BANKING SOUNDNESS INDICATORS AND SOVEREIGN RISK IN TIME OF CRISIS: THE CASE OF THE EUROPEAN UNION

Purificación Parrado-Martínez[a*], Antonio Partal-Ureña[a], Pilar Gómez Fernández-Aguado[a]

[a]Department of Financial Economics and Accounting, Universidad de Jaén, ES-23071, Jaén, Spain

Abstract

This paper examines the impact of the soundness of the banking sector on sovereign risk of EU member countries during the financial crisis by using a selection of financial soundness indicators (FSIs) and the sovereign ratings of the three main rating agencies. Unlike previous literature that typically focus on the ability of FSIs to foresee banking crises, we estimate ordered response models to assess the power of these indicators to explain sovereign risk. Our results show that evaluations made by the rating agencies are related to the lagged values of core FSIs such that an improvement in these indicators leads to improvements in upcoming sovereign ratings. Hence, reinforced banking soundness would reduce the sovereign risk. Accordingly, governments, supervisors and central banks should pay close attention to the evolution of certain FSIs related to the banking sector, in addition to other variables that have traditionally been taken into account in analyzing sovereign risk.

Keywords: financial soundness indicators, banking sector, sovereign risk, rating agencies, ordered response models, European Union.

JEL Classification: F33, F36, G24, G28

*Corresponding author at: Department of Financial Economics and Accounting, Universidad de Jaén, Paraje Las Lagunillas, s/n, 23071 Jaén, Spain. Tel.: +34 953212611. E-mail address: pparrado@ujaen.es (P. Parrado-Martínez).

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1. INTRODUCTION

Two main approaches exist in the research related to bank risk assessment: the microprudential approach and the macroprudential approach. The microprudential approach identifies weak banks by using mainly bank-specific variables and examining individual financial institutions. In contrast, the macroprudential approach seeks to monitor the stability of the financial system as a whole by examining aggregated micro-data and financial and macroeconomic information. Global financial difficulties have shown the limitations of traditional microprudential regulations in identifying the vulnerabilities of the financial system as a whole. Consequently, there has been a shift towards the macroprudential approach (Cheang and Choy, 2011).

Banking sector stability has received increasing attention following the latest disruptions of banking systems around the world, highlighting the need for appropriate instruments to assess and supervise risk. At the same time, banks have been at the centre of the recent European sovereign debt crisis. Although central banks and governments took extraordinary measures to prevent the effects of a potential collapse of the financial sector on the entire economy, the interconnections between the banking and the sovereign sector remain widely unknown (Alter and Schüler, 2012).

After exposure of the vulnerabilities of certain European sovereigns and disclosures of detailed information in the stress tests developed by the European Banking Authority (EBA), market participants were provided with valuable information on the risk profiles of European banks and their exposures to sovereign risk. In this

scenario, the financial conditions of banks and sovereigns became increasingly intertwined (De Bruyckere *et al.*, 2012).

Although in the last few years, several papers have investigated the links and feedback loops between bank risk and sovereign risk (e.g., Alter and Schüler, 2012; De Bruyckere *et al.*, 2012; Merler and Pisani-Ferry, 2012; Acharya *et al.*, 2013; Angelini *et al.*, 2014), our work is the first to examine the impact of the soundness of the banking sector on sovereign risk using a selection of FSIs[1] and the sovereign ratings of the three main rating agencies.

Unlike previous research on FSIs, research that examines global samples and focuses on the ability of these indicators to predict or foresee banking crises (e.g., Akhter and Daly, 2009; Čihák and Schaeck, 2010; Costa and Thegeya, 2013; Kasselaki and Tagkalakis, 2014), we extend the literature by assessing the ability of these indicators to explain sovereign risk, focusing on EU member countries due to the intensity of the sovereign debt crises in these countries. We believe that such research is necessary, especially now, when the European community is concerned with the soundness of the banking sector, systemic risk and the interrelations between banking risk and sovereign risk.

We demonstrate that the aggregate prudential ratios of banking soundness, as well as other traditional indicators (macroeconomic, social and political variables) impact sovereign risk. Our results support the ability of these ratios to explain the sovereign risk of EU member countries during the crisis and extend the findings of Čihák and Schaeck (2010) regarding the usefulness of FSIs. Specifically, we find that a high percentage of nonperfoming loans reduces the asset quality of the banking sector

[1] The International Monetary Fund (IMF) implemented an initiative to develop and compile a set of macroprudential indicators that resulted in publication of the '*Financial Soundness Indicators: Compilation Guide*' in 2006. Although other international agencies have implemented similar initiatives, the IMF work is arguably the most interesting because it aims to develop international standards for the compilation of financial soundness indicators (Mörttinen *et al.*, 2005).

and leads to a deterioration in forthcoming sovereign ratings. By contrast, banking diversification and profitability lead to an improvement in forthcoming ratings.

This paper proceeds as follows. The next section presents a review of related literature. Section 3 discusses relevant aspects of the data and methodology employed. Section 4 presents the main analysis and results. Finally, section 5 concludes the paper.

2. LITERATURE REVIEW

Our study is closely related to two strands of the literature: research on channels that transmit bank risk to sovereigns, including interactions between bank and sovereign risk, and research on FSIs.

2.1.Literature on links between bank risk and sovereign risk

With respect to links between sovereign and bank risks, sovereign difficulties spread rapidly to the domestic banking system, owing to the deterioration in the economic outlook, funding problems and depreciation of government bond portfolios (Angelini *et. al*, 2014).[2] At the same time, a banking crisis can lead to a sovereign crisis (Reinhart, 2009; Reinhart and Rogoff, 2010) because of the impact of government support of banks and other financial institutions on public finances. Candelon and Palm (2010) note two additional transmission channels: the fiscal cost and the increase in the risk premium in the event that contingent liabilities materialise and the effect of downturn in public revenues.[3]

Following the European sovereign debt crisis, a growing strand of the literature has focused on the feedback loops between sovereign and bank risk (e.g., Alter and

[2] De Bruyckere *et al.* (2012) explain in detail the main channels through which sovereign risk can impact financial institutions.
[3] Balteanu *et al.* (2011) offer a detailed explanation of the channels through which banking crises may affect sovereigns.

Schüler, 2012; De Bruyckere *et al.*, 2012; Merler and Pisani-Ferry, 2012; Acharya *et al.*, 2013; Angelini *et al.*, 2014; Farhi and Tirole, 2014; among others). However, research on the impact of the particular features of the banking system of a country on its sovereign risk is more limited.

In this paper, we contribute to the literature by examining the particular influences of capital adequacy, asset quality and profitability of the banking sector on sovereign risk in EU countries. On the one hand, unlike existing research, we do not examine credit default swaps (CDS) of individual banks but rather macroprudential indicators relating to the banking sector. These indicators allow us to capture the conditions of a country´s banking sector as a whole, including relationships between individual institutions. In this way, we consider bank risk at the country level, in contrast to previous studies, which analyse risk at the firm or bank level (Demirovic and Thomas, 2007; Poghosyan and Čihák, 2011; Alter and Schüler, 2012; Buch *et al.*, 2013; Trujillo-Ponce *et al.,* 2014). On the other hand, unlike recent studies of sovereign risk that focus on sovereign CDS spreads (e.g., Alter and Schüler, 2012; De Bruyckere *et al.*, 2012; Angelini *et al.*, 2014), we use the sovereign ratings of the three major rating agencies as proxies for the sovereign risk of a country and develop ordered response models.

2.2.Literature on FSIs

Within the second strand of the literature, three types of empirical study of FSIs are distinguished, based on their purposes. The first type examines the evolution of certain FSIs, to draw conclusions about the soundness of various banking systems. Daly and Akhter (2009) consider three aspects of financial soundness (capital adequacy, asset quality and profitability) and observe their evolution in a sample of countries

throughout the world from 1998 to 2006, using a set of indicators. They conclude that the analysed set of FSIs allows for comparative analysis of the financial health of different countries, despite certain methodological and compilation issues. More recently, Maudos (2012) studies the evolution of FSIs in the Spanish banking sector, comparing them with those of the Euro area. The results reveal the weaker position of the Spanish banking sector but capture improved solvency ratios.

The second type of empirical study analyses the macroeconomic determinants of certain FSIs. Babihuga (2007) uses data on capital adequacy, asset quality and profitability indicators for 96 countries from 1998 to 2005 to show that FSIs fluctuate strongly with the business cycle, inflation, real exchange rates and short-term interest rates. Akhter and Daly (2009) collect data for more than 50 countries and model each of these indicators individually, using different sets of explanatory variables. The analysis reveals the strong influence of business cycles, inflation, the real effective exchange rate and the size of industry on capital adequacy. Furthermore, the results provide evidence that bank profitability is determined by a combination of macroeconomic, bank specific and industry characteristics, such as inflation and credit risk.

The third type of empirical study examines the usefulness of FSIs. The main work in this group, thus far, is Čihák and Schaeck (2010). These authors draw upon a set of FSIs for 100 developed and developing economies to present an econometric analysis of the applicability of these ratios for the identification of banking crises during the 1994-2007 period. In particular, they focus on three FSIs from the core set and two from the encouraged set. The results suggest that bank return on equity and nonbank corporate leverage are good indicators of the build-up of systemic problems. They also find evidence that the contemporaneous ratio of nonperforming loans to total loans and capital adequacy are useful indicators of banking turmoil. More recently, Costa and

Thegeya (2013) test the usefulness of FSIs as harbingers of crises. Their results suggest that some indicators are precursors of systemic banking crises.

We contribute to this strand of the literature by empirically examining the ability of some FSIs (all related to the banking sector) to explain the risk of countries. In contrast to Čihák and Schaeck (2010) and Costa and Thegeya (2013), we do not examine the ability of these indicators to predict the particular event of a banking crisis but rather their usefulness to explain the general sovereign risk of countries. Unlike studies of banking risk that examine the probability of observing a banking crisis in an economy in a given year (e.g., Caprio and Klingebiel, 1996; Kaminsky and Reinhart, 1999; Demirgüç-Kunt and Detragiache, 2005; Čihák and Schaeck, 2010; Costa and Thegeya, 2013), we use the sovereign ratings of the three major rating agencies as a proxy for the risk EU countries face and develop ordered response models using this proxy.[4] Finally, unlike the existing literature on FSIs, which uses global samples (e.g., Akhter and Daly, 2009; Daly and Akhter, 2009; Čihák and Schaeck, 2010), we focus on EU member countries throughout the crisis period.

3. DATA, HYPOTHESES AND METHODOLOGICAL ASPECTS

3.1. Sample

Our sample consists of the EU-27 member countries. As the motivation of the paper is to examine the crisis period, and in view of the availability of data for our explanatory variables, our estimations cover the period 2008 to 2013. We consider data at the end of each year. Overall, we have an unbalanced panel, with 27 countries and a maximum of 6 yearly observations per country. Tables 1 and 2, organised by country and year, present the number of observations that constitute the sample.

[4] Appendix 1 lists some relevant studies that have used sovereign ratings as a dependent variable.

[INSERT TABLES 1 AND 2 ABOUT HERE]

3.2. Dependent variable: sovereign rating

Previous literature on the credit risk of companies and countries has used credit ratings as a proxy for credit risk (Butler and Fauver, 2006; Demirovic and Thomas, 2007; Afonso *et al.*, 2011). Sovereign ratings inform us of the ability and willingness of a country to repay its public debt on time (Afonso *et al.*, 2011), and they *'represent a measure of the credit risk of a given country'* (Alsakka and apGwilym, 2010, p. 141). We use long-term sovereign credit ratings as a proxy for sovereign risk: the better the rating, the lower the risk.

We build a database with the sovereign ratings assigned by the three major rating agencies -S&P, Moody's and Fitch Ratings- during the period 2008 to 2013.[5] The rating for a particular year is taken from December 31st. Because some countries are not rated by all three agencies (Table 3), models that use S&P ratings as the dependent variable have fewer observations than those that use the Moody's or Fitch ratings.

[INSERT TABLE 3 ABOUT HERE]

The ratings are converted into numerical equivalents and then grouped into 5 categories.[6] On our scale, 1 denotes the highest rating (AAA for S&P and Fitch, Aaa for Moody's), and 5 denotes the lowest (below BB+ for S&P and Fitch, below Ba1 for Moody's). The number of observations falling into each rating group is presented in Table 4. When a country is rated by more than one agency in a single year, each rating is considered a separate observation.

[INSERT TABLE 4 ABOUT HERE]

[5] We obtained rating information from the Bankscope-Bureau Van Dijk database.
[6] The number of categories is based on the sample size and economic considerations.

3.3. Explanatory variables

3.3.1. Selected FSIs

We obtain data for the Financial Soundness Indicators (FSIs) from the IMF´s database. This data set consists of homogeneous indicators that are collected under internationally accepted standards and are comparable across countries. FSIs are divided into two groups.[7] The first group consists of core indicators that relate to five relevant basic areas of the banking business. The remaining indicators belong to the encouraged set, which includes indicators pertaining to non-bank financial institutions, non-financial corporations, households, financial markets and property markets.

Our study considers three main aspects of the CAMELS methodology[8]: capital adequacy, asset quality and earnings/profitability.[9] Each aspect is represented by at least one indicator, and thus, four FSIs belonging to the core set are considered (see Table 5). The choice of this subset is driven by multicollinearity issues and availability considerations (a sufficient number of observations were recorded only for the selected variables).[10] Given the static specification in equation 1, a problem concerning the endogenous nature of the variables arises, as FSIs may impact sovereign credit ratings, but credit ratings may impact FSIs as well. We introduce lagged values of the indicators to avoid this problem.

Previous literature has found negative effects of capitalisation on bank distress (Čihák and Schaeck, 2010; Baselga-Pascual *et al.*, 2013), such that the higher the

[7] See IMF (2006).
[8] The methodology of the assessment of the soundness of individual financial institutions employs indicators of capital adequacy, asset quality, management soundness, earnings, liquidity and sensitivity to market risk.
[9] The *Survey on the Use, Compilation, and Dissemination of Macroprudential Indicators*, conducted by the IMF in 2000, revealed that all major categories of FSIs were broadly useful. In particular, capital adequacy, asset quality and profitability indicators were most widely deemed to be useful (Sundararajan *et al.*, 2002).
[10] Thus, although it would be reasonable to include sensitivity to market risk indicators in the study, especially given the sample period analysed, when bank risk exposure to movements in asset prices in financial markets was notable, we do not include it in the model due to the high proportion of missing data for this particular indicator.

capitalisation, the lower the risk. In the same way, we expect a negative relationship between the lagged regulatory capital ratio of the banking system and sovereign risk (*Hypothesis 1*). Thus, the better capitalised is the banking sector, the greater is its ability to absorb sudden losses, and therefore, the lower is sovereign risk and the better is the rating assessment.

In relation to the asset quality indicator, an increase in the percentage of non-performing loans (NPLs) may reduce the quality of the banking sector's assets and cause a deterioration of the country's financial health, i.e., an increase in sovereign risk. Therefore, we expect a positive relationship between the lagged NPLTGL ratio of the banking sector and sovereign risk (*Hypothesis 2*).

Finally, profitability and earnings indicators are related to the ability to absorb losses without any impact on capital (Sundararajan *et al.*, 2002). We select two indicators, each of which measures a different concept. The return on equity (ROE) measures the efficiency of deposit takers in using capital. Previous literature shows a negative relationship between bank ROE and risk (Čihák and Schaeck, 2010; Baselga-Pascual *et al.*, 2013). Because banks with higher earnings are less likely to experience distress (Poghosyan and Čihák, 2011), we expect a negative relationship between lagged banking sector ROE and sovereign risk (*Hypothesis 3*).

The last indicator, NIEGI, measures the proportion of non-interest expenses with respect to gross income. This measure is indicative of revenue diversification and bank efficiency. Although traditionally, the main source of bank revenues has been interest (deposit taking and lending), there are various activities that produce non-interest income (e.g., fees, trading, investment, commissions). Based on the portfolio theory and other studies (Diamond, 1984; Köhler, 2012), we should expect that diversification of banking system activity negatively affects risk, i.e., it reduces the risk of the banking

system and, as a result, reduces sovereign risk. However, there is a literature that supports the contrary argument (Demirgüç-Kunt and Huizinga, 2010; Altunbas *et al.*, 2011; Kölher, 2012). Therefore, we propose two possible hypotheses for this indicator: a negative relationship between lagged banking sector NIEGI and sovereign risk (*Hypothesis 4.1*) and a positive relationship between lagged banking sector NIEGI and sovereign risk (*Hypothesis 4.2*).

3.3.2. Control variables

- ***Financial development and structure***

We include a proxy for the financial development of countries to explore its influence on sovereign risk. A large body of economic literature supports the premise that, in addition to many other important factors, long-term economic growth of a country is related to its degree of financial development (Goldsmith, 1969; King and Levine, 1993; Arestis and Demetriades, 1997; Levine and Zervos, 1998; Rajan and Zingales, 1998; or Levine, 2004; among others). The main argument is that the services provided by the financial sector contribute to economic growth (Rajan and Zingales, 1998).[11] In addition, the higher the degree of financial development, the wider is the availability of financial services, which allows for diversification of risk (WEF, 2012).

Based on these factors, a financially developed country should allow for greater diversification of risk and economic growth, thereby improving its sovereign rating. At the same time, a country with a better sovereign rating is likely to achieve positive outcomes with respect to financial development. Lagged values of the proxy are used to avoid this endogeneity problem. We initially expect to find a negative relationship

[11] More recently, some papers have revealed a threshold above which financial development no longer has a positive effect on economic growth (Arcand *et al.*, 2012; Cecchetti and Kharroubi, 2012; Law and Singh, 2014).

between lagged values of the level of financial development and sovereign risk *(Hypothesis 5)*.

Financial development has typically been measured by the level of credit and the size of the stock market (Rajan and Zingales, 1998). Some variables commonly used to measure financial development are *Credit/GDP*, *Market capitalisation of listed companies/GDP* and the *Total Capitalisation/GDP* (Maudos and Fernández de Guevara, 2006).[12] We use the *Total Capitalisation/GDP* (FDL) variable to jointly consider two important forces of financial development: financial intermediaries and financial markets. The proxy used is the sum of *Credit/GDP* and *Capitalisation of listed companies/GDP*. [13] Data were obtained from the World Bank's database, World Development Indicators.

We also include a structural indicator to capture the influence of banking sector concentration on sovereign risk. We select a frequently used measured of the number and size of banks in a banking system: the Herfindahl Index for credit institutions to total assets (H-I). Data were obtained from the European Central Bank's database, Statistical Data Warehouse.

Initially, we expect a positive relationship between banking sector concentration and sovereign risk. Concentration may reduce competition and increase the systemic risk of "too big to fail" financial institutions, thus increasing risk not only to the banking sector but to the country as a whole (BIS, 2001; IMF, 2001; De Nicolò et al., 2003). However, some research suggests that the concentration of the banking sector can reduce fragility of the sector by enhancing profits and providing bigger "capital buffers"

[12] Levine and Zervos (1993), Rajan and Zingales (1998), Maudos and Fernández de Guevara (2006), Bena and Ondko (2012), among others, use some of these variables as proxies for financial development.
[13] *Credit/GDP* is calculated by dividing domestic credit provided by the banking sector to the private sector by GDP. *Capitalisation of listed companies* is calculated using the share price times the number of shares outstanding of the domestically incorporated companies listed on the country's stock exchanges at the end of the year.

(Allen and Gale, 2004; Beck *et al.*, 2007). Therefore, we propose two alternative hypotheses: a positive relationship between H-I and sovereign risk (*Hypothesis 6.1*); and a negative relationship between H-I and sovereign risk (*Hypothesis 6.2*).

- ***Macroeconomic variables***

Based on the previous literature on sovereign risk determinants (Appendix 1), we select four macroeconomic variables to control for the effects of economic growth, inflation, government debt and government budget on sovereign risk (Table 5). Economic growth and the government budget reduce sovereign risk, whereas inflation and government debt increase it. We obtained data from the World Economic Outlook Database (WEO) and Eurostat.

- ***Social, governance and political factors***

In addition, we introduce into our models a set of social, governance and political variables to control for non-financial factors that could affect sovereign risk, as suggested by previous studies (See Appendix 1).

As a social variable, we include the unemployment rate. We expect a positive relationship between this variable and risk, as unemployment may cause an increase in defaults and undermine the quality of banks' loan portfolios (Bofondi and Ropele, 2011). Data were obtained from the World Bank´s Database, World Development Indicators.

As governance and political factors, we introduce government effectivity and regulatory quality. The first variable reflects perceptions of the quality of public services, the civil service, policy formulation and degree of independence from political pressures. The second indicator measures perceptions of the ability of the government to formulate and implement sound policies and regulations to promote private sector development. For both of these indicators, we hypothesise a negative relationship with

sovereign risk, such that the more positive the perceptions of government effectiveness and regulatory quality are, the lower the sovereign risk. We obtained data from the World Bank´s Database, WorldWide Governance Indicators.

- ***Other control variables***

Finally, a set of year dummy variables are included to control for time-specific effects.

[INSERT TABLE 5 ABOUT HERE]

3.4. Methodology

There are two main econometric approaches in the credit ratings literature: linear regression methods (Cantor and Packer, 1996; Afonso, 2003; Mora, 2006; Butler and Fauver, 2006; Ratha *et al.*, 2011; Afonso *et al.*, 2011) and ordered response models (Trevino and Thomas, 2001; Hu *et al.*, 2002; Bissoondoyal-Bheenick, 2005; Demirovic and Thomas, 2007; Alsakka and apGwilym, 2010; Afonso *et al.*, 2011).

Linear regression methods that produce numerical representations of ratings allow for a straightforward generalisation to panel data, using a fixed and random effects estimation procedure (Mora, 2006). However, this method faces some criticisms. The traditional estimation procedures for a linear representation of the ratings are not adequate because rating is a qualitative ordinal measure. Accordingly, these techniques implicitly assume that the difference between any two adjacent categories is always equal and the coefficient estimates are biased (Afonso *et al.*, 2011). Ordered response models—a widely accepted approach in the literature related to credit ratings (Williams *et al.*, 2013)—can solve these problems because they take into account the nature of the dependent variable (the rating is a discrete variable and reflects an order in terms of the probability of default).

Ordered response models stem from a latent or unobserved variable model that satisfies the assumptions of the classic linear model.[14] R_{it}^{*} represents the credit risk of country i in year t, where such risk depends on several factors. How these factors enter the R_{it}^{*} function is uncertain, but it is conventional to use a linear function (Greene, 2012, p. 825). If we suppose that the unobserved latent variable R_{it}^{*} is a linear function of k factors, whose values for country i in year t are $X_{k,it}$, $k = 1,\ldots,K$, then country risk can be represented as:

$$R_{it}^{*} = \sum_{k=1}^{K} \beta_k X_{k,it} + \varepsilon_{it} = Z_{it} + \varepsilon_{it} \tag{1}$$

Because the ratings are arranged in descending order (AAA=1, AA+=2 and so on), an increase in the value of the k^{th} factor for a particular country will cause an increase in its risk if $\beta_k > 0$ and a decrease in its risk if $\beta_k < 0$.

Country risk is classified using the threshold values C_{j-1} (where j is the number of possible outcomes; in our case, $j = 5$), such that $C_1 < C_2 \ldots < C_{j-1}$, and the final rating (the observed variable, R_{it}) is given by:

$$\begin{aligned} R_{it} &= 1 \text{ if } R_{it}^{*} \le C_1 \\ R_{it} &= 2 \text{ if } C_1 < R_{it}^{*} \le C_2 \\ R_{it} &= 3 \text{ if } C_2 < R_{it}^{*} \le C_3 \\ &\cdots \\ R_{it} &= j \text{ if } C_{j-1} < R_{it}^{*} \end{aligned} \tag{2}$$

Based on previous literature, we assume that ε_{it} follows a normal distribution, $\varepsilon_{it} \sim N[0,1]$, so that we obtain an ordered probit model.[15] For an ordered probit model, the cumulative distribution function of the random variable X is:

[14] See Wooldridge (2002).
[15] This model is explained in detail in Greene (2012, Chapter 18).

$$F(X) = \Pr(X \le x) = \phi(x) = \int_{-\infty}^{X_0} \frac{1}{\sqrt{2\sigma^2\pi}} e^{\frac{-(X-\mu)^2}{2\sigma^2}} \quad (3)$$

The probabilities of a country taking any of the rating categories are defined by:

$$\Pr(R_{it} = 1) = P(R_{it}^* \le C_1) = P(Z_{it} + \varepsilon_{it} \le C_1) = P(\varepsilon_{it} \le C_1 - Z_{it}) = F(C_1 - Z_{it})$$

$$\Pr(R_{it} = 2) = P(C_1 < R_{it}^* \le C_2) = P(R_{it}^* \le C_2) - P(R_{it}^* \le C_1) = P(Z_{it} + \varepsilon_{it} \le C_2) - P(Z_{it} + \varepsilon_{it} \le C_1) = P(\varepsilon_{it} \le C_2 - Z_{it}) - P(\varepsilon_{it} \le C_1 - Z_{it}) = F(C_2 - Z_{it}) - F(C_1 - Z_{it})$$

$$\dots$$

$$\dots$$

$$\Pr(R_{it} = j) = P(R_{it}^* > C_{j-1}) = P(Z_{it} + \varepsilon_{it} > C_{j-1}) = P(\varepsilon_{it} > C_{j-1} - Z_{it}) = 1 - F(C_{j-1} - Z_{it})$$

(4)

The parameters of the equations and the cut-off points are estimated using maximum likelihood.[16] As our database has a panel data structure, we must control for unobserved heterogeneity and serial correlation. We follow the two approaches described by Wooldridge (2002). The first, although it is the quicker approach, is not the best. It assumes that there is only one error term that is serially correlated within countries (equation 1). Under this assumption, we can estimate a standard ordered probit model using a robust variance-covariance matrix clustered by countries to account for both serial correlation and heteroscedasticity. We report results of this approach as a robustness check.

The second approach, the random effect ordered probit model, is the better option (Afonso *et al.*, 2011). This model assumes that ε_{it} has two normally distributed components, u_i and e_{it} (Equation 5). The unobserved heterogeneity u_i represents the country-specific error term, capturing all the variation at the country level that is not controlled for by the independent variables in the model. The idiosyncratic error e_{it} captures all peculiarities, apart from the effects that are already controlled for in the

[16] The results are obtained using STATA/Special Edition, 12.0.

model, that affect the dependent variable for each county at each point in time (Andreß *et al.*, 2013).

$$R_{it}^{*} = \sum_{k=1}^{K} \beta_k X_{k,it} + u_i + e_{it} = Z_{it} + u_i + e_{it} \quad (5)$$

4. RESULTS

4.1. Random effects ordered probit results

Table 6 shows random effects ordered probit estimations for each rating agency. Globally, almost every variable included in the models appears to be statistically significant and has the expected sign.

With respect to the financial soundness indicators, the results show significant coefficients for the lagged ratios of NPLTGL and NIEGI, indicating that these variables significantly affect the ratings and the sovereign risks of countries. We find evidence to support hypotheses 2 and 4.1. The NPLTGL ratio has a significantly positive impact on sovereign risk: an increase of the percentage of non-performing loans reduces asset quality in the banking sector, causing an increase in sovereign risk. In addition, the negative sign for NIEGI confirms the argument that diversification of the banking activities reduce banking risk and thus sovereign risk. The greater is bank´s focus on non-interest activities, the lower is sovereign risk. Finally, if we consider the ratings of Moody´s, the lagged ROE ratio appears to be statistically significant with a negative sign, supporting hypothesis 3. The higher the return on equity of banks is, the higher their profits and the greater their ability to absorb losses. This relation contributes to a reduction in sovereign risk.

The variable related to the structure of the banking sector appears to also be significant. The positive sign of this indicator in the models confirms the hypothesis that

concentration in the banking sector increases sovereign risk (hypothesis 6.1). This relationship could be explained by the higher systemic risk associated with a more concentrated banking sector. Such concentration may increase risk not only for the banking sector but for the country as a whole.

In addition, the proxy for financial development also has significant coefficients. The negative sign of the lagged FDL proxy confirms hypothesis 5, as a negative relationship between financial development and sovereign risk can be observed. Thus, the more financially developed a country is, the lower is its sovereign risk. This relationship is most likely due to the greater availability of financial services in countries characterised by higher levels of financial development, allowing for greater diversification of risk.

With respect to the macroeconomic variables, all are found to significantly affect sovereign risk. As expected, economic growth and the government budget reduce sovereign risk, while inflation and government debt increase it. In general, economies with better perspectives of economic growth and government budget are associated with lower levels of risk, whereas inflation and government debt lead to a deterioration in public accounts, increasing risk.

Finally, all the social, governance and political factors considered in the models significantly affect sovereign risk. Unemployment increases sovereign risk due to a reduction in resources people can use to retire debt, while perceptions of government effectivity and regulatory quality attract foreign investors and reduce sovereign risk.

[INSERT TABLE 6 ABOUT HERE]

4.2. Robustness checks

In order to test the robustness of the results and the quality of the models, we present two robustness checks.

4.2.1. Ordered probit results

First, following Wooldridge (2002), we report the results for the standard ordered probit models for each rating agency (Table 7).[17] In terms of statistical significance, the results are worse than those presented in Table 6, probably because the random effects ordered probit model takes into account the panel data structure of our database.

Regarding the financial soundness indicators, the lagged value of the NPLTGL and NIEGI are again statistically significant and maintain the same sign in the equation. In addition, if we consider the ratings of S&P, the lagged ROE ratio appears to be statistically significant, so that the more profitable is banking sector, the lower is sovereign risk.

The variable related to the structure of the banking sector is again significant. However, in these models, the proxy for financial development is not significant.

With respect to the macroeconomic variables, GDPG and INFLAT significantly affect sovereign risk, while GGDGDP and GBGDP are not found to be statistically significant.

Finally, among the social, governance and political factors, only the indicator for regulatory quality shows a significant impact on sovereign risk: the higher is perceived regulatory quality in a country, the lower is sovereign risk.

[INSERT TABLE 7 ABOUT HERE]

[17] We also estimate standard ordered logit models. The results are similar for significant variables and are not reported due to space constraints.

To compare the two methodologies, we estimate the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The AIC and BIC are measures of the relative quality of statistical models, and as such, they can be used to evaluate the trade-off between the goodness of fit of models and their complexity. Models with lower values of AIC and BIC are preferred. In light of these measures, the random effects ordered probit model fits better than does the standard ordered probit model.

4.2.2. Ordered probit results using agency dummies

As a second robustness check, we re-estimate the models by considering only one dependent variable that jointly contemplates the ratings of the three major rating agencies, and we introduce agency dummy variables.[18] Thus, when a country is rated by more than one agency in any period, each rating is considered a separate observation.

The results for the significant variables (Table 8) are quite similar to those presented in Table 7, demonstrating the robustness of the lagged ratios of NPLTGL, NIEGI, banking sector concentration, economic growth, inflation, perceptions of government effectivity and perceptions of regulatory quality. These variables remain significant in alternative specifications of the dependent variable and in different models. Nevertheless, given the complexity of this methodology, the AIC and BIC suggest that these models have much poorer fit than models that separately consider the information of each rating agency.

[INSERT TABLE 8 ABOUT HERE]

[18] Demirovic and Thomas (2007) and Trujillo-Ponce *et al.*, (2014), among others, have used this methodology.

5. CONCLUSIONS

The consequences and detrimental effects of the financial crisis have been experienced all over the world. In the European Union, the banking crises of several countries caused a spiral of higher debt costs and falling sovereign ratings, which magnified the relationship between bank risk and sovereign risk, ultimately giving rise to the European sovereign debt crisis. This paper empirically examines the influence of FSIs related to the banking sector (capital adequacy, asset quality and earnings/profitability indicators) on sovereign ratings of EU countries during a period of a severe financial instability (2008-2013).

Additionally, to avoid endogeneity due to possible omitted variables, we consider the effects of other factors that may influence sovereign risk: financial development level, concentration of the banking sector, economic growth, inflation, government debt, the government budget, unemployment, government effectiveness and regulatory quality.

Using ratings from the three major international rating agencies as proxies for sovereign risk, we estimate ordered probit models at the country level, in contrast to previous studies, which analyse risk at the firm or bank levels (Demirovic and Thomas, 2007; Poghosyan and Čihák, 2011; Trujillo-Ponce *et al.*, 2014). With respect to the methodological contribution, the robustness checks confirm that the random effects ordered probit model fit better than the standard ordered probit model.

Four core FSIs are selected based on previous literature, multicollinearity issues and data availability. The random effects ordered probit models reflect the influence of FSIs on sovereign ratings. Thus, we contribute to the literature by demonstrating the effects of banking soundness on sovereign risk.

Our analyses yield some interesting results. Specifically, some FSIs, such as the lagged ratio of NPLTGL, have a significant positive impact on risk (i.e., an increase in the lagged value of NPLTGL causes an increase in sovereign risk), whereas other FSIs, such as the lagged ratios of ROE and NIEGI, appear to be significant but negatively impact risk (i.e., an increase in these lagged ratios causes a decrease in sovereign risk). The lagged value of the financial development level (FDL) of a country is also found to be significant; thus, the higher is the level of financial development, the lower is sovereign risk. In addition, concentration of the banking sector appears to increase sovereign risk, likely due to systemic risk. Finally, macroeconomic, social and political variables are also shown to influence sovereign risk.

In conclusion, the results support the hypothesis that banking soundness indicators provide signals that anticipate, to some extent, sovereign ratings. In this sense, these aggregate prudential ratios can contribute to macroprudential analysis, although they should be used jointly with other instruments (such as stress tests, early warning systems, or supervisory assessments) for a reliable and complete assessment of banking risk and sovereign risk.

In addition to many other variables, evaluations by the three major rating agencies are related to the lagged values of core FSIs, with improvements in these indicators associated with improvements in forthcoming sovereign ratings. Hence, reinforcement of banking soundness would reduce the probability of new banking crises, minimising the impact of bank risk on sovereign risk. Accordingly, governments, supervisors and central banks should pay close attention to the evolution of certain FSIs related to the banking sector along with other macroeconomic, political and social variables that have been traditionally considered in the analysis of sovereign risk.

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TABLE 1. Number of observations by country

Country	Observations	Percentage
Austria	6	4.38
Belgium	6	4.38
Bulgaria	5	3.65
Cyprus	5	3.65
Czech Republic	6	4.38
Denmark	3	2.19
Estonia	5	3.65
Finland	5	3.65
France	5	3.65
Germany	5	3.65
Greece	4	2.92
Hungary	5	3.65
Ireland	6	4.38
Italy	6	4.38
Latvia	5	3.65
Lithuania	5	3.65
Luxembourg	5	3.65
Malta	6	4.38
Netherlands	5	3.65
Poland	5	3.65
Portugal	6	4.38
Romania	6	4.38
Slovak Republic	1	0.73
Slovenia	5	3.65
Spain	6	4.38
Sweden	6	4.38
United Kingdom	4	2.92
Total	*137*	*100*

TABLE 2. Number of observations by year

Year	Observations	Percentage
2008	10	7.30
2009	26	18.98
2010	25	18.25
2011	26	18.98
2012	26	18.98
2013	24	17.52
Total	*137*	*100*

TABLE 3. Number of observations by rating agency

Year	Moody's	S&P	Fitch
2008	10	5	10
2009	26	17	26
2010	25	18	25
2011	26	26	26
2012	26	26	26
2013	24	24	24
Total	*137*	*116*	*137*

TABLE 4. Ratings conversion to numerical scale

Moody's	S&P	Fitch	Assigned value	No. of observations	Percentage
Aaa	AAA	AAA	1	136	34.87%
Aa1	AA+	AA+	2	65	16.67%
Aa2	AA	AA	2		
Aa3	AA-	AA-	2		
A1	A+	A+	3	60	15.38%
A2	A	A	3		
A3	A-	A-	3		
Baa1	BBB+	BBB+	4	93	23.85%
Baa2	BBB	BBB	4		
Baa3	BBB-	BBB-	4		
Ba1	BB+	BB+	5	36	9.23%
Ba2	BB	BB	5		
Ba3	BB-	BB-	5		
...	...	...	5		
C	C	C	5		
				390	100%

Note: The table shows the conversion of qualitative ratings to numerical values. The sample comprises 390 rating observations for the 27 countries during the 2008 to 2013 period. Table 3 shows the number of observations by rating agencies and year.

TABLE 5. Description of the explanatory variables

Category	Indicator	Notation	Source	Expected sign
FINANCIAL SOUNDNESS INDICATORS				
CAPITAL ADEQUACY	Regulatory capital to risk-weighted assets	**RCRWA**	IMF, FSI	-
ASSET QUALITY	Nonperforming loans to total gross loans	**NPLTGL**	IMF, FSI	+
EARNINGS AND PROFITABILITY	Return on equity	**ROE**	IMF, FSI	-
	Noninterest expenses to gross income	**NIEGI**	IMF, FSI	-/+
CONTROL VARIABLES				
FINANCIAL DEVELOPMENT AND STRUCTURE INDICATORS				
FINANCIAL DEVELOPMENT LEVEL	Total capitalisation by GDP	**FDL**	World Bank, WDI	-
BANKING SECTOR CONCENTRATION	Herfindahl Index for credit institutions to total assets	**H-I**	ECB, SDW	+/-
MACROECONOMIC VARIABLES				
NATIONAL ACCOUNTS	GDP growth	**GDPG**	IMF, WEO	-
MONETARY	Inflation	**INFLAT**	IMF, WEO	+
GOVERNMENT FINANCE	Government gross debt to GDP	**GGDGDP**	IMF, WEO	+
	Government budget to GDP	**GBGDP**	Eurostat	-
SOCIAL, GOVERNANCE AND POLITICAL FACTORS				
SOCIAL	Unemployment (% of total labour force)	**UNEMP**	World Bank, WDI	+
GOVERNANCE AND POLITICAL	Government effectiveness	**GOVEF**	World Bank, WGI	-
	Regulatory quality	**REGQUA**	World Bank, WGI	-
OTHER CONTROL VARIABLES				
Year Dummies				

Notes: A more detailed description of FSIs can be found at http://fsi.imf.org/misc/FSI%20Concepts%20and%20Definitions.pdf

TABLE 6. Random effects ordered probit for each rating agency

	MOODY'S	S&P	FITCH
$RCRWA_{t-1}$	0.4864	0.3770	-0.1707
	(0.1472)	*(0.1378)*	*(0.1591)*
$NPLTGL_{t-1}$	0.1817***	0.0697	0.2310***
	(0.0707)	*(0.0664)*	*(0.0825)*
ROE_{t-1}	-0.0368**	-0.0253	-0.0218
	(0.0177)	*(0.0163)*	*(0.0155)*
$NIEGI_{t-1}$	-0.0168*	-0.0105**	0.0006
	(0.0097)	*(0.0051)*	*(0.0088)*
FDL_{t-1}	-0.0162***	0.0132***	-0.0098**
	(0.0051)	*(0.0051)*	*(0.0048)*
H-I	51.7470***	12.3868**	35.0497***
	(10.7215)	*(4.8487)*	*(8.1141)*
GDPG	-0.2668***	-0.2273**	-0.1638*
	(0.0986)	*(0.1159)*	*(0.0872)*
INFLAT	0.3600**	0.2739	0.4125**
	(0.1752)	*(0.2039)*	*(0.1682)*
GGDGDP	0.1319***	0.0306***	0.0651***
	(0.0258)	*(0.0103)*	*(0.0147)*
GBGDP	-0.2135***	0.1008	-0.1065
	(0.0693)	*(0.0886)*	*(0.0672)*
UNEMP	0.6151***	0.3099***	0.7688***
	(0.1321)	*(0.0737)*	*(0.1740)*
GOVEF	-5.0362***	-4.5177***	-7.8270***
	(1.3603)	*(1.0242)*	*(1.9500)*
REGQUA	-11.5496***	-6.9422***	-6.7860***
	(2.5438)	*(1.8758)*	*(1.6823)*
Rho (ρ)	0.9531***	0.9360***	0.9713 ***
	(0.0170)	*(0.0241)*	*(0.0117)*
Year dummies	YES	YES	YES
C1	-2.3007	-4.1543	-9.1114
C2	2.9411	-0.8376	-1.8651
C3	10.0747	1.9217	2.0295
C4	17.4271	7.9829	10.8212
N	137	116	137
Log likelihood	-67.6736	-63.3045	-60.0477
LR chi^2*(df)*	190.23 *(18)*	102.21 *(18)*	170.10 *(18)*
Prob>$chic^2$	0.0000	0.0000	0.0000
AIC	181.3472	172.6089	166.0954
BIC	248.5067	235.9415	233.2550

Notes: This table reports the coefficients and the cut-off points (C1, C2, C3, C4) of the random effects ordered probit regressions of the sovereign ratings assigned by each rating agency. The standard errors are reported in parentheses. See Tables 3 and 4 for the numbers of observations by rating agencies and the numerical values assigned to the credit ratings. AIC is a measure of the relative quality of the statistical models. BIC is closely related to AIC and is based, in part, on the likelihood function. The number of observations used in calculating BIC is N.*, **, *** indicate statistical significance at the 10, 5 and 1% levels, respectively.

TABLE 7. Ordered probit for each rating agency

	MOODY'S	S&P	FITCH
$RCRWA_{t-1}$	0.0575	-0.0398	0.0530
	(0.0753)	*(0.0516)*	*(0.0603)*
$NPLTGL_{t-1}$	0.1559***	0.0804**	0.1082***
	(0.0480)	*(0.0317)*	*(0.0406)*
ROE_{t-1}	-0.0054	-0.0291***	-0.0103
	(0.0098)	*(0.0110)*	*(0.0119)*
$NIEGI_{t-1}$	-0.0110***	-0.0056*	-0.0052**
	(0.0037)	*(0.0031)*	*(0.0020)*
FDL_{t-1}	-0.0016	0.0004	0.0018
	(0.0046)	*(0.0041)*	*(0.0043)*
H-I	6.0975**	4.8632*	9.6472***
	(2.8625)	*(2.9141)*	*(2.4704)*
GDPG	-0.1039***	-0.0542	-0.0319
	(0.0316)	*(0.0500)*	*(0.0337)*
INFLAT	0.1625*	0.2809**	0.1151
	(0.0857)	*(0.1313)*	*(0.0892)*
GGDGDP	0.0096	0.0127	0.0091
	(0.0096)	*(0.0105)*	*(0.0096)*
GBGDP	-0.0638	0.0740	-0.0655
	(0.0633)	*(0.0751)*	*(0.0588)*
UNEMP	0.0801	0.1100**	0.0817
	(0.0585)	*(0.0560)*	*(0.0704)*
GOVEF	-0.6308	-2.3547**	-1.2154
	(0.7336)	*(0.9871)*	*(0.8365)*
REGQUA	-2.0269**	-0.8159	-2.2975**
	(0.9284)	*(1.0159)*	*(1.0099)*
Year dummies	YES	YES	YES
C1	-1.4866	-3.5986	-1.4069
C2	-0.5106	-2.0352	-0.0637
C3	0.9929	-1.2219	1.0916
C4	3.0385	1.1645	3.6439
N	137	116	137
Log pseudo-likelihood	-109.8383	-78.8338	-104.1396
Wald $chi^2(df)$	644.07 *(18)*	447.23 *(18)*	363.03 *(18)*
Prob>$chic^2$	0.0000	0.0000	0.0000
AIC	263.6767	201.6675	252.2791
BIC	327.9163	262.2465	316.5187

Notes: This table reports the coefficients and the cut-off points (C1, C2, C3, C4) of the standard ordered probit regressions of the sovereign ratings assigned by each rating agency. The robust standard errors (reported in parentheses) are clustered by countries (they are adjusted for 27 clusters). See Tables 3 and 4 for the number of observations by rating agencies and the numerical values assigned to the credit ratings. AIC is a measure of the relative quality of the different statistical models. BIC is closely related to AIC and is based, in part, on the likelihood function. The number of observations used in calculating BIC is N. *, **, *** indicate statistical significance at the 10, 5 and 1% levels, respectively.

TABLE 8. Ordered probit using agency dummies

	RATING MOODY'S, S&P and FITCH
$RCRWA_{t-1}$	0.0286
	(0.0562)
$NPLTGL_{t-1}$	0.1110***
	(0.0341)
ROE_{t-1}	-0.0119
	(0.0090)
$NIEGI_{t-1}$	-0.0064***
	(0.0021)
FDL_{t-1}	0.0001
	(0.0042)
H-I	6.7767***
	(2.2524)
GDPG	-0.0614**
	(0.0290)
INFLAT	0.1364
	(0.0846)
GGDGDP	0.0101
	(0.0093)
GBGDP	-0.0330
	(0.0614)
UNEMP	0.0841
	(0.0577)
GOVEF	-1.3446*
	(0.7430)
REGQUA	-1.5557*
	(0.9241)
Year dummies	YES
Agency dummies	YES
C1	-1.7325
C2	-0.5397
C3	0.6166
C4	2.7167
N	390
Log pseudolikelihood	-312.3382
Wald $chi^2(df)$	851.49 *(20)*
Prob>$chic^2$	0.0000
AIC	672.6764
BIC	767.8639

Notes: This table reports the standard ordered probit regressions of the sovereign ratings provided by the international rating agencies. The dependent variable jointly considers the ratings of the three major agencies. See Table 4 for the numerical values assigned to the credit ratings. C1, C2, C3, C4 are the cut-off points. The robust standard errors (reported in parentheses) are clustered by country and are adjusted for 27 clusters. The number of observations used in calculating BIC is N. *, **, *** indicate statistical significance at the 10, 5 and 1% levels, respectively.

APPENDIX 1. Relevant studies on sovereign ratings

AUTHOR	SAMPLE	AGENCY	METHODOLOGY	DEPENDENT VARIABLE	INDEPENDENT VARIABLES
Cantor and Packer (1996)	- Cross section data (49 countries in September 1995)	Moody's S&P	- Regression analysis; linear transformation of the rating scale	- A regression for each agency and another regression for the average rating. - Scale with 16 categories of ratings (AAA is 16)	Per capita income, GDP growth, inflation, fiscal balance, external balance, external debt, indicator for economic development, indicator for default history and other additional variables
Afonso (2003)	- Cross-section data (81 countries in June 2001)	Moody's S&P	- OLS estimation; linear, logistic and exponential transformation of the rating scale	- A regression variable for each agency. - Scale with 16 categories of ratings (AAA is 16)	Per capita income, GDP growth, inflation, current account surplus, government budget surplus, debt-to-exports ratio, economic development, default history
Altenkirch (2005)	- Panel data (26 countries from 1990 to 2000)	Moody's	- General to specific model selection strategy (GETS) -Dynamic panel data model estimation procedure	- Moody's rating transformed from a linear to a logistic scale	Total debt/GDP, foreign reserves/GDP, export growth rate, GDP growth rate, GDP per capita growth, inflation rate, fiscal balance/GDP, exchange rate, credit extended to private sector/GDP, growth in imports, gross domestic savings, gross fixed capital formation/GDP, total debt/exports, current account/GDP, ethnic warfare, state failure, regime change, democracy, autocracy, political party, political rights, civil liberties, revolutionary wars
Bissoondoyal-Bheenick (2005)	- Cross-sectional data by individual years (95 countries from Dec 1995 to Dec 1999)	S&P Moody's	-Ordered response models	- A regression variable for each agency - Ratings converted into two numerical scales with 21 and 9 categories (AAA is 1)	GNI per capita, inflation, govt. financial balance/GDP, govt. debt/GDP, real exchange rate, foreign reserve, net exports/ GDP, unemployment rate, unit labour cost, current account/GDP, foreign debt/GDP
Butler and Fauver (2006)	- Cross-sectional data (86 countries in March 2004)	*Institutional Investor* rating	- OLS estimation (and ordered probit regression)	- *Institutional Investor* rating - Moody's and S&P rating with 21 categories (AAA is 21). A regression for each agency	Per capita income, debt to GDP ratio, inflation, underdevelopment index, legal environment index, legal origin dummies
Afonso *et al.* (2011)	- Panel data (130 countries from 1970 to 2005)	Moody's S&P Fitch	- Linear regression models on a linear transformation of ratings (pooled, random effects, fixed effects) - Ordered response models (ordered probit and random effects ordered probit methods)	- A regression for each rating agency - Scale with 17 categories of ratings (AAA is category 17)	- GDP per capita, unemployment rate, inflation rate, real GDP growth, government debt, fiscal balance, government effectiveness, external debt, foreign reserves, current account balance, default history, EU and regional dummies
Ratha *et al.*(2011)	- Cross sectional data (Rated developing countries at end-2006)	Moody's S&P Fitch	- Estimation of a regression model of existing ratings (OLS regression) - Prediction of sovereign ratings for unrated developing countries	- A regression for each agency - Ratings are converted into a numerical scale with 21 categories (AAA is 1)	Gross national income per capita, GDP growth rate, debt/exports, reserves/(imports +short-term debt), growth volatility, inflation, rule of law