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Financial Stability in Europe: Banking and Sovereign Risk

Abstract

We analyze the link between banking sector quality and sovereign risk in the whole European Union over 1999–2014. We employ four different indicators of sovereign risk (including market- and opinion-based assessments), a rich set of theoretically and empirically motivated banking sector characteristics, and a Bayesian inference in panel estimation as a methodology. We show that a higher proportion of non-performing loans is the single most influential sector-specific variable that is associated with increased sovereign risk. The sector's depth provides mixed results. The stability (capital adequacy ratio) and size (TBA) of the industry are linked to lower sovereign risk in general. Foreign bank penetration and competition (a more diversified structure of the industry) are linked to lower sovereign risk. Our results also support the wake-up call hypothesis in that markets re-appraised a number of banking sector-related issues in the pricing of sovereign risk after the onset of the sovereign crisis in Europe.

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Keywords: sovereign default risk, banking sector, global financial crisis, financial stability, European Union.

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1. Introduction and motivation

We analyze the link between banking sector quality and sovereign risk in the whole European Union (EU). Sovereign risk characterizes a threat that under severe economic circumstances, governments may be unable or unwilling to repay their debts. Sovereign risk became an important issue with the outbreak of the global financial crisis (GFC). The crisis helped to unveil macroeconomic and fiscal imbalances in the Eurozone that subsequently led to the heightened sovereign risk of many of its members (Beirne and Fratzscher, 2013). The link between the quality of the banking sector and sovereign risk in Europe can be directly quantified: banks in the EU hold on average 9% of their total assets in a form of sovereign debt: government bonds (ECB Statistical Warehouse; Gennaioli et al., 2014).

The above facts are directly linked to an important channel for how banking sector quality potentially affects sovereign risk when governments are forced to step in: large and important banks are vital to countries and when they become seriously troubled, a cost-effective solution might be to bail them out because bankruptcy would exert costly and damaging effects on the economy (Gerlach et al., 2010). However, funds for a rescue package increase government indebtedness and consequently sovereign default risk increases (Campolongo et al., 2011; Reichlin, 2014; Acharya et al., 2014). Indeed, during the GFC and the ensuing European sovereign debt crisis many European governments heavily supported their banks and the banking sector has become increasingly interconnected with sovereign risk (European Commission, 2012; Correa et al., 2014; Cabrera et al., 2016).[1] The other channel linking the banking sector and sovereign risk is adjustments in banks' balance sheets and the consequent effect on aggregate liquidity (Adrian and Shin, 2009). The balance sheet dynamics affects the short-term funding available in the economy: the lack of credit, with some delay, affects a government's fiscal position and consequently sovereign risk increases (Correa et al., 2014).

Analyzing the link between banking sector quality and sovereign risk matters for a number of reasons. One is the further enlargement of the Eurozone and the integration of its financial markets. Shocks in one country might propagate in an unpleasant way across other EU members. In this respect, Breckenfelder and Schwaab (2017) show that a bank-risk surprise in one EU country can affect the credit risk of other EU sovereigns. In addition, the quality of the banking sector is important for the effectiveness of the macroprudential policies (Beirne and Friedrich, 2014). Further, following the global financial crisis, the traditional understanding of sovereign risk—the probability that a country will not pay its debts—have probably become too constricted as connections among public and private debt, fiscal balances, and the financial sector seem to be more complex. Understanding the link between the banking sector and sovereign risk is also important from an investment perspective. Stock market investors perceive sovereigns and domestic banks as markedly interconnected, partly through government guarantees (Correa et al., 2014). Domestic banks are natural creditors of domestic firms but often they become recipients of foreign funding as well. Further, when domestic sovereign risk becomes pronounced foreign creditors willing to extend loans to

[1] The volume of state aid provided to the EU banking sector between October 2008 and January 2012 is estimated by the European Commission (2012) at approximately 1.6 trillion euro (about 13% of the EU GDP). Buch et al. (2016) provide evidence of the determinants of the volume of bank sovereign debt exposure and the impact of sovereign bond exposure on at-risk banks in Germany.

domestic firms have to proceed in two steps: first, they judge the sovereign risk and then they consider the creditworthiness of the firm itself (Cooper and Argyris, 1998).

The literature linking various parameters of the banking sector directly to sovereign risk is not extensive.[2] Gerlach et al. (2010; p.1) "seek to understand what factors have been driving (the sovereign bond yield) spreads" in the euro area. They show that the size of the banking sector relative to GDP, when interacted with the risk factor, tends to negatively affect sovereign risk. Specifically, at a time when aggregate risk is high, countries with large banking sectors with low equity ratios exhibit larger spreads of sovereign bond yields. This result is intuitively appealing because high aggregate risk increases the probability of bank default, which translates into a risk for public budgets that is subsequently reflected in increased sovereign risk. Gerlach et al. (2010)'s analysis covers most of the Eurozone countries (as of 2010) but leaves out Luxembourg, Cyprus, Malta, Slovakia, and Slovenia. Gómez-Puig et al. (2015) aim to identify and trace inter-linkages between sovereign risk and banking risk in ten euro area countries.[3] They use an indicator of banking risk based on the Contingent Claim Analysis literature and 10-year government yield spreads over the German Bund to proxy sovereign risk. Based on a dynamic Granger causality approach they show that causal links tend to increase during financial crises and that contagion runs predominantly from banks to sovereigns.

Further, Erdem Aktug et al. (2013) assess the link between the banking sector and sovereign risk based on their hypothesis that more competitive and sophisticated financial systems are less prone to panics or bank runs, and consequently will be associated with superior sovereign credit ratings. They show that banking sector characteristics such as concentration in the banking system, the liquidity of bank assets, and the size of the financial system are significantly related to sovereign credit ratings. Kallestrup et al. (2016) use consolidated banking statistics of the Bank for International Settlements (BIS) and construct a simple risk-weighted measure of the foreign exposure of the banking system in 15 European countries (plus Japan and the U.S.). They show that the foreign asset holdings of the largest banks, as well as their riskiness, are important determinants of the CDS premia of the sovereigns in which the banks reside. Pagano and Sedunov (2016) provide evidence that the systemic risk of financial institutions in European countries and sovereign risk are interrelated, and that shocks to these links are stronger and longer lasting than international risk spillovers.

Another strand of the literature related to our analysis connects sovereign risk with bank bailouts. Acharya et al. (2014) analyze the link between bank bailouts and sovereign credit risk based on the two-way feedback between financial and sovereign credit risk. They use data on the credit default swaps (CDS) of the Eurozone countries and their banks over 2007–2011. They show that the announcement of bailouts is associated with the widening of sovereign CDS spreads while bank CDS spreads narrow. An increase in sovereign credit risk

[2] There also exist studies showing that sovereign risk is affected or determined by factors not related to banking. These include macroeconomic fundamentals (Frenkel et al., 2004; Remolona et al. (2008a), terms of trade (Hilscher and Nosbusch, 2010), constitutional rule (Kohlscheen, 2010), financial market returns (Ang and Longstaff, 2013), and the sovereign's public finances (Corsetti et al., 2013).

[3] They include Austria, Belgium, Finland, France, and the Netherlands as the center and Greece, Ireland, Italy, Portugal, and Spain as the periphery.

upon bailout then depends on the pre-bailout debt of the sovereign and the pre-bailout level of financial sector distress. Based on the CDS rates, the effect of bank bailouts on sovereign risk is also analyzed, for example, in Attinasi et al. (2011), Sgherri and Zoli (2011), Ejsing and Lemke (2011), and Alter and Schueler (2012), who provide similar descriptive evidence as Acharya et al. (2014). In a related empirical work, Banerjee et al. (2016) analyze the effectiveness of large scale bailouts during the European sovereign debt crisis and show that before the first Greek bailout, the sovereign and financial sectors exhibit a two-way feedback effect, but the pattern disappears during all later bailouts. In this respect, Fratscher and Rieth (2015) show that recent bank bailout policies in the EU have reduced solvency risk in the banking sector, but partly at the expense of raising the sovereign risk.[4]

A related change of the pattern in sovereign and bank interdependencies is shown in Yu (2017), who analyzes the dynamic linkage between European sovereign and bank CDS spreads from 2006 to 2012. She shows that risk initially transferred from banks to sovereigns soon led to a reverse spillover due to deteriorating fiscal conditions. De Bruyckere et al. (2013) analyze contagion between bank and sovereign default risk in Europe over the period 2007–2012 based on excess correlation between CDS spreads at the bank and sovereign levels. They show that banks with a weak capital buffer, a weak funding structure, and less traditional banking activities are particularly vulnerable to risk spillovers that might increase sovereign risk. Finally, Klinger and Teplý (2016) assess the link between financial system and sovereign debt crises by analyzing sovereign support to banks and banks' resulting exposure to the bonds issued by weak sovereigns that is reflected in the higher CDS spreads of these sovereigns.

Despite the fact that the literature linking the state of the banking industry with sovereign risk is not extensive, it provides, along with related literature, a clear message: economic health and sound finances are prerequisites for low sovereign risk. In this sense, the state or quality of the banking industry are most likely to be connected with sovereign risk. In this paper we assess the issue in detail based on our research questions: Is there an evidence of a direct link from banking sector quality toward sovereign risk? If yes, what banking sector characteristics impact sovereign risk most? Are the links different before and after the GFC, and across countries? How do the links relate to the wake-up call hypothesis?[5]

In this paper we focus on providing the first comprehensive assessment of the link between banking sector quality and sovereign risk from an all-EU perspective. To the best of our knowledge, research linking systemic and sector-specific features of the banking sector with sovereign risk in the whole EU is non-existent so far. We contribute to the literature in several ways. First, we estimate the impact of banking sector quality on sovereign risk based on theoretically and empirically motivated linkages. We employ four sovereign risk indicators that represent the perception of sovereign risk by the markets (sovereign bond yield and CDS spreads), experts (country risk score), and rating agencies (sovereign credit

[4] The quantification of the potential losses to the government that could arise from bank failures (in absence of bailouts) based on the banking sector contingent liability index (BCLI) is developed in Arslanalp and Liao (2015) and illustrated on a sample of 32 advanced and emerging market economies from 2006 to 2013.

[5] Goldstein (1998) suggested the wake-up call hypothesis to explain contagion between regions: a financial crisis in region A represents a wake-up call to investors in region B who re-assess and inquire about the fundamentals of region B. The reappraisal of risk may result in spreading crisis contagion to region B.

rating). The banking sector quality is proxied by a set of six relevant variables motivated in the literature and detailed in the data section. Second, our analysis does not include only selected countries but covers the entire EU. Further, the analysis spans a period well before and well after the GFC. Third, our Bayesian inference approach in a panel setting delivers solid results because it accounts for various data imperfections that are to be expected in the large data set we use.

As a complement to our analysis, we offer a sketch of a third channel how the state of the banking sector potentially impacts sovereign risk. We call it the *corporate credit risk channel*. The proliferation of bank credit contributes to economic growth and is, therefore, inversely related to sovereign risk. However, we believe that there is a private sector debt threshold beyond which further credit expansion can exacerbate sovereign risk. Overly expansive corporate credit exposure of the banking sector increases the probability that loans are being granted to inadequately efficient projects (Mehrez and Kaufmann, 2000). As a result, (i) tax revenues from companies with inefficient projects decline since their profits decline; this is combined with layoffs and less tax revenue from workers. Both effects directly worsen the government's fiscal position. Further, (ii) tax revenues from banks decline since, due to the creation of loan loss provisions for bad loans, their profits decline. In the end, the fiscal position of the government worsens as its revenues decrease and payments of unemployment benefits rise. Consequently, sovereign risk increases.

Our results come from a Bayesian inference in panel estimation. We show that a higher proportion of non-performing loans is the single most influential sector-specific variable that is associated with increased sovereign risk. The sector's depth provides mixed results. The stability (capital adequacy ratio) and size (TBA) of the industry are linked with lower sovereign risk in general. The diversified structure of the industry—higher foreign bank penetration and higher competition—is beneficial for the stability of the industry as it is linked to lower sovereign risk. Our results also support the wake-up call hypothesis that markets re-appraised a number of banking sector-related issues in the pricing of sovereign risk after the onset of the sovereign crisis in Europe.

The rest of our paper is organized as follows. Section 2 describes the data sources, definitions of the variables, and the link from the variables to sovereign risk. The employed methodology is introduced in Section 3. Empirical results are presented and interpreted in Section 4. Conclusions and policy implications are contained in Section 5.

2. Data and variables

In the following description we deliberately deviate from convention and introduce the data and description of variables first in order to better motivate the methodology and estimation section that follows. Further, the data description is intentionally longer than a standard data section because we also elaborate on issues that relate our variables to economic and econometric rationales.

We employ yearly and quarterly data covering sovereign risk and the state of the banking sector in 27 EU countries. The data spanning 1999–2014 were obtained from the Statistical Data Warehouse of the European Central Bank, the World Bank, and Euromoney Institutional Investor plc; on some occasions the data were checked for consistency against Eurostat, the OECD, the International Monetary Fund, and the Federal Reserve Bank of St.

Louis FRED. Despite of our efforts at data collection there are some missing data or doubtful items. We deal with this issue by employing the appropriate Bayesian technique, which is described in full detail in Section 4 and Appendix 2. In Table 1a we report details on frequencies, the number of observations, and the proportion of missing data.

In the following account we list the variables employed together with a description and justification of their use. We also discuss the variables' properties and the effects they are expected to exhibit with respect to sovereign risk as outlined in the related literature (Fink et al., 1998; Gerlach et al., 2010; Bernoth et al., 2012; Gómez-Puig et al., 2015; Buch et al., 2016).

Despite the fact that we analyze data originating in the considerably integrated EU, there is still heterogeneity in the data across countries. The heterogeneity is mainly due to differences in economic development and the uneven degree of integration among countries. Further, the banking sectors in the countries under research also exhibit substantial differences in terms of competition and credit availability; a quantification is provided in Section 2.4 (Table 1a). In order to minimize potential heterogeneity, we form several groups of countries corresponding to the above differences as well as the relevant literature on EU integration; the grouping also allows for more detailed interpretation of results. The old EU group consists of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom. We then form groups labelled as the Core (Austria, Belgium, France, Germany, Luxembourg, and the Netherlands) and the Periphery (Cyprus, Greece, Malta, Portugal, and Spain). Further, we form the new EU group consisting of Bulgaria, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia. The new EU group is further divided into the Visegrad Five countries (the Czech Republic, Hungary, Poland, Slovakia, Slovenia), Baltic countries (Estonia, Latvia, Lithuania), and Balkan countries (Bulgaria, Romania).

2.1 Sovereign risk

We use four measures of sovereign risk: the government bond yield spread, the sovereign credit default swap (CDS) spread, the overall country risk score, and the sovereign credit rating. The different measures reflect differences in the perception of sovereign risk by the market, experts, and rating agencies. The set of measures allows not only testing the impact of the banking sector on sovereign risk but also assessing whether the impact is sensitive to risk appraisal differences.

We start with two measures that assess sovereign risk from the perspective of how the market evaluates sovereign risk. First, the government bond yield spread is a standard measure of sovereign risk employed in the literature (Caporin et al., 2015). Specifically, we construct the difference between a ten-year government bond and the German Bund (as a proxy for the risk-free rate), which contains information on the government's creditworthiness and at the same time accounts for domestic factors affecting sovereign risk.

Second, we use sovereign credit default swap (CDS) spreads, as in the literature they are often used to proxy sovereign risk (Beirne and Fratzscher, 2013; Heinz and Sun, 2014; Gätjen and Schienle, 2015) and are found worthwhile in measuring contagion (Caporin et al., 2015). However, we acknowledge the suggestion that CDS is quite noisy and volatile, especially after 2008. Further, the sovereign CDS market exhibits widening spreads that might be more due to speculations rather than changes in sovereign risk; this feature became quite pronounced at the beginning of the Eurozone debt crisis. CDS also likely captures the market sentiment to the degree that a considerable amount of noise entering the data lowers its ability to capture economic developments reflecting sovereign risk. Because of insufficient data availability we do not use CDS for Baltic and Balkan countries at all, and for the Visegrad Five before the GFC. Nevertheless, we use the CDS-based measure in order to provide comprehensive coverage of sovereign risk and because of its growing importance in global financial markets (Augustin et al., 2014).

As an alternative, we employ two expert-assessment-based measures. Our third measure is the combined Euromoney Country Risk (ECR) score; the measure is described in detail in Appendix 1. The measure provides an assessment of sovereign risk from the expert opinion perspective and as such it provides an alternative to the market valuation based on the bond spread. The ECR measure of risk is derived from a forum that aggregates the opinions of over 400 international economists and policy analysts throughout the world. The ECR assessment provides updated rankings for each country's (investment) risk by using 15 criteria including political risk, economic performance, structural assessment, debt indicators, credit ratings, access to bank finance, and access to capital markets. Each country receives an ECR score on a 100-point scale, where 100 is considered the safest (no risk) and 0 equals maximum risk.[6] The ECR evaluates the risk of a country based on a combination of the qualitative score assigned by expert opinion on risk variables within a country (70% weighting) and three quantitative values (30% weighting). The three qualitative expert opinions are political risk (30% weighting), economic performance (30%), and structural assessment (10%).[7] The three quantitative values are debt indicators (10%), access to bank finance/capital markets (10%), and sovereign credit ratings (10%).[8]

A fourth, complementary, measure of risk is the sovereign credit rating, because it plays an important role in evaluating a country's risk profile in international finance (Kaminsky and Schmukler, 2002; Erdem Aktug et al., 2013). This measure of sovereign risk is based on the sovereign ratings released by Moody's, Standard & Poor's, and Fitch IBCA. Nominal values are assigned to the ratings that are converted into a score using a set scoring chart; the score is then averaged. A higher average value indicates a better standing or lower sovereign risk. Sovereign credit ratings are a valuable source of information and have been used as a basis to measure sovereign risk, for example, by Eichengreen et al. (2003), Borio

[6] Similar to the Euromoney Country Risk score, other investment companies publish their own measures. For example, the BlackRock Sovereign Risk Index is a quantitative measure based on a pool of financial data, surveys, and political insights; it is available only from 2011, though.

[7] The categories of economic risk scored are bank stability/risk, GNP outlook, unemployment rate, government finances, and monetary policy/currency stability. The categories of political risk are corruption, government non-payments/non-repatriation, government stability, information access/transparency, institutional risk, and the regulatory and policy environment. The categories of structural risk are demographics, hard infrastructure, labor market/industrial relations, and soft infrastructure.

[8] Access to bank finance/capital markets: a country's accessibility to international markets is rated on a scale of 0–10 (0 equals no access at all and 10 equals full access). Debt indicators are calculated using the following ratios from the World Bank's Global Development Finance figures: total debt stocks to GNP (A), debt service to exports (B), and current account balance to GNP (C). For the sovereign credit rating see the definition of the third sovereign risk measure.

and Packer (2004), Kim and Wu (2006), Remolona et al. (2008b), and Bissoondoyal-Bheenick et al. (2011).[9] A combination of ratings by three agencies to a large extent mitigates the discrepancies and inconsistencies among ratings that were documented before the global financial crisis (Altman and Rijken, 2004).

While a larger government bond yield spread and CDS spread mean higher sovereign risk, higher values of the original ECR score and sovereign credit rating mean lower risk. In order to interpret the regression results in a unified way, we transform the original ECR score and sovereign credit rating in such a way that higher values of all four types of sovereign risk represent a higher level of risk. Specifically, we normalize the original ECR score and sovereign credit rating with respect to their maximum values as follows:

$$ECR = 100 - \text{ECR score},$$
$$Rating = 100 - 10 \cdot (\text{Sovereign Credit Rating}).$$

The transformation represents a gap with respect to the best performing sovereign and thus offers an additional form of interpretation. More importantly, this simple transformation enables interpreting our findings in the same way for all four sovereign risk measures. Moreover, the transformed variables of the ECR score and rating are on the same scale (between 0 and 100, with 0 meaning the lowest possible risk).

We investigated both the presence of multicollinearity among the measures of risk as well as among the measures of quality of the banking sector. We did not find a multicollinearity among the explanatory variables that would corrupt the estimation results presented in Section 4. Also the correlations among our measures of risk (endogenous variables) are not strong and therefore we conclude that none of the measures is redundant. More detailed pieces of information are presented in Appendix 3, Figures A.3 and A.4.

2.2 Systemic variables

We employ the following three variables that characterize the systemic standing of the banking industry in each country and reflect the institutional characteristics of a country's financial institutions.

The size of the banking sector is measured as the ratio of total bank assets (TBA) to the gross domestic product (GDP) in percent. The values are in national currencies and the TBA/GDP ratio eliminates the impact of forex movements. The measure can also be interpreted as the depth of the intermediation that the banking sector plays in the economy. In this sense, the TBA/GDP ratio also represents the theoretical and natural upper bound for the extent of the potential financial package provided by the state in case of a severe need and in this respect it proxies the sovereign debt (Gerlach et al., 2010). The potential effect of the TBA/GDP ratio is relatively straightforward: as the ratio increases, the potential sovereign risk increases as well. For new EU members the ratio also has an additional implication. After privatizations and opening the markets for new private banks, the number of banks in the new EU economies, and consequently the amount of their TBA, has been separated from

[9] In terms of the empirical evidence, for example, Remolona et al. (2008b) show that the sovereign-credit-rating-based measure of sovereign risk is better than the sovereign CDS spread.

government reach. In this manner, the amount of TBA is not linked to the amount of debt a government accumulates and the variable (the size of the banking sector) is exogenous with respect to the sovereign risk measure.

The financial depth or the depth of the borrowing ability of an economy is measured as a percentage of bank private credit (BPC) to GDP. BPC is a sum of the household debt and non-financial-company debt; since we want to assess the extent of borrowing ability we use non-consolidated data. The measure shows the extent of the financial resources provided to the private sector by domestic banks and illustrates the extent of the funds that can be obtained on the market. The greater borrowing ability also implies that funds can be obtained easier on the market, without pressure that would heighten uncertainty or could result in damaging speculations related to the health of government finances. In this respect, greater depth should lead to reduced sovereign risk. However, a greater dependence of firms on credit with respect to other forms of financing (bonds, stocks) means that lending banks are more vulnerable to potential defaults. In the case of households, times of distress might force many households to experience difficulty with repayments. Hence, the combined effects might lead to an increase in sovereign risk as the room for a potential bailout widens. Finally, De Haas et al. (2010) show that private credit, in terms of the composition of the banks' loan portfolios in new EU countries, depends on bank ownership, bank size, and legal creditor protection.[10] The argument can be extended to old EU countries as well. In this sense the depth of borrowing ability is exogenous with respect to sovereign risk.

Foreign bank market participation or cross-border penetration is measured as a percentage of the banking assets that are held by foreign banks with respect to TBA. For this measure we consider branches and daughters of foreign banks where 50% or more shares are owned by foreigners (Claessens and van Horen, 2014). The potential link between foreign bank penetration and sovereign risk is ambiguous. Foreign owners are naturally cautious to enter a new and unknown market. But when they do so, they usually strive to have high performance. This is not only because of profit, but also because performance is associated with reputation. A well-performing bank does not pose a threat of impacting the government budget, so higher foreign bank penetration should be paired with lower sovereign risk. In the case of new EU countries, the presence of foreign banks has greatly increased after their banking sectors were privatized. Improved bank performance coupled with higher foreign bank penetration should be linked with lower sovereign risk in this part of the EU. On the other hand, foreign owners might be eager to repatriate profits in excess, especially during periods of financial distress. Such a step would show in the balance sheet and weaken the profitability of foreign owned banks, potentially lowering the credit available from this source. Then, more credit would be needed from domestic banks and this might make them more vulnerable to potential bailout. Under such a scenario, foreign bank penetration could be linked to increased sovereign risk. Foreign bank participation is exogenous with respect to sovereign risk. It is true that foreign investors are reluctant to enter politically weak economies but political (in)stability does not *a priori* mean either high or low sovereign risk.

[10] New EU countries experienced an exceptionally large expansion of private credit during the late transformation period (Bahadir and Valev, 2017). For example, in 2004 alone (at the moment of EU accession) Czech and Slovak banks recorded 33.8% and 36.7% increases in retail loans, respectively (Vojtek and Kočenda, 2006).

We checked multicollinearity among the above variables. Based on the results presented in Appendix 3, Figure A.2, the patterns of correlation among TBA, financial depth and foreign bank penetration is diverse across countries and far from being perfectly correlated. This means that multicollinearity does not present a problem for the efficiency of our estimation.

2.3 Sector performance variables

We employ three representative variables that characterize banking sector performance. Banking sector efficiency is proxied by the ratio of bank non-performing loans (NPL) to total gross loans in percent.[11] The lower the ratio, the more efficient the sector. By taking into account the defaulting loans where payments of interest and principal are past due by 90 days or more and the total value of the bank loan portfolio (total gross loans), this measure provides a straightforward efficiency perspective. The measure indicates the extent to which banks need (are required) to create provisions for non-performing loans. A lower proportion of NPL means that banks do not need to allocate large loan-loss provisions, meaning that banks need to devote less money to create allowances for doubtful accounts that are required based on specific categories of the five-tier system of NPL established by the BIS. Hence, the increased efficiency should lead to a decrease in sovereign risk as higher efficiency exerts less pressure for the potential bailout of banks. Finally, according to De Haas et al. (2010), the ratio of NPL to total loans can be considered exogenous with respect to sovereign risk.

We quantify the stability of the banking sector with the Capital Adequacy Ratio (CAR), which measures the amount of a bank's capital expressed as a percentage of its risk-weighted asset.[12] The CAR is defined as [(*Tier 1 capital* + *Tier 2 capital*)/(*Risk weighted assets*)]. Two types of capital account for two types of losses. Tier 1 capital is an ordinary share capital that can absorb losses without a bank stopping its operations. Tier 2 capital represents a subordinated debt that can absorb losses in the event of bank's liquidation.[13] Since credit exposures need to be adjusted for degree of riskiness, banks' assets are weighted according to specified rules. BIS sets an international standard recommending a minimum CAR of 8% (BIS, 2001). From 2018, BIS also foresees a conservation buffer of an additional 2.5% according to the Basel III principle (BIS, 2011), as well as a counter-cyclical buffer of 2.5%. An application of the minimum CAR protects depositors and promotes stability and low risk in the banking and financial system. Moreover, Tian et al. (2013) show that such a conservation capital buffer as in Basel III could increase

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[11] We do not assess banking sector efficiency with a proxy of the interest rate spread, which is the difference between the lending and deposit rates. The reason is that the interest rate spread really depends on monetary policy rather than sector performance. Also, the interest rate spread might be driven down due to market competition.

[12] We do not use a leverage ratio as an alternative measure. Despite the fact that this is a very useful measure, its use by banks and regulators is not widespread (Danielsson, 2008) and in terms of availability we would face a critical data problem.

[13] We use the standard definition of the CAR as the data are readily available. We acknowledge the existence of Tier 3 capital but do not use it. Tier 3 capital is used to support market risk, commodities risk and foreign currency risk. Assets must be limited to 250% of a bank's Tier 1 capital, be unsecured, be subordinated, and have a minimum maturity of two years to qualify as Tier 3 capital. Banks may employ Tier 3 capital at the discretion of their national authority, which makes data availability at a sufficient degree of harmonization problematic.

the bank's resilience to contagion. Hence, maintaining the minimum CAR or higher should make banks less vulnerable and should not exert pressure on sovereign risk. On the other hand, capital kept in an unproductive way due to a capital adequacy requirement is likely to reduce the efficiency of banks. Lower efficiency, as we argued earlier, might lead to increased sovereign risk. Finally, since the standard recommended minimum CAR is set independently by BIS, CAR is exogenous with respect to sovereign risk.

Finally, we employ a measure of market competition in the banking sector. It is defined as the share of the five largest banks in total assets in the sector. This measure could also represent the market power of the largest banks. However, since higher market power means a less competitive market environment, we prefer to work with the following measure of market competition:

$$Competition = -100\log(\text{Share of 5 largest banks}/100).$$

A higher value of the transformed variable means higher competition.[14] The potential effect of market competition is paradoxically ambiguous. Greater competition is likely to lead to improved profitability of banks, lower potential of bailout, and lower sovereign risk. At the same time, more competition might force banks to engage in riskier projects that might lower profitability and increase sovereign risk. The development of the banking sector and growth of individual banks in particular does not depend on the way governments operate and, therefore, the market competition measure is considered exogenous to sovereign risk.

We checked the multicollinearity among the sector performance variables. Similar to the case of systemic variables, the pattern of correlation among these variables is diverse across countries (see Appendix 3, Figure A.1). Only for Baltic and Balkan countries, we find a strong correlation between NPL and CAR in the pre-crisis period, which may inflate the standard errors of coefficients when estimating the model for the two subsets of countries. For other subsets and for the post-crisis period, the multicollinearity does not jeopardize the efficiency of our estimation.

2.4 Summary statistics

In Table 1a we provide summary statistics for the four dependent variables and the six independent variables. The summary statistics are provided for all countries in the sample as well as for subsets of countries (defined earlier) that are then used for regression analyses. We also formally test for the structural break that is found to materialize in 2008 (see Table 1b for details). The existence of the break serves as a background reason for dividing the sample and estimating our specifications before and after the GFC. Finally, our variables are composite variables or ratios and based on the ADF test (while accounting for the break) we reject the unit-root hypothesis for individual series.

[14] A similar logic applies to an alternative measure—the Herfindahl index—that captures, on a scale from 0 to 1, the degree of market concentration. Since higher market concentration implies a less competitive environment, the inverse of the measure captures well the market competition in the banking sector. The results based on the Herfindahl index are not materially different from those based on the share of the five largest banks in total assets in the sector, but are not presented. We do not use the Lerner index as a measure of a bank's power because sufficient data are not available for our set of countries and time span.

Based on the statistics in Table 1a we document that according to sovereign risk measures our sample contains both very risky countries and very safe countries. Old EU countries include both very safe and very risky countries. Although new EU countries have been on average somehow more risky than old EU countries, they are not typically among the most risky countries.

There are some noteworthy differences between old and new EU countries with respect to variables characterizing the banking sector. Competition in the banking sector is most intensive in old EU countries, while new EU countries have on average less competitive banking sectors. The distribution of the share of non-performing loans during the crisis is spread equally across the EU. The penetration of the banking sector is high especially in the new EU countries, although even some of old EU countries also have relatively high penetration. The main difference between these two groups of countries is in the credit-to-GDP ratio, which is high especially in old EU countries. Although new EU countries are slowly catching up, the credit availability is much lower in these countries; the feature has also been documented by Bahadir and Valev (2017). All in all, the banking sector in new EU countries is less developed in terms of competition and credit availability. The convergence of these characteristics to old EU countries is taking place but it is not completed yet.

Finally, we formally tested for the endogeneity of the variables that characterize the quality of the banking sector with respect to four measures of risk. We performed the Hausman test for endogeneity (Hausman, 1978) and present the results in Appendix 3, Tables A.1-A.4. We find endogeneity for CAR, Competition, TBA, and Credit with respect to CDS; for Penetration with respect to credit rating; and for TBA with respect to ECR in the pre-crisis period and for Penetration with respect to CDS in the post-crisis period. The results show that (i) there is a limited endogeneity during the pre-crisis period, (ii) the limited endogeneity is related mostly to the CDS risk measure, and (iii) there is practically no endogeneity during the post-crisis period. These results largely corroborate the links among variables described in Sections 3.2 and 3.3. The aim of our analysis is not to test for causality among variables. Rather, we strive to assess the prediction properties of our model. In other words, we are more interested in the statistical association between explanatory variables and the measure of risk. Hence, even the presence of endogeneity would not represent a critical problem that would invalidate our results presented in Section 4. Nevertheless, as the test reveals only a limited presence of endogeneity, the statistical association that we document is probably not far from the true causal links. This further increases the usefulness of our results.

3. Methodological approach

3.1 Model specification

In order to assess the common systemic and sector-specific effects of the banking sector on sovereign risk, we relate several measures of sovereign risk to systemic and sector-specific factors characterizing the banking sector in each country under research. In our estimation strategy we also aim to account for changes affecting the banking sector due to the global financial crisis (the GFC materializes in the data as a structural break, see Section 2.4). From the perspective of comparing regulatory and supervisory practices, Čihák et al. (2013)

document that after the GFC capital ratios increased, bank governance and resolution regimes were strengthened, and private sector incentives to monitor banks deteriorated. Hence, we aim to account not only for GFC-related changes in sovereign risk but to changes in banking sector characteristics as well.

We consider two regression models of sovereign risk (*SR*) because we want to distinguish banking sector characteristics from performance variables and at the same time we aim to estimate parsimonious models in order to prevent a loss of statistical significance. Further, since both models contain control variables to account for common underlying factors, we minimize the risk of biased estimates due to omitted variables and keep only the theoretically and empirically motivated variables discussed in Section 2. The first regression equation is specified for systemic variables as follows:

$$SR_{i,t} = \alpha_i + \beta TBA_{i,t} + \gamma CREDIT_{i,t} + \delta PENETRATION_{i,t} + \theta Debt/GDP_{i,t} + e_{i,t}, \qquad (1)$$

where α_i is the country fixed effect, *TBA* is total banking assets to GDP, *CREDIT* is total credit to GDP, and PENETRATION is the penetration of the domestic banking sector by foreign banks. Debt/GDP is a control variable used to capture potential non-banking determinants of the sovereign risk and to account for common underlying factors influencing both banking sector performance and sovereign risk;[15] $e_{i,t}$ are error terms.

The second regression model is specified for sector-specific variables as follows:

$$SR_{i,t} = \alpha_i + \beta NPL_{i,t} + \gamma CAR_{i,t} + \delta COMPETITION_{i,t} + \theta Debt/GDP_{i,t} + u_{i,t}, \qquad (2)$$

where *NPL* is the share of non-performing loans in total loans, *CAR* is the weighted capital adequacy ratio, and COMPETITION is the measure of competition in the banking industry. Debt/GDP is a control variable as defined in (1); α_i is the country fixed effect, and $u_{i,t}$ are the usual error terms.

3.2 Estimation method

During data collection we aimed to create a rich and informative data set. However, despite our efforts we are faced with some missing data and some uncertainty due to doubtful items and heterogeneity among countries. How should we obtain consistent estimates under these circumstances? Following the authoritative literature on the above issues (Daniels and Hogan, 2014; Gelman et al., 2014), we decided to effectively cope with these obstacles by employing the Bayesian technique described below.

We estimate both regression models in a panel setting with country fixed effects to account for any level differences between the countries. With this approach we eliminate any possible time-invariant endogeneity (Greene, 2003, p. 291; Wooldridge, 2002, p. 248), despite the fact that our independent variables are in general exogenous with respect to sovereign risk as shown in Section 3.4 and in Appendix 3. Further, we estimate both

[15] For the same purpose we also include GDP growth and the unemployment recession gap as additional variables to control for the business cycle position of an economy. Since the results were not materially different we decided to keep a more parsimonious specification with Debt/GDP control only.

specifications separately for the period before the GFC (prior to 2008) and for the period after 2008. Finally, we estimate both regressions separately for all groups of countries listed in Table 1a.

The estimation itself is performed with the Bayesian paradigm as it efficiently deals with missing data under the assumption that data are missing at random. In our case, this assumption is reasonable as the pattern at which the data are missing is determined by idiosyncratic features of the national statistical procedures of data collection and is unrelated to the actual economic situation in specific countries. Hence, the Bayesian inference in panel-data estimation represents a computationally conventional tool for estimating our models because it enables to provide consistent coefficients and a valid inference (Daniels and Hogan, 2014) as well as correctly quantifies the effect of uncertainty (Gelman et al., 2014). Finally, Bayesian posterior intervals are interpreted as classical confidence intervals associated with obtained coefficient estimates.

We perform the inference by extending the usual Gibbs sampler for a panel data model with iterations that draw from the conditional distribution of missing data. Specifically, in the estimation itself, we use the normal-Wishart non-informative prior.[16] To get the posterior distribution, we extend the usual Gibbs sampler (see e.g. Greenberg 2008, chapter 9, for details on the algorithm) with the iterations that impute the missing data. If, in the below specifications, D_{obs} is the set of observed data, D_{mis} is the set of missing data, and θ is the vector of parameters, then the Gibbs sampler is composed from the following iterations:

$$\theta^{(g)} \sim F\left(\theta \middle| D_{mis}^{(g-1)}, D_{obs}\right),$$
$$D_{mis}^{(g)} \sim G\left(D_{mis} | \theta^{(g)}, D_{obs}\right),$$

where F is the conditional distribution of parameters given the complete data and G is the conditional distribution of missing data given the parameters and observed data. The sampler for our choice of prior distributions is described in full detail in Appendix 2.

4. Empirical results

A diverse set of sovereign risk measures provides the diverse results presented in Tables 2–5. Links between variables quantifying the state of the banking sector differ before and after the 2008 crisis and across groups of countries, and are also sensitive to the type of sovereign risk measure. Nevertheless, there are patterns that enable sufficient generalization.

In Tables 2–5 we report the posterior means and indicate whether posterior credible intervals contain zero or not. This way we follow the convention in the literature and report the statistical significance of our results as it is well known that even in small samples the Bayesian posterior intervals are close to classical confidence intervals (for details see Gelman et al., 2014). In terms of our dependent variables, the government bond yield spread is one of the most employed sovereign risk measures. Yet, coefficients associated with banking sector

[16] The application of the non-informative prior implies that in the balanced panel setting with complete data, the posterior mean would be equal to the OLS fixed-effect estimates.

quality indicators are mostly statistically insignificant and in this respect a comprehensive assessment is limited (Table 2). Results based on the CDS are reported in Table 3. A lack of statistical significance during the pre-crisis period prevents assessment across periods. Specifications with both opinion-based risk measures—the ECR score (Table 4) and the sovereign credit rating (Table 5)—provide a consistently larger amount of statistically significant results.

4.1. Systemic variables and sovereign risk

Among the variables that characterize the systemic state of the banking industry in each country, the penetration of the sector by foreign banks is mostly linked to decreased sovereign risk. In case of the bond measure, coefficients lack statistical significance before the GFC (Table 2), but a pattern emerges for the CDS score, the ECR score, and the sovereign credit rating measures (Tables 3–5). The impact of foreign penetration is also typically larger after the 2008 crisis.

The overall effect exhibits various degrees of impact depending on the group of countries. Within the old EU group an important difference emerges. In Core countries foreign bank penetration is linked to increased sovereign risk (Table 4 and 5) while the results are mixed for the old EU Periphery, depending on the risk measure used. Foreign bank penetration in the old EU countries reflects a gradual expansion of large EU banks to widen their networks in Europe. Hence, in the case of Core countries we can hardly talk about truly foreign bank penetration. Consequently, its effect should be rather limited if not counterproductive. In the EU Periphery, large negative coefficients indicate the constructive impact of foreign bank penetration that might even be considered as a sort of safeguard before the GFC (Tables 3 and 5). However, the picture changes after the crisis when penetration becomes linked with increased risk (Tables 2 and 4). We conjecture that worse post-GFC position of the Core EU banks, potentially associated with profit repatriation, is behind this result.

In the new EU subgroups the helpful effect of foreign penetration is evidenced in all sub-groups (Tables 4 and 5); lack of data (Table 3) and statistical significance (Table 2) precludes assessment for all four measures of risk, though. Foreign bank penetration in the new EU countries correlates with the privatizations of their banking sectors that were completed only in the early 2000s and led to an improved performance of the industry in general (Hanousek et al., 2007). The presence of private foreign banks also implicitly means a lower share of the state in TBA. It has been shown that private banks in new EU countries exhibited better performance than state-owned banks (Bonin et al., 2005a, 2005b). This might well be related to the findings of Brei and Schclarek (2013), who analyze lending patterns during distress periods and show that government-owned banks increase their lending during crises relative to normal times but private banks tighten their lending activities. Hence, more efficient private banks positively affect the government's fiscal stance because they generate more taxable profit and thus represent a smaller burden in case of a potential bailout. For less efficient banks or in the case of profit repatriation the opposite would be true. Based on the results, the former development is more accurate as foreign bank penetration is linked to lower sovereign risk in new EU members.

The size of the banking sector, proxied by scaled TBA, delivers ambiguous results. It provides only limited evidence before the 2008 crisis due to a lack of statistical significance: still, the extent of TBA in the sector is mostly linked to lower sovereign risk (Tables 4–5). The exceptions are the Core EU group (Table 4) and the Baltics (Table 5) where the Size is linked with higher sovereign risk. After the crisis, the statistical significance improves and the Size correlates mostly with lower sovereign risk (Tables 3 and 4). The Core EU and new EU sub-groups form an exception in the case of the credit rating risk measure, though: after the crisis the Size is linked with higher risk (Table 5). In this case, the reversal of the impact between periods resonates with the argument of Gerlach et al. (2010) and hints that after the 2008 crisis the extent of TBA became an upper bound for a potential bailout partially supported by the evidence that the banking sectors in most countries came under pressure and a number of the EU governments performed bank bailouts (Correa et al., 2014). Before the crisis, the threat of the bailout was not perceived as imminent and at that time the Size could be thus understood as a simple share of the industry in the economy. This more general evidence can be drawn also for the post-crisis period when assessed with CDS and ECR as risk measures (Tables 3 and 4).

The Depth of the banking sector (measured by bank private credit to GDP) before the crisis cannot be assessed because of a general lack of statistical significance. Otherwise, after the crisis and in terms of general findings Depth correlates with higher sovereign risk. In terms of detailed assessment, the same finding is true based on consistently similar results from the bond yield spread and CDS (Tables 2 and 3) and (in most sub-groups) for the sovereign credit rating (Table 5). This finding suggests that Depth indicates greater dependency on credit when compared with other forms of financing and that such dependency translates into a more vulnerable perspective of banks in terms of the potential bailout that represents higher risk. The evidence is mixed when the credit rating measure is assessed. Still, some pattern in this mixed evidence emerges: decreased risk linked to Depth is demonstrated for the Core and Visegrad Five sub-groups (Table 5). Both sub-groups represent the most developed and relatively fiscally stable countries among the old and new EU members. Further, Core banks are heavily represented in the Visegrad Five banking sectors. These characteristics might explain the distinctive finding as they resonate well with the greater borrowing ability and access to credit in these economies. The finding can be further corroborated by the fact that after the crisis banks internationally active in Europe decreased their cross-border lending, while local lending by their branches and subsidiaries continued (IMF, 2015; p.78).

4.2. Banking sector performance variables and sovereign risk

Banking sector efficiency characterized by nonperforming loans (NPL) is the single most influential sector-specific variable that is associated with increased sovereign risk across measures of risk, country sub-groups, and the pre- and post-crisis periods. The impact of the NPL measure (in terms of the coefficients' values) is relatively smaller when the bond yield spread and ECR are used as sovereign risk proxies (Tables 2 and 4) compared to CDS and credit rating measures (Tables 3 and 5). However, we refrain from interpreting their economic impact at the moment and postpone it to Section 4.3. More important is that, despite the above variation, the NPL provides a clear message that an increase in loan-loss provisions due to an increase in NPL seriously affects bank profitability and signals an unquestionable increase in sovereign risk. Laeven and Valencia (2013) document that banking crises frequently occur together with currency or sovereign debt crises. Hence, the rising level of NPL is naturally a good signal why sovereign risk should increase as well, despite the fact that the simultaneous occurrence of banking and sovereign debt crises is less common.

Before the GFC, the Stability of the banking sector (proxied by the capital adequacy ratio CAR) is consistently linked with increased sovereign risk assessed by the ECR and credit rating measures (Table 4 and 5). The bond yield spread or CDS measure deliver statistically insignificant coefficients, though (Tables 2 and 3). After the crisis the CAR is consistently linked with decreasing sovereign risk when the risk is measured as the bond yield spread or CDS (Tables 2 and 3). With the other two risk measures, the decreasing impact on risk prevails on the aggregate as well as sub-group levels, albeit the evidence is somewhat mixed for new EU countries (Tables 4 and 5). The result can be related to the claim of Ratnovski (2015) who argues that CAR could be as much as 18%. Surely, higher CAR brings more stability but at the cost of lower productivity. In this respect, opinion and rating-based risk assessment (Tables 4 and 5) correlate with the notion that CAR represents unproductive assets linked with lower profitability and thus increasing sovereign risk. However, the overall evidence points to the fact that after the crisis, the market assessment of the risk (Tables 2 and 3) views the capital adequacy ratio as a beneficial instrument to provide the stability of the industry that favorably translates into sovereign risk evaluation.

Higher competition among banks is linked to a reduction of sovereign risk during the post-crisis period, while before the crisis more competition leads mainly to increased risk; the evidence is based on the ECR score and the new EU sub-groups (Table 4).[17] Higher competition is linked to lower sovereign risk after the crisis also in the old EU sub-groups (Table 4). Evidence based on the bond yield and CDS spreads (Tables 2 and 3) is scant after the crisis and missing before the crisis, while evidence based on the sovereign credit rating is limited and available mainly after the crisis (Table 5). The change in the pattern in the case of the new EU sub-groups suggests that before the crisis the higher competition steered banks to engage in riskier projects, behavior that ultimately led to increased sovereign risk. The combination of the results on Penetration and Competition indicates that the diversified structure of the industry—higher foreign bank penetration and higher competition—is beneficial as it is linked to lower sovereign risk.

4.3 Economic impact and wake-up call hypothesis

How should we interpret the economic significance of our results given that we use four different measures of the sovereign risk? In the case of market based measures (bond yield spreads and CDS), the economic interpretation is quite straightforward as the coefficients are directly interpretable as a change in the percentage points of the respective yields. Specifically, a change in one percentage point (p.p.) in the NPL would produce an increase in

[17] We employed the share of the assets of the five largest banks to TBA as our primary measure of competition, on which we base our inferences. We used also the inverse of the Herfindahl market concentration index to assess bank competition in an alternative way (results are not reported but available upon request). The results based on the two measures are fully in line.

the government bond yields equal to the coefficients shown for each country group in the NPL row in Table 2. This can be illustrated on the example that also compares the development between the old and new EU country groups. In Table 2, post-crisis period, we report values of 0.143 (old EU) and 0.181 (new EU). Between years 2009 and 2008, the NPL rose on average by 3.1 p.p. in the old EU. Hence, the change in the NPL would produce an increase of 0.44 p.p. in government bond yields (0.143 x 3.1 = 0.44). For the new-EU group the impact is even larger: the average increase in NPL was 6.1 p.p. that results in a government bond yields increase of 1.1 p.p. (0.181 x 6.1 = 1.1). Similar inferences can be drawn from the coefficients associated with other variables. Even without further computations we can generalize that larger coefficients indicate a larger impact on the sovereign risk as the government bond yields rise and make the debt burden larger and more costly.

The interpretation of economic significance for credit rating and ECR scores is more difficult. Nevertheless, to get a sense of the economic significance, a benchmarking among countries can be used. We can compare the sovereign ratings of some country group with a suitable benchmark; we chose Germany as it exhibits (along with Luxembourg and Sweden) most favorable credit rating during the post-crisis period. Recall that better credit rating signals lower sovereign risk. After the GFC, the average difference in the (normalized) credit rating between Germany and the old EU (new EU) is 21.05 (52.02). Again, we use the NPL coefficients as a source for our illustration. In Table 5, post-crisis period, we report values of 1.271 (old EU) and 1.263 (new EU). Between 2009 and 2008, the NPL rose on average by 3.1 p.p. in the old EU. Hence, the change in the NPL would raise the distance from the highest credit-rated benchmark country (Germany) by 3.94. (1.271 x 3.1 = 3.94). For the new-EU group the impact is even larger: the average increase in NPL was 6.1 p.p., which results in a distance-from-the-benchmark increase of 7.68 (1.263 x 6.1 = 7.68). Similar inferences can be drawn from the coefficients associated with other variables. Again, we can generalize that larger coefficients associated with credit rating indicate a larger impact on sovereign risk. From this perspective, the following three variables—total banking assets, NPL, and the capital adequacy ratio—exhibit the highest economic significance. The changes in these variables between countries and/or over time show the highest impact on the differences in credit rating and ECR scores.

Finally, the structural break test that we performed serves also as a test of the no-coefficient-change hypothesis. The results of the test (Table 1b) strongly favor the idea of a coefficient change in 2008. They also resonate well with the evidence presented in Sections 4.1 and 4.2 where coefficients associated with many banking variables altered their signs between the two researched periods. Hence, the results of the test along with the differences between the results from the pre- and after-crisis samples are in line with the wake-up call hypothesis of Goldstein (1998). In this case, markets revisited the perception of private credit and banking sector issues in the pricing of sovereign risk after the onset of the sovereign crisis in Ireland and later in other countries. In this respect, our results are also in line with Giordano et al. (2013) who analyzed the Eurozone sovereign bond markets and found evidence for contagion based on the wake-up call of the Greek crisis.

5. Conclusions

We study the underexplored issue of the link between the quality of the banking sector and sovereign risk. Given the recent economic developments related to the global financial crisis, the process of European (financial) integration, and the European debt crisis, we analyze the issue by employing data for the European Union banking sectors and sovereigns during 1999–2014.

Our analysis is rich in that we use four different indicators of sovereign risk: the long-term (10-year) government bond yield spread, the CDS spread, the overall country risk score, and the sovereign credit rating. With these four measures we are also able to analyze how results differ given market- or opinion-based assessments of sovereign risk. Further, we employ several systemic and banking-sector-specific variables that exhibit theoretical or empirical potential to be related to sovereign risk. Since our dataset contains some missing data, we opt for the Bayesian inference in panel-data estimation as it provides consistent coefficients and a valid inference (Daniels and Hogan, 2014) as well as correctly quantifying the effect of uncertainty (Gelman et al., 2014). We perform the inference by extending the usual Gibbs sampler for a panel data model with iterations that draw from the conditional distribution of missing data.

Results on the link between banking and sovereign risk are abundant. We summarize them along with the dominant effects on risk and stability. We begin with the prevailing increased risk first. Banking sector efficiency—characterized by nonperforming loans (NPL)—is the single most influential sector-specific variable that is associated with increased sovereign risk. Hence, an increase in NPL signals an increase in sovereign risk and correlates with the simultaneous occurrence of the banking and sovereign debt crises. Further, the Depth of the sector—proxied by the available private credit—correlates with higher sovereign risk, but the effect is small and the evidence is mixed. A higher dependency on credit potentially translates into the more vulnerable position of banks with respect to their bailout. However, the most developed and relatively fiscally stable old and new EU countries exhibit lower risk in connection to higher Depth. We conjecture that local lending by branches and subsidiaries of Core EU banks is behind the result.

A decrease in sovereign risk can be chiefly characterized by the following measures. The Size of the industry (TBA) mostly correlates with lower sovereign risk before and after the crisis. Still, there are some measure- and country group-related exceptions where the effect is the opposite. Capital Adequacy Ratio (CAR)—a proxy for the sector's stability—is linked with increased sovereign risk before the GFC (based on the ECR and credit rating measures) and decreased sovereign risk after the crisis. The Penetration of the banking sectors by foreign banks is systematically linked to lower sovereign risk and the impact is larger after the 2008 crisis. Higher competition among banks is linked to a reduction of sovereign risk during the post-crisis period, while before the crisis more competition leads mainly to increased risk. The pattern suggests that before the crisis the competition pushes banks towards riskier projects that ultimately lead to increased sovereign risk. After the crisis, it seems that competition reflects a healthier environment, though.

Our key results resonate well with some stylized facts related to other fields of economics: a combination of the results on Penetration and Competition indicates that the diversified structure of the industry—higher foreign bank penetration and higher competition—is beneficial for the stability of the industry as it is linked to lower sovereign risk. Finally, our results also yield support for the wake-up call hypothesis that markets revisited the perception of private credit and banking sector issues in the pricing of sovereign risk after the onset of the sovereign crisis in Europe.

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Appendix 1: Details on the Euromoney Country Risk score

The Euromoney Country Risk (ECR) score (www.euromoneycountryrisk.com) is a measure of risk produced by the Euromoney Institutional Investor PLC (www.euromoneyplc.com).

According to ECR (2016), the "Euromoney Country Risk (ECR) is an online community of economic and political experts that provide real time scores in 15 categories that relate to economic, structural and political risk. The consensus expert scores, combined with data from the IMF/World Bank on debt indicators, a survey of debt syndicate managers at international banks on access to capital and Moodys/Fitch credit ratings create the Euromoney Country Risk score (100) for 187 individual countries. ECR evaluates the investment risk of a country, such as risk of default on a bond, risk of losing direct investment, risk to global business relations etc, by taking a qualitative model, which seeks an expert opinion on risk variables within a country (70% weighting) and combining it with three basic quantitative values (30% weighting)."

The ECR assessment provides updated rankings for each country's investment risk by using 15 criteria, including political risk, economic performance, structural assessment, debt indicators, credit ratings, access to bank finance, and access to capital markets. Each country receives an ECR score on a 100-point scale, where 100 is considered the safest (no risk) and 0 means maximum risk.

The three qualitative expert opinions are political risk (30% weighting), economic performance (30%), and structural assessment (10%). The categories of economic risk/performance scored are bank stability/risk, GNP outlook, unemployment rate, government finances, and monetary policy/currency stability. The categories of political risk scored are corruption, government non-payments/non-repatriation, government stability, information access/transparency, institutional risk, and the regulatory and policy environment. The categories of structural risk scored are demographics, hard infrastructure, labor market/industrial relations, and soft infrastructure.

The three quantitative values are debt indicators (10%), access to bank finance/capital markets (10%), and sovereign credit ratings (10%) released by Moody's, Standard & Poor's, and Fitch IBCA. Nominal values are assigned to the ratings, which are converted into a score using a set scoring chart; the score is then averaged. A higher average value indicates a better standing, meaning lower sovereign risk.

Appendix 2: Details on the implementation of the Gibbs sampler

We estimate our models using a Bayesian technique. Our regression models can be re-cast as follows:

$$y_{i,t} = x_{i,t}'\theta + \omega_{i,t},$$

where $y_{i,t}$ is the value of the dependent variable in country *i* in year *t*, $x_{i,t}'$ is the vector of explanatory variables (which includes country-specific dummies), θ is the vector of unknown parameters, and $\omega_{i,t}$ is the error term, which is distributed according to a normal distribution with zero mean and variance σ^2.

We allow that some of the explanatory variables may be missing (at random). Our Gibbs sampler is then a straightforward extension of the usual Gibbs sampler for a Bayesian panel data model (see e.g., Greenberg, 2008, chapter 9) that allows for missing covariates (see e.g. Daniels and Hogan, 2014, for a Bayesian treatment of missing data).

The prior distribution for θ is multivariate normal and the prior for the inverse of the variance is the following gamma distribution:

$$\theta \sim N(\theta_0, B_0),$$
$$h \stackrel{\text{def}}{=} \frac{1}{\sigma^2} \sim G(a_0/2, c_0/2).$$

Let T_i be the number of observations for country *i* and $T = \sum_i T_i$ be the total number of observations (note that we allow for unbalanced panels). Assuming non-informative priors on the missing values of $x_{i,t}$, which will be denoted as $x_{k,i,t}^*$ (i.e., the k-th variable in the vector $x_{i,t}$, is missing), the Gibbs sampler reads as follows:

1. Choose starting values $\theta^{(0)}, h^{(0)}, x_{k,it,}^{*(0)}$
2. At the *g*-th iteration, sample:

$$h \sim G\left(\frac{a_1}{2}, \frac{c_1^{(g)}}{2}\right),$$
$$\theta \sim N\left(\theta^{(g)}, B_1^{(g)}\right),$$
$$x_{k,i,t}^* \sim N\left(m_{k,i,t}^{(g)}, 1/\tau_{k,i,t}^{(g)}\right),$$

where

$$a_1 = a_0 + \sum\nolimits_i T_i,$$
$$c_1^{(g)} = \sum\nolimits_i \left(y_{i,t} - x_{i,t}^{\prime(g)}\theta^{(g)}\right)^2,$$
$$B_1^{(g)} = \left[h^{(g)} \sum\nolimits_i X_i^{\prime(g)} X_i^{(g)} + B_0^{-1}\right]^{-1},$$

$$\theta^{(g)} = B_1^{(g)} \left[h^{(g)} \sum\nolimits_i X_i'^{(g)} y_i + B_0^{-1} \theta_0 \right],$$
$$m_{k,i,t}^{(g)} = \frac{y_{i,t} - \theta_{-k}^{(g)} x_{-k,i,t}^{(g)}}{\theta_k^{(g)}},$$
$$\tau_{k,i,t}^{(g)} = h^{(g)} \left[\theta_k^{(g)} \right]^2.$$

$x_{i,t}'^{(g)}$ is the vector of explanatory variables with the imputed values of missing data, $X_i^{(g)} = \left(x_{i,1}^{(g)}, \dots, x_{i,T_i}^{(g)} \right)'$ is the stacked vector of the explanatory variables for country *i*, θ_k is the *k*-th element of the parameter vector θ, and θ_{-k} denotes—as usual—vector θ *without* the *k*-th element. The analogical notation applies for vector $x_{-k,i,t}^{(g)}$.

In our estimation, we set non-informative priors: $\theta_0 = 0, B_0^{-1} = 0$ and $a_0 = c_0 = 0$. Our inference is based on 4,000 iterations, from which we disregard the first 1,000 burn-in iterations. The calculations were done in Matlab (version 2015b) using codes developed by Brůha et al. (2014). The codes are available upon request.

We also considered the model with *t*-distributed errors. Such a model can be estimated using a straightforward extension of the above Gibbs sampler. The sampling of model parameters is then extended as follows:

$$h \sim G\left(\frac{a_1}{2}, \frac{c_1^{(g)}}{2} \right),$$
$$\theta \sim N\left(\theta^{(g)}, B_1^{(g)} \right),$$

$\lambda_i \sim G\left(\frac{\nu+1}{2}, \frac{\nu_{2i}^{(g)}}{2} \right),$

where

$$c_1^{(g)} = \sum\nolimits_i \lambda_i \left(y_{i,t} - x_{i,t}'^{(g)} \theta^{(g)} \right)^2,$$
$$\nu_{2i}^{(g)} = \nu + h^{(g)} \sum\nolimits_t \left(y_{i,t} - x_{i,t}'^{(g)} \theta^{(g)} \right)^2.$$

The rest of the sampler is the same as above.

Appendix 3

Appendix 3.1 Testing multicollinearity

We investigate the problem of multicollinearity among explanatory variables. First, we computed the conditional numbers of the regression matrices and in all cases they are well below 100. This is surely an acceptable value and we conclude that the multicollinearity does not jeopardize our estimation.

Second, Figure A.1 shows the histograms of cross-correlations among the sector performance variables for each country in our sample. The subfigures in the upper row are correlations for the pre-2008 sample, while the lower row figures show the result for the post-2008 sample. Figure A.2 shows the analogical histogram of correlations among systemic variables. In both cases, there are countries, where the correlation among explanatory variable is high and close to 1, but there are also countries with weak or even negative correlation. This implies that we have enough variability in data to identify the effects of interest.

Figure A.1: Histograms of correlations among sector performance variables:

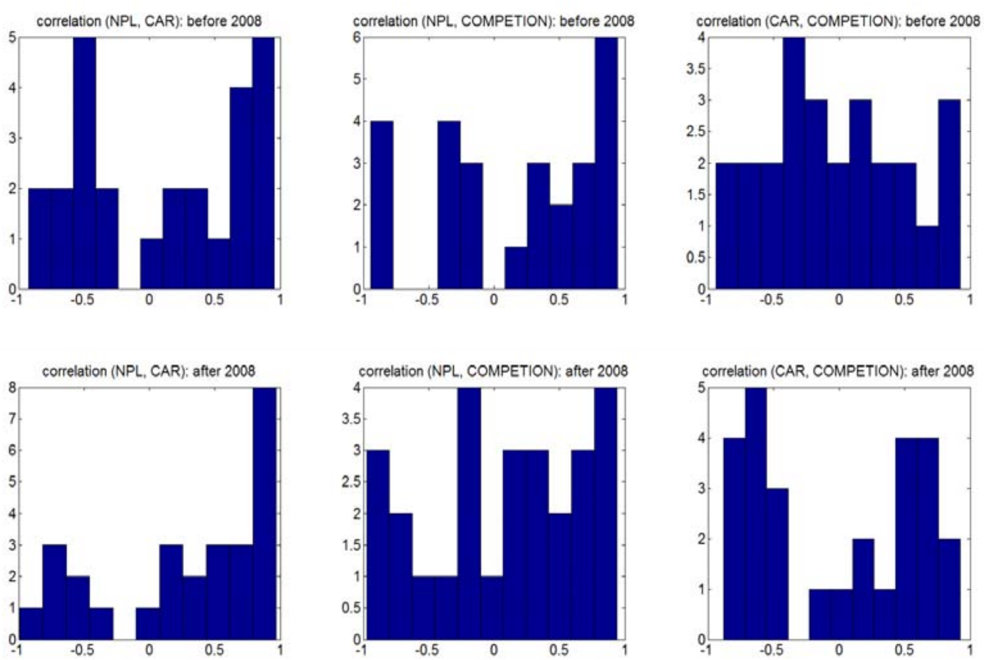
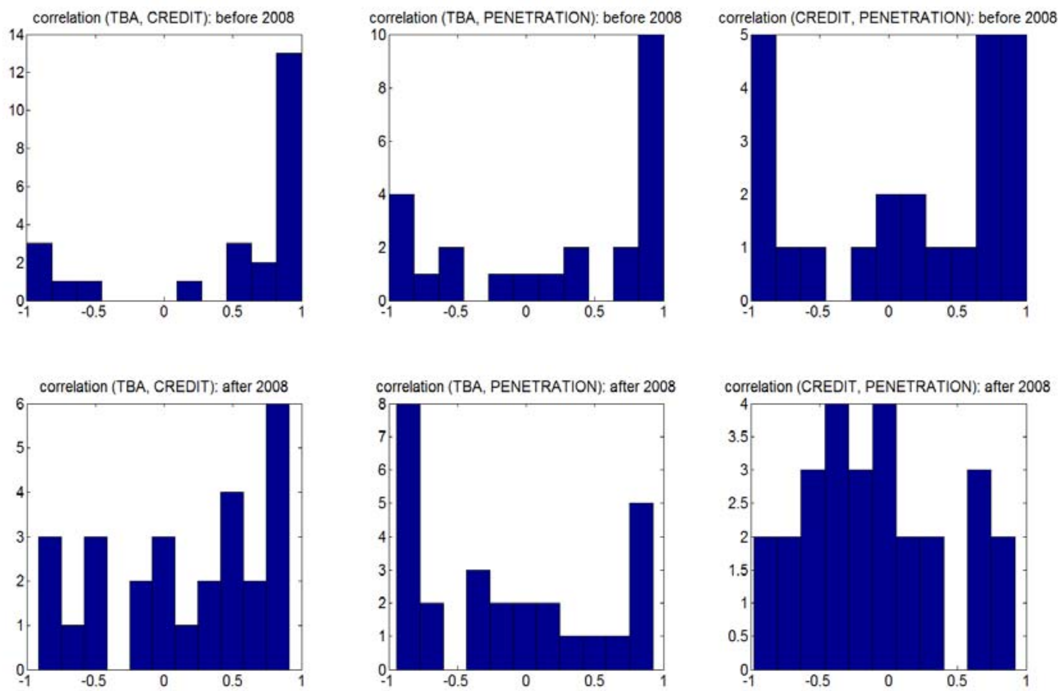


Figure A.2: Histograms of correlations among systemic variables:



Appendix 3.2 Correlation among endogenous variables

Figure A.3 shows the histogram of country specific correlations among endogenous variables for the sample before 2008. Figure A.4 displays the analogical histograms for the sample after 2008.

Apparently, the risk measures tend to be positively correlated (as can be expected). Nevertheless, there are countries for which there is a negative correlation between some risk measures. Therefore we can conclude that the risk measures capture different aspects of country risks and that none of our endogenous variables is redundant.

Figure A.3: Histograms of correlations among endogenous variables (sample before 2008)

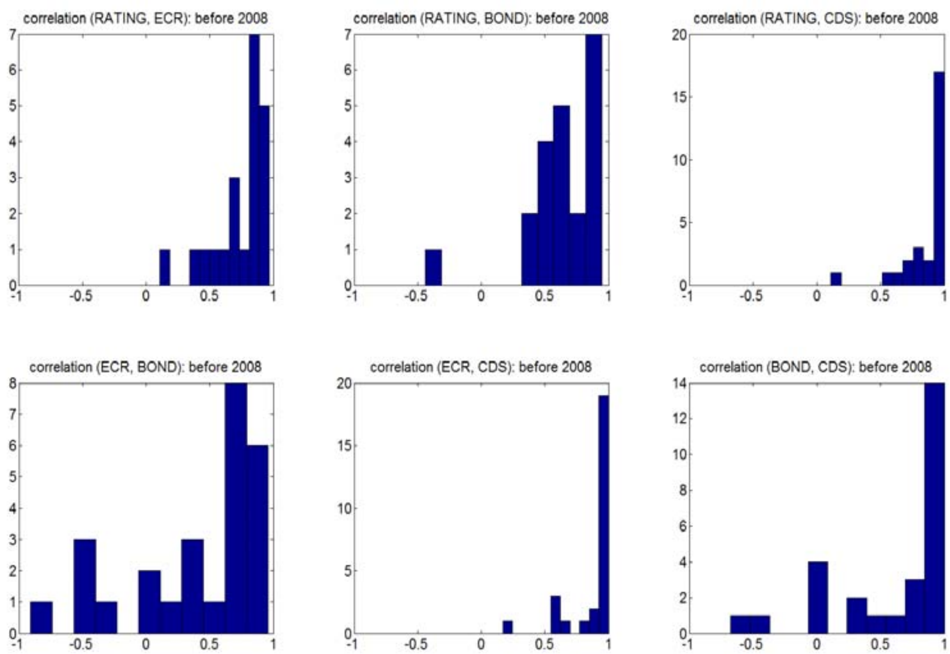
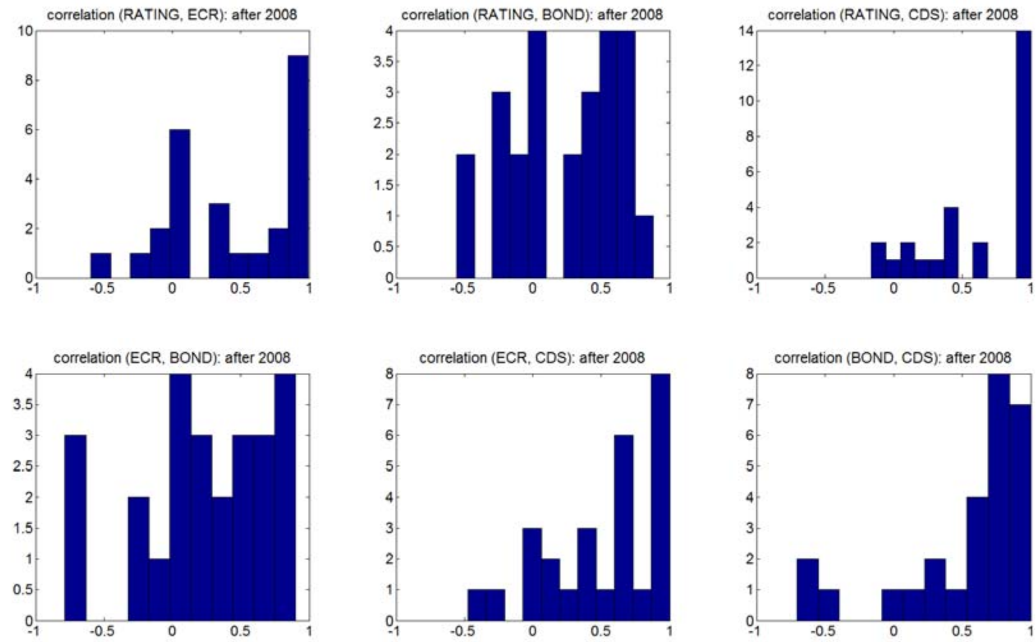


Figure A.4: Histograms of correlations among endogenous variables (sample after 2008)



Appendix 3.3 Testing endogeneity

Finally, we tested the potential endogeneity of the explanatory variables. We used the Hausman (1978) test [Hausman, J. A. (1978). "Specification Tests in Econometrics". *Econometrica*,46 (6): pp. 1251–1271] that evaluates the consistency of an estimator (panel data model estimated by OLS) when compared to an alternative instrumental variable estimator that is consistent but less efficient. As instruments, we use the lagged endogenous variables.

The test statistics has the following form:

$$J = (b_{OLS} - b_{IV})^T (var(b_{IV}) - var(b_{OLS}))^+ (b_{OLS} - b_{IV}),$$

where b_{OLS} is the OLS estimator, b_{IV} is the instrumental variable estimator, and + denotes the pseudo-inverse matrix. Under the null hypothesis of no endogeneity, the test statistics has the χ^2 distribution.

The results are provided in the following tables (we highlight in grey the cases of the rejection of the null hypothesis (of no endogeneity in explanatory variable with respect to explained variable – risk measure)):

Table A.1: Endogeneity test - banking sector characteristics with respect to risk (performance variables before 2008)

Sample: prior 2008		NPL	CAR	Competion
Equation: credit rating	Test statistics	0.01	0.14	0.00
	p-value	*0.91*	*0.71*	*1.00*
Equation: ECR	Test statistics	0.01	0.01	0.03
	p-value	*0.91*	*0.93*	*0.87*
Equation: bond spread	Test statistics	0.09	0.00	0.00
	p-value	*0.76*	*1.00*	*0.98*
Equation: CDS	Test statistics	3.42	8.77	7.46
	p-value	*0.06*	*0.00*	*0.01*

Table A.2: Endogeneity test - banking sector characteristics with respect to risk (systemic variables before 2008)

Sample: prior 2008		TBA	CREDIT	PENETRATION
Equation: credit rating	Test statistics	0.09	0.01	12.52
	p-value	*0.77*	*0.91*	*0.00*
Equation: ECR	Test statistics	8.41	0.01	0.90
	p-value	*0.00*	*0.93*	*0.34*
Equation: bond spread	Test statistics	1.52	0.02	0.00
	p-value	*0.22*	*0.89*	*0.99*
Equation: CDS	Test statistics	6.15	6.14	0.04
	p-value	*0.01*	*0.01*	*0.83*

Table A.3: Endogeneity test - banking sector characteristics with respect to risk (performance variables after 2008)

Sample: post2008		NPL	CAR	Competion
Equation: credit rating	Test statistics	0.01	2.15	0.56
	p-value	*0.94*	*0.14*	*0.45*
Equation: ECR	Test statistics	0.00	2.37	0.28
	p-value	*0.99*	*0.12*	*0.60*
Equation: bond spread	Test statistics	0.35	2.35	0.13
	p-value	*0.55*	*0.13*	*0.72*
Equation: CDS	Test statistics	0.05	0.01	0.00
	p-value	*0.82*	*0.92*	*0.98*

Table A.4: Endogeneity test - banking sector characteristics with respect to risk (systemic variables after 2008)

Sample: post2008		TBA	CREDIT	PENETRATION
Equation: credit rating	Test statistics	0.03	0.43	1.76
	p-value	*0.87*	*0.51*	*0.18*
Equation: ECR	Test statistics	0.05	0.34	1.46
	p-value	*0.82*	*0.56*	*0.23*
Equation: bond spread	Test statistics	0.20	0.00	0.27
	p-value	*0.65*	*0.95*	*0.60*
Equation: CDS	Test statistics	0.65	0.60	7.61
	p-value	*0.42*	*0.44*	*0.01*

The results show that (i) there is a limited endogeneity during pre-crisis period, (ii) it is related mostly to the CDS risk measure, (iii) there is practically no endogeneity during post-crisis period. These results in large corroborate the links among variables described in Sections 3.2 and 3.3. The aim of our analysis is not to test causality among variables. Rather, we strive to assess prediction properties of our model. In other words, we are more interested in a statistical association between explanatory variables and the measure of risk. Hence, even the presence of endogeneity would not represent a critical problem that would invalidate our results presented in Section 4. Nevertheless, as the test reveals only a limited presence of endogeneity, the statistical association that we document is probably not far from the true causal links. This further increases the usefulness of our results.

Table 1a: Summary statistics

	Frequency	No of observations	Missing values	All countries				Old EU countries				New EU countries			
				Min	Mean	Median	Max	Min	Mean	Median	Max	Min	Mean	Median	Max
Credit rating	quarterly*	1107	0%	0.00	23.62	19.23	97.90	0.00	9.11	0.26	97.90	10.90	43.22	39.99	92.70
ECR scores	quarterly*	1107	0%	0.35	24.71	22.67	66.44	0.35	14.84	11.59	66.44	17.96	38.93	38.01	64.79
Bond yield spread	quarterly	874	21%	-1.19	1.29	0.49	21.00	-1.19	0.67	0.25	21.00	-1.09	2.33	2.10	9.14
CDS	quarterly	641	42%	0.06	4.69	0.73	149.04	0.06	5.59	0.61	149.04	0.47	1.49	1.29	4.18
Competition	annual	420	14%	0.83	57.89	51.01	166.36	6.12	68.90	68.58	166.36	0.83	44.60	47.08	83.54
Non performing loans (%)	annual	411	15%	0.08	5.71	3.31	52.60	0.08	3.91	2.70	33.78	0.20	7.50	5.17	52.60
Penetration (%)	annual	397	18%	2.47	39.22	29.18	99.00	2.47	25.46	19.40	83.48	18.84	70.94	73.19	99.00
TBA/GDP (%)	quarterly	941	15%	1.38	14.52	10.00	134.43	1.70	9.91	10.51	21.36	1.38	10.80	8.82	38.47
Credit /GDP (%)	quarterly	876	22%	25.40	89.26	80.65	405.10	33.60	99.04	84.60	405.10	25.40	58.51	49.95	115.90
Capital adequacy ratio	annual	426	12%	2.00	7.00	6.50	15.50	2.70	5.72	5.50	12.67	2.00	9.00	8.53	15.50

*semi-annual prior to 2010

Table 1b: Structural Break Test

Model / dependent variable	Credit rating	ECR	Bond yields	CDS
systemic variables (with control)	19.71	21.07	17.04	9.30
sector performance variables (with control)	27.46	31.20	23.10	11.04

Note: The structural break test is performed in the following way. We calculate the Bayes factor of two models: (i) the model with distinct coefficients before and after 2008 and (ii) the model with coefficients constant over the whole sample. For all regression specifications performed, the Bayes factor favors the type of model with the coefficient change (the Bayes factor is larger than 1, which supports the structural break hypothesis). For almost all regression specifications, the Bayes factors are larger than 10, which gives a strong support for the structural break hypothesis.

Table 2: Estimation results for the sovereign bond yield spread

Dependent variable: bond yield spread	All countries	Old EU countries	Core EU	Periphery	New EU countries	Visegrad 5	Baltics	Balkan countries
Sample period: before 2008								
TBA	-0.061	-0.085	-0.012	-0.127	-0.024	-0.075	-0.055	0.460
Credit	0.004	0.004	0.005	0.007	-0.010	-0.015	0.016	-0.118
Penetration	-0.004	-0.001	-0.004	-0.004	-0.029	-0.039	0.109	-0.024
Debt/GDP	0.005	0.002	0.010	0.007	-0.047	-0.039	-0.543	-0.242
Sample period: after 2008								
TBA	0.017	0.055	0.075	-1.419 ***	0.167 **	0.248	0.045	-2.220
Credit	0.084 ***	0.053 ***	0.013	0.188 ***	0.168 ***	0.052	0.338 ***	0.237 ***
Penetration	0.060 ***	0.045	0.018	0.558 ***	0.053	0.007	-0.153	0.018
Debt/GDP	0.057 ***	0.063 ***	0.007	0.104 ***	0.046 **	0.044 **	0.000	0.080
Sample period: before 2008								
NPL	0.120 ***	0.106	-0.047	0.097	0.118	0.110	0.502 **	-0.167
CAR	0.002	-0.041	-0.079	0.111	0.060	-0.095	0.190	0.210
Competition	-0.001	0.001	0.027	0.002	-0.011	-0.031	0.118	0.008
Debt/GDP	0.012	0.007	0.006	-0.004	0.032	0.032	-0.261	0.020
Sample period: after 2008								
NPL	0.116 ***	0.143 ***	0.071	0.263 ***	0.181 ***	0.116	0.144	0.075
CAR	-0.744 ***	-0.817 ***	-0.084	-2.356 ***	-0.518 ***	-0.045	-1.595 ***	-0.241
Competition	0.012	0.024	0.010	0.058 **	-0.035	0.056	-0.138 **	-0.057
Debt/GDP	0.049 ***	0.050 ***	0.012	0.055	-0.001	0.014	0.211	-0.080

Note: In the table we report posterior means. Symbols ***, **, and * indicate that the 99, 95, and 90 percent posterior credible intervals do not contain zero. Bayesian credible posterior intervals converge in large samples to classical confidence intervals. Hence, ***, **, *, can be interpreted as the conventional statistical significance at 10, 5, and 1 % levels.

Table 3: Estimation results for credit default swap (CDS)

Dependent variable: CDS	All countries	Old EU countries	Core EU	Periphery	New EU countries	Visegrad 5	Baltics	Balkan countries
Sample period: before 2008								
TBA	-0.004	0.001	0.001	0.000				
Credit	0.000	0.000	0.001	0.001				
Penetration	0.009	0.003	0.004	0.000				
Debt/GDP	0.000	0.001	-0.001	0.002				
Sample period: after 2008								
TBA	-5.966 ***	-8.155 ***	0.162	-9.992 ***	0.261	0.268		
Credit	0.924 ***	1.125 ***	-0.034	1.046 ***	0.075	0.076		
Penetration	-1.163 ***	-1.573 ***	0.030	-4.693 ***	0.008	0.007		
Debt/GDP	0.487 ***	0.454 ***	-0.003	0.088 ***	-0.023	-0.025		
Sample period: before 2008								
NPL	0.000	-0.006	-0.017	0.000				
CAR	0.034	0.026	-0.009	0.000				
Competition	-0.001	0.000	0.000	0.001				
Debt/GDP	0.000	0.000	0.002	0.002				
Sample period: after 2008								
NPL	4.622 ***	5.392	0.012 ***	7.442 ***	0.194	0.193		
CAR	-4.340 ***	-4.815	-0.189 ***	-10.348 ***	-0.217	-0.194		
Competition	-0.375 ***	-0.331	0.008 ***	-0.231 ***	0.080	0.080		
Debt/GDP	-0.456	-0.620	0.024 ***	-0.759	-0.004	-0.007		

Note: In the table we report posterior means. Symbols ***, **, and * indicate that the 99, 95, and 90 percent posterior credible intervals do not contain zero. Bayesian credible posterior intervals converge in large samples to classical confidence intervals. Hence, ***, **, *, can be interpreted as the conventional statistical significance at 10, 5, and 1 % levels. Coefficients are missing for some countries and periods because the CDS data are not available.

Table 4: Estimation results for the ECR score

Dependent variable: ECR,	All countries	Old EU countries	Core EU	Periphery	New EU countries	Visegrad 5	Baltics	Balkan countries
Sample period: before 2008								
TBA	-0.005	0.073	0.391 **	-0.075	-0.516 **	-0.517 **	0.301	-1.173
Credit	-0.003	-0.001	-0.002	-0.003	-0.053	-0.024	0.378	-0.175
Penetration	-0.030 **	-0.019	-0.037	-0.008	-0.087 **	-0.085	-0.734	-0.134 **
Debt/GDP	0.071 ***	0.061 ***	0.118 ***	0.032	0.225 **	0.199	4.757 **	-0.326
Sample period: after 2008								
TBA	-0.201 ***	-1.278 ***	-0.720 ***	-4.002 ***	-0.203 ***	-0.725 ***	-0.425 ***	6.423 ***
Credit	0.037 ***	0.017	-0.034 *	0.130 ***	0.298 ***	-0.086 *	0.664 ***	-0.056
Penetration	0.007	0.067 ***	0.110 ***	0.481 ***	-0.239 ***	-0.438 ***	-0.716 ***	-0.091
Debt/GDP	0.562 ***	0.646 ***	0.794 ***	0.612 ***	0.378 ***	0.407 ***	0.149 ***	0.220 **
Sample period: before 2008								
NPL	0.571 ***	0.255 ***	-0.346	0.428 ***	0.600 ***	0.517 ***	1.620 ***	0.516
CAR	0.130 **	-0.051	-0.320	0.015	0.516 ***	-0.094	0.928 ***	0.391
Competition	0.004	0.003	-0.015	0.029	0.106 ***	0.125 ***	0.413 ***	0.108
Debt/GDP	0.146 ***	0.076 ***	0.098 ***	0.074	0.345 ***	0.301 ***	-0.106	0.247 **
Sample period: after 2008								
NPL	0.260 ***	0.512 ***	-0.375	0.469 ***	0.595 ***	0.797 ***	0.430 ***	0.275 **
CAR	-0.412 ***	-0.029	2.772 ***	-3.596 ***	0.406 **	1.034 **	-0.292	0.495
Competition	-0.138 ***	-0.059 *	0.033	-0.235 ***	-0.166 ***	0.113	-0.283 ***	0.094
Debt/GDP	0.479 ***	0.483 *	0.593 ***	0.480 ***	0.080 **	-0.035	0.232 ***	0.305 ***

Note: In the table we report posterior means. Symbols ***, **, and * indicate that the 99, 95, and 90 percent posterior credible intervals do not contain zero. Bayesian credible posterior intervals converge in large samples to classical confidence intervals. Hence, ***, **, *, can be interpreted as the conventional statistical significance at 10, 5, and 1 % levels.

Table 5: Estimation results for the credit rating

Dependent variable: Credit Rating,	All countries	Old EU countries	Core EU	Periphery	New EU countries	Visegrad 5	Baltics	Balkan countries
Sample period: before 2008								
TBA	-0.363 ***	-0.617 ***	-0.216	-0.725 ***	-0.565 ***	-0.806 ***	0.952 ***	-7.020 ***
Credit	-0.006	0.000	0.000	-0.021	-0.012	0.075	-0.431	1.139 ***
Penetration	-0.077 ***	-0.007	0.022	-0.150 ***	-0.374 ***	-0.416 ***	0.594	-0.265 ***
Debt/GDP	0.125 ***	0.078 ***	0.107 ***	0.133 ***	0.368 ***	0.160	-0.272	1.454 ***
Sample period: after 2008								
TBA	-0.018	-0.966 ***	0.558 ***	-1.277 ***	0.860 ***	0.928 ***	0.607 ***	1.636
Credit	0.281 ***	0.157 ***	-0.084 ***	0.256 ***	0.264 ***	-0.650 ***	0.295 ***	1.099 ***
Penetration	-0.147 ***	-0.112 ***	0.193 ***	0.028	-0.259 ***	-0.683 ***	0.275 **	0.015
Debt/GDP	0.870 ***	0.874 ***	0.159 ***	1.101 ***	0.570 ***	0.496 ***	0.969 ***	0.428 ***
Sample period: before 2008								
NPL	0.996 ***	1.551 ***	0.060	1.536 ***	0.956 ***	0.777 ***	2.106 ***	2.187 ***
CAR	0.974 ***	0.544 ***	-0.026	2.052 ***	1.147 ***	0.696 ***	1.674 ***	1.071 **
Competition	-0.010	-0.056 ***	0.022	0.020	-0.038	-0.024	0.374	-0.007
Debt/GDP	0.399 ***	0.158 ***	0.096 ***	0.135 ***	1.073 ***	0.900 ***	0.956 ***	0.924 ***
Sample period: after 2008								
NPL	1.052 ***	1.271 ***	0.711	0.894 ***	1.263 ***	2.450	1.167 ***	0.567 ***
CAR	-0.688 ***	-1.530 ***	0.337	-2.704 ***	1.584 ***	-2.325	0.087	0.046
Competition	-0.127 ***	-0.052 ***	0.040	0.069 *	-0.078	0.166	-0.309 ***	-0.029
Debt/GDP	0.568 ***	0.592 ***	0.173 ***	0.919 ***	-0.069 *	0.043	0.583 ***	-0.036

Note: In the table we report posterior means. Symbols ***, **, and * indicate that the 99, 95, and 90 percent posterior credible intervals do not contain zero. Bayesian credible posterior intervals converge in large samples to classical confidence intervals. Hence, ***, **, *, can be interpreted as the conventional statistical significance at 10, 5, and 1 % levels.