Journal of Business, Economicsand Finance - (JBEF), ISSN: 2146 – 7943, , http://www.pressacademia.org/journals/jbef

PressAcademia

Journal of Business, Economics and Finance

Year: 2017 Volume: 6 Issue: 3

NON-FINANCIAL CREDIT INFORMATION SHARING AND NON-PERFORMING LOANS: AN ANALYSIS USING DOING BUSINESS DATABASE

DOI: 10.17261/Pressacademia.2017.686
JBEF- V.6-ISS.3-2017(7)-p.264-279

Arzu Sahin[1]
[1]Adana Science and Technology University, Adana, Turkey. asahin@adanabtu.edu.tr

To cite this document
Sahin, A., (2017). Non-financial credit information sharing and non-performing loans: an analysis using doing business database. Journal of Business Economics and Finance (JBEF), V.6, Iss.3, p.264-279.
Permemant link to this document: http://doi.org/10.17261/Pressacademia.2017. 686

ABSTRACT

Purpose- This paper suggests that sharing of credit information from non-financial information sources decrease the non-performing loan rate. To analyze whether the differences in non-financial information sharing across countries have any effect on the percentage of non-performing loan, a sample of 55 countries from Doing Business 2017 is analyzed.
Methodology- Cross section regressions on country level data for the year 2015 is estimated by Ordinary Least Squares Method.
Findings- Analysis findings reveal that availability of non-financial credit information from retails and utilities companies, as addition to financial sources, in a credit reporting institution lower the bank non-performing loan rates.
Conclusion- It can be concluded that the payment behavior reported by non-financial information providers can cause to a reduction in information asymmetries between lenders and borrowers.

Keywords: Credit information sharing, non-financial information, comprehensive credit reporting, non-performing loans
JEL Codes: D82, G21, E44

1. INTRODUCTION

Theoretical and empirical studies have revealed that credit information sharing has usually positive effects on financial markets. One of these effects is its reducing effect on default rates through solving adverse selection and moral hazard problems. Asymmetric information between creditors and borrowers induce adverse selection and moral hazard problems. During due diligence, lenders may not evaluate creditworthiness and repayment performance of borrowers effectively because of lack of reliable information. After extending loans, creditors cannot intervene directly to incentive borrowers make their loan payments and to prevent them from engaging into risky investments. First cause adverse selection and the latter cause moral hazard problems.

One way to overcome asymmetric information problems of lenders is to generate specific information from monitoring borrowers past behaviors during the bank relationship. But capturing these special borrower information has some drawbacks such as being costly, time consuming, having limited scope and coverage and causing informational rent (Miller, 2003: 26; International Finance Corporation [IFC], 2012: 1-4). Sharing information about borrowers between lenders is the more common and beneficial way to gain reliable information and to reduce information asymmetries. On the lender’s adverse selection effect, creditors can improve their ability to predict repayment probability using broad information exchanged. On the borrower’s moral hazard effect (or incentive effect), information sharing can have incentive effect on repayment behavior thus reduce moral hazard problem. Incentive effect of information sharing can be in the form of disciplinary effect and hold up effect.

The theory confirms that, as a result of credit information sharing, the increase in the accuracy of loan repayment predictions and the improvement in the debt repayment incentives cause the default rates to drop in micro or macro level analyzes. Some studies explain the reducing effect of credit information on default rates with the improvements in banks' ability to predict loan defaults (Pagano& Japelli, 1993; Kallberg & Udell, 2003; Powell, Mylenko, Miller & Majnoni, 2004; Dierkes, Erner, Langer & Norden, 2013), while others with the enhancements in borrower’s incentive to make repayments

(Padilla & Pagano, 1997; Brown & Zehnder, 2007; Doblas & Minetti, 2013; Büyükkarabacak & Valev, 2012). Houston, Lin, Lin and Ma (2010) and Jappelli and Pagano (2002) discuss this relationship by looking at both adverse selection and the moral hazard sides.

The depth (scope, content or quality) of credit information systems varies across countries and within countries (Lyman, Lythgoe, Miller, Reille & Sankaranarayan, 2011: 5; Houston et al. 2010: 487; IFC, 2012: 17). The scope of information, as much as the existence of a credit reporting system, may influence the defaults. Based on this idea Jappelli and Pagano (2002) and Powell et al. (2004) focused on the impact of sharing negative and positive data. Padilla and Pagano (2000) discuss the positive information relation with disciplinary effect. The comprehensive credit reporting system not only combines black (negative) information with white (positive) information but also combine information obtained from non-financial (non-traditional) sources as well as from financial (traditional) sources. Doing Business (DB) (2017) research revealed the importance of a comprehensive credit reporting system including credit history data from non-financial institutions such as trade creditors, leasing and factoring companies, retailers and utilities and microfinance institutions. It is seen that there has not been enough papers to investigate the effect of non-financial information sharing on defaults. The only empirical study that directly incorporates non-financial data sharing with credit market performance (access to credit) is Peria and Singh (2014).

This paper contributes to the existing literature aiming to investigate the relationship between the non-financial credit information sharing and non-performing loans as proxy for defaults. Ordinary least squares (OLS) method with heteroskedasticity robust standard error is applied on country level sample covering 55 countries for 2015, controlling country specific macroeconomic and institutional factors. The results suggest that non-performing loan rate depends on the level of non-financial information sharing and unemployment rate in a country. The plan of the paper is organized as follows: section 1 includes introduction, section 2 details comprehensive credit information sharing, section 3 is a literature review, section 4 contains data structure and methodology, section 5 reports the results and section 6 concludes.

2. COMPREHENSIVE CEDIT REPORTING SYSTEM

Borrowers evaluate their investment risks and repayment probability better than lenders do. In the credit market, the existence of borrowers with different repayment possibilities and the presence of creditors with inability to estimate these probabilities correctly lead to adverse selection. Failure of creditors to make accurate evaluations of creditworthiness increases the default rates[1] (Stiglitz & Weiss, 1981: 393; Doing Business [DB], 2017: 59). Lenders having more information about characteristics and behavior of their borrowers (Brown & Zehnder, 2007: 1884) through information sharing can improve their credit failure prediction ability. Banks that benefit credit information also can prevent lending to high risk credit applicants with bad payment history or can make better pricing for them (Miller, 2003: 26-27; Jappelli & Pagano, 2002: 2018-2019).

First incentive effect of information sharing is to discipline borrowers into exerting high effort in repaying loans (Brown & Zehnder, 2007: 1884). When borrowers realize that default information will be shared with other creditors and will damage their reputation with other lenders, they have greater incentive to repay and thus try harder to avoid defaults (Padilla & Pagano, 2000: 1952, 1978). The information shared becomes part of the borrower's reputation collateral. Borrowers try to develop a good morality of payment because late payments or defaults, as a signal of bad quality, reduce the value of this reputation collaterals making credit accessibility difficult or more expensive. This incentive mechanism, known as disciplinary effect reduces moral hazard (Padilla & Pagano, 2000: 1953; Jappelli & Pagano, 2002: 2018-2019; Miller, 2003: 26-27).

Second positive incentive effect of information sharing on borrower behavior is to lower the informational rents that banks extract from borrowers. If lenders don't share private information developed throughout the relationship, other creditors and quality borrowers cannot be aware of this information. This lowers the bargaining power of the good borrowers and causes banks to receive informational rents from them (Miller, 2003: 26). Under this situation that is also expressed as "hold-up", banks apply interest for the low-risk customer as high as for the risky customers and worsens incentive to perform and repayment performance of quality borrower's. Information sharing reduces the extraction of informational rents. Exchange of private information forces banks to make fairer loan pricing. Reduced interest rates increase borrower return and encourage borrowers to make timely payments and consequently lower delinquency and default rates (Padilla & Pagano, 1997: 227; Jappelli & Pagano, 2002: 2018-2020; Kallberg & Udell, 2003: 453; Doblas & Minetti, 2013: 202).

[1] Default is the failure to complete a payment obligation under a credit or loan agreement. Delinquency is the situation where the borrower fails to meet his/her financial obligations as and when due (World Bank, 2011: 68).

Most common vehicle of credit information sharing has been public credit registers and private credit bureaus that are also known as credit reporting service providers (CRSP)[2]. Public credit registers and private credit bureaus differentiate from each other basically in objectives, ownership and information collection way. The main objective of most credit registries is to assist banking supervision, provide high quality data for supervised financial intermediaries, improve their credit risk management and increase quality of their credit portfolios (Lyman et al. 2011: 6; IFC, 2012: 24). Credit registries are usually owned and managed by central banks or bank supervisory authorities (Peria & Singh, 2014: 7) and sharing of information is compulsory by regulations (Jappelli & Pagano, 2002: 2028). Many credit registries were established to improve the banking industry after crises led by large defaults (Powell et al. 2004: 18). Credit bureaus are usually privately owned commercial enterprises generally focusing on providing credit information to lenders to use for credit decisions (IFC, 2012: 24). They are founded by volunteer members and operate on the principle of reciprocity; members who do not provide information to the system cannot receive information (Pagano & Japelli, 1993: 1714). Public credit registries have higher coverage and are perceived more reliable. On the other hand credit bureaus present more detailed and informative information in individual loans, so more capable of solving the credibility problems (Kallberg & Udell, 2003: 451; Jappelli & Pagano, 2002: 2028) and they can provide additional value-added services such as credit scores (Peria & Singh, 2014: 7) on a competitive basis (Powell et al. 2004:25). Each types of credit reporting service providers (CRSP) have its own positive and negative aspects. No type is superior to another and each type can coexist in a market by meeting a need (IFC, 2012: 2). So registries and bureaus complement each other (Miller, 2003: 54; Powell et al. 2004: 25) even as stated in Jappelli and Pagano (2002: 2034, 2036), private and public information sharing arrangements are substitutes and they have similar effects on lending behavior and default rates.

Payment history data may be black or white. Lenders may share only black information about delinquent debts, defaults, arrears amounts, court judgments and other negative (blacklist) information. On the other hand, most credit reporting systems[3] gather also positive data that could have a bearing on creditworthiness. Positive credit data includes timely repayment, debt maturity structure, current debt exposure, credit limits, loan type, lending institution, main financial ratios, guarantees and private information such as address, birth date, family, job history and various information from public institutions (Padilla & Pagano, 1997: 206; IFC, 2012: 12; Padilla & Pagano, 2000: 1952-1953; Jappelli & Pagano, 2002: 2022; Miller, 2003: 27).

In systems where positive information is not shared, a borrower's loan application may be denied due to a single negative behavior in the past, even if the current payments are regular. In addition, in these systems, there is no information available for potential debtors with no delayed payment (IFC, 2012: 12). The most banks (76%) stated that any negative information would disqualify borrowers from receiving credit. This indicates that lack of positive data prevent lenders from making a complete credit analysis using a fuller picture of a borrower's credit history (Miller, 2003: 51). There may be disciplinary effect of black information but it has less predictive power than white and black information combined (Jappelli & Pagano, 2002: 2033; Powell et al. 2004: 13) and often result in inaccurate credit risk assessment (IFC, 2012: 14). The evaluation of positive and negative information together is more effective in establishing reputation collateral. The credit history is sometimes referred to as reputational collateral because physical collateral can be supplemented with a good payment history especially for borrowers who do not have sufficient physical. The value of reputational collateral tends to be greater when positive information is added to negative ones. Positive data are also needed for developing some decisions tools like scoring (Powell et al. 2004: 13; IFC, 2012: 1, 4). IFC (2012) includes some research that has shown that comprehensive credit reporting systems including positive information in scoring models improve the repayment prediction ability of lenders. For example findings of Powell et al. (2004) for Brazil and Argentina indicate that inclusion of positive information decrease default rate or increase credit decision success and increase lending volumes to new categories of borrowers. At the end of the 1990s, Hong Kong SAR, China and the Republic of Korea experienced a significant increase in credit defaults due to the lack of positive information. Lenders who were not aware of the debt level of current and potential borrowers continue aggressively to market credit card and faced a large number of credit card defaults. After crises, these countries switched to a comprehensive credit reporting system including both positive and negative information (IFC, 2012: 12-14).

Financial (traditional) data providers include commercial banks, other financial institutions and credit card companies. Non-financial (non-traditional) data sources usually include retailers, utilities providers, suppliers extending trade credit and all

[2] Credit registries and credit bureaus are expressed as the credit reporting service providers that administers a networked credit information exchange (World Bank, 2011: 67). A networked credit information exchange is a mechanism enabling credit information collection, processing and further disclosure to users of data, as well as value-added services based on such data (World Bank, 2011: 68). Credit reporting system is used to express networked credit information exchange. Padilla and Pagano (1997), use reputation system or reputation mechanism terms as credit information sharing system.

[3] According to Doing Business 2012 survey data, the ratio of providing both positive and negative data at credit reporting agencies is about 70 percent.

private and public entities that collect information on consumer[4] (IFC, 2012: 10; Jappelli and Pagano, 2002: 2021). Non-financial data contributors are categorized as trade creditors, retailers and utilities, leasing and factoring companies and microfinance institutions according to Doing Business (2017). Retailers may have a long history of payment data on both individuals and firms in some markets (Lyman et al. 2011: 4). Utility companies (gas, water, electricity, cable, telephone, internet, and other service providers) may also provide payment data. Trade creditors that are the source of costless and unsecured credits can also share information about how firms are committed to their payments (DB, 2017: 60; IFC, 2012: 17). Trade credit data provide fairly reliable information for small firms, but this information is not available in many systems. Similarly, leasing and factoring companies can also provide valuable data but very few factoring companies share their data with credit reporting providers. There are 36 economies collecting data from trade creditors and 110 economies reporting repayment history from financing corporations and leasing companies (DB, 2017: 61-63). Comprehensive credit reporting is expanding and the main CRSP in 50 countries report these data (DB, 2017: 63-64). Doing Business 2012 survey data report that over 40 percent of credit bureaus include data from utility companies (IFC, 2012: 17). In a survey conducted by Miller (2003), of the 63 private reporting firms that provides information about the source of their credit data, 50 included trade credit data and 43 gathered data from retail merchants (Miller, 2003: 46).

However the greatest source of credit data for most credit bureaus and credit registries is the financial sector (Miller, 2003: 37), non-financial sources of data improve the accuracy and scope of credit information and this broader information generates incentives to improve borrower discipline and allows lenders to evaluate more clearly the creditworthiness of their potential clients (DB, 2017: 64). Utility bill payment behavior may be a reliable predictor of future repayment behaviors and defaults. Collecting credit data from utility companies expand to access to finance for customers with no prior credit history and lower the arrears. For example, collecting data from telecoms can enhance the predictive power of the inquiry database and increase the acceptance rate of new loans for new borrowers who lack past payment information (IFC, 2012: 77; DB, 2017: 63).

Small business in developing countries (Miller, 2003: 46) and low-income individual borrower (at the base of the pyramid)[5] with a thin credit files may most benefit from non-financial white data. Creditors may not be willing to extend credit to unbanked (underserved) borrowers who do not have a banking relationship and tend to charge high interest rate or require collateral to cover the losses of default and the cost of due diligence. Non-financial sources of data bolster information on thin file clients most of whom lack assets to secure a loan and enhance the value of reputational collateral (IFC, 2012: 1-4; DB, 2017: 61). Developing countries are striving to increase credit access for these thin file borrowers which has limited access to the credit market (IFC, 2012: 27). As the need for reliable and accurate information on these unbanked borrowers grows (Lyman et al. 2011:3,6), the importance of non-financial resources offering credit history for them (IFC, 2012: 17) increases. Credit reporting tends to decrease defaults and delinquencies especially for the informationally opaque firms (Doblas & Minetti, 2013). Low income borrowers and micro, small, medium size enterprises (MSMEs) have been also benefited from microcredit industry that establishes repayment histories for them over the past 30 years. Some countries (Egypt and Pakistan) that have witnessed an increase in non-performing loans have reduced the level of non-performing loans by integrating microfinance institutions into their formal credit reporting systems and (IFC, 2012: 32, 33, 89). Similarly in Bolivia and Bosnia and Herzegovina inclusion of microcredit data reduced non-performing loans (DB, 2017: 63).

3. LITERATURE REVIEW

Although the aim of this study is to explore the impact of non-financial credit information sharing on the cross- country default rates, the lack of empirical studies that directly examine the relationship between them cause to focus on the literature investigating traditional credit information sharing. Therefore the paper builds on the earlier studies that have examined the role of credit information sharing on credit markets as well as the default rates. Most of the studies at country, firm, individual, contract level or model based suggested that credit information sharing has positive effects on lenders, borrowers and so whole financial market and economic conditions.

Based on their own credit market models, two premise studies, Jaffee and Russell (1976) and Stiglitz and Weiss, (1981) show that credit rationing is a rational response to adverse selection and that interest rate or any other instrument could not clear the credit market. Jaffee and Russell (1976) develop a model to analyze the loan market behavior in the case of information asymmetry about the likelihood of default between borrowers and lenders. Their model divides borrowers into two groups as honest and dishonest and lenders are unable to differentiate them. Stiglitz and Weiss, (1981) suggest a credit

[4] Public records (for instance court judgment data, bankruptcy notices, and telephone directory information) and other data sources such as databases on bounced cheques, promissory notes and protested bills of exchange, collateral registries, vehicle registries, real estate registries, personal identity records, company registries, tax authority databases, and some court records are potential data sources supplied from private and public entities that collect information on consumers (World Bank 2011: 9; IFC, 2012: 10, 12, 17; Jappelli & Pagano, 2002: 2021).

[5] Micro borrowers who are generally unbanked, poor, informally employed and having irregular income are implied as the consumers at the base of the pyramid in Lyman et al. (2011).

rationing model focusing on the role of interest rate as a means of separating low and high risks. The adverse selection aspect of interest rate emerges from risky borrowers who are willing to pay high interest rate because of their low repayment possibility.

Other researchers examined, except for two articles (Jaffee & Russell, 1976; Stiglitz & Weiss, 1981) can be divided into 4 categories. The first group includes the studies which directly (Brown & Zehnder, 2007; Doblas & Minetti, 2013; Dierkes, Erner, Langer and Norden, 2013) or indirectly (Houston et al, 2012) investigate the effect of information sharing on default rates as the basic purpose of them. In the second stage, the papers (Pagano & Japelli, 1993; Padilla & Pagano, 1997; Jappelli & Pagano, 2002; Kallberg & Udell, 2003¸ Milller, 2003; Powell et al. 2004) examining the role of exchanged information or credit reporting systems on the financial market performance and also presenting additionally findings or discussions about default rates are included. The third category consists of studies (Padilla & Pagano, 2000; Djankov, McLiesh & Shleifer, 2007; Brown, Jappelli & Pagano, 2009; Giannetti & Jentzsch, 2013; Beck, Lin & Ma, 2014; Peria & Singh, 2014) that investigate the impact of credit information system on the overall credit market, without examining its effect on the default rates. Finally, last category covers researches or working papers (Lyman et al. 2011; IFC, 2012; DB, 2017) aiming to present detailed information about credit reporting systems worldwide.

Among these studies Peria and Singh (2014) is the only paper that incorporates non-financial credit information sharing into the empirical analysis as an independent variable. Also Kallberg and Udell (2003) show that trade credit information sharing helps lenders for failure prediction by building a default prediction model.

Three of the first group authors include default rate indicators such as repayment rate, delinquency or days past due and probability of defaults as the dependent variable. Brown and Zehnder (2007) examine how credit information sharing affects loan repayment and how this incentive effect of information sharing related to relationship banking. They document that information sharing has positive effect on repayment behavior. They also find a high relationship between the incentive effect and credit activity and the presence of relationship banking conducting an experimental credit market model having 17 subjects during 20 sessions. According to their model, relationship between lenders and borrowers substitute disciplining effect of credit information sharing mechanism. Doblas and Minetti (2013) confirm that information sharing has reducing effect on contract delinquencies and defaults and this effect is more pronounced for the informationally opaque firms. They concluded that information sharing among creditors tends to enhance the repayments of firms reducing the defaults probability using firm and contract-level data. Main findings of Dierkes et al. (2013) providing aggregate and firm level evidence, document that credit information sharing improves the default prediction accuracy ratio (by nearly 20 percent) of unlisted private firms from the largest credit bureau of Germany. Firm's repayment behavior sharing and coverage ratio of the credit bureau enhance this improvement and as the value of credit information increases, the default rates decrease.

The relationship between information sharing and bank risk taking and banking crises has been tested by two cross-country studies assessed in the first group. Houston et al. (2010) examined the interactions between the creditor rights and information sharing and bank risk taking analyzing the bank data in 69 countries. Their findings suggest that stronger the creditor rights higher the bank risk taking and likelihood of financial crisis, whereas greater information sharing is associated with lower bank risk taking and reduced likelihood of financial crisis. Non-performing loan is used as one of the proxy for bank risk taking. Büyükkarabacak and Valev (2012) examine the relationship between credit information sharing and likelihood of banking crises using data from 98 countries. They offer evidence that information sharing decrease the likelihood of banking crises and this effect is more powerful in low income countries. Dependent variable is dummy variable covering systematically important banking crises in which financial and corporate sectors experience sharp increase in defaults, delinquencies and non-performing loans. It can be said that the bank crises variable is an indicator for the aggregate level of default rates.

Studies categorized in the second group aim to examine whether information sharing can enhances credit market performance by solving moral hazard and adverse selection problems and they present findings about default rates. Pagano and Japelli (1993) build a model of adverse selection when information sharing arises. Their findings show that information sharing through credit bureaus increase lending volume, decrease interest rates and default rates benefiting safe borrowers who are priced out of market by adverse selection. Kallberg and Udell (2003) conclude that past payment information sharing helps lenders for prediction of borrower failure. Including several firm-specific credibility variables gathered from Dun and Bradstreet paydex score on trade payments, they construct a failure prediction model. According to a worldwide survey conducted by Miller (2003) and aimed to collect detailed data on the credit reporting systems, 70 percent of the surveyed banks indicated that a lack of credit information would increase defaults by 25 percent or more. Also for credit review process of bankers, credit information gathered from CRSPs is more important than other data such as collateral, financial data and previous banking accounts.

Other three study included in second group provide empirical and theoretical evidence about both on general information sharing and white data inclusion. Results of a credit market model focused on the incentive problems and developed by

Padilla and Pagano (1997) show that information sharing stimulates incentive effects (hold up and disciplinary), more in the case of black information rather than white information. Also sharing information is related to lowered default rates, decreased interest rate on average and increased lending. Jappelli and Pagano (2002) provide cross-country survey based evidence revealing that information sharing increases bank lending and decreases default rates. Credit risk proxies for default rates and information sharing are also related with reduced non-performing loan. While the disciplinary effect arises only from the exchange of black information, both black and white information sharing are accepted to increase bank ability of credit evaluation. According to the findings of Powell et al. (2004) presenting empirical evidence for Argentina, Brazil and Mexico, public credit registries may improve credit access or reduce bank credit risk. The findings showed that information sharing improves the bank's ability to determine the likelihood of loan default. Also inclusion of positive information in addition to negative ones increases this predictive power.

The third category of researchers offer evidences of what effects information shared have on the financial markets, lenders and borrowers. Padilla and Pagano (2000) examined whether information sharing can correct moral hazard problem, focusing on disciplinary effect in their two-period model. Confirming experimental evidence of their earlier research (Padilla & Pagano, 1997), they indicate that sharing more information (white information or characteristics) than just past defaults (black information or behavior) reduces borrowers' incentive to make payments. When high-quality borrowers realized that banks will disclose main characteristic about their creditworthiness, they may spend less effort to avoid defaults. Brown et al. (2009) investigated the credit information sharing effect on credit market performance in 24 countries combining the Doing Business country level data and Business Environment and Enterprise Performance Survey (BEEPS) firm-level data. Findings reveal that information sharing is correlated with higher credit access and cheaper credit especially for opaque firms and in countries with weak creditor protection. Covering a data set of 129 countries, Djankov et al. (2007) argue that private credit ratios are higher in countries having creditor rights protective legal systems and credit reporting institutions. Positive effect of both public registries and private bureaus on private credit is more powerful in developing countries whereas public registries are more common in French civil law. Giannetti and Jentzsch (2013) found a positive correlation between the introduction of a compulsory identification system and financial service quality and credit access and show that this correlation is higher in countries with a credit reporting system. Beck et al. (2014) provide evidence that firms in countries with better credit information sharing systems and higher branch penetration tend to disclose all of their sales and pay higher taxes.

Among other authors, only Peria and Singh (2014) included the non-financial data into the empirical analysis investigating the impact of introducing credit information sharing systems on firms' access to bank finance. They combined firm-level World Bank Enterprise Survey (WBES) data with Doing Business (DB), World Development Indicators (WDI) and International Country Risk Guide (ICRG). The results reveal that after credit bureau reforms, access to finance increases, interest rates drop, maturity lengthens, and the share of working capital financed by banks increases. These effects are more pronounced in the presence of higher coverage, scope and accessibility of the credit reporting systems and the weaker the legal environment. Relatively small, young and opaque firms are more likely to benefit from the effects of credit bureau reform.

Finally, last category refers to the researches or working papers covering detailed information about credit reporting systems worldwide. Lyman et al. (2011) focused on the effective credit reporting for microcredit industry and suggest that bureaus, registries and microfinance institutions serve similarly but each have different limitations. IFC (2012) presents detailed information on credit reporting systems via second "Credit Reporting Knowledge Guide". This guide focuses primarily on the emerging markets, individuals and MSMEs that will benefit greatly from the development of credit reporting systems. DB (2017) provide results of a research focusing on the importance of a comprehensive credit reporting system including credit history data from non-financial institutions such as trade creditors, leasing and factoring companies, retailers and utilities and microfinance institutions. This research shows that in economies utilizing these alternative entities that provide payment history information especially on low-income or non-bank clients, coverage ratios of credit reporting system are higher.

In summary, the reducing effect of information sharing on default rates through solving either adverse selection or moral hazard problems has been reported in the credit information literature. Literature review is summarized in Table 1 covering data level, observation number, analysis period and the impact of credit information sharing on the main factor examined as well as on the default rate.

Table 1: Summary of the Credit Information Sharing Literature Review

Authors, Publication Year	Data level	Observation No.	Period	Default effect	Main effect
Jaffee and Russell, 1976	model				credit rationing
Stiglitz and Weiss, 1981	model				credit rationing
Brown and Zehnder, 2007	model			lower default	lower default
Doblas and Minetti, 2013	firm + contract	USA, 28.623	1995-2007	lower default	lower default
Dierkes et al. 2013	firm	Germany, 25.344	2002-2005	lower default	lower default
Houston et al. 2010	country + bank	69 + 2.400	2000-2007	lower default	lower bank risk
Büyükkarabacak and Valev, 2012	country	98	1975-2006	lower default*	lower bank crises
Pagano and Japelli, 1993	model			lower default	higher lending
Padilla and Pagano, 1997	model			lower default	higher incentive effect
Jappelli and Pagano, 2002	country	40	1994-1995	lower default	higher lending
Kallberg and Udell, 2003	firm	USA, 2.723	1988	lower default	higher predictive power
Milller, 2003	country	77	1999-2001	lower default	reporting systems
Powell et al. 2004	country+ contract	3+ 316.6313	1999-2002	lower default	higher access, lower credit risk
Padilla and Pagano, 2000	model				lower disciplinary effect**
Djankov et al. 2007	country	129	1978-2003		higher private credit ratio
Brown et al. 2009	country + firm	24+ 5.717	1996-2004		higher access, lower credit cost
Giannetti and Jentzsch, 2013	country	172	2000-2008		higher financial services
Peria and Singh, 2014	country + firm	63+75.000	2002-2013		higher access
Beck, Lin and Ma, 2014,	country + firm	102 +64.000	2002-2010		sales and tax
Lyman et al. 2011					microcredit industry
IFC, 2012					low income borrower
DB, 2017					comprehensive reporting

Note: The data level in the second column indicates whether the researches are conducted at the country or firm level or both or use a hypothetical model. The third column shows the observation numbers as the number of countries, firms or contracts. Period covered by analyzes can be seen in the fourth column. While fourth column shows researches that have findings about default rates, the last column exhibits how the main dependent variable of articles is affected from information sharing.
* denote indirectly. Information sharing has a reducing effect on bank crises that is an indicator for the aggregate level of default rates.
** represent the conditions when white information shared. Sharing more information than negative black data reduces borrowers' repayment incentive rather than increasing them (Padilla & Pagano, 2000: 1978).

Apart from the literature on credit information sharing, papers that investigate the determinants of non-performing loan are reviewed in this part of the article. Berger and Young (1997) relate non-performing loans (problem loans) to bank efficiency. Salas and Saurina (2002) investigate the macroeconomic and bank-level determinants of problem loans (credit risk) of Spanish banks. Ranjan and Dhal (2003) indicate that non-performing loans of Indian banks are influenced by terms of credit in the presence of bank size and macroeconomic conditions. Fofack (2005) searched the main driving factors of non-performing loans in Sub-Saharan Africa. Jiménez and Saurina (2006) find strong relation between non-performing loans (loan losses) and credit growth. Louzis, Vouldis and Metaxas (2012) explain the non-performing loans in Greek banking system by macroeconomic factors and by bank ownership concentration. Atanasijević and Božović (2016) found that exchange rate, GDP growth rate and loan size induce non-performing loans in Serbian banks. Yağcılar and Demir (2015) and Isik and Bolat (2016) explain the main determinants of non-performing loan in the Turkish banking sector by bank-specific and macroeconomic variables. Findings of Cifter, Yilmazer and Cifter (2009) reveal a relationship between sectorial production cycle and sectorial non-performing loans in the Turkey. Boss (2002) for Austrian banking sector and Jakubik and Schmieder (2008) for Czech and the German credit risk environment modeled credit risk on macroeconomic factors. Rinaldi and Sanchis (2006) build an empirical model of non-performing loan ratio to find the best combination of factors causing financial fragility for seven euro area countries. Empirical model developed by Berge and Boye (2007) reveals that real interest rate and unemployment significantly contribute to the banks share of problem loans rises.[6]

4. DATA AND METHODOLOGY

To analyze whether the differences in non-financial information sharing across countries have any effect on the percentage of non-performing loan, cross-sectional analysis method is employed on a sample of 55 countries for 2015. Data set is mainly shaped according to the basic independent variable, non-financial information sharing (NFIS) data. Data on non-financial data availability that is collected from "depth of credit information index" of World Bank Doing Business 2017 (WBDB, 2017) includes data between June 2015 and June 2016. Therefore 2015 is the analysis year on which all other variables are collected.

[6] Although there are differences in their meanings, it is seen that non-performing loans are often expressed as problem loans, bad loans, loan losses, loss loans, doubtful loans, default, delinquency, arrears, past due or overdue loans. And also non-performing loan can proxy for bank credit risk, bank asset quality and bank crises.

4.1. Data Construction

Based on the literature on credit information sharing and on the non-performing loan, information sharing variables and cross-country control variables are determined and explained in the data construction section.

4.1.1. Non-Performing Loan

The dependent variable, non-performing loan (NPL) data is obtained from the WDI. The ratio of bank non-performing loans to total gross loans measures asset quality in the loan portfolio and a high ratio may be an indicator of the increased risk of credit portfolio. Loans with delays in principal or interest payments over 90 days or with payments that are not expected to be received are classified as non-performing (www.worldbank.org). Volume of non-performing loans is one of the indicators of exposure to credit risk of a financial institution (IFC, 2012: 85). Non-performing loan rate was used as alternative measure of bank risk taking in Houston et al. (2010: 496) and as instrumental variable in Beck et al. (2014: 777). In Jappelli and Pagano (2002), information sharing is associated with lower non-performing loan and according to Büyükkarabacak and Valev (2012) bank crises include sharp increases in the non-performing loans.

4.1.2. Non-Financial Information Sharing

WBDB index measures rules and practices affecting the coverage, scope and accessibility of credit information available through CRSPs. This index ranges from zero to eight and these eight characteristics included are (www.doingbusiness.org):

1. Data on both firms and individuals are distributed,

2. Both positive and negative credit data are distributed,

3. Data from retailers and utility companies (in addition to data from banks and financial institutions) are distributed,

4. At least 2 years of historical data are distributed

5. Data on loan amounts below 1% of income per capita are distributed

6. Borrowers have the legal right to access their data in the credit bureau or credit registry

7. Banks and financial institutions can access borrower' credit information online,

8. Credit bureau or credit registry offer credit scores as a value-added service to help banks and financial institutions evaluate the creditworthiness of borrowers?

When a country's credit information providers have each of these attributes; a value of one is added to the index. Data on the use of non-financial credit information is obtained from the third question that includes credit information sourced from retailers and utility companies. There are 30 economies with 8 score, highest level of the index, answering all question as yes and so utilizing credit information from retailers and utilities. 23 economies of 48 economies with 7 score utilizing data from retailers and utilities are excluded from sample because they are lacking of one of the other characteristics. Remaining 25 economies having 7 score and not using non-traditional source of credit information from bureaus or registries are included in the sample. So the sample is limited to 55 economies according to the main explanatory dummy variable, NFIS. Peria and Singh (2014), Houston et al. (2010), Büyükkarabacak and Valev (2012), Beck et al. (2014), Brown et al. (2009) either used this index directly or constructed their own index based on the depth of credit information.

4.1.3. Coverage Ratio

One of the independent variable, coverage ratio (COVER), represents the percentage of adult population covered by the largest credit bureau or credit registry of the economy (DB, 2017). Coverage ratio is the number of records (about individual and firms) in the bureau or registry divided by the adult population in the country (IFC, 2012: 7). The data is derived from the main index, depth of credit information index-WBDB 2017. However coverage data are obtained from WBDB-2017 reports, the information is mainly on the information of the year 2015. The 2017 coverage ratio discloses the number of adults and companies listed in a bureau or registry as of January 1, 2016 taking into account the credit information for the past five years. Also those that have no borrowing history in the past five years but for whom a creditor requested a credit report from the system in the period between January 2, 2015, and January 1, 2016, are also included in the coverage ratio (www.doingbusiness.org). Depth of credit information index includes both credit bureau and credit registry coverage separately. Higher coverage ratios are used for each economy. Averaging the bureau coverage and registry coverage may not generate meaningful information because of differences in their primary objectives and benefits. So using the higher one of these coverage ratios fits more this research purpose. As explained and exemplified in the DB (2017), collecting negative or full payment data from non-financial companies can lower the arrears by increasing coverage ratio of the CRSPs. Houston et al. (2010) use coverage ratio of both registries and bureaus to capture their effect on NPL as proxy of banks risk taking and found significant negative relation. Coverage ratio is one of the variables analyzed in the Giannetti and Jentzsch (2013) and Peria and Singh (2014).

4.1.4. Macroeconomic Factors

Several variables are added to control macroeconomic and institutional differences. Seven of among the nine control variables included in this research; gross domestic product per capita (LGDPPC), gross domestic product (LGDP), gross domestic product growth (GDPG), unemployment rate (UNEMP), interest rate (INTR), inflation (INF), bank capital to asset ratio data (CAR) were obtained from the WDI. These seven WDI based variable are used to homogenize economic and financial performance of countries.

As the most relevant summary of aggregated economic performance (www.worldbank.org), gross domestic product (GDP), GDP per capita and GDP growth rate variables are entered in the regressions. Houston et al. (2010), Büyükkarabacak and Valev (2012), Jappelli and Pagano (2002), Djankov et al (2007), Giannetti and Jentzsch (2013) and Beck et al (2014) use all of these economic indicators together or separately. And also papers (Jiménez & Saurina, 2006; Louzis et al. 2012; Atanasijević and Božović, 2016; Fofack, 2005; Salas & Saurina, 2002; Isik & Bolat, 2016) exploring the causes of non-performing loans analyzied GDP growth rate. Unemployment rate (UNEMP) is the broadest indicator of economic activity as reflected by the labor market and usually high values point to inefficiencies in resource allocation (www.worldbank.org). Unemployment rate is one of the macroeconomic indicators in bad loan literature (Louzis et al.2012; Berge & Boye, 2007; Boss, 2002; Jakubik & Schmieder, 2008; Isik & Bolat, 2016). As in a number of credit information studies (Brown & Zehnder, 2007; Houston et al., 2010; Büyükkarabacak & Valev, 2012) and general non-performing loan studies (Louzis et al. 2012; Fofack, 2005), real interest rate (INTR) reflects the differences in competitive conditions of economies. Inflation, annual GDP deflator, (INF) that shows the rate of price change in the economy is one of the economic control variables as in the other papers examined (Houston et al. 2010; Büyükkarabacak & Valev, 2012; Powell et al. 2004; Djankov et al. 2007; Brown et al. 2009; Giannetti & Jentzsch, 2013; Peria & Singh, 2014; Fofack, 2005; Isik & Bolat, 2016). The ratio of bank capital to total assets ratio (CAR) indicates the level of financing of assets with leverage ratio. As measure of capital adequacy, CAR shows the extent to which banks can cope with unexpected losses (www.worldbank.org). Higher CAR implies stability in Houston et al (2010) and lower CAR reflects solvency ratio in Salas and Saurina (2002). Berger and Young (1997) found that reduction in bank capital leads to increased problem loans.

4.1.5. Institutional Factors

The institutional environment will likely influence lending decisions. Weak institutional and judicial systems deteriorate the credit market performance through increasing information asymmetries, bank risk taking, contract enforcement costs and reducing incentives to lend and to make repayment and so decreasing access to finance. Credit reporting can mitigate these negative effects and even may substitute for inadequate institutional environment. General view is incentive effect of information sharing is stronger in economies with weak institutional environment and poor legal protection (Jappelli & Pagano, 2002; Brown et al. 2009; Houston et al., 2010; Peria & Singh, 2014; DB, 2017). However, legal and regulatory framework that is clear, predictable and supportive for all participants in the system, contributes to the effective operation of credit reporting systems in the long run (IFC, 2012:2, 3739).

Different indicators from various sources have been used to proxy for the institutional quality differences in country level researches. Rule or Law, Corruption, Government Effectiveness indicators from WGI project and Law and Order, Contract Enforcement, Creditor Rights, Legal Origin indicators from other sources are among the commonly used variables in articles examined (Jappelli &Pagano, 2002; Büyükkarabacak & Valev, 2012; Beck et al. 2014; Houston et al. 2010; Djankov et al. 2007; Giannetti & Jentzsch, 2013; Peria & Singh, 2014). To be able to control legal and institutional discrepancies among economies, legal rights (LEGAL) and governance (GOVERN) variables are included.

Legal Rights: Jappelli and Pagano (2002); Djankov et al. (2007); Brown et al. (2009), Houston et al. (2010) used creditor rights index. These authors take into account only creditor right that provide more protection to lenders in case of default, however according the IFC (2012: 37), the legal framework should be designed to protect consumer rights as well as the creditors. Therefore, “strength of legal rights index-WBDB, 2017” including legal rights of both borrowers and lenders is used to control for the changes in legal environment of countries. The strength of legal rights index indicates the protective level of collateral and bankruptcy laws for borrower and lenders rights. This variable ranges from 0 to 12, and higher values correspond to stronger legal rights facilitating credit access (www.doingbusiness.org).

Governance: Governance control variable, sourced from Worldwide Governance Indicators (WGI) project, is a broader institutional quality indicator. The WGI project, initiated by Daniel Kaufmann and Aart Kraay, are composite governance indicators based on over 30 underlying data sources (www.govindicator.org). The WGI measures governance with six comprehensive sub-components, covering more than 200 countries since 1996. Six indicators are Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law, and

Control of Corruption (Kaufmann, Kraay & Mastruzzi, 2010: 2). Houston et al. (2010) include all of six dimensions of WGI as separate variables; Beck et al. (2014) use Rule of Law, Control of Corruption and Government Effectiveness from the WGI database. Rule of Law and the Corruption Index in the Büyükkarabacak and Valev (2012) are from ICRG and Jappelli and Pagano (2002) use rule of law index from La Porta, Lopez-De-Silanes, Shleifer and Vishny (1997). The simple average of six governance dimensions of WGI index is measured and entered in the regressions to proxy for governance quality[7]. This index provides a variable that can ranges from 0 and 100. Higher governance scores indicate that corporate governance can create an appropriate environment to enhance the performance of the credit market.

4.2. Descriptive Statistics and Methodology

Descriptive statistics of variables are reported at the Table 2. Apart from governance (0-100) and legal rights (0-12) variables that are index values, variables are percentage and logarithmic values of the related data. NFIS is the only dummy variable that takes 1 in the case of non-financial data availability. Research sample contains economies with different income level (21 high income, 17 upper middle income, 14 lower middle income and 3 low income economies). Summary statistics appear to reflect these differences which are controlled in analyzes. The average of the NPL ratio is 6.7%. NPL takes the minimum value in Uzbekistan (0.4) and highest value in Greece (36.7). Coverage ratio of the sample with a 64% mean is relatively high. The high variability in coverage (32.2) and in governance (24.2) variables represents the diversity among countries.

Table 2: Summary Statistics of Variables

Variable	Symbol	Data type	Source	Mean	St.Dev	Min	Max
Non-performing Loan	NPL	%	WDI	6.7	7.6	0.4	36.7
Non-financial Information Sharing	NFIS	dummy	WBDB	0.5	0.5	0.0	1.0
Credit Provider Coverage	COVER	%	WBDB	64.3	32.2	7.0	100.0
Gross Domestic Product Per Capita	LGDPPC	Log	WDI	3.9	0.5	2.8	4.8
Gross Domestic Product	LGDP	Log	WDI	11.2	0.8	9.9	13.3
Gross Domestic Product Growth	GDPG	%	WDI	3.7	4.6	-9.9	26.3
Unemployment Rate	UNEMP	%	WDI	7.7	5.3	0.5	25.9
Real Interest Rate	INTR	%	WDI	7.1	6.5	-12.0	25.7
Inflation, GDP deflator	INF	%	WDI	3.5	7.6	-17.2	38.4
Bank Capital to Assets	CAR	%	WDI	10.5	2.9	5.1	20.3
Legal Rights	LEGAL	index	WBDB	5.4	3.1	0.0	12.0
Governance	GOVERN	index	WGI	52.5	24.2	8.5	98.9

Note: The analysis covers a sample of 55 countries; Argentina, Armenia, Bahrain, Belarus, Canada, China, Czech Republic, Dominican Republic, Ecuador, Egypt, Georgia, Germany, Greece, Honduras, Hong Kong, India, Iran, Ireland, Italy, Jamaica, Kenya, Korea, Latvia, Lithuania, Malaysia, Mexico, Morocco, New Zealand, Nicaragua, Pakistan, Panama, Peru, Poland, Portugal, Romania, Russian Federation Rwanda, Saudi Arabia, Serbia, Singapore, Taiwan, Tajikistan, Tanzania, Thailand, Turkey, Uganda, Ukraine, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, Vietnam, West Bank-Gaza and Zambia.

This paper regresses the NPL on the 11 explanatory variables in 6 regression specifications determined according to the correlation between the variables. Following equations express this relationship, where, NPL: dependent variable, X_i: independent variables, ε_i: error term.

$$NPL_i = \alpha + \beta X_i + \varepsilon_i$$

NPL_i = ƒ (credit information sharing variables, macroeconomic variables, institutional quality variables)

$$NPL_i = \alpha + \beta_0(NFIS) + \beta_0(COVER) + \beta_0(LGDPC) + \beta_0(LGDP) + \beta_0(GDPG) + \beta_0(UNEMP) + \beta_0(INTR) + \beta_0(INF) + \beta_0(CAR) + \beta_0(LEGAL) + \beta_0(GOVERN) + \varepsilon_i$$

Table 3 presents correlations among variables included in the analysis. NPL is negatively correlated with the main explanatory variable NFIS and positively correlated with UNEMP. Variance inflation factor values (VIF) in the Table 3 and Table 4 that are below 5 indicate that there is not an important multicollinearity problem[8].

[7] A simple average index of the six subcomponents of WGI is also measured in the Kaufman, Kraay and Mastruzzi (2003, 2008, and 2009). Daly and Vo (2013) and Şahin, Doğukanlı and Şengül (2016) also used the average of the WGI index in their analysis about the international portfolio investment.

[8] The VIF value is commonly compared to 5 (or 10) to determine whether multicollinearity is effective and if VIF is greater than 5 (or 10), multicollinearity is accepted as important (Güriş, Çağlayan & Güriş 2013: 294).

Table 3: Correlations between Variables

	NPL	NFIS	COVER	LGDPPC	LGDP	GDPG	UNEMP	INTR	INF	CAR	LEGAL
NFIS	**-0.49***	1.00									
COVER	-0.06	0.25	1.00								
LGDPPC	-0.14	0.14	**0.77***	1.00							
LGDP	-0.15	0.00	**0.48***	**0.57***	1.00						
GDPG	-0.19	0.03	-0.15	-0.06	-0.07	1.00					
UNEMP	**0.49***	-0.08	0.01	-0.07	-0.29	0.09	1.00				
İNTR	-0.12	0.07	-0.34	-0.40	**-0.52***	**0.53***	0.12	1.00			
İNF	0.27	-0.23	-0.06	-0.27	-0.10	-0.33	0.00	**-0.55***	1.00		
CAR	0.12	0.01	-0.18	-0.32	**-0.52***	0.16	0.18	**0.48***	-0.04	1.00	
LEGAL	-0.17	0.13	0.23	0.14	0.07	-0.04	-0.24	-0.21	0.08	-0.09	1.00
GOVERN	-0.15	0.22	**0.67***	**0.80***	0.35	0.05	-0.10	-0.29	-0.29	-0.31	**0.46***
VIF	3.99	4.10	3.72	2.49	2.20	2.01	2.15	1.40	1.21	1.20	1.00

Note: * denotes the correlation coefficients of variables are significant at the 1% level. The last row shows variance inflation factor values (VIF) that ranges from 1 and 4.10.

According to correlation matrix of variables in the Table 3, statistically significant correlations among independent variables are accepted to be decisive when constructed regression models. Variables that are found to be statistically high correlated with each other are not included in the same regression model. For example COVER variable is not entered in the same regression with variables that has significant correlation with itself such as LGDPPC (0.77), LGDP (0.48) and GOVERN (0.67). It can be said that LGDP may be substitutes for LGDP variables. CAR and LGDP are analyzed in different regression equations. The INTR variable is not entered into the regressions model in which the one of the variables INF, CAR, LGDP or GDPG are included. Due to the high correlations, GOVERN excludes LGDPPC and LEGAL in the same equations. In this way, 6 regression equations were formed considering the level of correlation and mutually exclusive variables. The 6 regression equations generated by considering this correlation constraint are as follows.

1. $NPL_i = \alpha + \beta_0(NFIS) + \beta_0(COVER) + \beta_0(GDPG) + \beta_0(UNEMP) + \beta_0(INF) + \beta_0(CAR) + \beta_0(LEGAL) + \varepsilon_i$

2. $NPL_i = \alpha + \beta_0(NFIS) + \beta_0(COVER) + \beta_0(UNEMP) + \beta_0(INTR) + \beta_0(LEGAL) + \varepsilon_i$

3. $NPL_i = \alpha + \beta_0(NFIS) + \beta_0(LGDPPC) + \beta_0(GDPG) + \beta_0(UNEMP) + \beta_0(INF) + \beta_0(CAR) + \beta_0(LEGAL) + \varepsilon_i$

4. $NPL_i = \alpha + \beta_0(NFIS) + \beta_0(LGDPPC) + \beta_0(UNEMP) + \beta_0(INTR) + \beta_0(LEGAL) + \varepsilon_i$

5. $NPL_i = \alpha + \beta_0(NFIS) + \beta_0(GDPG) + \beta_0(UNEMP) + \beta_0(INF) + \beta_0(LEGAL) + \varepsilon_i$

6. $NPL_i = \alpha + \beta_0(NFIS) + \beta_0(GDPG) + \beta_0(UNEMP) + \beta_0(INF) + \beta_0(GOVERN) + \varepsilon_i$

All parameter estimates of 6 regressions based on ordinary least squares (OLS) are presented in Table 4. Heteroscedasticity is common in cross-sectional data and the presence of heteroscedasticity leads to inefficient OLS estimates (Long & Ervin, 2000: 217; White, 1980: 817). Breush-Pagan/Cook–Weisberg (BP/CW) test and White test are applied to determine the presence of heteroscedastic errors. According to the BP/CW test results, the rejection of the hypothesis Ho, which expresses the constant variance, at 1% level in all of the regressions reveals the the heteroscedasticity problem. Results of White test that have the same Ho hypothesis confirm the heteroscedasticity problem at %5 level for most of the regressions. The heteroscedasticity problem was corrected by using robust standard errors.

5. FINDINGS AND DISCUSSIONS

Table 4 presents the results of cross-sectional ordinary least squares regressions with heteroskedasticity robust standard errors for a sample of 55 countries in the year of 2015.

Table 4: Coefficient Estimates of Explanatory Variables.

Dependent variable: Non-Performing Loan (NPL)						
	1	2	3	4	5	6
NFIS	**-6.744**	**-5.552**	**-6.866**	**-5.420**	**-6.816**	**-6.762**
	[0.002][a]	[0.026][b]	[0.001][a]	[0.017][b]	[0.000][a]	[0.000][a]
COVER	-0.013	-0.045				
	[0.742]	[0.299]				
LGDPPC			-0.365	-3.921		
			[0.865]	[0.115]		
LGDP						
GDPG	-0.336		-0.326		-0.300	-0.298
	[0.326]		[0.323]		[0.340]	[0.348]
UNEMP	**0.677**	0.335	**0.663**	0.269	**0.679**	**0.671**
	[0.021][b]	[0.192]	[0.017][b]	[0.259]	[0.009][a]	[0.011][b]
INTR		-0.151		-0.225		
		[0.626]		[0.444]		
INF	0.082		0.076		0.086	0.086
	[0.601]		[0.646]		[0.565]	[0.580]
CAR	0.246		0.247			
	[0.356]		[0.367]			
LEGAL	0.091	0.013	0.069	-0.086	0.047	
	[0.703]	[0.959]	[0.774]	[0.746]	[0.841]	
GOVERN						-0.003
						[0.942]
CONSTANT	3.829	10.388	4.652	24.072	5.695	6.142
	[0.362]	[0.018][b]	[0.646]	[0.034][b]	[0.015][b]	[0.033][b]
Nu. of obser.	45	32	45	32	46	46
F statistics	4.28	1.94	4.41	2.00	4.62	4.55
prob > F	[0.002][a]	[0.122]	[0.001][a]	[0.112]	[0.002][a]	[0.002][a]
R2	0.53	0.36	0.53	0.41	0.52	0.52
BP/CW Test	16.02	20.55	15.17	16.58	12.8	13.51
prob > chi2	[0.000][a]	[0.000][a]	[0.000][a]	[0.000][a]	[0.000][a]	[0.000][a]
White's test	42.98	30.79	43.27	30.49	37.41	37.44
prob > chi2	[0.139]	[0.043][b]	[0.132]	[0.046][b]	[0.007][a]	[0.007][a]
Mean VIF	1.18	1.24	1.19	1.26	1.14	1.12

Note: Table 4 reports the estimations of the 6 cross section regressions estimated by OLS. P-values that are presented in parenthesis under independent variables imply heteroskedasticity robust standard errors. a, b and c represent the significance at the 1%, 5% and 10% levels, respectively.

The dependent variable is non-performing loan (NPL). Main explanatory variable is the non-financial information sharing (NFIS). Control variables are coverage ratio (COVER), gross domestic product (LGDP), gross domestic product (LGDPPC), gross domestic product growth (GDPG), unemployment rate (UNEMP), interest rate (INTR), inflation (INF), bank capital to asset ratio (CAR), legal rights (LEGAL) and governance (GOVERN). NFIS is a binary variable that equals 1 for countries in which information from retailers and utility companies are shared via credit reporting institutions.

Examining the heteroskedasticity consistent OLS estimation results in Table 4, it is seen that coefficients of NFIS are negative and statistically significant and this negative relation are meaningful for the 4 of the 6 specifications. The coefficients of NFIS are significantly different from zero at the 1% level in these four estimation (1., 3., 5. and 6. regressions). In countries where credit reporting institutions collect data from retailers and utility companies, the non-performing loan rate tends to be lower than in those where such information is not available.

This relationship is similar to findings of the Peria and Singh (2014) and Kallberg and Udell (2003). Peria and Singh (2014) provide evidence that non-financial information sources facilitate the access to finance. In their research, to reflect the scope and quality of credit information, depth of credit information index and its subcomponents are entered in the regressions separately. Data from non-financial institutions (retailers and utility companies) is analyzed as one of the credit bureau reform indicators. It is found that non-financial credit information has positive impact on the access to finance at the 10% significance level but its contribution is lower than other components. According to the model developed by Kallberg and Udell (2003), trade credit information sharing allows creditors to more accurately predict defaults.

Also empirical evidence confirms the results of Jappelli and Pagano (2002) and Powell et al. (2004) concluding that sharing positive information in addition to negative payment history data provides more information to lenders for accurate credit risk evaluation and thus reduces the level of problem loans. Furthermore, findings is consistent with the Doing Business (2017) research focusing on the comprehensive credit reporting system and with the existing literature (detailed in the literature review section as first and second group) suggesting that credit information sharing has reducing effect on default rates.

This cross-sectional relationship continues when the other economic and institutional determinants of the NPL are controlled. Examining the 4 specifications, there is a significant positive correlation between NLP and only one of the control variables, the unemployment rate. This relationship is consistent with the findings of some NPL studies (Berge & Boye, 2007; Jakubik & Schmieder, 2008; Louzis et al. 2012). These studies conclude that unemployment significantly contribute to the problem loans, non-performing loans or household defaults. The explanation for these similar findings is often that unemployment reduces the income level and increases the borrowing rate, thereby reducing the repayment ability and contributing to default rates.

Overall, the suggestion that credit information collected from a broader source of information reduce non-performing loan rates is confirmed. However with these country level findings, any clear conclusions cannot be drawn as to how non-financial information sharing reduces asymmetric information, theory confirm that this can be possible through reducing adverse selection or moral hazard problems. Non-financial information sharing can solve the problem of adverse selection by helping lenders to determine the default risk of borrowers. Payment behavior data reported by non-financial sources, in this case by retailers and utility companies may be combined with financial information and allows for a full credit analysis by creditors. These data may be more valuable for the credit evaluation process of borrowers with limited borrowing history with a financial institution. Comprehensive data may contribute to establish good relationship with lenders and to create credit records. Utility bill and retailer payment record of small and young firm's owners may be also needed. Evaluating credit history of a business and its owner together gives more accurate insight for risk assessment. Non-financial information sharing can be helpful in solving the problem of moral hazard by promoting borrowers who have delays in past payments to non-financial institutions. That is, the reputation of a loan candidate who has a delayed telephone or gas payment, or fails to pay a trade credit on time, or who has trouble with leasing and factoring payments, is relatively weak. When this borrower knows that this non-financial payment information is shared via credit bureaus or credit registries, he will be able to pay more attention to financial payments in order to strengthen his reputation and increase his credibility in banks.

6. CONCLUSION

The information asymmetries on the credit market brings with it adverse selection problems during the credit appraisal process and moral hazard problems after extending the credit line. Theory confirms that credit information sharing systems reduce information asymmetries, adverse selection and moral hazard problems. Information shared are presented to led to reduced default rates by increasing the prediction accuracy of borrower defaults and enhancing the incentives for debt repayments in the micro or macro level analyses. This reducing effect of information sharing on the defaults may be more pronounced in the credit reporting systems that collect information from all related sources beyond just financial institutions. Although the relationship between the comprehensive information sharing and defaults has not been investigated empirically sufficiently, a few detailed universal research (DB, 2017; WB, 2011; IFC, 2012) discuss that information collecting from broader source of data contribute more to the credit market performance.

The aim of this study is to examine whether sharing information from wider data sources is a mitigating effect on defaults. To achieve this aim, the relationship between the presence of non-financial information sharing and the bank non-performing loan was investigated at the country level. According to the depth of the credit information index, 55 countries considered having a comprehensive credit reporting system for collecting and distributing data from retailers and utilities were analyzed by controlling country-specific economic and institutional factors. Estimation results indicate that countries that integrate the data of retailers and utility companies into their credit reporting systems have lower non-performing loan rate. It can be concluded that information asymmetries between lenders and borrowers tend to be decreased by comprehensive information sharing. By extending the scope of shared information, creditors can access more information for a broader borrower group and can more accurately predict repayment probability of their potential borrowers. In addition, the negative non-financial payment history can motivate borrowers to regularly make credit payments and maintain a good reputation.

The findings of this study should be confirmed by further research conducted at firm or contract level. The impact of the development within the scope of a country's credit reporting system on non-performing loans can be examined in detail. If appropriate data is available, the effects of information obtained from other non-financial sources, such as microfinance institutions or trade creditors, on credit repayment behavior may be listed also among the topics to be discussed in the future.

REFERENCES

Atanasijević, J., & Božović, M. 2016, "Exchange rate as a determinant of corporate loan defaults in a euroized economy: Evidence from micro-level data", *Eastern European Economics*, *54*(3), 228-250. doi:10.1080/00128775.2015.1137198.

Beck, T., Lin, C., & Ma, Y. 2014, "Why Do Firms Evade Taxes? The Role Of Information Sharing And Financial Sector Outreach", *Journal of Finance*, *69* (2), 763-817. doi:10.1111/jofi.12123.

Berge, T. O., & Boye, K. G. 2007, "An analysis of banks' problem loans", *Economic Bulletin*, (2), 65.

.http://static.norges- ank.no/pages/60660/an_analysis_of_bank's_problem_loans_Economic_Bulletin_2_2007-2.pdf

Berger, A., & DeYoung, R. 1997, "Problem loans and cost efficiency in commercial banks", *Journal of Banking and Finance*, *21*(6), 849-870. doi:10.1016/S0378-4266(97)00003-4.

Boss, M. 2002, *A Macroeconomic credit risk model for stress testing the Austrian credit portfolio.* In Oesterreichische Nationalbank (Eds.), Financail Stability Report 4 (pp. 64-82). Vienna: Oesterreichische Nationalbank, Printing Office

Brown, M., & Zehnder, C. 2007, "Credit Reporting, relationship banking, and loan repayment", *Journal of Money, Credit and Banking*, (8). 1883-1918.

Brown, M., Jappelli, T., & Pagano, M. 2009, "Information sharing and credit: Firm-level evidence from transition countries", *Journal of Financial Intermediation*, *18,* 151-172. doi:10.1016/j.jfi.2008.04.002.

Büyükkarabacak, B., & Valev, N. 2012, "Credit information sharing and banking crises: An empirical investigation", *Journal of Macroeconomics*, *34 (3),* 788-800. doi:10.1016/j.jmacro.2012.03.002.

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

Daly, K. & Vo, X.V. 2013, "The determinants of home bias puzzle in equity portfolio investment in Australia", *International Rewiew of Financial Analysis*, 27, 34-42.

Dierkes, M., Erner, C., Langer, T., & Norden, L. 2013, "Business credit information sharing and default risk of private firms", *Journal of Banking and Finance*, *37,* 2867-2878. doi:10.1016/j.jbankfin.2013.03.018.

Djankov, S., McLiesh, C., & Shleifer, A. 2007, "Private credit in 129 countries", *Journal of Financial Economics*, *84,* 299-329. doi:10.1016/j.jfineco.2006.03.004.

Doblas, M. A., & Minetti, R. 2013, "Sharing information in the credit market: Contract-level evidence from US firms", *Journal of Financial Economics*, *109*(1), 198-223.

Doing Business. 2017, "Doing Business 2017, Getting Credit: Credit information. Casting a wide net to expand financial inclusion. 58-64", http://www.doingbusiness.org/reports/case-studies/2016/gc-credit-info 31.01.2017.

Fofack, H. 2005, "Non-Performing loans in Sub-Saharan Africa: Causal analysis and macroeconomic implications", *World Bank Policy Research Working Paper No. 3769*, World Bank, Washington.

Giannetti, C., & Jentzsch, N. 2013, "Credit reporting, financial intermediation and identification systems: International evidence", *Journal of International Money and Finance*, *33,* 60-80. doi:10.1016/j.jimonfin.2012.10.005.

Güriş, S., Çağlayan, E. & Güriş, B. 2013, *Eviews ile temel ekonometri.* İstanbul: Der Kitabevi. ISBN:978-975-353-370-6.

Houston, J. F., Lin, C., Lin, P., & Ma, Y. 2010, "Creditor rights, information sharing, and bank risk taking", *Journal of Finanial Economics*, *96,* 485-512. doi:10.1016/j.jfineco.2010.02.008.

International Finance Corporation. 2012, "Credit Reporting Knowledge Guide.1-120", http://www.ifc.org, 14.02.2017.

Isik, O., & Bolat, S.2016, "Determinants of non-performing loans of deposit banks in Turkey", *Journal of Business, Economics and Finance*, 5 (4), 341-350. ISSN: 2146 – 7943.

Jaffee, D. M., & Russell, T. 1976, "Imperfect information, Uucertainty and credit rationing", *The Quarterly Journal of Economics*, 4, 651-666.

Jakubik, P., & C. Schmieder. 2008, "Stress testing credit risk: Comparison of the Czech Republic and Germany", *Working paper, Bank for International Settlements, Financial Stability Institute*, Basel, Switzerland. http://www.bis.org, 15.02.2017.

Jappelli, T., & Pagano, M. 2002, "Information sharing, lending and defaults: Cross-country evidence", *Journal of Banking And Finance*, *26,* 2017-2045. doi:10.1016/S0378-4266(01)00185-6.

Jiménez, G., & J. Saurina. 2006, "Credit cycles, credit risk, and prudential regulation", *International Journal of Central Banking,* 2 (2):65–98. http://www.ijcb.org/journal/ijcb06q2a3.pdf.

Kallberg, J. G., & Udell, G. F. 2003, "The value of private sector business credit information sharing: The US case", *Journal of Banking and Finance*, *27,* 449-469. doi:10.1016/S0378-4266(02)00387-4.

Kaufman, D., Kraay, A. & Mastruzzi, M. 2003, "Governance matters III: Governance indicators for 1996-2002". *Washington: World Bank.*

Kaufman, D., Kraay, A. & Mastruzzi, M. 2008, "Governance matters VII: Aggregate and individual governance Indicators for 1996-2007", *Worldbank Policy Research Working Paper*, No. 4654.

Kaufman, D., Kraay, A. & Mastruzzi, M. 2009, "Governance Matters VIII: Aggregate and individual governance indicators for 1996-2008", *Worldbank Policy Research Working Paper*, No. 4978.

Kaufman, D., Kraay, A. & Mastruzzi, M. 2010, "The Worldwide Governance Indicators: A Summary of Methodology, Data and Analytical Issues", *World Bank Policy Research Working Paper*, No. 5430.

La Porta, R., Lopez-De-Silanes, F., Shleifer, A. & Vishny, R. W. 1997, "Legal determinants of external finance", *Journal of Finance,* 52 (3), 1131–1150.

Lyman, T., Lythgoe,T., Miller, M., Reille, M. & Sankaranarayan., S.2011, "Credit reporting at the base of the pyramid: Key Issues and Success Factors. FORUM 1", Washington, D.C.: CGAP and IFC.

Long, J. S. & Ervin, L. H. 2000, "Using heteroscedasticity consistent standard errors in the linear regression model", *The American Statistician*, *54 (3),* 217-224.

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. 2012, "Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios" *Journal of Banking & Finance*, (4). 1012.

Miller, M. 2003, *Credit reporting around the globe: the state of the art in public credit registries and private credit reporting firms.* In: Miller, M. (Ed.), Credit Reporting Systems and International Economy. MIT Press, Cambridge, MA, pp. 25–80.

Padilla, A.J., & Pagano, M. 1997, "Endogenous communication among lenders and entrepreneurial incentives", *The Review of Financial Studies*, 10 (1). 205-236.

Padilla, A.J., & Pagano, M. 2000, "Sharing default information as a borrower discipline device", *European Economic Review*, *44*(10), 1951-1980. doi:10.1016/S0014-2921(00)00055-6.

Pagano, M., & Jappelli, T. 1993, "Information sharing in credit markets", *Journal of Finance*, *48*(5), 1693-1718.

Peria, M.S.M., & Singh, S. 2014, " The impact of credit information sharing reforms on firm financing", *Policy Research Working Paper;No. 7013.* World Bank Group, Washington, DC. © World Bank.

Powell, A., Mylenko,N., Miller, M., & Majnoni G. 2004, "Improving credit ınformation, bank regulation and supervision: On the role and design of public credit registries", *World Bank Policy Research Working Paper 3443.*

Ranjan, R., &S. C. Dhal. 2003, "Non-performing loans and terms of credit of public sector banks in India: An Empirical Assessment", *Occasional Papers 24, No. 3, Reserve Bank of India,* Mumbai, India.

Rinaldi, L., & Sanchis, A. A. 2006, "Household debt sustainability: What explains household non-performing loans? An empirical analysis", *ECB Working Paper.*

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

Stiglitz, J. E., & Weiss, A. 1981, "Credit rationing in markets with imperfect information", *The American Economic Review*, 71 (3). 393-410.

Şahin, A., Doğukanlı, H., & Şengül, S. 2016, "Determinants of equity home bias in Turkey", *Journal of Accounting and Finance,* 72, 163-186. ISSN: 2146-3042.

White, H. 1980, "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity", *Econometrica, 48 (4),* 817–838.

World Bank. 2011, "General principles for credit reporting", Washington DC: World Bank.

http://siteresources.worldbank.org/FINANCIALSECTOR/Resources/Credit_Reporting_text.pdf, 06.04.2017

Yağcılar, G.G. & Demir, S. 2015, "Determination of the factors effecting non-performing loans in Turkish banking sector", *International Journal of Alanya Faculty of Business*, 7 (1), 221-229.

Web references

http://www.doingbusiness.org, 23. 02.2017

http://www.doingbusiness.org/Methodology/Getting-Credit, 31.01.2017 http://www.doingbusiness.org/reports/case-studies/2016/gc-credit-info, 31.01.2017

http://www.doingbusiness.org/data/exploretopics/getting-credit, 23.02.2017

http://www.doingbusiness.org/reports/global-reports/doing-business-2017, 12.06.2017

http://data.worldbank.org, 23.02.2017

http://data.worldbank.org/indicator/FB.AST.NPER.ZS?view=chart, 23.02.2017

http://data.worldbank.org/indicator/NY.GDP.PCAP.CD?view=chart, 24.02.2017

http://data.worldbank.org/indicator/NY.GDP.MKTP.CD?view=chart, 24.02.2017

http://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?view=chart, 24.02.2017

http://data.worldbank.org/indicator/SL.UEM.TOTL.ZS?view=chart, 12.06.2017

http://data.worldbank.org/indicator/FR.INR.RINR?view=chart, 24.02.2017

http://data.worldbank.org/indicator/NY.GDP.DEFL.KD.ZG?view=chart, 24.02.2017

http://data.worldbank.org/indicator/FB.BNK.CAPA.ZS?view=chart, 24.02.2017

http://info.worldbank.org/governance/wgi/#home, 20.02.20017

http://info.worldbank.org/governance/wgi/#doc, 30.05.2017

www.govindicator.org, 30.05.2017

http://siteresources.worldbank.org/INTWBIGOVANTCOR/Resources/govmatters3_wber.pdf, 04.07.2017

https://rbidocs.rbi.org.in/rdocs/Publications/PDFs/60613.pdf, 15.02.2017