random effects are controlled for, only the first lag of the dependent variable is statistically significant. The FE estimator seems to be the most appropriate – according to the F-test, Breusch-Pagan Lagrange multiplier test and Hausman test – when the economic environment is controlled for using the growth rate of real GDP. However, the RE estimator is preferable when the unemployment variable is used instead (see Table 1). The inclusion of additional macroeconomic variables makes the pooled-OLS preferable according to the F-test (see Table 2).[14] In any case, the results are quite similar and the coefficient estimates seem to be robust to these different estimation techniques.

As expected, the results reported in Table 1 indicate that when GDP grows and the unemployment rate falls the rate of nonperforming loans decreases significantly.[15] Looking at these results from a different perspective, we conclude that the credit risk tends to increase when the economic environment deteriorates, which is in line with the findings of Salas and Saurina (2002), Bonfim (2006), Quagliarello (2007), Bohachova (2006), Cifter et al. (2009), Kattai, (2010) and Louzis et al. (2012). An additional confirmation of that fact is given by the impact of the financial crisis on the credit risk: during the financial crisis period – here collected by the dummy *FinCrisis* – the credit risk has increased substantially.

[14] As the number of countries in our sample is lower than the number of variables included in all the estimations in Table 2, it is not possible to estimate the model controlling for random effects.

[15] One lag of *GDP* and *ΔUR* are considered to take into account the plausible delay with which economic shocks affect the likelihood of default and to avoid reverse causality issues and simultaneity problems. As the variable *UR* is not stationary, we use its first difference, which provides more consistent and robust estimates. We prefer to estimate the effects of *GDP* and *ΔUR* separately to avoid the bias generated by the strong link between these two variables. In fact, they are both used as proxies to the economic environment.

As mentioned above, to overcome the bias and inconsistency of the OLS estimation methods, we employ the Arellano-Bond estimator to the data. Four lags of the dependent variable are used as instruments and the macroeconomic variables are considered as strictly exogenous since they are all lagged by (at least) one period. This procedure avoids a huge number of instruments given that we have just five cross-sectional units in the sample. The consistence of the estimator is assured since the AR tests for serial correlation in the differenced residuals provide evidence of significant negative first-order autocorrelation but no evidence of second-order autocorrelation. Moreover, the validity of the instruments used in this analysis is also confirmed by the Sargan test.

The results reported in Table 1 for the AB estimator are quite interesting because they reinforce the conclusion that the economic conditions influence greatly the level of credit risk in the economy. On one hand, a decrease of one percentage point in the growth rate of real GDP conducts to an immediate increase in the risk of credit of about 0.035 percentage points, ceteris paribus.[16] On the other hand, an acceleration of one point in the unemployment rate generates an increase of 0.175 percentage points in the rate of nonperforming loans, ceteris paribus. Our results also show that during the recent financial crises that rate has increased, on average, by about 0.3 to 0.4 percentage points. Thus, these findings point out to the importance that economic policies should give to the promotion of growth and employment to avoid serious problems of credit default and banking crises.

To explore a little more the impact of the macroeconomic environment on the credit risk, we include in the model some additional variables that can influence it and that can be controlled more directly by the fiscal and monetary authorities. One important example is the interest rate as it affects the debt burden and, consequently, the likelihood of a borrower paying his debt. The long-term interest rate (*IR_lt*) is used as a benchmark in our analysis

[16] The long-run coefficients can be computed dividing each short-run coefficient by one minus the sum of the coefficients on the lags of the dependent variable; the standard errors can be obtained by the delta method.

because most of the loans are usually agreed for a long period of time. The results reported in Table 2 reinforce the importance of the economic environment and show that higher interest rates tend to increase the credit risk significantly. This evidence is more robust when the more adequate and consistent AB estimator is used. In particular, we will rely on the results provided in columns 7 and 8 because, with the additional macroeconomic conditionings in the AB estimator, we only need one lag of the dependent variable to account for its persistence.[17]

Thus, for the interest rate we observe that for each percentage point increase in the long-term interest rate the rate of nonperforming loans increases by about 0.06 percentage points, ceteris paribus. This result confirms the important link between the interest rate and the credit risk pointed out by Nkusu (2011) and Louzis et al. (2012) calls our attention to the essential role that monetary authorities can play in the stabilization of that risk.

We also consider that when credit expands or grows faster, the risk of more defaults in the future may increase because that expansion might be achieved at the cost of more risky loans. As that effect may not be felt immediately, we decided to try several lags of the quarterly growth rate of the loans provided by banks (*Cred_gr*) and found that its effect is felt with more significance three periods after the expansion in the loans granted to the economy. Moreover, that impact is positive, as expected. This means that a substantial expansion in credit may reflect that several risky loans are being approved increasing the number of potential defaults in the future. The role of the regulatory authorities is very important here to prevent such situations and to supervise whether the prudential rules for granting loans to the economy are being followed or not.

The annual growth rate of the share price indices (*Shares_ygr*) is another variable that we consider in the analysis as an indicator for the state of the economy. In particular, it provides a general indication of the firms' financial conditions. The results show that an

[17] All the additional macroeconomic regressors are included with (at least) one lag by the same reasons pointed out above for *GDP* and *ΔUR*.

increase in the stock prices – that reflect an improvement in the financial conditions – contributes to a reduction of the rate of nonperforming loans.

The lag of the real effective exchange rate (*REER*), with reference to the 27 EU members, is also included in the equation to control for external competitiveness. Our findings point out to the fact that an increase in this variable contributes to an increase in the credit risk. In fact, a real appreciation of the local currency reflects the fact that the goods and services produced in the country are relatively more expensive. This weakens the competitiveness of export-oriented firms and affects adversely their ability to service their debts. Consequently, the ratio of nonperforming loans increases. As the countries in our sample share a single currency – the Euro – that is beyond their control, the only way for them to achieve a real depreciation is by reducing their costs of production and/or creating the necessary conditions to increase their productivity levels. This is a strategy that they should take not only to reduce the credit risk, but also to make their economies more competitive.

The recent financial crisis has exposed several weaknesses and structural problems in these five economies and our results point out to and additional one: the increase in the credit risk. Thus, all the structural measures and programmes that can be implemented – and some are being implemented, especially in those countries that are receiving external financial help – to promote their external competitiveness, to increase the productivity, to reduce the external and public debt and to support growth and employment are fundamental to stabilize their economies. Consequently, the ratio of nonperforming loans may decrease substantially.

5.2. Sensitivity analysis

The variables selected to the empirical analysis presented in the previous sub-section are considered the most representative of the macroeconomic environment that may influence the credit risk. In Table 3, we provide a sensitivity analysis where some of those variables are replaced by other related proxies that try to collect the same kind of effect. We should stress that despite all the experiments made with the (additional) macroeconomic variables, the effect of the economic environment on the credit risk remains statistically significant.

[Insert Table 3 around here]

We start by replacing the long-term interest rate by the real interest rate (*RIR*) and by the spread between the long and short-term interest rates (*IR_spd*). The coefficients on these variables remain positive, but only the coefficient on *IR_spd* is marginally significant. Even though the results point out in the same direction, the nominal long-term interest rate is more suitable because most of the loans are usually agreed for a long period of time and economic agents tend to look at the available nominal rates when they take their decisions.

As the variable *Cred_gr* does not distinguishes between private and public loans, we decided to replace this variable by the private and public indebtedness. The private indebtedness (*Indebtness*) is measured by the ratio of total private loans to GDP, while the public indebtedness is proxied by the government public debt as percentage of GDP (*PubDebt*).[18] The results provided in columns 3 and 4 show that increases in private indebtedness have the same effect as credit growth. This means that high private debt burdens make borrowers more vulnerable to adverse shocks affecting their wealth or income, which raises the chances that they would run into debt servicing problems. However, the level or even the changes in public debt have not proved to be relevant to the level of credit risk in the economies considered in our sample.

In regression 5, we replace the annual growth rate in the share price indices by the respective quarterly growth rate (*Shares_qgr*), lagged three periods. The results show an effect that is quite similar to the one found for *Shares_ygr*. Moreover, they also show that it takes some time before the changes in the stock market affect the credit risk significantly.

---

[18] As private indebtedness is not stationary, we use its first difference in the model. The coefficient on *Indebtness* has also proved to be more statistically significant three periods after its expansion.

The terms of trade (*TermsTrade*) are used in regression 6 instead of *REER*, but no significant effects are found for this variable. This might mean that simple nominal changes in exports relatively to imports are not as relevant to erode borrowers' profitability or purchasing power as changes in the real exchange rate.

Inflation is another variable considered in this analysis. However, this variable has no relevant impact on credit risk. We believe this is the case because inflation not only erodes the real value of the outstanding loans but also the borrowers' real income. As one effect is virtually cancelled by the other, the final impact of the inflation on the credit risk is null.

5.3. Robustness checks

To evaluate the robustness of our results to the data and to the estimation procedures, we provide here an analysis restricting the sample at time and individual levels (Table 4) and considering other alternative estimators (Table 5).

We start by limiting the sample to the period in which the Euro is in circulation (from the first quarter of 2001 onwards). The results are not significantly affected with this time-truncation and the main conclusions remain valid. The same happens when we exclude the financial crisis period from the sample. Looking at the first four regressions in Table 4, we observe that only the coefficient on *GDP* looses its statistical significance with the reduction of the sample size, but the unemployment rate is still supporting the relevance of the economic environment on the credit risk (as well as the dummy for the financial crisis).

[Insert Table 4 around here]

In the next step, we decided to exclude a country at a time from the sample. We start by excluding those countries that are under an external financial help programme (Greece, Ireland and Portugal); the others (Spain and Italy) are excluded next. In general, the main findings and conclusions remain unchanged, but there are two results that deserve some consideration. First, the coefficient on GDP is no longer significant when Ireland is excluded from the sample. This country presents high rates of growth in the 1990s and in the first half of the 2000s which are linked to lower rates of nonperforming loans. In the second half of the 2000s this relation was inverted, with a substantial decrease in the growth rate of GDP being followed by an increase in the credit risk. This can be an indication that this country contributes greatly to the significant negative relation between *GDP* and *CredRisk* in our sample. Second, Portugal, Spain and Italy also contribute significantly to the relation found between the interest rate and credit risk. When those countries are excluded from the sample the statistical link between these two variables is not so strong. In fact, the increase in the interest rates contributed considerably to unveil their weaknesses at the private and public levels, consequently affecting the credit risk in those economies.

Another set of robustness checks takes into consideration how the data behaves with regards to different estimators. We consider first the system-GMM estimator. This was develop by Arellano and Bover (1995) and Blundell and Bond (1998) to solve the problem that the lagged-level instruments in the AB estimator become weak when the autoregressive process becomes too persistent or the ratio of the variance of the panel-level effects to the variance of the idiosyncratic error becomes too large. This estimator considers additional moment conditions in which lagged differences are used as instruments for the level equation in addition to the moment conditions of lagged levels as instruments for the differenced equation. This method assumes that there is no autocorrelation in the idiosyncratic errors and requires the initial condition that the panel-level effects be uncorrelated with the first difference of the first observation of the dependent variable.

The results are presented in Table 5 (columns 1 and 2) and show that only the coefficient on the interest rate has lost its statistical significance. However, this may not be the most adequate estimator to apply to the available data for the following reasons: first, the Sargan test clearly rejects the underlying assumptions of the model; second, the coefficient on the lag of the dependent variable is higher than one; third, this estimator is specifically designed for datasets with many panels and (very) few periods, which is not really the case in our dataset. Nevertheless, despite all this problems, the main results provided by this estimator are not very different from the ones obtained with the AB estimator.

[Insert Table 5 around here]

Even though the AB is more efficient than the Anderson-Hsiao (AH) estimator, we report the results from the AH estimator to check whether the differences in the results are significant or not. Looking at regressions 3 and 4, we conclude that our findings remain unchanged. Despite the tests indicating that the instruments used are not weak and the presence of endogeneity (Wu-Hausman test), the overidentifying restrictions are not valid (see Sargan test). Hence, it is better to rely on the AB estimator, which is more efficient than this.

An alternative estimation procedure is suggested by Kiviet (1995), especially for small panels (with a small number of individuals). He derives a formula for the bias of the least-square dummy variables (LSDV) estimator and recommends subtracting this from the estimated LSDV coefficients. The estimation of the LSDV correction involves a two-step procedure in which the residuals from a first-step consistent estimator (for simplicity, we use the AH estimator) are employed in the second-stage calculation of the bias. Judson and Owen (1999) notice that the Kiviet's corrected LSDV estimator (LSDVC) can outperform the AB estimator in some cases. In Monte Carlo experiments they show that its bias tends to be lower and that it produces the most efficient estimates, especially in small panels. As the number of individuals in or sample is small, we decided to employ this estimator in the regressions 5 and 6. Once again, the main conclusions of this paper are supported by this alternative estimator.[19]

[19] Although this estimator is theoretically appealing, it is computationally slower to retrieve the results because it not only involves two estimation steps but also the estimation of bootstrap standard errors. Moreover, it presents an estimate for the coefficient on the lag of the dependent variable that is almost equal to one, which could point out to a re-specification of the model with the dependent variable in first differences. We will check this below.

With the increase in time observations in a dynamic panel, nonstationarity can be a concern. Recent papers by Pesaran, Shin, and Smith (1999) offer a different technique to estimate stationary and nonstationary dynamic panels in which the time (and the number of groups) is large and some parameters are considered heterogeneous across groups: the pooled mean-group (PMG) estimator. This estimator relies on a combination of pooling and averaging of coefficients. Given the advantages of this estimator, we also apply it to our model constraining the coefficients on the macroeconomic variables to be identical, but allowing the coefficient on the lag of the dependent variable and the error variances to differ across groups. Looking at regressions 7 and 8, we conclude that, despite the number of individuals being small, the results that we get with this estimator are very similar to the ones obtained with the AB estimator.

A final robustness check takes into account the fact that the coefficient on the lagged dependent variable is very close to one in the Sys-GMM, AH and LSDVC estimators. Allowing for the possibility of being equal to one, we transform the model in such a way that the dependent variable is now the first difference of credit risk (*ΔCredRisk*) and it is a function of the other regressors. Employing the OLS estimator over this new specification (called here OLS-Diff), we found no significant differences in the results in comparison with the other estimators.[20]

Thus, we conclude that our results and conclusions are robust to different kinds of estimators. Given their specificities, some are more suitable to our data than others. However, our preference for the AB estimator in this study is justified by its consistence, efficiency and reasonable adequacy to the data (as indicated by all diagnostic tests).

---

[20] We are not controlling for fixed effects because the F-test does not reject the simple pooling. Moreover, this estimator and specification would be very appealing if *ΔCredRisk* was stationary, but that is not the case. For example the IPS-test presents a p-value of 0.4699 for *ΔCredRisk*.

6. Conclusions

The recent financial crisis has revived the interest on the analysis of the problems that banking crises can have over the economy and on the factors that may trigger a banking crisis. However, before looking at the causes of banking crisis, we should give some attention to the conditionings of the banking credit risk. In reality, before a banking crisis arises, banks can be struggling with liquidity and/or insolvency problems caused by the increase of bad or nonperforming loans in their balance sheets. Thus, to understand the origin of banking crises it is necessary starting by considering the factors that affect baking credit risk in first place.

Several studies have focused their attention on this matter and have concluded that the macroeconomic environment has a strong influence on banking credit risk. In this paper, we analyse deeply the link between the macroeconomics and banking credit risk in the GIPSI. Employing dynamic panel data approaches to these group countries over the period 1997q1-2011q3, we conclude that the banking credit risk is significantly affected by the macroeconomic environment: the credit risk increases when GDP growth and the share price indices decrease and rises when the unemployment rate, interest rate, and credit growth increase; it is also positively affected by an appreciation of the real exchange rate; moreover, we observe a substantial increase in the credit risk during the recent financial crisis period. Several robustness tests with different estimators have also confirmed these results.

In terms of policy implications, this means that structural measures and programmes that can be implemented to promote external competitiveness, to increase productivity, to reduce external and public debt and to support growth and employment in these countries are fundamental to stabilize their economies.

From this analysis we may think of some interesting avenues for future research. First, it would be interesting to extend it to other EU countries. The problem is that comparable aggregate data for credit risk is not always available. Thus, a possible alternative would be to look at the disaggregated banking level, provided that reliable (and comparable) time series for nonperforming loans are available for the most relevant credit institutions. In this case, in particular, the group of regressors could be extended with the inclusion of some unsystematic or microeconomics factors, which will provide a deeper understanding of banking credit risk as well as additional insights on the link between the recent financial crisis and the risk taken by some financial and banking institutions. Finally, as the output effects of credit market frictions could be nonlinear, it may also be worth exploring possible threshold effects.

Acknowledgements

The author wishes to thank the financial support provided by the Portuguese Foundation for Science and Technology under research grant PEst-C/EGE/UI3182/2011 (partially funded by COMPTE, QREN and FEDER). This article also benefited from the excellent research assistance of Catarina Sebastião to whom the author is very grateful.

References

Agnello, L., Sousa, R., 2011. How do Banking Crises Impact on Income Inequality? *NIPE Working Papers*, WP 30/2011. University of Minho.

Agnello, L., Furceri, D., Sousa, R., 2011. "Fiscal Policy Discretion, Private Spending, and Crisis Episodes. *NIPE Working Papers*, WP 31/2011. University of Minho.

Ahmad, N., Ariff, M., 2007. Multi-country study of Bank Credit Risk determinants, *International Journal of Banking and Finance*, 5 (1), 135-152.

Ali, A., Daly, K., 2010. Macroeconomic determinants of credit risk: Recent evidence from a cross country study. *International Review of Financial Analysis*, 19, 165-171.

Anderson, T., Hsiao, C., 1981. Estimation of dynamic models with error components. *Journal of the American Statistical Association*, 76, 598-606.

Arellano, M., Bond, S., 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies*, 58, 277-297.

Athanasoglou, P., Brissimis, S., Delis, M., 2008. Bank-Specific, Industry-Specific and Macroeconomic Determinants of Bank Profitability. *Journal of International Financial Markets, Institutions and Money*, 18 (2), 121-136.

Aver, B., 2008. An Empirical Analysis of Credit Risk Factors of the Slovenian Banking System. *Managing Global Transitions*. 6 (3), 317-334.

Baltagi, B., 2008. *Econometric Analysis of Panel Data*, 4th Ed. Chichester, UK. John Wiley & Sons, Ltd.

Blundell, R., Bond, S., 1998. Initial Conditions and Moment Conditions in Dynamic Panel Data Models. *Journal of Econometrics*, 87, 115-143.

Blundell, R., Bond, S., Windmeijer F., 2000. Estimation in Dynamic Panel Data Models: Improving on The Performance of the Standard GMM Estimator. in B. Baltagi (ed). *Advances in Econometrics*, Volume 15: Non-stationary Panels, Panel Cointegration and Dynamic Panels, JAI Elsevier Science.

Bohachova, O., 2008. The impact of macroeconomic factors on risks in the banking sector: a cross-country empirical assessment. *IAW Discussion Papers*, 44.

Bond, S., 2002. Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice, *Portuguese Economic Journal*, 1 (2), 141-162.

Bond, S., Windmeijer, F., 2002. Finite Sample Inference for GMM Estimators in linear Panel Data Models: A Comparison of Alternative Tests. Mimeo, Institute for fiscal studies, London.

Bonfim, D., 2009. Credit risk drivers: Evaluating the contribution of a firm level information and macroeconomic dynamics. *Journal of Banking and Finance*, 33 (2), 281-299

Casu, B., Girardone, C., Molyneuxra, P., 2006. *Introducing to banking*. USA: Financial Times Prentice Hall.

Cifter, A., Yilmazer, S., Cifter, E., 2009. Analysis of sectoral credit default cycle dependency with wavelet networks: Evidence from Turkey. *Economic Modelling*, 26, 1382-1388.

De Grauwe, P., 2008. The banking crisis: Causes, consequences and remedies. University of Leuven and CESifo. Mimeo.

Demirguç-Kunt, A., Detragiache, E., 1998. The Determinants of Banking Crises and Developed Countries. *IMF Staff Papers*, 45 (1), 81-109.

Fainstein, G., Novikov, I., 2011. The Comparative Analysis of Credit Risk Determinants in the Banking Sector of the Baltic States. *Review of Economics and Finance*, March 2011.

Festic, M., Kavkler, A., Repina, S., 2011. The macroeconomic sources of systemic risk in the banking sectors of five new EU member states. *Journal of Banking and Finance*, 35, 310-322.

Jakubík, P., 2007. Macroeconomic Environment and Credit Risk. *Czech Journal of Economics and Finance*, 57 (1-2), 60-78.

Jiménez, G., Saurina, J., 2004. Collateral, type of lender and relationship banking as determinants of credit risk. *Journal of Banking and Finance*, 28, 2191-2212.

Jiménez, G., Saurina, J., 2006. Credit cycles, credit risk and prudential regulation. *International Journal of Central Banking*, 2 (2), 65-98.

Judson, R., Owen, L., 1999. Estimating Dynamic Panel Data Models: A Guide for Macroeconomists. *Economics Letters*, 65, 9-15.

Kattai, R., 2010 Credit risk model for the Estonian banking Sector. *Bank of Estonia Working Papers*, 1.

Kiviet, J., 1995. On Bias, Inconsistency, and Efficiency of Various Estimators in Dynamic Panel Data Models. *Journal of Econometrics*, 68, 53-78.

Laeven, L., Valencia, F., 2008. Systemic banking crises: A new database. *International Monetary Fund Working Paper* 08/224.

Laeven, L., Valencia, F., 2010. Resolution of banking crises: The good, the bad, and the ugly. *International Monetary Fund Working Paper* 10/146.

Llewellyn, D., 2002. An Analysis of the Causes of Recent Banking Crises. *European Journal of Finance*, 8, 152-175.

Louzis, D., Vouldis, A., Metaxas, V., 2012. Macroeconomic and bank-specific determinants of nonperforming loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking and Finance*, 36 (4), 1012-1027.

Merkl, C., Stolz S., 2009. Banks Regulatory Buffers, Liquidity Networks and Monetary Policy Transmission. *Applied Economics*, 41, 2013-2024.

Nkusu, M., 2011. Nonperforming loans and macrofinancial vulnerabilities in advanced economies. *IMF Working Papers*, 161.

Pesaran, M., Shin, Y., Smith, R., 1999. Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, 94: 621-634.

Pesola, J., 2005. Banking fragility and distress: An econometric study of macroeconomic determinants. *Bank of Finland Research Discussion Papers*, 13/2005.

Quagliarello, M., 2007. Banks' riskiness over the business cycle: A panel analysis on Italian intermediaries. *Applied Financial Economics*, 17, 119-138.

Salas, V., Saurina, J., 2002. Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, 22 (3), 203-224.

Saunders, A., Cornett, M., 2008. *Financial Institutions Management: a Risk Management Approach.* London: McGraw-Hill.

Windmeijer, F., 2005. A Finite Sample Correction for the Variance of Linear Efficient Two-Step GMM Estimators. *Journal of Econometrics*, 126 (1), 25-51.

Zribi, N., Boujelbène, Y., 2011. The Factors Influencing Bank Credit Risk: The Case of Tunisia. *Journal of Accounting and Taxation*, 3 (4), 70–78.

Tables

Table 1. Empirical results based simply on the economic behaviour

	OLS	OLS	FE	FE	RE	RE	AB	AB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CredRisk(-1)	1.410***	1.402***	1.303***	1.370***	0.967***	0.957***	1.136***	1.156***
	(14.36)	(14.66)	(12.52)	(11.22)	(65.16)	(50.07)	(11.51)	(10.97)
CredRisk(-2)	-0.433***	-0.426***	-0.334***	-0.406***			-0.194*	-0.217**
	(-4.52)	(-4.59)	(-2.90)	(-3.31)			(-1.72)	(-1.96)
GDP(-1)	-0.024**		-0.041***		-0.056***		-0.034***	
	(-2.50)		(-3.82)		(-4.02)		(-2.62)	
ΔUR(-1)		0.180***		0.185**		0.291***		0.174*
		(2.93)		(2.50)		(3.61)		(1.92)
FinCrisis	0.225***	0.245***	0.196***	0.271***	0.291***	0.428***	0.308**	0.397***
	(3.32)	(3.93)	(3.37)	(4.98)	(3.18)	(3.26)	(2.46)	(3.75)
No. Obs.	236	241	236	241	240	246	231	236
R^2	0.9912	0.9928	0.9909	0.9927	0.9892	0.9917		
SBIC	45.59	38.05	20.25	24.06				
F-test			4.99	2.08				
			[0.001]	[0.084]				
LM-test					75.74	4.11		
					[0.000]	[0.043]		
Hausman-test					33.59	3.10		
					[0.000]	[0.377]		
AR1-test							-1.91	-1.99
							[0.056]	[0.047]
AR2-test							1.58	1.68
							[0.115]	[0.092]
Sargan-test							206.75	202.32
							[0.207]	[0.345]

Notes: For sources, see Table A.1 in Annex. All models were estimated with a constant. Robust t-statistics are in parentheses. Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%; and *, 10%. The model was estimated by ordinary least squares (OLS), fixed-effects (FE); random-effects (RE); and one-step Arellano-Bond (AB) GMM estimator. For each regression are presented the number of observations (No. Obs.), the coefficient of determination (R^2) and the Schwarz's Bayesian information criterion (SBIC). The F-test presents the statistics and respective p-values (in square brackets) for the test to the presence of fixed effects; The LM-test is the Breusch-Pagan test for random effects; The Hausman-test is used to select between a random or a fixed-effects estimator; AR1 and AR2 tests are the Arellano-Bond tests for first and second-order autocorrelation in first-differenced errors; The statistics and p-values (in square brackets) for the Sargan-test of overidentifying restrictions are also reported for the AB estimations.

Table 2. Empirical results based on additional macroeconomic conditionings

	OLS	OLS	FE	FE	AB	AB	AB	AB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CredRisk(-1)	1.177***	1.186***	1.149***	1.179***	0.999***	1.003***	0.978***	0.982***
	(12.19)	(11.38)	(11.18)	(10.66)	(7.62)	(7.19)	(59.03)	(52.87)
CredRisk(-2)	-0.170*	-0.177*	-0.153	-0.180*	-0.021	-0.021		
	(-1.80)	(-1.72)	(-1.56)	(-1.70)	(-0.16)	(-0.15)		
GDP(-1)	-0.024***		-0.029**		-0.022**		-0.023**	
	(-3.15)		(-2.25)		(2.23)		(-2.20)	
ΔUR(-1)		0.089		0.085		0.100**		0.103***
		(1.58)		(1.48)		(2.33)		(2.17)
IR_lt(-1)	0.044	0.041*	0.049	0.052*	0.056**	0.060**	0.060***	0.063***
	(1.58)	(1.75)	(1.56)	(1.92)	(2.49)	(2.48)	(2.65)	(2.61)
Cred_gr(-3)	0.030***	0.024***	0.026***	0.022**	0.024***	0.022***	0.023***	0.022***
	(3.80)	(3.11)	(2.88)	(2.48)	(5.79)	(5.22)	(4.70)	(5.15)
Shares_ygr(-1)	-0.003***	-0.003***	-0.002***	-0.003***	-0.002***	-0.002***	-0.002**	-0.002***
	(-4.24)	(-4.53)	(-3.38)	(-4.09)	(-3.66)	(-4-43)	(-2.53)	(-3.10)
REER(-1)	0.027***	0.025***	0.027***	0.032***	0.033***	0.038***	0.031***	0.037***
	(6.40)	(5.86)	(3.65)	(5.69)	(2.75)	(3.70)	(3.06)	(4.91)
FinCrisis	0.133**	0.179***	0.131*	0.157**	0.178***	0.207***	0.193***	0.224***
	(1.98)	(2.95)	(1.89)	(2.48)	(3.97)	(5.58)	(3.48)	(4.55)
No. Obs.	225	226	225	226	220	221	223	224
R^2	0.9927	0.9925	0.9928	0.9926				
SBIC	-11.09	-6.47	5.92	10.37				
F-test			1.28	1.10				
			[0.279]	[0.358]				
AR1-test					-2.13	-2.10	-1.83	-1.87
					[0.034]	[0.036]	[0.067]	[0.060]
AR2-test					1.13	1.12	0.95	0.98
					[0.260]	[0.264]	[0.341]	[0.3280]
Sargan-test					205.40	202.74	207.40	203.77
					[0.134]	[0.177]	[0.158]	[0.219]

Notes: For sources, see Table A.1 in Annex. All models were estimated with a constant. Robust t-statistics are in parentheses. Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%; and *, 10%. The model was estimated by ordinary least squares (OLS), fixed-effects (FE); and one-step Arellano-Bond (AB) GMM estimator. For each regression are presented the number of observations (No. Obs.), the coefficient of determination (R^2) and the Schwarz's Bayesian information criterion (SBIC) – except for the AB regressions. The F-test presents the statistics and respective p-values (in square brackets) for the test to the presence of fixed effects; AR1 and AR2 tests are the Arellano-Bond tests for first and second-order autocorrelation in first-differenced errors; The statistics and p-values (in square brackets) for the Sargan-test of overidentifying restrictions are also reported for the AB estimations.

Table 3. Sensitivity analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CredRisk(-1)	0.977***	0.967***	0.964***	0.982***	0.968***	0.953***	0.970***	0.969***
	(56.77)	(55.13)	(93.12)	(55.42)	(57.12)	(50.82)	(68.34)	(81.84)
GDP(-1)	-0.014*		-0.023*		-0.025**		-0.015**	
	(-1.78)		(-1.75)		(-2.46)		(-2.11)	
ΔUR(-1)		0.111**		0.098**		0.164***		0.085**
		(2.30)		(2.38)		(3.00)		(2.22)
IR_lt(-1)			0.045	0.066***	0.068***	0.057***	0.077***	0.085***
			(1.51)	(2.77)	(3.01)	(3.73)	(3.06)	(3.10)
RIR(-1)	0.033							
	(1.53)							
IR_spd		0.040*						
		(1.95)						
Cred_gr(-3)	0.025***	0.026***			0.019***	0.015***	0.023***	0.022***
	(5.03)	(4.23)			(3.62)	(3.65)	(4.72)	(5.19)
ΔIndebtness(-3)			0.307**	0.325**				
			(2.10)	(2.01)				
PubDebt(-3)			0.006					
			(0.90)					
ΔPubDebt(-3)				-0.002				
				(-0.13)				
Shares_ygr(-1)	-0.003***	-0.003***	-0.002**	-0.002***		-0.002**	-0.002***	-0.002***
	(-3.30)	(3.52)	(-2.29)	(-3.00)		(-2.29)	(-2.75)	(-3.43)
Shares_qgr(-3)					-0.004**			
					(-2.45)			
REER(-1)	0.032***	0.026***	0.026**	0.033***	0.030***		0.035***	0.037***
	(3.02)	(9.01)	(2.40)	(6.65)	(2.75)		(3.14)	(4.06)
TermsTrade(-1)						-0.054		
						(-0.05)		
Infl(-1)							-0.028	-0.032
							(-1.13)	(1.19)
FinCrisis	0.190***	0.245***	0.128	0.204***	0.207***	0.394***	0.161***	0.173***
	(2.97)	(3.89)	(1.34)	(2.59)	(3.01)	(6.36)	(2.93)	(3.37)
No. Obs.	223	224	223	224	223	224	223	224
AR1-test	-1.80	-1.88	-1.76	-1.85	-1.91	-1.91	-1.82	-1.87
	[0.071]	[0.061]	[0.077]	[0.0644]	[0.055]	[0.057]	[0.068]	[0.062]
AR2-test	0.97	1.10	1.11	1.10	1.14	1.26	0.89	0.91
	[0.333]	[0.271]	[0.265]	[0.269]	[0.254]	[0.208]	[0.373]	[0.364]
Sargan-test	212.21	216.40	214.87	207.41	215.31	215.45	206.70	213.24
	[0.109]	[0.084]	[0.087]	[0.171]	[0.084]	[0.091]	[0.166]	[0.109]

Notes: See Table 2. All models were estimated with a constant. Robust t-statistics are in parentheses. Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%; and *, 10%.

Table 4. Robustness checks: data

	Year>2000	Year>2000	Year<2009	Year<2009	GRC out	GRC out	IRE out	IRE out	PRT out	PRT out	SP, IT out	SP, IT out
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CredRisk(-1)	0.985***	0.987***	0.972***	0.973***	0.973***	0.981***	0.972***	0.972***	0.976***	0.985***	0.965***	0.982***
	(49.94)	(44.72)	(31.52)	(32.90)	(55.50)	(46.23)	(48.42)	(48.09)	(38.10)	(37.71)	(33.63)	42.40
GDP(-1)	-0.018		-0.017		-0.025**		-0.010		-0.021***		-0.035***	
	(-1.56)		(-1.30)		(-2.24)		(-0.72)		(-2.97)		(-4.47)	
ΔUR(-1)		0.112**		0.075***		0.085*		0.040***		0.095*		0.116*
		(2.28)		(4.59)		(1.87)		(2.76)		(1.72)		(1.66)
IR_lt(-1)	0.052**	0.059**	0.066**	0.058*	0.141***	0.136***	0.069***	0.073***	0.069	0.061	0.046	0.050
	(2.15)	(2.15)	(2.04)	(1.71)	(4.83)	(6.27)	(2.90)	(3.27)	(1.49)	(1.38)	(1.54)	(1.40)
Cred_qgr(-3)	0.021***	0.021***	0.026**	0.026**	0.024***	0.022***	0.029***	0.028***	0.025***	0.025***	0.019***	0.021***
	(3.50)	(3.91)	(2.00)	(2.15)	(2.91)	(3.87)	(3.68)	(4.59)	(3.63)	(5.07)	(3.97)	(5.84)
Shares_ygr(-1)	-0.003***	-0.003***	-0.002***	-0.002***	-0.001	-0.002**	-0.002*	-0.002**	-0.003***	-0.003***	-0.001	-0.002**
	(-4.29)	(4.36)	(-2.77)	(-3.15)	(-1.56)	(-2.18)	(-1.69)	(-2.48)	(-5.79)	(-5.84)	(-1.36)	(-2.15)
REER(-1)	0.037***	0.040***	0.030***	0.031***	0.052***	0.060***	0.041***	0.042***	0.044***	0.049***	0.022**	0.035***
	(3.52)	(6.01)	(5.31)	(5.32)	(3.91)	(4.71)	(2.82)	(3.38)	(4.15)	(5.11)	(2.12)	(12.56)
FinCrisis	0.168***	0.180***			0.100***	0.122***	0.147**	0.162**	0.134**	0.165***	0.295***	0.311***
	(2.95)	(3.73)			(2.84)	(3.99)	(2.20)	(2.13)	(2.26)	(2.86)	(4.06)	(6.34)
No. Obs.	199	200	172	172	188	189	184	185	170	170	127	128
AR1-test	-1.92	-1.96	-1.50	-1.51	-1.60	-1.63	-1.71	-1.71	-1.54	-1.58	-1.66	-1.68
	[0.055]	[0.050]	[0.134]	[0.132]	[0.110]	[0.104]	[0.087]	[0.087]	[0.123]	[0.114]	[0.097]	[0.092]
AR2-test	0.66	0.66	0.83	0.81	1.33	1.31	0.92	0.95	0.45	0.43	0.26	0.30
	[0.512]	[0.507]	[0.405]	[0.417]	[0.1849]	[0.189]	[0.358]	[0.345]	[0.651]	[0.671]	[0.797]	[0.764]
Sargan-test	197.11	192.29	161.27	160.53	160.06	159.60	160.93	160.53	158.50	157.42	105.90	106.85
	[0.040]	[0.072]	[0.183]	[0.194]	[0.218]	(0.243)	[0.204]	[0.227]	[0.082]	[0.091]	[0.153]	[0.155]

Notes: See Table 2. All models were estimated with a constant. Robust t-statistics are in parentheses. Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%; and *, 10%. In regressions (1) and (2) only the period 2001q1-2011q1 is considered. In regressions (3) and (4) the financial crisis period (after 2008q4) is excluded. In regressions (5) and (6) Greece is excluded from the sample; In regressions (7) and (8) Ireland is excluded from the sample; In regressions (9) and (10) Portugal is excluded from the sample; In regressions (11) and (12) Spain and Italy are excluded from the sample.

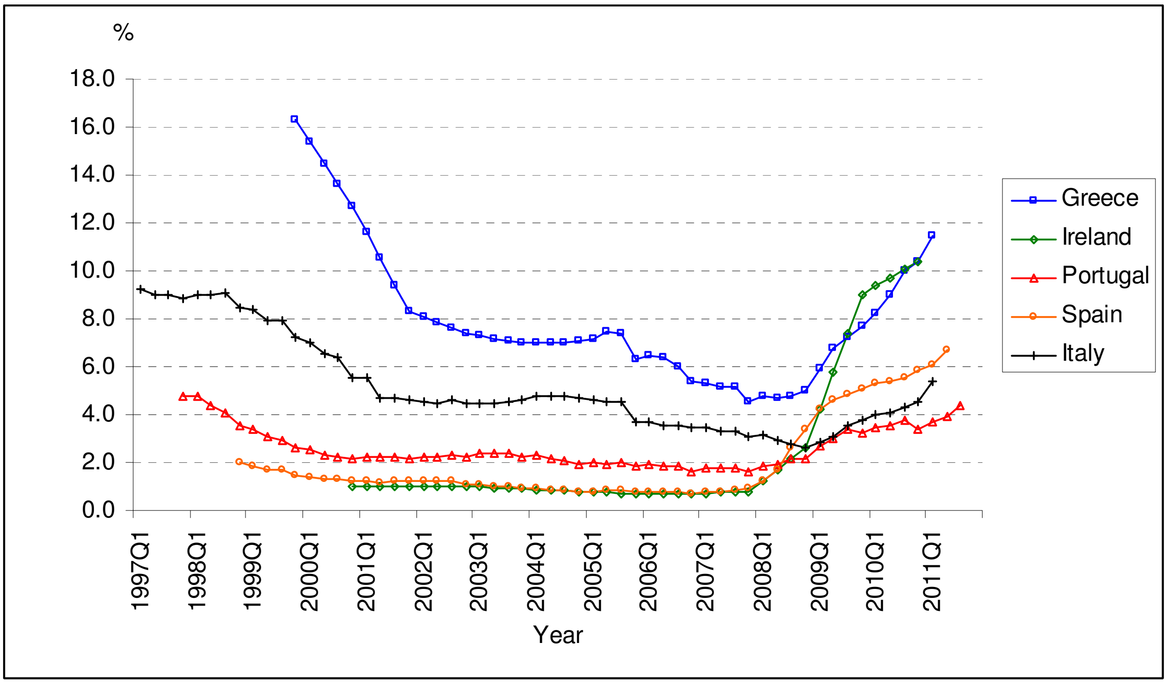
Table 5. Robustness checks: different estimators

	Sys-GMM	Sys-GMM	AH	AH	LSDVC	LSDVC	PMG	PMG	OLS-Diff	OLS-Diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CredRisk(-1)	1.013***	1.016***	0.991***	0.998***	0.997***	1.004***	0.974***	0.972***		
	(96.96)	(73.93)	(77.65)	(80.83)	(51.79)	(70.05)	(54.64)	(46.72)		
GDP(-1)	-0.030**		-0.037***		-0.036**		-0.022**		-0.028***	
	(-2.42)		(-3.84)		(-2.41)		(2.60)		(-3.32)	
ΔUR(-1)		0.124**		0.116***		0.117**		0.114***		0.124**
		(2.09)		(2.57)		(2.09)		(3.42)		(2.26)
IR_lt(-1)	0.030	0.035	0.057***	0.058***	0.057*	0.059**	0.088***	0.089***	0.061**	0.055**
	(0.99)	(1.16)	(2.93)	(3.27)	(1.84)	(2.53)	(4.78)	(5.60)	(2.29)	(2.49)
Cred_qgr(-3)	0.033***	0.029***	0.023***	0.019**	0.025**	0.021**	0.027***	0.023***	0.027***	0.019***
	(6.79)	(7.20)	(2.80)	(2.25)	(2.32)	(2.03)	(3.60)	(3.28)	(3.55)	(2.59)
Shares_ygr(-1)	-0.003***	-0.003***	-0.002***	-0.003***	-0.002**	-0.003***	-0.002***	-0.002***	-0.003***	-0.003***
	(-3.06)	(-3.31)	(-3.17)	(-4.39)	(-2.28)	(-3.85)	(-3.04)	(-3.01)	(4.18)	(-4.45)
REER(-1)	0.039***	0.041***	0.028***	0.036***	0.027***	0.034***	0.032***	0.033***	0.031***	0.028***
	(4.44)	(6.52)	(4.36)	(6.07)	(2.77)	(4.72)	(3.42)	(4.70)	(7.38)	(6.52)
FinCrisis	0.137**	0.182***	-0.150***	0.184***	0.156**	0.191***	0.169***	0.188***	0.172***	0.230***
	(2.07)	(2.62)	(2.61)	(3.27)	(1.98)	(3.15)	(2.90)	(3.49)	(2.73)	(4.21)
No. Obs.	228	229	222	225	228	229	251	251	228	229
R^2			0.9920	0.9918					0.6277	0.6201
SBIC							-54.57	-62.07	-12.57	-7.67
F-test									1.69	1.26
									[0.154]	[0.286]
AR1-test	-1.82	-1.87								
	[0.068]	[0.061]								
AR2-test	0.86	0.94								
	[0.392]	[0.348]								
Sargan-test	287.27	285.32	12.70	8.85						
	[0.022]	[0.032]	[0.013]	[0.065]						
Weak instr. test			1223.2	1229.1						
			[0.000]	[0.000]						
Wu-Hausman test			5.00	7.62						
			[0.026]	[0.006]						
Log-L							49.39	53.14		

Notes: See Table 2. All models were estimated with a constant. Robust t-statistics are in parentheses. Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%; and *, 10%. A one-step Arellano-Bover/Blundell-Bond system-GMM (Sys-GMM) estimator is employed in regressions (1) and (2). The results presented in columns (3) and (4) were obtained using the Anderson-Hsiao (AH) estimator. The statistics and respective p-values (in square brackets) for the overidentifying restrictions (Sargan-test), weak instruments test and endogeneity test (Wu-Hausman test) are also shown for these regressions. In columns (5) and (6) are reported the results from the Kiviet's bias-corrected least squares dummy variable estimator (LSDVC), with the respective bootstrap standard errors in parenthesis; in these regressions the Anderson-Hsiao estimator is used to initialize the bias correction. A pooled mean group (PMG) estimator is employed in regressions (7) and (8), assuming for simplicity that only the coefficient on the lag of the dependent varies over the countries in the sample; the respective z-statistics and the value of the log-likelihood function are presented in this case. A simple OLS estimator with the dependent variable in first differences (OLS-Diff) is used to estimate the regressions in columns (9) and (10); the F-test presents the statistics and respective p-values (in square brackets) for the test to the presence of fixed effects.

Figures

Figure 1. Evolution of the credit risk in the GIPSI



Sources: See Table A.1 in Annex.

ANEXOS

Table A.1. Description of the variables

Variables	Description	Expected Signs
Dependent		
CredRisk	Credit risk measured as the ratio between the banks' nonperforming loans and the total gross loans, in percentage.	
Independent		
GDP	Year-on-year growth rate of real gross domestic product, in percentage and seasonally adjusted.	-
UR	Unemployment rate, in percentage.	+
IR_lt	Long-term interest rate, in percentage.	+
RIR	Real interest rate computed as the difference between the long-term interest rate and the inflation rate.	+
IR_spd	Interest rate spread between the long-term and short-term interest rates.	+
Cred_gr	Quarterly growth rate of the loans provided by banks to the economy, in percentage.	+
Indebtness	Private indebtedness in the country measured as the ratio of total gross loans to GDP, in percentage.	+
PubDebt	Government public debt as percentage of GDP.	+
Shares_ygr	Annual growth rate of the share price indices, in percentage.	-
Shares_qgr	Quarterly growth rate of the share price indices, in percentage.	-
REER	Real effective exchange rate, with reference to the 27 EU members.	+
TermsTrade	Terms of trade computed as the ratio between the price of exports and the price of imports.	-
Infl	Inflation rate, in percentage.	-
FinCrisis	Dummy variable that takes the value of 1 for the financial crises period, i.e. after the third quarter of 2008, and 0 otherwise.	+

Sources: Central banks of Portugal, Italy, Ireland, Greece and Spain; OECD Main Economic Indicators; Eurostat Statistics; and European Commission.
Notes:

Table A.2. Descriptive Statistics

Variables	Obs.	Mean	S.D.	Min.	Max.
CredRisk	251	4.03	3.10	0.70	16.29
GDP	333	2.24	3.06	-8.37	14.45
UR	550	10.22	4.05	3.73	22.20
IR_lt	502	7.98	4.10	3.11	19.03
RIR	482	3.33	2.83	-5.00	14.23
IR_spd	436	1.17	2.32	-13.99	15.05
Cred_gr	461	3.24	2.60	-4.55	20.08
Indebtness	266	4.64	2.21	1.37	9.66
PubDebt	605	72.27	27.66	16.80	142.80
Shares_ygr	416	9.72	35.22	-65.22	286.78
Shares_qgr	431	1.82	12.18	-38.91	82.29
REER	350	103.64	5.29	85.15	120.41
TermsTrade	321	0.99	0.03	0.93	1.11
Infl	635	7.06	6.63	-6.11	32.01
FinCrisis	635	0.09	0.29	0	1

Sources: See Table A.1.

Table 3. Correlation Matrix

Variables	*CredRisk*	*GDP*	*UR*	*IR_lt*	*IR_spd*	*RIR*	*Cred_gr*	*Infl*	*Shares_ygr*	*Shares_mgr*	*PubDebt*	*Indebtness*	*REER*	*TermsTrade*	*FinCrisis*
CredRisk	1														
GDP	-0.3384	1													
UR	0.4439	-0.3713	1												
IR_lt	0.3612	-0.2116	0.1254	1											
IR_spd	0.5253	-0.4622	0.4497	0.5243	1										
RIR	0.4919	-0.5863	0.4409	0.3955	0.6176	1									
Cred_gr	-0.2470	0.4992	-0.3430	0.0008	-0.2127	-0.3898	1								
Infl	-0.3335	0.5176	-0.4076	0.1213	-0.3797	-0.8637	0.4217	1							
Shares_ygr	-0.0392	0.5092	-0.0687	-0.2857	-0.1449	-0.1503	0.2690	0.0056	1						
Shares_qgr	0.0130	0.1849	0.0307	-0.2357	0.1102	0.1007	0.0462	-0.2382	0.5360	1					
PubDebt	0.7444	-0.3226	0.2513	0.2797	0.3458	0.3050	-0.1913	-0.1761	-0.1053	-0.0494	1				
Indebtness	0.0382	-0.4461	0.3911	0.0343	0.2476	0.2312	-0.1894	-0.2311	-0.1983	-0.1221	-0.2589	1			
REER	-0.1726	-0.3735	0.1238	-0.1349	0.1890	0.1433	-0.1732	-0.2290	-0.1654	-0.0644	-0.4591	0.8663	1		
TermsTrade	0.0918	-0.0542	-0.0132	-0.0320	0.2213	0.0451	0.1301	-0.0663	0.0667	0.2360	0.0302	-0.1480	-0.0847	1	
FinCrisis	0.4007	-0.6848	0.5154	0.2423	0.6627	0.6554	-0.4090	-0.5753	-0.3207	-0.1195	0.2677	0.5673	0.4319	0.0046	1

Sources: See Table A.1.

Table A.4. Panel unit root tests

	LLC	IPS	Fisher-ADF			
			Inv. χ^2	Inv. N	Inv. L	M.Inv. χ^2
CredRisk	-1.93	-1.84	23.71	-2.53	-2.60	3.06
	[0.032]	[0.033]	[0.008]	[0.006]	[0.007]	[0.001]
GDP	-2.15	-1.66	41.08	-4.04	-4.89	6.95
	[0.015]	[0.049]	[0.000]	[0.000]	[0.000]	[0.000]
UR	1.47	1.17	11.42	0.39	0.55	0.317
	[0.929]	[0.878]	[0.326]	[0.652]	[0.706]	[0.376]
ΔUR	-2.26	-4.46	77.85	-7.05	9.73	15.17
	[0.012]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
IR_lt	-2.79	-1.44	23.64	-2.58	-2.63	3.05
	[0.007]	[0.073]	[0.009]	[0.005]	[0.007]	[0.001]
RIR	-3.04	-0.95	40.35	-4.16	-4.79	6.79
	[0.001]	[0.171]	[0.000]	[0.000]	[0.000]	[0.000]
IR_spd	-3.03	-3.07	45.86	-3.37	-4.65	8.02
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Cred_gr	-4.87	-3.58	66.53	-6.21	-8.22	12.64
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Indebtness	1.30	2.67	8.11	0.84	0.98	-0.42
	[0.904]	[0.996]	[0.618]	[0.799]	[0.833]	[0.664]
ΔIndebtness	-1.07	-0.33	62.01	-5.89	-7.71	11.63
	[0.142]	[0.372]	[0.000]	[0.000]	[0.000]	[0.000]
PubDebt	-3.01	-1.99	29.63	-3.17	-3.43	4.39
	[0.002]	[0.023]	[0.001]	[0.001]	[0.001]	[0.000]
Shares_ygr	-4.50	-5.92	90.80	-8.15	-11.40	18.07
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Shares_qgr	-6.45	-10.26	156.32	-11.30	-19.63	32.72
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
REER	-1.91	-1.48	20.90	-2.32	-2.30	2.44
	[0.028]	[0.071]	[0.022]	[0.010]	[0.014]	[0.007]
TermsTrade	-1.44	-2.72	58.04	-5.36	-7.10	10.74
	[0.075]	[0.003]	[0.000]	[0.000]	[0.000]	[0.000]
Infl	-5.79	-4.62	46.41	-5.22	-5.81	8.14
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: For sources, see Table A.1 in Annex. The Levin-Lin-Chu (LLC) unit root tests are performed over a balanced panel for the period 2000q4-2011q1 with constant and one lag for all regressions; the null hypothesis is that "all panels contain unit-roots"; from the test for each variable, we report the respective statistic and p-value (in square brackets). The Im-Pesaran-Shin (IPS) unit root tests do not require a the use of a balanced panel, hence they are performed over the available data considering a constant and one lag in all regressions; the null hypothesis is that "all panels contain unit-roots"; from the test for each variable, we report the respective statistic and p-value (in square brackets). The LLC test assumes that all panels have the same autocorrelation coefficient, but the IPS test relaxes that assumption and allows each panel to have its own autocorrelation coefficient. The Fisher-type unit-root tests are based on augmented Dickey-Fuller (Fisher-ADF) tests with drift and one lag in all regressions; the null hypothesis is that "all panels contain unit-roots"; this test does not requires a balanced panel because the tests are conducted for each panel individually before combining the p-values from those tests to produce the overall test; the statistics and respective p-values (in square brackets) are reported for each type of Fisher test: inverse chi-squared, inverse normal, inverse logit and modified inverse chi-squared. *Δ* is the first difference operator.

Most Recent Working Paper

NIPE WP 11/2012	**Castro, Vítor** " Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI", 2012
NIPE WP 10/2012	Bastos, Paulo, **Natália Pimenta Monteiro e Odd Rune Straume** "Privatization and corporate restructuring", 2012
NIPE WP 09/2012	**Castro, Vítor** e Rodrigo Martins "Is there duration dependence in Portuguese local governments' tenure?", 2012
NIPE WP 08/2012	**Monteiro, Natália Pimenta** e Geoff Stewart " Scale, Scope and Survival: A Comparison of Labour-Managed, and Capitalist Modes of Production", 2012
NIPE WP 07/2012	**Aguiar - Conraria, Luís,** Teresa Maria Rodrigues **e Maria Joana Soares** " Oil Shocks and the Euro as an Optimum Currency Area", 2012
NIPE WP 06/2012	Bastos, Paulo,**Odd Rune Straume** e Jaime A. Urrego "Rain, Food and Tariffs ", 2012
NIPE WP 05/2012	Brekke, Kurt R., Luigi Siciliani e **Odd Rune Straume,** "Can competition reduce quality?", 2012
NIPE WP 04/2012	Brekke, Kurt R., Luigi Siciliani e **Odd Rune Straume,** "Hospital competition with soft budgets", 2012
NIPE WP 03/2012	Lommerud, Kjell Erik, **Odd Rune Straume** e Steinar Vagstad**,** " Employment protection and unemployment benefits: On technology adoption and job creation in a matching model", 2012
NIPE WP 02/2012	**Amado, Cristina** e Timo Teräsvirta, "Modelling Changes in the Unconditional Variance of Long Stock Return Series", 2012
NIPE WP 01/2012	Martins, Rodrigo e **Francisco José Veiga**, " Turnout and the modeling of economic conditions: Evidence from Portuguese elections", 2012
NIPE WP 34/2011	Agnello, L e **Ricardo M. Sousa**, " Fiscal Consolidation and Income Inequality ", 2011
NIPE WP 33/2011	Maria Caporale, G e **Ricardo M. Sousa**, "Are Stock and Housing Returns Complements or Substitutes? Evidence from OECD Countries", 2011
NIPE WP 32/2011	Maria Caporale, G e **Ricardo M. Sousa**, "Consumption, Wealth, Stock and Housing Returns: Evidence from Emerging Markets ", 2011
NIPE WP 31/2011	Luca Agnello, Davide Furceri e **Ricardo M. Sousa**, "Fiscal Policy Discretion, Private Spending, and Crisis Episodes ? ", 2011
NIPE WP 30/2011	Agnello, L e **Ricardo M. Sousa**, "How do Banking Crises Impact on Income Inequality? ", 2011
NIPE WP 29/2011	**Alexandre, Fernando, Luís Aguiar-Conraria,** Pedro Bação e **Miguel Portela**, "A Poupança em Portugal", 2011
NIPE WP 28/2011	**Alexandre, Fernando** e Carmen Mendes, "Growth, Consumption and Political Stability in China", 2011
NIPE WP 27/2011	**Baleiras, Rui Nuno**, "Collective Efficiency Strategies: A Regional Development Policy Contribution for Competitiveness Enhancement", 2011
NIPE WP 26/2011	Brekke, Kurt R., Rosella Levaggi, Luigi Siciliani e **Odd Rune Straume,** "Patient Mobility, Health Care Quality and Welfare", 2011
NIPE WP 25/2011	**Aguiar - Conraria, Luís,** Pedro C. Magalhães **e Maria Joana Soares** "Cycles in Politics: Wavelet Analysis of Political Time-Series", 2011
NIPE WP 24/2011	Agnello,Luca, **Vitor Castro e Ricardo M. Sousa** "How Does Fiscal Policy React to Wealth Composition and Asset Prices? ", 2011
NIPE WP 23/2011	Silva, Hélia**, Linda Veiga e Miguel Portela** "Strategic Interaction in Local Fiscal Policy: Evidence from Portuguese Municipalities", 2011
NIPE WP 22/2011	**Sousa, Ricardo M.**, "Wealth, Labour Income, Stock Returns and Government Bond Yields, and Financial Stress in the Euro Area", 2011
NIPE WP 21/2011	Sousa, João e **Ricardo M. Sousa**, "Asset Returns Under Model Uncertainty: Evidence from the euro area, the U.K. and the U.S. ", 2011
NIPE WP 20/2011	Sila, U e **Ricardo M. Sousa**, "Do Windfall Gains Affect Labour Supply? Evidence from the European Household Panel ", 2011