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THE MORE THE BETTER? INFORMATION SHARING AND CREDIT RISK

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Correctly estimating borrower credit risk is a task of particular and growing importance for banks all around the globe. Formal information sharing mechanisms are aimed to reduce information asymmetry in the credit markets and to enhance the precision of those estimates. In the literature, however, whether more, and more detailed, borrower information shared by credit bureaus and credit registries is always associated with higher quality bank credit portfolios and lower credit risk is not completely unambiguous. More credit information disclosed by information intermediaries tends to result in a weaker disciplinary effect of credit history, which means higher credit risk. The accuracy of assessing the creditworthiness of borrowers grows due to an increase in the predictive power of scoring models, which leads to a reduction in credit risk. In this paper, we make a first attempt to examine the nonlinearity of this effect. We study the relationship between the depth of credit information disclosed and the stability of the banking sector in terms of credit risk. Based on data on 80 countries for 2004–2015, we show that the relationship between disclosure and credit risk is non-linear: we observe the lowest levels of credit risk at the minimum and maximum levels of disclosure. We analyze the influence of national institutional quality and financial development on the nature of the relationship. We show that credit risk decreases with increasing amounts of disclosure by credit bureaus and credit registers in well-developed financial markets and in a high-quality institutional environment.

Keywords: Credit risk, Credit bureau, Credit registry, Bank, Information sharing

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1. Introduction

Correctly estimating borrower credit risk is a task of particular and growing importance for the banks all around the globe. Formal information sharing mechanisms are aimed to reduce information asymmetry in the credit markets and to enhance the precision of those estimates. In the literature, however, whether more detailed borrower information accumulated and shared by credit bureaus and credit registries is always associated with higher quality of bank credit portfolios and lower credit risks is not clear.

Information exchange is designed to improve the functioning of credit markets. It solves the problems of information asymmetry, adverse selection and moral hazard ((Stiglitz and Weiss 1981); (Pagano and Jappelli 1993); (Jappelli and Pagano 2002)). With access to borrowers' credit histories, banks can more accurately assess their creditworthiness, make more informed decisions about granting loans, and set fair interest rates (Kallberg and Udell 2003; Nakamura and Roszbach 2018). The exchange of information prevents borrowers from being overlooked, as banks are aware of the size of the debt burden of customers ((Bennardo, Pagano, and Piccolo 2015)). The sharing of information has a disciplining effect on borrowers: they make more efforts to repay the loan in order to maintain a good credit history and not face higher interest rates on loans in the future ((Brown and Zehnder 2007; Vercammen 1995). More detailed credit reports increase the predictive power of scoring models (Barren and Staten 2003; Chandler and Parker 1989). All these effects tend to reduce credit risk.

The degree of credit disclosure, however, may have the opposite effect. The more information contained in credit histories, the less the disciplining effect on borrowers. Default is perceived as a sign of the borrower's unreliability if credit reports contain only negative information. A credit report containing negative and positive information can accurately determine the degree of risk for the lender, and default is no longer perceived as a sign of the poor quality of the client. Borrowers make less effort to avoid default and credit risk increases (Padilla and Pagano 2000). If the borrower rating in a full credit report falls below a certain level, in equilibrium they can choose to strategically default so as not to pay higher interest rates in the future (Sharma 2017) and credit risk increases.

Is it possible that the dependence of credit risk on the amount of information disclosed is non-linear? If the degree of disclosure of credit information is minimal, banks cannot accurately assess the creditworthiness of borrowers and credit risks are high. The more information disclosed, the more accurate the predictive power of scoring models becomes and credit risk is reduced. However, above a certain level of information disclosure, disciplinary action on borrowers weakens and credit risk grows. The situation may be the opposite. In this case, the minimum disclosure of credit information has the most disciplining effect on borrowers and credit risk is low. The more information disclosed, the weaker the disciplinary action and credit risk increases, but the accuracy of assessing the creditworthiness of borrowers also increases. When the degree of disclosure of credit information is high, the predictive power of scoring models is also high and credit risk is reduced.

In this paper we make a first attempt to examine the nonlinearity of this effect. We study the relationship between the amount of credit information disclosed and the stability of the banking sector in terms of credit risk.

Based on data from 80 countries for 2004–2015, we show that the relationship between disclosure and credit risk is non-linear: we observe the lowest levels of credit risk at the minimum and maximum levels of disclosure. We analyze the influence of the country's institutional quality and financial development on the nature of the relationship. We show that credit risk decreases with increasing disclosure by credit bureaus and credit registers in well-developed financial markets and in high-quality institutional environments.

This paper is organized as follows. Section 2 reviews the theoretical and empirical literature on the influence of credit information sharing on bank credit risk. Section 3 describes the methodology and the data we use. Section 4 presents the estimation results and the robustness checks. Section 5 concludes.

2. Literature

Credit markets without interbank information exchange are characterized by information asymmetry between banks and borrowers: borrowers know much more about the degree of their and their projects' risk compared to lenders. Information asymmetry has a certain number of well-known negative consequences for credit markets, leading to adverse selection and moral hazard.

Information asymmetry also leads to credit rationing, when banks limit the volumes of lending at a certain interest rate and some borrowers, even those able to pay more, are refused a loan. (Stiglitz and Weiss 1981) show that an equilibrium is established when demand for loans exceeds their supply and the interest rate is lower than it would be at market equilibrium. By increasing the interest rate banks increase the riskiness of their loan portfolios, reducing their expected profits. The riskiness of the portfolio increases due to adverse selection and improper incentives for borrowers. The higher the interest rate, the riskier the borrowers who agree to pay it, because the probability that they will back pay the loan is low, therefore risky borrowers drive reliable borrowers from the credit market, leading to adverse selection. When the interest rate is high, borrowers are more likely to choose riskier projects with lower probability of success but with higher profits if such projects are effectively completed. This is the effect of improper incentives for borrowers when interest rates are high.

Information sharing in credit markets eliminates information asymmetry between lenders and borrowers. When banks share their borrowers' credit profiles with each other, they can much better estimate the riskiness of potential customers. Accordingly, the problems of credit rationing and adverse selection are eliminated. (Pagano and Jappelli 1993) show that banks have incentives to exchange information about their borrowers when there is adverse selection in the market. In their models, banks have information about resident borrowers but cannot determine the riskiness of newcomers. The authors theoretically and empirically show that there is a positive relationship between information exchange, population mobility and the size of credit market. On the contrary, banks' incentives to share credit reports are reduced due to the danger of new banks entering the market and increasing competition. In that case, older banks lose their monopoly on information about their borrowers.

Moral hazard can also be manifested in that borrowers can borrow from several banks. This leads to over-indebtedness—a situation when borrowers' debts exceed their income, and they can no longer repay their loans, and overdue payments and default rates rise. Information sharing solves the problem of moral hazard because such opportunistic financial behavior of borrowers is recorded in their credit reports available to all the banks. This is discussed in more detail in (Vercammen 1995) and (Bennardo, Pagano, and Piccolo 2015).

(Vercammen 1995) shows that the disclosure of information encourages borrowers to protect their reputation and credit discipline. According to his model, more reliable borrowers are rewarded with lower interest rates in the future. If a borrower does not make a payment on time, this undermines their reputation. Risky borrowers are penalized with higher interest rates or exclusion from the credit market. (Bennardo, Pagano, and Piccolo 2015) explore the relationship between the ability to obtain loans from several banks (multiple-bank lending) and the probability of default. The authors investigate this correlation depending on the presence of information exchange, the volatility of collateral and the degree of protection of creditor rights. The model shows that information exchange accompanied by non-volatile collateral and moderate creditor rights protection helps to reduce defaults, interest rates and rationing because creditors can prevent the opportunistic behavior of borrowers.

Information sharing not only solves the problems of information asymmetry, adverse selection and moral hazard but also disciplines borrowers. (Padilla and Pagano 2000) show that, from the banks' point of view, information exchange creates the correct incentives for borrowers to make more efforts in the projects they borrow for. Banks who wish to create the right incentives for borrowers announce that they have joined an information exchange mechanism and borrowers exert more effort as they expect that information sharing dilutes information rents for banks, and they will charge more efficient interest rates.

Many empirical papers show that information sharing in credit markets reduces credit risks. (Jappelli and Pagano 2002) tested hypotheses that information exchange increases lending and reduces defaults on data from approximately 40 countries. They gathered information about credit bureaus and credit registers from questionnaires that were sent to these organizations in 49 countries and show that if the system of information exchange was better developed, the volume of loans was also higher. In two other models the ratio of overdue loans to total loans and a credit risk indicator calculated according to the methodology of the International Country Risk Guide Financial Indicator were used as an approximation of credit risk. They show that the longer credit bureaus exist, the more information they collect and disclose and the lower the credit risk. However, the negative correlation between information exchange and credit risk was weaker than the positive correlation between information exchange and the volume of loans.

(Kallberg and Udell 2003) complement (Jappelli and Pagano 2002). However, the former consider the influence of information exchange on the micro level. Using credit reports for 1988 provided by the largest US credit bureau at that time—Dun & Bradstreet—they show that information provided to banks by information intermediaries significantly improves the accuracy of assessing the borrower's credit risk and has high predictive power in assessing the probability of default. This effect was stronger for credit reports compared to other types of information that creditors take into account when deciding whether to give a loan. A similar idea on the advantage of information from credit bureaus over other types of information is discussed in (Nakamura and Roszbach 2018). The authors used data on credit ratings which were compiled by two major Swedish banks for corporate borrowers. They found that use of external information from credit bureaus in addition to internal banking information increases the accuracy of predicting bankruptcies and defaults.

(Doblas-Madrid and Minetti 2013) show that the effect of information asymmetry reduction under information sharing is especially strong for young and opaque firms. The authors use unique data provided by the credit bureau PayNet, which specializes in investment in equipment, and show that the disclosure of credit information reduces the number of overdue payments and the probability of default.

(Chandler and Parker 1989) assessed the creditworthiness of borrowers who applied for a credit card. They also proved that more detailed information from a credit bureau improves the predictive power of scoring models. (Barren and Staten 2003) compared the quality of scoring models depending on the information they contain: only negative ("black") information, for example, like in Australia, or negative and positive ("black" and "white") information, for example, like in the US. They show that in the model with negative information the share of reliable borrowers who could repay the loan but who did not receive it was higher than in the model with negative and positive information. In the model with only negative information the share of risky borrowers who received a loan and defaulted was higher than in the negative and positive model. In general, the disclosure of complete information about borrowers makes the loan available to a wider population and more reliable borrowers.

(Kusi et al. 2017) studied the impact of information exchange on credit risk using a sample of 548 African banks for 2006–2012. They show a negative relationship between information disclosure and credit risk. The negative correlation was significantly higher for credit bureaus in low-income countries, and the results also suggest that in Africa, private credit bureaus are more effective as information intermediaries than public credit registers. (Fosu et al. 2020) consider the practice of information sharing in developing countries and its influence on loan default rates. Based on a sample of 879 banks from 87 countries, the study shows that information exchange results in a decrease in default rates. (Gietzen 2016), using the data of the African banking industry, shows that information sharing allows high-quality borrowers to receive credit at lower interest rates. (Sahin 2017) discusses the particular characteristics of information sharing mechanisms, namely, to what extent the disclosure of non-financial information might influence non-performing loans. Using the data from 55 countries, the author concludes that the countries which combine information about borrowers not only from financial institutions but also from retailers and utility companies, have a much lower non-performing loan rate.

The disciplining effect of information exchange on borrowers was tested empirically. (Brown and Zehnder 2007) were the first to test the impact of interbank information exchange on borrowers' incentives depending on the existence of relationship banking – lending based on an established relationship between the lender and borrower as a result of repeated interactions between them. They found that in the absence of relationship banking the disclosure of credit information significantly increases incentives of borrowers to repay their loan. However, when there appearsthe relationship banking credit information disclosure has a weak impact on incentives to repay loans.

Credit information sharing can affect the financial performance of banks. (Omar and Makori 2018) use data from 43 commercial banks in Kenya and conclude that information sharing has a positive and significant effect on the financial performance of lenders. The explanation of this effect is that better quality information sharing results in better risk assessment and lower administrative costs.

(Guérineau and Léon 2019) revealed the relationship between information sharing and financial vulnerability using a large sample of countries. The results suggest that information exchange has a stabilizing effect on the financial system of a country, especially for developing countries with small shocks They also study the relationships between information sharing, credit booms, and financial vulnerability. The results show that there is a direct effect of the quality of credit information on the probability of credit booms and that information sharing can alleviate the detrimental effects of credit booms.

However there are several explanations why information exchange can increase credit risks. (Vercammen 1995) emphasizes that the longer the credit histories, the less the reputational costs from single overdue payments and defaults. (Jappelli and Pagano 2002) noted that the negative correlation between information disclosure and risk of default is true for individual borrowers but at the aggregate level it can have a multidirectional impact on credit risk in the banking system.

While information exchange encourages borrowers to repay loans, the more information disclosed in credit reports, the weaker the disciplining effect on borrowers can be. This leads to higher credit risks. As shown by (Padilla and Pagano 2000), if only negative information is shared, borrowers exert more efforts than if negative and positive information is disclosed. In the latter case borrowers do not make enough effort to prevent a default because default is no longer perceived as a sign of the poor quality of the borrower. A lender having access to all the credit information about the borrower can also define the risk, therefore the authors argue that information exchange encourages borrowers to make maximal efforts to repay loans.

(Sharma 2017) models the impact of information exchange on borrowers' incentives in the same direction: the more information disclosed in the credit report, the less the incentive borrowers have to repay the loan. If not only the history of repayments is disclosed in the credit report but also information about all the characteristics of the borrower, then in equilibrium the borrower can choose a strategic default, i.e., stop repaying a loan regardless of their solvency.

According to (Giannetti, Liberti, and Sturgess 2017), information sharing might be ineffective due to manipulations of borrowers’ credit ratings prior to sharing credit information with other banks. Using the mechanism of information disclosure by a public credit registry, they show that banks misreport the data on high-quality borrowers for which they have positive private data to protect their informational rents. Another form of manipulation is upgrading low-quality borrowers with several lenders to avoid the flight to other creditors. The incentives to misreport borrower data is also modelled in (Semenova 2008).

(Ali et al. 2019) utilize a game model to demonstrate that information sharing might change the allocation of credit resources and then use data from EU countries to verify whether information sharing affects the aggregate credit volume and default ratio of lenders. The results demonstrate that a comprehensive information exchange system is associated with greater credit access and, hence, a greater aggregate credit volume and higher default ratios.

(Balakrishnan and Ertan 2017) provide a detailed analysis of to what extent information might improve loan loss recognition. Information intermediaries help banks determine loan loss recognition in a timely manner and the effect of the timeliness of loan loss recognition is greater when public credit registries collect more information about borrowers. This may result in a higher share of non-performing loans reported, as banks have fewer opportunities to window-dress this part of their balance sheets.

The literature suggests that the introduction of information exchange mechanisms helps reduce credit risks in the banking sector. However, more detailed and complete disclosure can either increase or reduce credit risk. A non-linear relationship between the amount of information disclosed and credit risk has not yet been investigated. This paper attempts to fill this gap. We assume that the relationship between credit risk and the degree of information disclosure is a(n inverse) U-shaped curve. If a U-shaped relationship is proven by the data, this would mean that with minimal information disclosure credit risks are high as banks cannot accurately assess the creditworthiness of borrowers. The more information disclosed, the more accurate the credit assessment becomes and credit risks decrease. However, the disciplining effect on borrowers weakens and credit risks begin to increase with some degree of information disclosure. The reverse order of these effects can also be assumed, meaning an inverse U-shaped dependence. This would mean that with minimal information exchange the disciplining effect on borrowers is maximal and credit risk is low. The greater the degree of disclosure, the weaker the disciplining effect on borrowers, and credit risk grows. However, when the credit report reveals as much information as possible about the financial behavior of borrowers, the accuracy of scoring models increases and credit risk falls.

3. Data and Methodology

Using panel GMM techniques we estimate the following dynamic model:

$$Credit\ risk_{it} = \gamma Credit\ risk_{it-1} + \beta_1 Cii \cdot dummy1_{it-1} + \beta_2 Cii \cdot dummy2_{it-1} +$$
$$+\beta_3 (Cii \cdot dummy1)^2{}_{it-1} + \beta_4 (Cii \cdot dummy2)^2{}_{it-1} + Bank\ controls_{it} \cdot \delta_1 +$$
$$+Macro_{it} \cdot \delta_2 + Year_{it} \cdot \delta_3 + \alpha_i + \varepsilon_{it},\ \ i = 1, \dots, N, t = 1, \dots, T,$$

where *i* is a country index, *t* is a year index, α_i is an individual fixed effect. $Credit\ risk_{it}$ is the measure of credit risk for country *i* in period *t*, *Cii* (credit information index) is the index of the depth of credit information disclosure. *Bank controls* are variables related to the banking sector, *Macro* is a vector of macroeconomic control variables, *Year* denotes year fixed effects. Among the independent variables, the lagged value of the dependent variable is also used.

The dependent variable *Credit risk* is the ratio of overdue loans to the total amount of loans issued, which is a generally accepted measure of credit risk. If payments on loan principal and interest were not made for more than 90 days, then such loans are classified as overdue.

The variable of primary interest is *Cii*, the credit disclosure depth index. It began to be calculated within the World Bank's Doing Business project in 2004. This index had 6 criteria: if a criterion was met for information intermediaries in the selected country, then it was assigned the value of 1, and 0 otherwise. Then the criteria were summed. The resulting number reflected the amount of credit information disclosed: the higher the index, the more information disclosed in credit reports. The criteria used in the index are:

1) information intermediaries collect information on both individuals and legal entities;

2) both positive and negative information is distributed;

3) information is collected from financial institutions, retailers and utilities;

4) credit reports contain information for at least the two past years;

5) data on loans, the amount of which is less than 1% of income per capita, is disseminated;

6) borrowers have access to their credit reports.

In 2013, the methodology for calculating this index was supplemented with two more criteria:

1) banks can access credit reports online;

2) as an additional service the assessment of the borrower's creditworthiness is offered to banks.

From 2004 to 2012 the index took values from 0 to 6, and from 2013 it ranges from 0 to 8, its values for these two periods are not comparable. However, to combine the data into one panel, dummy variables are entered for two periods: *dummy1* equal to 1 for 2004–2012 and 0 otherwise, and *dummy2* equal to 1 for 2013–2015 and 0 otherwise. Then we introduce a pair of multiplied variables into the regression.

As the literature provides arguments in favor of both a negative and a positive effect of information exchange on credit risk, this paper tests the hypothesis of a nonlinear relationship between the share of overdue loans and the depth of information disclosure by credit bureaus and credit registers. To test this hypothesis, the squared disclosure depth variable is introduced into the regression equation: $(Cii \cdot dummy1)^2$, $(Cii \cdot dummy2)^2$. As discussed in Section 2, β_1 and β_2 (β_3 and β_4) can be expected to be either negative (positive), meaning a U-shaped relationship, or positive (negative), meaning an inverse U-shaped relationship.

The model includes lagged values for *Cii* as an increase affects credit risk with a delay. This does not change the interpretation: a higher *Cii* value in the past year reduces or increases the credit risk in the current year, or decreases and then increases, and vice versa. On the other hand, the introduction of lagged values for the main variable solves the problem of endogeneity: there are hardly any missed factors that affect both the credit risk in the current period and *Cii* in the past. Such a model specification helps avoid simultaneity—one of the causes of endogeneity.

We introduce the following characteristics of the banking system as control variables. When examining credit risk, it is important to consider the size of the banking system itself. This variable is designated as *Size* and equals the ratio of the assets of commercial banks in a given country to the GDP of that country. If, on average, banks are characterized by increasing returns to scale, then with an increase in the size of the banking system, credit risk will decrease. Large banks have more opportunity to correctly assess the creditworthiness of borrowers and monitor their loan repayments (Kusi et al. 2017). Another explanation is that large banks have more options to diversify their loan portfolios (Brei, Jacolin, and Noah 2018), therefore, the credit risk is lower. Finally, larger banks mostly deal with large, transparent companies and therefore have lower credit risk (Škrabić Perić, Rimac Smiljanić, and Aljinović 2018). If, on average, the country's banking system is characterized by diminishing returns to scale, it means that banks have become so large that they can no longer effectively assess the riskiness of borrowers and control loan repayment, and credit risk increases (Kusi et al. 2017). Banks that are "too-big-to-fail" can take on more credit risk because, they count on the support of the regulator (Brei, Jacolin, and Noah 2018).

In our context, it is also important to consider concentration in the banking system. The variable *Concentration* is introduced to control for this factor and is calculated as the ratio of the assets of the three largest commercial banks to the total bank assets in the country (C3). In this paper, this variable is used instead of the Lerner or Herfindahl-Hirschman indices, which characterize the degree of competition, since we have more observations for C3 than for these indices. *Concentration* is one aspect of competition: it is expected that the higher the concentration in the banking system, the lower the competition. With high competition, an effective balance is achieved, and credit risk should be reduced (the competition-stability hypothesis). On the other hand, the higher the competition, the riskier the activities banks engage in, in order to increase their profits, and credit risk increases (the competition-fragility hypothesis) (Boyd and Nicolo 2005; Fecht, Thum, and Weber 2019; Kusi et al. 2017; Schaeck, Cihak, and Wolfe 2009).

The next control variable is *Capitalization*, calculated as the ratio of bank capital and reserves to assets, which measures a bank's appetite for risk. The larger the capitalization, the more unexpected losses can be absorbed by the bank (Brei, Jacolin, and Noah 2018). (Berger and DeYoung 1997) indicated that the lower the capitalization, the more the banks conduct risky policies, which increases the amount of overdue loans. However, a positive relationship between capitalization and credit risk can also be explained. High capitalization may reflect high capital requirements on the part of the regulator due to the fact that the bank has a risky asset portfolio, therefore, the share of overdue loans is higher (Brei, Jacolin, and Noah 2018). The more the capital, the more the shareholders want a return on their investments, which forces managers to make riskier decisions, and the credit risk increases (Kusi et al. 2017).

ROA stands for the return per unit of asset and is calculated as the ratio of the bank's net profit to the its average annual assets: the greater the net profit, the greater the profitability per unit of assets and the less the amount of overdue loans. However higher returns come with greater risk, and therefore greater credit risk (Kusi et al. 2017).

The diversification of bank income is measured by noninterest income (*NII*) and equals the share of the bank's non-interest income in total income. The more the bank diversifies its sources of income, the lower the credit risk. However, if the bank does not generate non-interest income or the bank does not have a comparative advantage in this area, greater diversification can lead to greater risk (Kusi et al. 2017). An alternative explanation for the positive impact of diversification on credit risk is presented in (Brei, Jacolin, and Noah 2018). If banks focus on non-traditional banking activities, they do not pay enough attention to assessing and monitoring borrowers, and credit risk increases.

The variable *CtoD ratio* is the ratio of loans issued by commercial banks to the private sector to deposits. The higher the ratio of loans to deposits, the more aggressively banks lend, and the greater the credit risk (Swamy 2012).

Private credit denotes the share of loans issued by national banks to the private sector in total bank assets and approximates the degree of financial intermediation. An increase in the ratio of loans to assets is usually associated with an increase in credit risk, which is explained by increased competition among banks, weakening requirements for borrowers, and increased problems of adverse selection and moral hazard (Mpofu and Nikolaidou 2018; Škrabić Perić, Rimac Smiljanić, and Aljinović 2018).

Overhead costs is the ratio of the bank's operating expenses to its assets. If a bank has high operating costs, it tends to pass them on to customers (Fungáčová and Poghosyan 2011), loan rates rise, borrowers find it more difficult to pay off loans, and credit risk increases.

It is important to control for the share of *Foreign banks' assets*, reflecting the share of assets of foreign banks in the assets of the country's banking system. This variable is available up to and including 2013. For this reason, the impact of *Foreign banks' assets* is explored in the supplementary specification (3). The larger the share of foreign banks' assets, the lower the credit risk, as proven in a number of empirical studies for the countries of Central and Eastern Europe (Škrabić Perić, Rimac Smiljanić, and Aljinović 2018). For Argentina and Uruguay, it was found that branches of foreign banks headquartered in developed countries bear less credit risk than other banks (Brei, Jacolin, and Noah 2018). In general, this should reduce the credit risk of the banking system of the host country. However, there are studies that show that foreign banks take on more risks than national banks (Chen et al. 2017), although in this paper the Z-score was considered as a measure of bank riskiness. However, the higher riskiness of foreign banks can be explained by the fact that they are less informed about the local market and the creditworthiness of local borrowers compared to local banks.

A group of macroeconomic control variables is described below. It is important to include the annual growth rate of real GDP (GDP growth, base year 2010 in USD) in the regression equation. The GDP growth rate is linked to economic cycles. If the economy is on the rise, the GDP growth rate is higher and the number of non-performing loans is lower (Brei, Jacolin, and Noah 2018; Mpofu and Nikolaidou 2018).

The impact of inflation (*Inflation*) on credit risk is ambiguous. Inflation reduces the real cost of credit. On the one hand, this should make it easier for borrowers to pay back borrowed funds and reduce overdue loans (Brei, Jacolin, and Noah 2018). On the other hand, inflation reduces the real income of borrowers, making it more difficult for them to repay their debt, and credit risk increases (Mpofu and Nikolaidou 2018).

We also control for the *Rule of law*, including the index of law and order in the regression. This reflects the perception of society about the rule of law in their country, about the culture of the execution of contracts, the protection of property rights, the work of courts and the police, and the likelihood of crime and violence, and takes values from -2.5 to 2.5. It is assumed that the more favorable the legal environment, the lower the credit risk (Jappelli and Pagano 2002).

It is important to take into account the reverse exchange rate (*Exchange rate*) and the country's lending interest rate (*Lending rate*) among macroeconomic factors (Mpofu and Nikolaidou 2018). However, these variables were not used in the main model because there are few observations for them, and they drain the panel. For a dynamic model, this is undesirable since the length of the time series is reduced. For this reason, the influence of these factors is tested in the supplementary specification (4). The nominal exchange rate is the opposite for all countries except the US, because it reflects the value of the dollar in local currency. The interest rate is the real lending rate adjusted for inflation by the deflator. The higher the real interest rate, the higher the nominal interest rate, the more expensive loans are for borrowers, the more difficult it is for them to pay them off, and the higher the level of default. Changes in the nominal exchange rate have different effects on exporters and importers. The depreciation of the national currency (growth in the nominal exchange rate) makes domestic goods more competitive in the world market, and exports grow. As the solvency of exporting firms with bank loans grows, the credit risk falls. A cheaper currency makes imports more expensive. The solvency of importing firms with bank loans falls, and the credit risk increases.

We estimate the regression on the panel data from 2004 to 2015 and the dataset we use is combined from the data from several World Bank databases: World Development Indicators (WDI)[5], Doing Business;[6] Global Financial Development;[7] Worldwide Governance Indicators.[8]

The next step in our estimations is related to the influence of the country's institutional and financial development on the relationship we analyze. First, we introduce a measure of the overall quality of formal institutions in the country. We use Government Effectiveness index (*GE*) compiled by the World Bank for more than 200 countries over the period 1996–2018.[9] This indicator is based on the opinion of a large number of surveyed enterprises, citizens, and experts, in addition, a number of data sources are prepared by research institutions, analytical centers, non-profit organizations, etc. The indicator measures the quality of public service delivery and its independence from political pressure and ranges from -2.5 to 2.5. The variable also aggregates indicators of the quality of policy development and implementation, and the level of government confidence in this policy.

We use Physical Property Rights index (*PPR*) to proxy the extent to which private property rights are legally protected in the country. This index is a component of the International Property Right Index, compiled by the Property Rights Alliance.[10] *PPR* represents the degree of registration of properties, the availability of loans, and actual compliance with property rights (i.e., how the de facto system works). It takes values from 0 to 10 and represents annual data from 2007 to 2019. For 2019, representatives of 129 countries participated in the surveys.

[5] http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
[6] http://databank.worldbank.org/data/reports.aspx?source=doing-business
[7] http://databank.worldbank.org/data/reports.aspx?source=global-financial-development
[8] http://databank.worldbank.org/data/reports.aspx?source=worldwide-governance-indicators
[9] https://databank.worldbank.org/reports.aspx?source=worldwide-governance-indicators
[10] https://www.internationalpropertyrightsindex.org/full-report

Finally, we check for the influence of the country's financial development. We use two indices for that purpose: Financial Institutions Depth Index (*FID*) and the Financial Markets Depth Index (*FMD*), compiled by the IMF over the period 1980–2019 for 192 countries.[11] These indicators, together with a number of others, form the Financial Development index that reflects the size, availability, and effectiveness of financial institutions and the financial market. *FID* aggregates data on bank loans to the private sector as a percentage of GDP, pension fund assets as a percentage of GDP, and so on. *FMD* reflects the size of the financial market as a whole; it aggregates data on stock market capitalization to GDP, traded shares to GDP, and so on. Each index takes values from 0 to 1.

For each of the variables, we divide our sample into two subsamples above and below the median of the indicator and re-estimate our basic regressions. This allows us to compare the nature of the relationship between the depth of credit information disclosure and credit risk for the countries with high and low degrees of institutional and financial development.

The initial collection of data and their aggregation into one panel resulted in a sample of 194 countries, but the panel was very unbalanced: some countries had short time series, some lacked data on a number of variables. When evaluating dynamic models with two-step GMM we need the time series to be at least three years long and with not many missing observations. For this reason, the final panel included 80 countries in which no more than two observations (no more than two years) were missing for any of the variables selected in the main model.

Table 1 shows the descriptive statistics for all the variables, Table 2 presents the pairwise correlation matrix.

Table 1. Descriptive statistics

Variable	N	Mean	St.Dev.	Min	Max
Credit risk	947	0.0592	0.0596	0.0010	0.3730
Cii*dummy1$_{t-1}$	957	3.1588	2.3696	0.0000	6.0000
Cii*dummy2$_{t-1}$	957	1.5569	2.8707	0.0000	8.0000
Size	955	0.6646	0.4596	0.0646	2.5743
Concentration	958	0.6289	0.1725	0.2048	1.0000
Capitalization	949	0.1003	0.0379	0.0149	0.2390
ROA	959	0.0133	0.0133	-0.0852	0.0832
NII	957	0.3343	0.1497	0.0247	0.9229
CtoD ratio	956	1.0694	0.4923	0.1797	3.6708
Domestic credit	955	0.5511	0.4136	0.0294	2.1912
Overhead costs	960	0.0393	0.0407	0.0011	0.8000
GDP growth	959	0.0397	0.0415	-0.2049	0.3374
Inflation	956	0.0528	0.0711	-0.3584	1.2174
Rule of law	960	0.1390	0.9198	-2.0324	2.0964

[11] https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B&sId=1480712464593

Foreign banks’ share	718	0.3961	0.3229	0.0000	1.0000
Exchange rate	828	485.2396	2060.2460	0.2136	25000.0000
Lending rate	647	0.0540	0.0830	-0.4322	0.4464

As macroeconomic variables are highly correlated, we do not include *GDP growth*, *Inflation*, *Rule of law* in the model simultaneously. Instead, we introduce two principal components (*PC1* and *PC2*) calculated using these three variables. They cover 82% of the overall variation.

Table 2. Descriptive statistics

	Cii·dummy1	Cii·dummy2	Size	Concentration	Capitalization	ROA	NII	Credit to deposits ratio	Overhead costs	Private credit	Principal component1	Principal component2	Foreign banks' assets	Exchange rate	Lending rate
Cii·dummy1	1														
Cii·dummy2	-0.7238*	1													
Size	0.0813*	0.1016*	1												
Concentration	-0.0113	-0.0661*	0.1698*	1											
Capitalization	-0.1376*	0.0265	-0.5257*	-0.1650*	1										
ROA	-0.0710*	-0.1027*	-0.4760*	-0.0072	0.3281*	1									
NII	0.3417*	-0.4035*	-0.0787*	0.0074	0.0682*	0.0124	1								
Credit to deposits ratio	0.1030*	0.0302	0.4159*	0.1242*	-0.1514*	-0.2351*	-0.0018	1							
Overhead costs	-0.0327	-0.0579	-0.4335*	-0.1406*	0.3324*	0.2398*	0.3936*	-0.1598*	1						
Private credit	0.1588*	0.036	0.2225*	0.1230*	-0.0245	-0.1534*	0.0853*	0.5421*	-0.0573	1					
Principal component1	-0.0842*	-0.1341*	-0.6731*	-0.2546*	0.4289*	0.4528*	0.0863*	-0.2861*	0.3909*	-0.2657*	1				
Principal component2	-0.0311	-0.0436	-0.0252	0.0645*	-0.0232	0.2608*	-0.0447	-0.0206	-0.0634*	0.0532	0	1			
Foreign banks' assets	-0.0228	-0.008	-0.3176*	0.0395	0.2842*	0.1391*	-0.0295	-0.1759*	0.1020*	-0.0255	0.1003*	-0.0265	1		
Exchange rate	-0.0281	-0.0268	-0.1764*	-0.1029*	0.021	-0.0118	0.037	-0.0526	0.1231*	0.0029	0.1078*	0.0303	-0.0635	1	
Lending rate	-0.0549	0.0768	-0.1009*	0.0517	0.1181*	0.1084*	-0.0792*	-0.007	0.2093*	-0.023	-0.1492*	0.1247*	0.1508*	0.0668	1

* p-value<0.05

4. Results

The impact of the depth of information disclosure on credit risk

The results of the model estimation are presented in Table 3. In column 1, the basic regression without year fixed effects is estimated. All variables referring to the index of information disclosure are statistically significant, and the relationship is non-linear. It is an inverse U-shaped curve for both periods: 2004–2012 and 2013–2015. Credit risk is maximal when the depth of information disclosure was 2.9 points in 2004–2012 and 3.2 points in 2013–2015 (Figure 1). When the information disclosure index is less than 3 points, credit risk increases with higher levels of information depth, when the index exceeds 3 points the credit risk begins to decline.

Table 3. The impact of information disclosure on credit risks

Independent variables	1	2	3	4
Credit $risk_{t-1}$	0.643***	0.671***	0.633***	0.654***
$Cii \cdot dummy1_{t-1}$	0.00222***	0.00607***	0.00326***	0.00916***
$Cii \cdot dummy2_{t-1}$	0.00343***	0.0000681		-0.000346
${(Cii \cdot dummy1)^2}_{t-1}$	-0.000382***	-0.000795***	-0.000610***	-0.00108***
${(Cii \cdot dummy2)^2}_{t-1}$	-0.000544***	-0.000277**		-0.000109
Size	0.0707***	0.0695***	0.0713***	0.00603
Concentration	0.0336***	0.0466***	0.0375***	0.0474***
Capitalization	-0.0592***	-0.0284**	0.0386	-0.00528
ROA	-0.157***	-0.132***	-0.128***	-0.313***
NII	0.00387***	0.00704***	0.0106***	0.0114**
CtoD ratio	0.0213***	0.0175***	0.0202***	0.0341***
Overhead costs	-0.0104	-0.0142**	0.00418	-0.0613***
Private credit	-0.0694***	-0.0189**	-0.00511	-0.0218*
Principal component 1	-0.00196***	-0.000202	-0.00330***	-0.00101
Principal component 2	-0.00542***	-0.00496***	-0.00192***	-0.00630***
2005		-0.0582***	-0.0723***	-0.0525***
2006		-0.0605***	-0.0747***	-0.0521***
2007		-0.0611***	-0.0763***	-0.0509***
2008		-0.0638***	-0.0766***	-0.0548***
2009		-0.0579***	-0.0696***	-0.0508***
2010		-0.0586***	-0.0725***	-0.0470***
2011		-0.0634***	-0.0745***	-0.0549***
2012		-0.0592***	-0.0712***	-0.0501***
2013		-0.0595***	-0.0727***	-0.0509***
2014		-0.0408***		-0.0279***
2015		-0.0395***		-0.0279***
Foreign banks′ assets			0.0261***	
Exchange rate				0.00000568***
Lending rate				0.0153***
Observations	845	845	648	556
Number of countries	80	80	78	57
AR(1)	0.0018	0.0013	0.0337	0.0025
AR(2)	0.0706	0.0655	0.0915	0.3924
Sargan test	0.2332**	0.4336**	0.1397**	0.9971**

*** p-value<0.01, ** p-value<0.05, * p-value<0.1

The lagged value of credit risk is significant: a high value of credit risk in the previous period increases its value in the current period. All control variables except for operating costs are also significant. A larger banking system, its concentration and reliance on non-interest income, lower capitalization, profitability and credit market exposure are associated with a higher share of non-performing loans in the country’s banks’ portfolios.

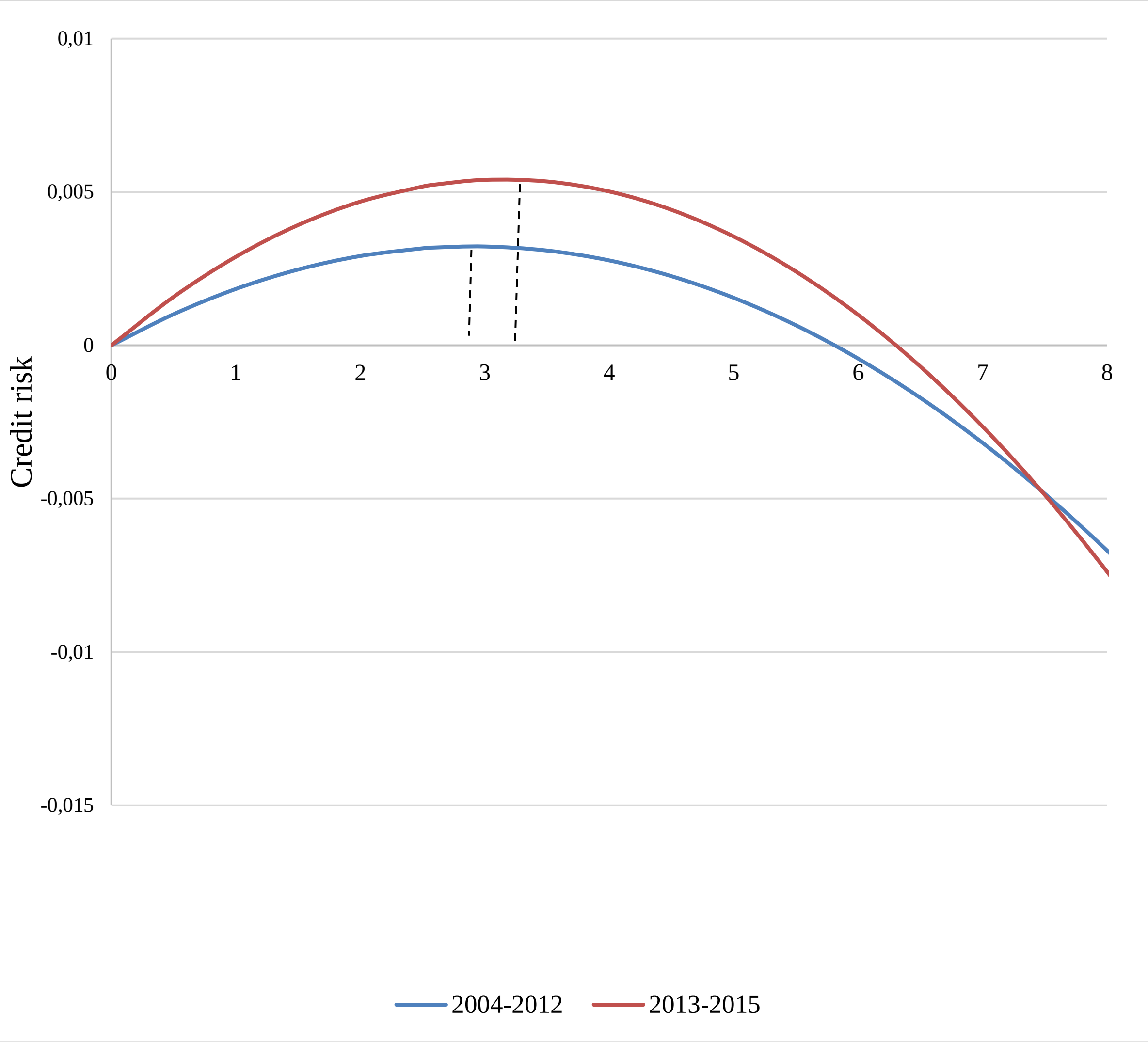

Figure 1 Model I: Credit risk and information disclosure index

Year fixed effects are added in Model 2. Time effects are significant and generally have a negative sign. Credit risk declined during 2005–2008 in comparison to 2004, then increased in 2009–2010, then fell till 2011 and finally gradually rose till the end of 2015. After the introduction of time effects, the non-squared variable of the information disclosure index retained its significance only for the first period, but the dependence of credit risk on the depth of information disclosure remained inverse U-shaped with credit risk being maximal when the disclosure index is 3.8. This value is slightly larger than 2.9 and 3.2 which were obtained in the model without time effects. For the second period only the square of the index retained its significance, meaning that the credit risks decline with more information sharing, which is in line with many empirical studies.

Additional variables are added in other specifications. They are important when assessing credit risk, but these variables were not included in the main model, as few observations are available for them, severely depleting the sample. In the Model 3 (see Table 2), the variable *Foreign banks' assets* is added, meaning that the influence of variables for the information disclosure index for the second period are not evaluated due to the fact that the indicator *Foreign banks' assets* was calculated only until 2013. This variable is significant and has a positive sign: when there are more foreign banks in the country, credit risk is higher. As for the information disclosure index, for the first period it retained its significance and non-linear influence on credit risk, with the credit risk being at the highest level when the depth of information disclosure is 2.7. This is almost the same as the 3 points that were obtained in the first model.

In Model 4, macroeconomic variables such as *Exchange rate* and *Lending rate* are added. The information disclosure index remains significant for the first period, the dependence is inverse U-shaped. The amount of overdue loans in the loan portfolio is maximal when the depth of information disclosure is 4.2. The maximum of the inverse U-shaped curve lies within the 3–4 points that were obtained in the previous specifications.

The results of the main model estimation suggest the non-linearity of the influence of the credit information sharing index (*Cii*) and the share of non-performing loans, showing that bank credit risks do not decrease if the quality of information sharing is not very high. If the information exchange mechanisms are estimated by the Doing Business methodology at the above-average level (more that 3–4 points of the *Cii*) credit risk decreases with more information sharing.

Robustness checks

The results are checked for robustness. In Model 5 (see Table 4), the regression is estimated using the initial sample which contained 194 countries. However, the number of countries remaining in the estimated sample is 117 as the initial panel was unbalanced. The quadratic dependence of credit risk on the index of credit information disclosure persisted for 2004–2012 and the credit risk is maximal when the index value is 3.3 points. For 2013–2015 only the variable *Cii·dummy2* is significant: when more credit information is disclosed, credit risk is linearly lower.

Table 4. Robustness checks

Independent variables	5	6
Credit $risk_{t-1}$	0.691***	0.635***
$Cii \cdot dummy1_{t-1}$	0.00527***	0.00376***
$Cii \cdot dummy2_{t-1}$	-0.00184***	-0.000151
$(Cii \cdot dummy1)^2{}_{t-1}$	-0.000793***	-0.000496***
$(Cii \cdot dummy2)^2{}_{t-1}$	0.000128	-0.000178*
Size	0.0769***	0.0807***
Concentration	0.0522***	
Capitalization	0.0136	
ROA	-0.182***	-0.115***
NII	0.00259	0.00648***
CtoD ratio	0.00942***	0.0124***
Overhead costs	-0.0198	
Private credit	-0.00581	-0.0128*
Principal component 1	-0.00335	0.000175
Principal component 2	0.0156*	-0.00449***
2005	-0.0664***	-0.0617***
2006	-0.0690***	-0.0646***
2007	-0.0694***	-0.0646***
2008	-0.0696***	-0.0684***
2009	-0.0656***	-0.0622***
2010	-0.0663***	-0.0637***
2011	-0.0676***	-0.0678***
2012	-0.0645***	-0.0644***
2013	-0.0656***	-0.0649***
2014	-0.0571***	-0.0549***
2015	-0.0573***	-0.0533***
Concentration (5)		0.0283***
Capital to RWA		0.00469
Cost to income ratio		0.0113***
Observations	1,047	822
Number of countries	117	79
AR(1)	0.0008	0.0045
AR(2)	0.0391	0.1643
Sargan test	0.2100	0.5588

*** p-value<0.01, ** p-value<0.05, * p-value<0.1

In Model 6, we replaced some control variables with ones characterizing the same country characteristics: *Concentration* is replaced by *Concentration (5)* (assets of the five largest banks to assets of the banking system), *Capitalization* is replaced by *Capital to RWA*, *Overhead costs* are replaced by *Cost to income ratio* (bank expenses to income). When these control variables were replaced, the significance of the information disclosure index and the non-linear dependence of credit risk on it were preserved. Credit risk in 2004–2012 was maximal when the information disclosure index was 3.7, which corresponds to the values obtained during the estimation of the main model.

The results are stable and robust to the changes in sample size and control variables.

The role of country financial and institutional development

This section presents the pairwise comparisons of the results of regression estimations for the sub-samples of countries with different levels of the institutional quality and financial development. We re-estimate the basic model specifications 1 and 2 for each of the sub-samples. Table 5 demonstrates the results for government effectiveness and physical property rights protection.

Countries with higher government effectiveness tend to have lower depth of information disclosure for the credit risk to be maximal. It is 2.0 points for 2004–2012 (Figure 2). Above 2.0 points, the credit risk decreases. For countries with lower government effectiveness, credit risk reaches its maximum when the value of information disclosure is 4.1 points. Better policy development and implementation, and better quality public service delivery result in a lower threshold of the depth of credit information for the information sharing to start working properly, reducing the bank credit risks.

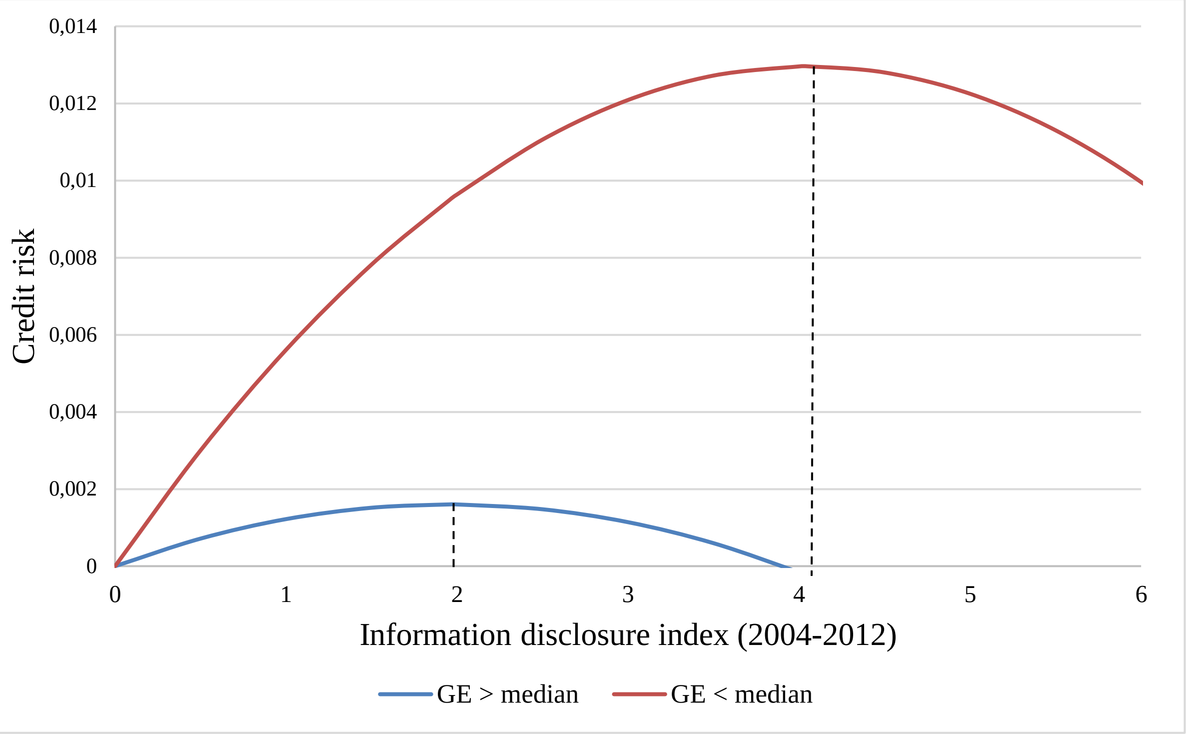

Figure 2 Model GE: Credit risk and information disclosure index (2004–2012)

Another important difference is represented by the two models with countries with higher and lower degrees of proprety rights protection. A higher value of *PPR* is related to a much lower value of the information disclosure index at which credit risk is maximal. This value for countries with higher *PPR* is between 1–2 points (Figure 3), meaning that information sharing starts reducing credit risks almost immediately. Countries with lower *PPR* represent a much different trajectory. Credit risk increases until the disclosure index is approximately 3 points. This result supports the idea that institutional quality adds to the power of information sharing to reduce credit risks.

Table 5. The impact of information disclosure on credit risks depending on regulatory environment

	GE>median		*GE<median*		*PPR>median*		*PPR<median*	
Variables	1	2	1	2	1	2	1	2
$Credit\_risk_{t-1}$	0.58584***	0.61533***	0.87172***	0.84646***	0.63685***	0.61267***	0.72372***	0.74304***
$Cii*dummy1_{t-1}$	0.00164***	0.00612***	0.00640***	0.00833***	0.00172***	0.00543***	0.00198***	0.00294***
$Cii*dummy2_{t-1}$	-0.00094	-0.00385**	0.00662***	0.00488***	0.00305***	0.00109	0.00261***	0.00218**
$(Cii*dummy1)^2_{t-1}$	-0.00042***	-0.00086***	-0.00079***	-0.00086***	-0.00066***	-0.00103***	-0.00029***	-0.00038***
$(Cii*dummy2)^2_{t-1}$	0.00004	0.00021	-0.00070***	-0.00045***	-0.00058***	-0.00041*	-0.00029***	-0.00022**
Size	0.06506***	0.01601	0.05473***	0.04725***	0.11480***	0.10011***	0.04710***	0.03499***
Concentration	0.04284***	0.06325***	-0.01302***	-0.01771***	0.03226***	0.03622***	0.01821***	0.01355***
Capitalization	-0.02156	-0.02485	-0.03694	-0.06041	0.35338***	0.22035***	-0.01113**	-0.07981***
ROA	-0.29497***	-0.30317***	-0.13581***	-0.18806***	-0.36409***	-0.31135***	-0.15416***	-0.14699***
NII	0.00223	0.01171*	0.01662***	0.00696	0.01220***	0.00990	0.01094***	0.01272***
CtoD ratio	0.02188***	0.02481***	0.00722**	0.01056**	0.01956***	0.02045**	0.01021***	0.01261***
Overhead costs	0.00117	-0.00828	-0.00544	0.09405	-0.02224***	-0.01129*	-0.02116***	-0.03496***
Private credit	-0.05109***	0.00100	-0.05912***	-0.10494***	-0.10433***	-0.08651***	-0.05103***	-0.06773***
PC1	-0.00299***	-0.00075	-0.00355***	-0.00454**	-0.00254***	-0.00074	0.00144***	0.00250***
PC2	-0.00635***	-0.00590***	-0.00402***	-0.00249**	-0.00709***	-0.00873***	-0.00597***	-0.00490***
Year FE	-	+	-	+	-	+	-	+
Observations	411	411	434	434	272	272	554	554
Number of countries	48	48	48	48	54	54	79	79
AR(1)	-2.849	-2.962	-2.784	-3.230	-2.261	-2.309	-2.219	-2.285
AR(2)	-1.188	-0.737	-1.825	-1.824	-1.635	-1.286	-1.872	-1.777
Sargan test	30.76	26.20	35.63	27.27	41.95	37.94	67.54	53.60

*** p-value<0.01, ** p-value<0.05, * p-value<0.1

Table 6. The impact of information disclosure on credit risks depending on financial development

	FID>median		*FID<median*		*FMD>median*		*FMD<median*	
Independent variables	1	2	1	2	1	2	1	2
$Credit\_risk_{t-1}$	0.58858***	0.60395***	0.91129***	0.89976***	0.58308***	0.67306***	0.91829***	0.87913***
$Cii*dummy1_{t-1}$	0.00409***	0.00607***	0.00989***	0.01314***	0.00471***	0.01221***	0.00556***	0.00189*
$Cii*dummy2_{t-1}$	0.00096	0.00009	0.00999***	0.00663***	0.00365***	0.00051	0.00560***	0.00940***
$(Cii*dummy1)^2_{t-1}$	-0.00080***	-0.00094***	-0.00084***	-0.00122**	-0.00091***	-0.00129***	-0.00033***	0.00004
$(Cii*dummy2)^2_{t-1}$	-0.00027	-0.00031	-0.00083***	-0.00059**	-0.00073***	-0.00031	-0.00030**	-0.00057*
Size	0.06876***	0.01679	0.03933***	0.02881***	0.15685***	0.13961***	0.02717***	0.03417***
Concentration	0.04548***	0.03529***	-0.01064**	-0.00560	0.03943***	0.04841***	-0.00503	0.00782
Capitalization	-0.08011***	-0.08552***	-0.12062***	-0.13804***	-0.12112***	-0.14676**	-0.14502***	-0.11259**
ROA	-0.28341***	-0.42892***	-0.06458***	-0.08550***	-0.17464***	0.57806**	-0.12227***	-0.13258***
NII	-0.00084	-0.00202	0.01399***	0.02245***	-0.01451***	0.00231	0.03226***	0.03383***
CtoD ratio	0.02702***	0.01320	0.01761***	0.02057***	-0.00554	0.00010	0.01083***	0.01098*
Overhead costs	0.00893	-0.00908	-0.07507	-0.07267	0.01279	-0.03059	-0.05723***	-0.03974**
Private credit	-0.05896***	-0.00778	-0.07429***	-0.05926***	-0.04609***	0.01748	-0.04655***	-0.05427***
PC1	-0.00114***	0.00027	-0.00462***	-0.00438***	0.00021	0.00144	-0.00543***	-0.00578***
PC2	-0.00620***	-0.00537***	-0.00506***	-0.00290***	-0.00624***	-0.00701***	-0.00456***	-0.00239**
Year FE	-	+	-	+	-	+	-	+
Observations	400	400	445	445	398	398	447	447
Number of countries	46	46	48	48	46	46	48	48
AR(1)	-2.927	-3.004	-2.736	-2.761	-3.138	-3.261	-2.042	-2.040
AR(2)	-0.724	-0.671	-1.847	-1.909	-2.018	-2.066	0.0746	0.0806
Sargan test	26.99	19.85	37.86	29.72	31.70	18.12	38.94	33.15

*** p-value<0.01, ** p-value<0.05, * p-value<0.1

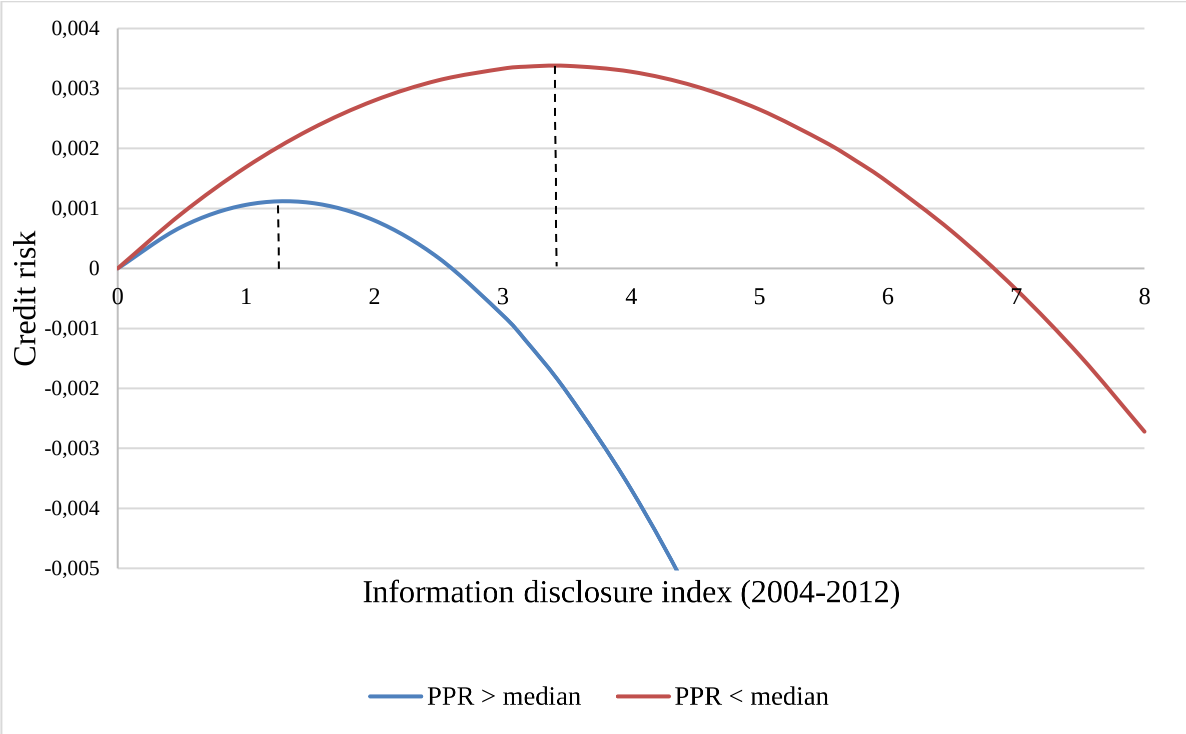

Figure 3 Model PPR: Credit risk and information disclosure index (2004–2012)

Table 6 shows the results of the estimations for the countries with different levels of financial development.

Samples of countries according to the Financial Institutions Development index (*FID*) also represent a significant difference in the level of information disclosure for the period of 2004–2012 when credit risk is maximal. Countries with higher *FID* have maximum credit risk at 2.6 points of credit information disclosure (Figure 4). Above 2.6 points, the credit risk decreases. Countries with lower *FID* demonstrate a higher value of information disclosure needed to reach the peak of credit risk (about 6 points). As it is the maximum value of information disclosure for 2004–2012 period, the relationship between credit risk and credit information cannot be considered as an inverse U-shaped one; lower values of *FID* are associated with a permanent increase in credit risk together along with an increase of credit information disclosure. The countries with higher *FID* might be related to better practices of financial resource management and better credit scoring to provide such a result.

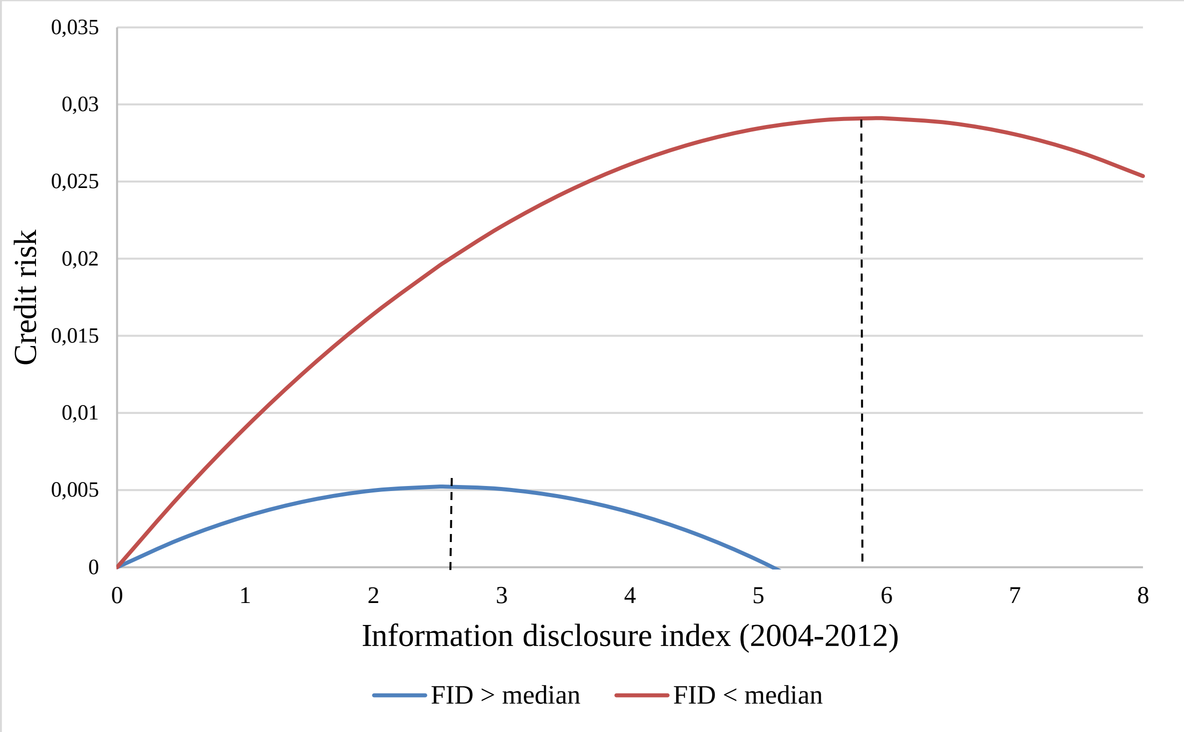

Figure 4 Model FID: Credit risk and information disclosure index (2004–2012)

This difference is even more pronounced if we consider the financial market depth index (*FMD*). Countries with higher *FMD* have lower depth of information disclosure (2.6 points) when credit risk reaches its maximum in 2004–2012 (Figure 5). Higher values of credit information disclosure for these countries are associated with lower credit risk. The result for countries with lower FMD is much different. The credit risk increases until the value of information disclosure is 8.4 points. Since the maximum value for information disclosure is 6 points for the period of 2004–2012, lower *FMD* is related to an approximately positive linear relationship between credit risk and credit information disclosure. As *FMD* represents the size of the financial market, the larger size is associated with lower credit information needed to reach the maximum of credit risk.

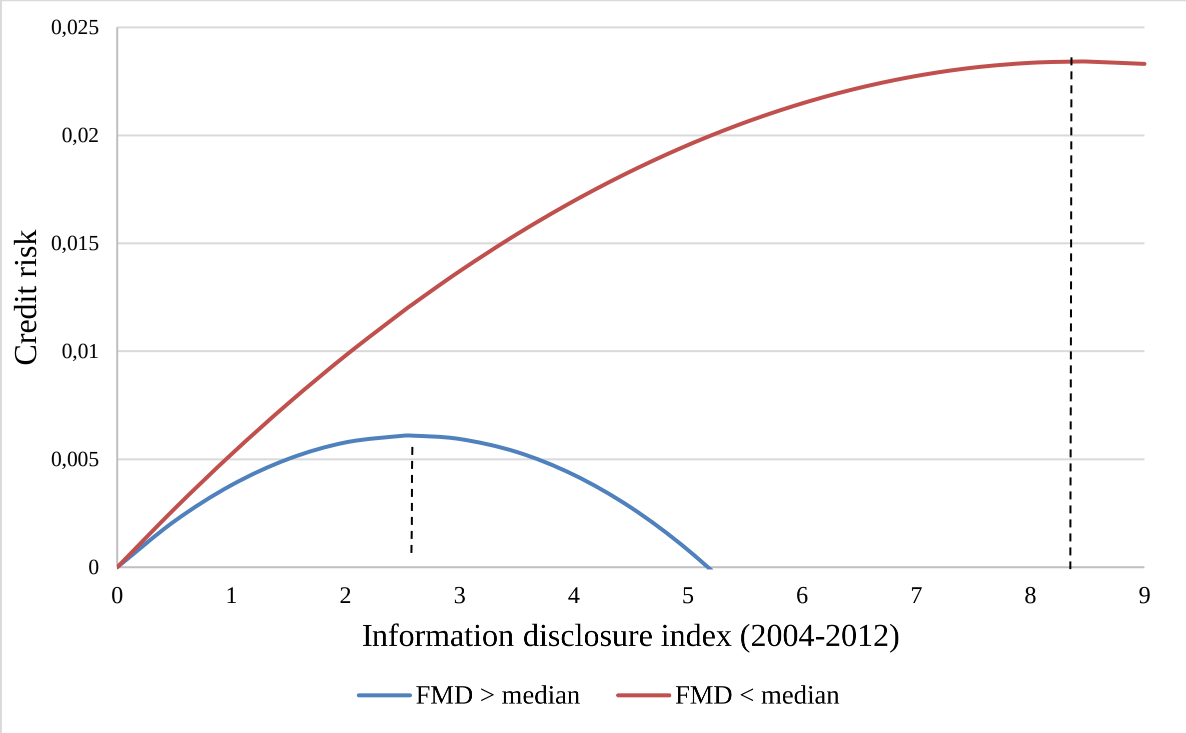

Figure 5 Model FMD: Credit risk and information disclosure index (2004–2012)

5. Conclusion

In this paper, we test for a non-linear relationship between bank credit risk and the depth of credit disclosure. Our empirical results show that the relationship is inverse U-shaped and is stable at least for the 2004–2012 country-level data. Credit risk is low when credit bureaus either disclose very little information (for instance when the information sharing is just introduced) or disclose full, detailed information about borrowers. An increase in the level of credit risk with an increase in the detail of credit reports is consistent with theoretical modeling by (Padilla and Pagano 2000) and (Sharma 2017). The disciplining effect of credit histories on borrowers weakens, but only up to a point. After a certain information index level, with even more detailed credit information, the credit risk begins to decrease. This can be explained by an increase in the predictive power of bank scoring models. Reducing credit risk while increasing the detail of credit reports is consistent with all the empirical work studied.

Based on the results of this study, the policy implications seem to be straightforward: the information sharing regime in credit markets should require information intermediaries either to disclose only negative information about borrowers, or full information about all the characteristics of the borrower. The results obtained would be especially relevant for developing economies, in which the information exchange market does not have a long history, and the credit risks are higher than in developed economies. We found that the values of the information index at which the credit risk is at its maximum is 3–4 points. According to the 2017 World Bank data, there are several countries with such credit disclosure index values, for example, Malta, Mauritania, Mozambique, Timor Leste, Tonga, Vanuatu and Zimbabwe. Our results suggest moving towards either pole: either disclose very little information or disclose it fully.

We also prove the importance of the institutional and financial development for the nature of the dependence of the credit risk of the country's banking sector on the depth of information disclosure by credit bureaus and credit registers. Our results indicate that in countries where the quality of regulatory governance is high, an increase in the information sharing index leads to a decrease in credit risk, starting from low values, while for countries with a low quality institutional environment, this effect is observed only with the highest rates of information disclosure. As a result of the analysis of the differences in the development of financial markets, measured using the indices of the depth of financial intermediation and financial markets, we received additional confirmation of our hypotheses. In countries where the indicators of financial market development are higher, only at lowest levels of depth of credit information sharing, is a positive effect on credit risks is observed, at other values the effect is negative.

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