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Article:
Agyei-Boapeah, Henry orcid.org/0000-0003-4798-6324, Fosu, Samuel, Ntim, Collins et al. (2 more authors) (2019) Credit Information Sharing and Loan Default in Developing Countries: The Moderating Effect of Banking Market Concentration and National Governance Quality. Review of Quantitative Finance and Accounting. ISSN 0924-865X

https://doi.org/10.1007/s11156-019-00836-1

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Credit Information Sharing and Loan Default in Developing Countries: The Moderating Effect of Banking Market Concentration and National Governance Quality

Abstract

Departing from the existing literature, which associates credit information sharing with improved access to credit in advanced economies, we examine whether credit information sharing can also reduce loan default rate for banks domiciled in developing countries. Using a large dataset covering 879 unique banks from 87 developing countries from every continent, over a nine-year period (i.e., over 6,300 observations), we uncover three new findings. First, we find that credit information sharing reduces loan default rate. Second, we show that the relationship between credit information sharing and loan default rate is conditional on banking market concentration. Third, our findings suggest that governance quality at the country level does not have a strong moderating role on the effect of credit information sharing on loan default rate.

Keywords

- Credit information sharing
- Developing countries
- Banking market concentration
- Governance quality

JEL Classification:

- G14
- G21

G38

1. Introduction

This study makes a number of new contributions to the existing literature by examining the: (i) effect of credit information sharing on loan default rates; and (ii) potential moderating roles that banking market concentration and national governance quality may play in the information sharing–loan default nexus, using a large dataset of 879 unique banks across 87 developing countries from every continent over a period of nine years (i.e., over 6,300 observations). This study is very important because recent years have witnessed some crucial reforms in several developing countries, including the development of credit information sharing schemes, financial sector reforms and improvements in political governance that are aimed at strengthening financial institutions by reducing credit default rates (see Marquez, 2002; Brown et al., 2009). For instance, Brown et al. (2009) report that 17 out of the 27 transition countries in Eastern Europe and the former Soviet Union established information sharing institutions between 1991 and 2005 alone. Furthermore, statistics based on World Bank data[1] suggest that the depth of credit information shared among lenders in developing countries surged by over 72% from 2004 to 2012 (i.e., depth of credit information index climbed from an average of 2.47 in 2004 to 4.26 in 2012). Meanwhile, the quality of lending deteriorated over the same period, with the size of non-performing loans in banks' portfolios rising from 6.3% in 2004 to 7.0% in 2012. These developments make it an extremely relevant academic and policy issue to consider whether and under what industrial/institutional environments do credit information sharing schemes yield net benefits in developing economies.

Against this backdrop, the current paper seeks to contribute to this topical issue regarding the value of credit information sharing schemes by examining the impact of credit information sharing on loan default rates in banks domiciled in developing economies. Economic theory suggests that information asymmetry leads to adverse selection and moral hazard problems in credit markets (Stiglitz and Weiss, 1981). When lenders cannot *ex ante* differentiate between safe and risky borrowers, they may lend in an inefficient manner by refusing credit to safe borrowers, while advancing loans to the risky ones and thereby increasing the average lending rate. This could adversely affect aggregate credit and credit risk, particularly when lending to risky borrowers becomes disproportionately higher to necessitate increasing interest rates.

[1]These statistics are based on our own computations using the relevant World Bank Doing Business (2016) data for our sampled countries over the period of investigation.

However, credit information sharing among lenders may help to overcome adverse selection problems in credit markets (Pagano and Jappelli, 1993) and reduce moral hazards by incentivising borrowers to repay loans (Padilla and Pagano, 2000) or by avoiding over-borrowing when borrowers patronise multiple banks (Bennardo et al., 2015). Therefore, credit information could improve credit allocation and loan quality, especially in environments where severe information asymmetry prevails.

While information problems arise in any market, they are particularly problematic in developing countries, often characterised by underdeveloped financial structures and institutional voids (Fosu, 2013; Amaeshi, Adegbite and Rajwani, 2016). Most developing countries tend to have relatively weak company laws and regulations protecting creditors' rights coupled with weak enforcement of contracts, as well as a lack of transparency in corporate reporting (La Porta et al., 1997; Brown et al., 2009). The weak governance environment exacerbates the adverse selection and moral hazard problems, making it unfavourable for bank lending. These features make developing countries an interesting setting to study the potential role of credit information sharing in enhancing the quality of loans advanced by banks, as measured by the loan default rates.

Prior studies considering the relevance of information sharing schemes have often focused on their effect on availability of credit and largely reported a positive information sharing effect (Jappelli and Pagano, 2002; Love and Mylenko, 2003; Brown et al., 2009; Fosu, 2014). However, evidence on the information sharing effect on credit default rates is relatively limited, with those few studies exploring the issue undertaking single-country analysis, and also often ignoring banks operating in other developing regions of the world. For example, Kallberg and Udell (2003), De Janvry et al. (2010) and Behr and Sonnekalb (2012) examine the issue in the specific contexts of the US, Guatemala and Albania, respectively. The lack of attention to the other markets, such as those in Africa, Asia and the Middle East is significant since information and credit accessibility problems are acute in most of these countries (Gwatidzo and Ojah, 2014; Tunyi and Ntim, 2016; Agyei-Boapeah and Machokoto, 2018). Furthermore, the generalisability of the existing literature to these ignored contexts may be problematic, given the heterogeneity in the banking industry dynamics and macro-governance factors across countries. We, therefore, take advantage of the recent improvements in data coverage for information sharing to examine the effect of credit information sharing on loan default rates

using a large dataset of 879 banks across 87 developing countries (including banks from 26 African markets) over a period of nine years (i.e., over 6,300 observations).

The current study provides a number of important findings. First, we observe that credit information sharing leads to a decrease in banks' loan default rate. Second, our findings suggest that the effect of credit information sharing on loan default rate is moderated by banking market concentration. Third, we find that country-level governance quality has little or no moderating role in shaping the effect of credit information sharing on loan default rate. Finally, our results indicate that banking market concentration increases loan default rate and its effect is accentuated by credit information sharing.

The findings of this study, thus, allow us to make new contributions to the existing literature. First, we open up a new research space by providing the first evidence (to the best of our knowledge) on the relationship between credit information sharing and loan default rate for a large sample of banks in developing economies. In doing so, we shed light on the potential effect of recent reforms in most developing countries that seek to encourage information sharing through the establishment of credit bureaus or registries. Second, by conditioning the effect of credit information sharing on banking market concentration, we shed light on the complex interactions between credit information sharing, banking market concentration and loan default rate. In particular, we show that banking market concentration and credit information sharing are to some extent substitutes as far as loan default rate is concerned; hence, we highlight the potential distortions and risk-shifting effects of the pro-competition banking sector reforms in the absence of effective credit information sharing schemes. This further has policy implications given the on-going reforms in the financial sector of most developing countries that are aimed at promoting competition through credit information sharing (Marquez, 2002). Third, by conditioning the effect of credit information sharing on governance quality, we assess the extent to which national governance quality could substitute for or complement the role of credit information sharing in reducing bank loan defaults. Finally, we provide the first comprehensive study of the determinants of loan default rate in banks in developing economies, which are usually characterised by relatively significant institutional voids but remain severely under-researched.

The rest of the paper proceeds as follows: Section 2 examines the relevant literature and develops our hypotheses. In Section 3, we discuss the sample, empirical design and

measurement of the key variables. Regression results and robustness checks are presented in Section 4 and, finally, Section 5 concludes the study with a summary of the main findings.

2. Related literature and hypotheses

2.1 Theory, credit information, bank lending and loan default

Theoretically, the traditional functions of banks, which include liquidity provision (Diamond, 1984) and delegated monitoring (Diamond and Dybvig, 1983), become more challenging when banks operate in opaque and weak governance environments such as those that prevail in many developing economies. Within this context, the quantity and quality of credit information that banks possess on existing and potential borrowers become critical resources that do not only assist them to effectively deliver a significant contribution to the financial system, but also help them in creating competitive advantage. Credit information sharing represents an effective means of enhancing both the quantity and quality of information available to banks to enable them make their lending decisions.

The prior literature identifies at least two major theoretical channels through which credit information sharing can affect a bank's lending decision (see Figure 1 in Appendix 1). The first is the adverse selection channel, shown in Pagano and Jappelli (1993), relating to banks deciding whether or not to lend to a new pool of potential borrowers. Pagano and Jappelli (1993) show that credit information sharing amongst banks can help lending banks make an accurate assessment of the credit worthiness of new (potential) borrowers. When each bank has private information about the credit worthiness of its 'local' borrowers but no information about other banks' borrowers, they could face adverse selection in granting credit. However, if banks share private information about their 'local' borrowers, they can lend safely to other banks' customers as well, in a way that decreases default rate. Overall, credit information sharing eases adverse selection problems by improving banks' knowledge of credit applicants' characteristics and permit more accurate prediction of repayment probability. This leads to an increased lending to safe borrowers and a reduced lending to risky borrowers and, thus, a decrease in loan default rate.

Second, and from the moral hazard theoretical perspective, credit information sharing can further reduce borrower default by curbing the borrower hold-up problems as well as increasing borrower discipline (e.g., Vercammen, 1995; Padilla and Pagano, 2000). In the absence of a

credit information sharing scheme, individual banks incur the cost of obtaining private information about borrowers and shift these costs to borrowers (and perhaps even extract rent) by pricing their loans relatively high, and thereby leading to borrower default. By contrast, the presence of a credit information sharing system helps to reduce banks' private costs and the extraction of informational rent, which in turn encourages borrowers' repayment efforts, and subsequently reduces default risks (Padilla and Pagano, 1997). Moreover, an effective information sharing scheme enables defaulting borrowers to be blacklisted, making it virtually impossible for such 'bad' borrowers to access finance in the future or if they do, it is at an excessively higher cost. By this mechanism, credit information sharing mitigates borrowers' moral hazards by instilling borrower discipline, improving repayment efforts and consequently minimising default risks (Klein, 1992; Vercammen, 1995; Padilla and Pagano, 2000). Furthermore, since the overall indebtedness of an individual borrower from all lending sources is revealed through information sharing, potential over-borrowing from multiple lenders is mitigated (Bennardo et al., 2015), which subsequently reduces individual borrowers' debt burden as well as loan default rates. Collectively, both the adverse selection and moral hazard theoretical perspectives predict that credit information sharing should lead to enhanced bank lending and a reduced loan default rate.

Empirically, several studies have investigated the link between credit information sharing and banking outcomes such as lending and loan default rates. For example, in a cross-sectional study of 43 countries, Jappelli and Pagano (2002) find that credit information sharing among lenders increases bank lending to the private sector, measured as the ratio of private credit to gross domestic product. They also find information sharing to significantly reduce country-level (aggregate) borrower default. In a bank-level dataset from African economies and focusing exclusively on bank lending, Fosu (2014) reports that credit information sharing increases bank lending. Similarly, Brown et al. (2009) and Love and Mylenko (2003) report that information sharing reduces credit constraints on firms. Focusing more directly on the information sharing effect on borrowers, Gietzen (2017) provides evidence to suggest that information sharing in African banking markets reduces the interest rate profile of borrowers, especially for those repeated borrowers who switched banks.

On the information sharing effect on loan default probability, Kallberg and Udell (2003), relying on US data, demonstrate that information sharing schemes have a predictive effect on business credit default, implying that information sharing could help banks to improve the

quality of their loans to corporations. Also, in Guatemala, De Janvry et al. (2010) show that credit information sharing schemes induce a moderate improvement in loan repayments. Similarly, Behr and Sonnekalb (2012), using loan-level data from a commercial bank serving micro-enterprises and SME borrowers in Albania report that the establishment of the information sharing scheme improved credit performance. They further find this effect to be more pronounced among repeat borrowers and conclude that the disciplinary effect of information sharing is stronger for clients that have already secured a relationship with the lender. Recently, Bos, de Haas, and Millone (2016) show that information sharing through credit registries in Bosnia and Herzegovina increases loan quality by tightening lending and increasing the rejection rate for small-business loan applications.

While these prior studies enhance our understanding of the potential impact of information sharing on bank loan default, they have often been conducted within the context of a single country-specific setting, thus, limiting the generalisability of their findings. Additionally, the potential roles of industry-level concentration and country-level governance quality in shaping the information sharing effect remain largely unexplored in existing literature. We address these gaps in the current paper. Overall, the foregoing discussion suggests that credit information sharing reduces adverse selection costs and moral hazard problems, and thus enhances banks' loan quality. Therefore, credit information sharing is expected to reduce loan default rate. We, therefore, formulate our first hypothesis as follows:

H1: Credit information sharing reduces banks' loan default rate.

2.2 Credit information, banking concentration and loan default

We argue in this section that the link between credit information sharing and the loan default rate of banks may be contingent on the levels of concentration in the banking industry. Specifically, we draw on the literature suggesting that banking market concentration may have an impact on banks' lending decisions (e.g., Petersen and Rajan, 1995; Marquez, 2002; Hauswald and Marquez, 2006; Gietzen, 2017). Since banking sector concentration tends to be associated with a few large banks that have a large pool of borrowers (Marquez, 2002; Hauswald and Marquez, 2006), competition is generally stifled in such banking markets (Berger and Hannan, 1998) and the few large banks are able to easily assume a 'too-big-to-fail' status (Acharya et al., 2013). These features generally incentivise banks in concentrated markets to make risky and/or inefficient lending decisions, which increase loan default rates.

Based on a sample of 3,404 US firms surveyed in 1988-1989, Petersen and Rajan (1995) offer empirical evidence to suggest that risky decisions, such as lending to young firms, which are likely to be financially constrained, are encouraged in concentrated banking markets than in less concentrated markets. Similarly, Bonaccorsi and Dell'Ariccia (2004) analyse cross-industry Italian data and find a positive effect of bank concentration on the emergence of new firms, suggesting an increased lending to risky entrepreneurial activities and business start-ups in concentrated banking markets. They further show an amplification of such risky lending in more informationally opaque industrial sectors.

These arguments and evidence suggest that risky lending and, by extension, loan default rates may be higher in concentrated markets, and for that matter, credit information sharing may have a more critical role to play in such markets. However, a closer look at the theoretical rationale for the risky lending behaviour in concentrated markets rather suggests the opposite (i.e., a minimal role for credit information sharing in concentrated banking markets). For instance, in Petersen and Rajan's (1995) theoretical framework, banking market concentration permits the building of closer and long-term ties between lenders and borrowers in such a way that the lender-banks are able to share in the future surplus of the borrower-firms. This is because, unlike in competitive banking markets, where borrowers can easily switch banks, the dynamics prevailing in concentrated banking markets lead to the establishment of a long-term lending relationship between the few top banks and their 'loyal' borrowers. This then facilitates the acquisition of 'soft' credit information by banks about their borrowers, as well as a willingness on the part of the lenders to disregard available negative credit information about important customers, but rather focus on the future rent that the bank can extract from its borrowers. In such an environment, credit information sharing is likely to yield minimal benefits, and the average quality of loans will be lower, resulting in higher default rates.

Similar conclusions are drawn from Cetorelli and Peretto (2000), who present a model in which banks have access to a costly screening technology which allows them to discriminate between high- and low-quality borrowers. If a bank incurs the cost to acquire this screening technology, competitor banks are able to freely extract the information about the screened borrower through that bank's decision to grant or deny a loan to the screened borrower. This leads to informational externality that generates a free-riding problem, and thus weakening banks' incentives to incur the cost of screening and to carry out an information-based (efficient) lending strategy. Within this theoretical framework, concentrated banking markets have a

higher incentive to internally produce information and effectively screen loan applicants due to a reduced free-riding problem when competitors are few. Therefore, the potential benefits accruing from a public credit information sharing scheme may be minimal in concentrated banking markets. A related argument is that since banks in concentrated markets may find information sharing to be less useful, the individual banks may be less willing to share information with each other.[2] This can again reduce any potential benefit of credit information sharing schemes in concentrated banking markets.

In sum, the key implication of both theoretical models of Petersen and Rajan (1995) and Cetorelli and Peretto (2000) with respect to the relevance of credit information sharing schemes is that the potential benefits of reduced loan default rates associated with having a public credit information sharing system may be minimal, if not completely absent, in concentrated banking markets. This is due to the view that banks in concentrated markets may possess adequate internal mechanisms (e.g., long-term relationships or screening tools) to be able to generate quality information about their borrowers. Accordingly, our second hypothesis is as follows:

H2: The effect of credit information sharing on loan default rate is conditional on banking market concentration.

2.3 Credit information, governance quality and loan default

We take the view that the nature of the institutional environment in which banks operate is likely to impact the relationship between information sharing and loan default rate. Drawing from institutional theory in the management and international business literature (e.g., Barley and Tolbet, 1997; Hanousek and Kochanova, 2016), our core argument in this section is that banks in specific institutional settings may reap more or fewer benefits from credit information sharing than their counterparts operating elsewhere. To start with, organisational behaviour, culture, practices and performance generally differ across countries due to institutional differences such as governance quality in the form of the effectiveness of rule of law, regulatory quality and control of corruption, among others (Dodd and Gilbert, 2016; Hearn et al., 2017). Martins et al. (2014) argue that enforcement of contracts depends on the quality of country-level governance, implying that moral hazard problems arising from weak legal structures may vary across countries. Although countries in developing economies are largely characterised by institutional voids (Amaeshi et. al. 2016; Agyei-Boapeah and Machokoto, 2018) such as

[2]We are grateful to an anonymous reviewer for suggesting this argument.

weak enforcement of laws and laxity in fighting corruption, there is also a wide variation in the quality of governance across countries, with some having better governance structures than others. Banks operating in countries with severe institutional voids may thus face relatively higher cost since they need to incur additional costs in order to enforce their loan contracts. Higher loan enforcement costs may subsequently lead to greater agency problems and higher loan default rates in countries with poor national governance quality.

The empirical literature largely suggests that corporate outcomes are adversely affected when firms operate in poor macro-governance environments. For example, Hanousek and Kochanova (2016) utilise a sample from 14 Central and Eastern European countries to suggest that bribery and corruption at the national level negatively impact firms' sales and productivity growth. This implies increased loan default rates in highly corrupt countries. Similarly, Li et al. (2006) find that macro-governance characteristics substantially explain the cross-country variations in the effectiveness of managerial monitoring mechanisms at the firm level. Specifically, they show that effective managerial monitoring systems (i.e., reduced agency problems) are more prevalent in countries with stronger shareholder rights, greater access to voting rights, more effective legal enforcement and extensive financial disclosures. To the extent that poor corporate governance in the form of ineffective managerial monitoring may be correlated with poor financial performance, it is reasonable to equally suggest that higher loan default rates for banks operating in poor national governance environments are highly likely.

Within the context of the role of information sharing in shaping lending decisions and default risk in the banking sector, research on the effect of national governance quality is very much lacking. The few existing studies examining the issue have largely focused on the link between information sharing and bank lending (e.g., Brown et al., 2009; Fosu, 2014) and they note that, although information sharing is associated with improved credit availability and lower cost of credit to firms, its effect is minimal in countries with high governance quality. Thus, it seems that the relatively lower agency and information asymmetry problems in better-governed countries limit the expected benefits of credit information sharing in such environments. Credit information sharing may, therefore, not significantly impact loan default risks in better-governed countries. Put differently, information sharing may play a substitution role to institutional (national governance) quality as it mitigates the effects of weak protection afforded to creditors. In the light of the above discussion, we formulate our final hypothesis as follows:

H3: The effect of credit information sharing on loan default rate is moderated by national governance quality.

3. Data and empirical methodology

3.1. Data description

Bank-level data for this study was obtained from Bankscope, which contains information on banks around the world. The study's sample period is from 2004 – 2012.[3] In line with existing literature (e.g., Fosu, 2013; Beck et al., 2013), a number of exclusion criteria were applied. These include the exclusion of countries with fewer than 10 bank-year observations. Also, banks with fewer than three consecutive years of observations were excluded. Finally, bank-year observations with missing data on key variables were also dropped. Overall, a total of 879 banks from 87 developing countries[4] from every continent were employed in our analysis. The list of countries and distribution of the sample showing the contribution of each country is presented as an appendix (see Table 12). The top five countries represented in the sample are Turkey (5.69%), Argentina (3.75%), Hong Kong (3.64%), Kenya (3.19%), and South Africa (3.07%). The least represented countries are Algeria, Benin, Ethiopia, Grenada, Guyana, Maldives, Montenegro, Rwanda, Sierra Leone, Tajikistan, and Togo, all contributing 0.23% each to the sample. Information sharing variables and other macroeconomic variables used in the study were obtained from the World Bank Doing Business and the World Bank World

[3]Our sample period starts from 2004 because the World Bank Doing Business (WBDB) database on credit information sharing starts from 2004. There was a methodological change in the construction of the credit information sharing index in 2012. The index, therefore, now ranged from 0 to 8 instead of 0 to 6. To avoid the potential confounding effects of this methodological change, as well as to be consistent with prior studies (e.g. Kalyvas and Mamatzakis, 2017), we decided to employ 2012 as our cut-off period. We also note that our sample period covers the period of the recent global financial crisis (2007-2009) which affected the level of bank loans and default rates. In unreported robustness analysis, which excludes the crisis period, our main results reported in this study and the conclusions drawn from them are not affected. These results are available upon request.

[4]We define developing countries based on United Nation's Country Classifications contained in the World Economic Situation and Prospects. See links for the UN reports containing list of countries in 2014 (p.146) and 2018 (p.142):
http://www.un.org/en/development/desa/policy/wesp/wesp_current/2014wesp_country_classification.pdf
https://www.un.org/development/desa/dpad/wp-content/uploads/sites/45/publication/WESP2018_Full_Web-1.pdf
Although China and India are classed as developing countries, they are excluded from our sample because they do not have country-level credit information sharing indexes. Rather, these countries have city-level credit information sharing indexes. In untabulated analyses, which include the city-level indexes for Shanghai (China) and Mumbai (India), with our main conclusions remaining unchanged.

Development Indicators, respectively. Governance variables were obtained from the World Bank's Worldwide Governance indicators.

3.2. Measurement of variables

The measures used in this study were chosen in line with the previously discussed empirical and theoretical literature, which enabled us to compare our results with prior research. We draw on the extant literature (e.g., Berger, 2009; Louzis et al., 2012; Vazquez et al., 2012; Jiménez et al., 2013 Demirgüç-Kunt et al., 2003; Ghosh, 2015; Kalyvas and Mamatzakis, 2017) and include a number of bank-specific and macroeconomic variables in our analysis. These variables are presented in Table 1 and are discussed below.

3.2.1. Credit information sharing and loan default rate

Consistent with the emerging empirical literature on the role of information sharing on credit markets (e.g., Fosu, 2014; Nana, 2014; Kalyvas and Mamatzakis, 2017), we adopt the depth of credit information sharing index as our main measure of information sharing. This index "*measures rules and practices affecting the coverage, scope and accessibility of credit information available through either a public credit registry or a private credit bureau*" (World Bank Doing Business, 2016)[5]. The index is constructed by the World Bank in two stages. First, banking supervision authorities and other public sources (e.g., government officials) are surveyed to confirm the presence of public credit registries and private credit bureaus. Second, a detailed survey about their structure, law, and associated rules is administered to the registry or bureau. Over our sample period, the index ranges from 0 to 6, where higher values indicate the availability of more credit information to help in lending decisions. An index of zero means that the public credit registry or private credit bureau is non-operational, or its coverage falls below 0.1% of the adult population. By contrast, the maximum score of six is assigned to a country that has an operational credit registry or private credit bureau (and covers at least 0.1% of the adult population) in addition to the following five pieces of information: (i) both positive and negative information; (ii) data on households and firms; (iii) data on retailers and utility providers as well as financial institutions; (iv) more than 2 years of data; and (v) data on loans below 1% of income per capita. Thus, an index of 2 and above does not merely indicate the

[5]A more detailed description of the information sharing measures can be found at World Bank, Doing Business project (http://www.doingbusiness.org/).

presence of a credit information sharing system in a country but captures the quality (depth) of a country's credit information sharing infrastructure.

For our robustness checks, we adopt two other measures of credit information sharing. These are credit registry (public) coverage and credit bureau (private) coverage, both expressed as a percentage of the adult population. Credit registry coverage measures the number of individuals and firms listed by a public credit registry concerning the information on their borrowing and credit history (e.g., repayment history, unpaid debts, or credit outstanding) for the past five years. Similarly, credit bureau coverage measures the number of individuals or firms listed in a private credit bureau concerning the information on their borrowing history for the past five years. Overall, our measures of credit information sharing are consistent with Barth et al. (2009) and Büyükkarabacak and Valev (2012) who, respectively, explore the effect of credit information sharing on corruption in bank lending and on banking crisis. Unlike studies such as Kallberg and Udell (2003) and Giannetti et al. (2017) who employed micro-level measures of credit information sharing, our macro-level alternative allows us to consider a broad array of credit information about households and firms, from both public (mandatory) and private (voluntary) sources. Moreover, the use of the country-level measure of credit information sharing helps to minimize endogeneity concerns since the variable is largely exogenous to the firm. However, our measures of credit information sharing are not without limitation. For instance, they only capture "hard information" on creditworthiness (Büyükkarabacak and Valev, 2012) and also provide less detailed breakdown of the type of information shared (Kallberg and Udell, 2003).

Following the literature (e.g., Chu et al., 2007; Berger et al., 2009; Louzis et al., 2012; Vazquez et al., 2012; Jiménez et al., 2013; Ghosh, 2015), our study utilises the ratio of non-performing loans to total loans (NPL) as the measure of loan default rate. In our robustness analysis in Section 4.6, we utilise the net charge off rates as an alternative measure of loan default rates. Table 13 in the appendix presents the mean values of our loan default measure and our main measure of credit information sharing (Depth). As can be seen from Table 13, there is high variability in loan default and the depth of credit information sharing across countries in our sample.

3.2.2. Concentration

In the light of the extant literature (e.g., Beck et al., 2006; Fosu, 2014; Dietrich, 2016, Chen et al., 2018), we measure banking market concentration by using the three-bank concentration

ratio defined as the share of assets of the three largest banks, expressed as a percentage of the entire banking assets. The choice of this measure as against other alternative measures (e.g., the Lerner index, Herfindahl–Hirschman Index and five-bank concentration as in Sharma et al. (2015) and Fosu et al. (2018)) is due to the fact that the sample size changes over the sample period and this could lead to a measurement error if we utilised more than the top three banks (see Beck et al., 2006).

3.2.3. Other bank-specific factors

The econometric models we specify in our study also account for other bank-specific variables. These include bank size, lending specialisation, bank capital and profit. Bank size may be an important determinant of loan default because larger banks can assume a 'too-big-to-fail' attitude and thus engage in more risky lending (Kane, 2010; Acharya et al., 2013; Ghosh, 2013; Hu and Mao, 2017; Goenner, 2018). This can result in increased loan default rate. Bank size is defined as the logarithm of total bank assets. An increase in the lending specialisation may lead to an increase in efficiency, hence, a lower loan default rate (e.g., Petersen and Rajan 1995). However, increased lending growth driven by supply side incentives can lead to less stringent lending and ultimately increased loan default rate (Keeton, 2013). We measure lending specialisation as the percentage of total loans to total assets.

Furthermore, bank capital accounts for the effects of leverage on risk level and the required risk premium (Lepetit et al., 2008). From a moral hazard perspective, banks with significant equity capital may have lower incentives to take risk (Sharpe, 1978; Furlong and Keeley, 1989). However, the 'too-big-to-fail' hypothesis suggests that highly capitalised banks may have stronger incentives to engage in more risky lending due to their larger capital base (Kane, 2010; Acharya et al., 2013). Thus, the impact of capital on bank default can be ambiguous. Bank capital is measured as the ratio of book value of equity to total assets. Finally, bank profitability may be associated with managerial efficiency, in which case highly profitable banks are expected to have a lower default rate (Berger and DeYoung, 1997). However, profitability could be driven by managerial incentives, which can result in lower loan quality (Rajan, 1994; Ghosh, 2015). We measure profit as the ratio of operating profit to total assets.

3.2.4. Macroeconomic and governance variables

In line with other past empirical studies (e.g., Berger et al., 2009; Demirgüç-Kunt et al., 2003; Ghosh, 2015), we control for a number of country-specific traits. This is to ensure that the relationship between credit information sharing and loan default rate is not driven by

macroeconomic variations. These variables include inflation, measured as the annual percentage change in consumer price index. This accounts for possible uncertainty in the credit market (Fosu, 2014). We also include growth in gross domestic product (GDP Growth), which is measured as the annual percentage change in real GDP. The inclusion of this variable is to account for changes in credit demand within a country, as well as the possible variations in adverse selection and moral hazards in business cycles (Altunbas et al., 2009; Andrianova et al., 2015). In addition to the variables described above, we also include a number of governance indicators. These include rule of law, control of corruption and regulatory quality. The rule of law measures "*perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence*" (Kaufmann et al., 2011, p. 223). The control of corruption index measures "*perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests*" (Kaufmann et al., 2011, p. 223). Finally, the regulatory quality index captures "*perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development*" (Kaufmann et al., 2011, p. 223).

3.3. Descriptive statistics and correlations

In Table 1, we present the summary statistics of the variables used in this study. The information is confined to 6,323 observations.

[Table 1 about here]

A few findings are worth noting. The average value of loan default is 6% and ranges between 0% and 28%. This suggests a high degree of heterogeneity across banks. The mean value of depth of credit information index (which is our main measure of credit information sharing) is 3.54. This variable ranges between 0 and 6 and has a standard deviation of 2.41. These values suggest a moderate depth of credit information with a fair degree of heterogeneity across countries. The mean values of our alternative measures of credit information sharing (i.e., credit registry coverage and credit bureau coverage) are 9.37% and 29%, respectively. Credit bureau exhibits the highest degree of variability with a standard deviation of 18.20. The mean values of the governance measures of rule of law and control of corruption are both negative, suggesting that governance quality for developing countries is below the world average. The

only exception is the governance indicator of regulatory quality, which is marginally above the world average.

It is noteworthy that most of our variables (including our measures for loan default and information sharing), exhibit considerable between- and moderate within-country variations, permitting the use of panel data estimation methods to identify our parameters of interest (see, Baltagi et al, 2009). For instance, our primary information sharing measure, the depth of credit information index, shows a within-country standard deviation of 1.12, suggesting some improvements in information sharing in some, if not all, developing countries over our sample period. In fact, as many as 23 countries in our sample showed major improvements in credit information sharing over the sample period. We define significant improvement to include cases where we observe at least a 5-unit change in the depth of credit information index from the beginning to the end of the sample period (2004-2012). For example, a country with an initial index of zero (one) but moves to five or above (six) during the sample period is classified as having showed a major improvement. Out of the 23 countries that showed major improvements, 12 showed sharp improvements, with the remaining 11 taking a gradual process towards attaining improved information sharing.[6] We define sharp improvements to include improvements where the increase in the depth of credit information index between any two consecutive years is at least 5. All other cases of improvements are classified as gradual. Figure 2 shows the average indices over time for the group of countries with sharp and those with gradual improvements.

[Figure 2 about here]

[Table 2 about here]

Finally, Table 2 presents the correlation among the variables, and it shows that the depth of credit information is negatively associated with bank loan default rate. Similarly, the credit bureau coverage is negatively related to loan default, whilst credit registry coverage has a seemingly weak positive correlation with loan default. This suggest that the two measures perhaps capture different attributes of information sharing, as credit registry, unlike private bureau, is largely a regulatory tool. All the governance indicators are negatively correlated with

[6]The list of countries showing major improvements in information sharing include: *Costa Rica, Croatia, Kazakhstan, Lithuania, Macedonia (Fyrom), Mauritius, Mongolia, Oman, Romania, Saudi Arabia, Serbia,* **Albania, Armenia, Azerbaijan, Belarus, Egypt, Georgia, Ghana, Latvia, Morocco, Rwanda, United Arab Emirates, Zambia**. Please note that the countries in *italics* (**bold**) experienced *gradual* (**sharp**) improvements in information sharing during the sample period.

loan default. These indicators are strongly correlated with one another; however, this poses no concerns about multicollinearity as these variables do not enter the regression at the same time. Further, there is no issue of multicollinearity with any of the causal variables employed. Overall, the descriptive statistics and the correlation matrix suggest that statistical problems such as lack of variations and multicollinearity are unlikely to plague our analysis.

3.4 Estimation method

We formulate empirical models in this section to test out our main hypotheses. To do this, and consistent with the extant literature, we adopt a panel data approach which permits bank- and country-level variables to vary across time. To cater for the likelihood that loan default rate may not have been observed under long-run equilibrium for any given year, we adopt a dynamic estimation approach (Vazquez et al. 2012; Jiménez et al. 2013) in order to accommodate the possibility of partial adjustment towards equilibrium (see Baltagi et al, 2009). Also, we adopt a logit transformation of NPL in our empirical modelling to map the dependent variable, which has a theoretical range between 0 and 1, to the real number line (Jiménez et al., 2013) and also to permit inference based on Gaussian errors (Vazquez, 2012). Our baseline model is, therefore, presented as:

$$\ln\left(\frac{NPL_{i,t}}{1-NPL_{i,t}}\right)=\alpha+\delta\ln\left(\frac{NPL_{i,t-1}}{1-NPL_{i,t-1}}\right)+\beta_1 Info_{j,t}+\beta_2 CR_{j,t}+\sum_{K=1}^{N}\phi_k BS_{i,k,t}+\gamma MG_{j,t}+\varepsilon_{i,t} \quad (1)$$

where $i \in j$ represents the bank i in country j in t time period. $NPL_{i,t}$, our main measure of loan default rate, is the ratio of non-performing loans to total loans; $Info_{i,t}$ is the credit information sharing index, which is alternately the depth of credit information sharing, credit registry coverage and private credit bureau coverage. $CR_{i,t}$ is the banking market concentration ratio; $BS_{i,t}$ is bank-specific variables; $MG_{i,t}$ is macroeconomic and governance variables (that is, GDP growth rate and inflation) and governance indicator, which is alternately rule of law, regulatory quality and control of corruption; and $\varepsilon_{i,t}$ is an error term composed of bank fixed effect (μ_i) and an independently and identically distributed component with zero mean and constant variance ($\nu_{i,t}$).

We derive the effect of credit information sharing on the untransformed NPL, evaluated at the sample mean of NPL (Vazquez et al., 2012). Specifically, the short-run and the long-run effects are derived as in Eqs. (2) and (3), respectively:

$$\left(\frac{\partial NPL}{\partial Info}\right) = \overline{NPL} \times \left(1 - \overline{NPL}\right) \times \left(e^{\beta_1} - 1\right) \times 100 \tag{2}$$

$$\left(\frac{\partial NPL}{\partial Info}\right) = \frac{1}{1-\delta} \times \overline{NPL} \times \left(1 - \overline{NPL}\right) \times \left(e^{\beta_1} - 1\right) \times 100 \tag{3}$$

Eqs. (1) to (3) permit us to test our first hypothesis. In order to test the next two hypotheses, we modify Eq. (1) by including interaction terms of credit information sharing variables with banking market concentration. We then obtain Eq. (4) as follows:

$$\ln\left(\frac{NPL_{i,t}}{1-NPL_{i,t}}\right) = \alpha + \ln\delta\left(\frac{NPL_{i,t-1}}{1-NPL_{i,t-1}}\right) + \beta_1 Info_{j,t} + \beta_2 CR_{j,t} + \eta\left(CR_{j,t} \times Info_{j,t}\right) + \sum_{K=1}^{N} \phi_k X_{i,k,t} + \gamma M_{j,t} \tag{4}$$

The equivalent short-run and long-run marginal effects of credit information sharing on the untransformed NPL are, respectively, derived as follows:

$$\left(\frac{\partial NPL}{\partial Info}\right) = \overline{NPL} \times \left(1 - \overline{NPL}\right) \times \left(e^{(\beta_1 + \eta CR)} - 1\right) \times 100 \tag{5}$$

$$\left(\frac{\partial NPL}{\partial Info}\right) = \frac{1}{1-\delta} \times \overline{NPL} \times \left(1 - \overline{NPL}\right) \times \left(e^{(\beta_1 + \eta CR)} - 1\right) \times 100 \tag{6}$$

Similarly, we derive the marginal effect of banking market concentration on the untransformed NPL by differentiating Eq. (4) with respect to the information sharing variable, and evaluating at the sample mean of NPL as follows:

$$\left(\frac{\partial NPL}{\partial CR}\right) = \overline{NPL} \times \left(1 - \overline{NPL}\right) \times \left(e^{(\beta_2 + \eta Info)} - 1\right) \times 100 \tag{7}$$

$$\left(\frac{\partial NPL}{\partial CR}\right) = \frac{1}{1-\delta} \times \overline{NPL} \times \left(1 - \overline{NPL}\right) \times \left(e^{(\beta_2 + \eta Info)} - 1\right) \times 100 \tag{8}$$

We adopt a similar approach to provide further extensions, for example, to assess the moderating roles of governance quality on the marginal effect of credit information sharing.

The estimation of Eqs. (1) and (4) poses an endogeneity problem. First, the bank fixed effects may be correlated with other explanatory variables. We address this problem by first differencing the equations to wipe out the bank fixed effects. Second, the lagged dependent variables are, by construction, correlated with the differenced error terms. This problem can be addressed by using the difference generalised method of moments (GMM) estimator proposed by Arellano and Bond (1991), where the lagged levels of the endogenous variables are used as instruments for the differenced equation in Eqs. (1) and (4). The absence of serial correlation in the original error term, $\varepsilon_{i,t}$, and the weak exogeneity of the explanatory variables will permit the following moment conditions:

$$E\left(y_{i,t-S}\Delta\varepsilon_{i,t}\right)=0;\ \text{for}\ s\geq 2;\ \ t=3,...,T \tag{9}$$

$$E\left(X_{i,t-s}\Delta\varepsilon_{i,t}\right)=0;\ \text{for}\ s\geq 2;\ \ t=3,...,T \tag{10}$$

However, for reasons such as persistence or measurement errors, lagged levels of the explanatory variables may not be efficient instruments for their first differences (Blundell and Bond, 1998; Alonso-Borrego and Arellano, 1999). Efficiency can be improved by combining the levels equation with the differenced equation as a system of equations (Arellano and Bover, 1995; Blundell and Bond, 1998). In this case, the lagged first-differenced variables can serve as instruments for the corresponding variables in levels, leading to the following additional moment conditions[7]:

$$E\left(\Delta y_{i,t-S}\varepsilon_{i,t}\right)=0;\ \text{for}\ s=1 \tag{11}$$

$$E\left(\Delta X_{i,t-s}\varepsilon_{i,t}\right)=0;\ \text{for}\ s=1 \tag{12}$$

By construction, first-order serial correlation in the first-differenced equation is expected. However, second-order serial correlation in the differenced equation would suggest possible first-order serial correlation in the level equations (Roodman, 2009) and undermine the moment

[7]Note that the most recent lagged differences are used in order to avoid redundant moment conditions (see Arellano and Bover, 1995).

condition. Hence, we compute diagnostic tests of first-order and second-order serial correlation tests. We also test for the validity of the over-identification restrictions using Hansen test of over-identifying restrictions. Finally, we correct the standard errors for finite sample bias using the two-step covariance matrix proposed by Windmeijer (2005).

4. Results and discussion

This section presents the estimation results of the paper. We first present the results for our baseline models, where loan default rate is explained by credit information sharing (Tables 3 and 4). We then follow this up by conditioning the effect of credit information sharing individually on banking market concentration (in Tables 5 and 6) and national governance quality (in Table 7). We further subject our results to a range of robustness tests in Tables 8 and 9. We restrict the maximum lag-dependent variable to 1 since we seek to reduce the number of moment conditions. As can be seen in Tables 3 to 9, the lagged dependent variables do enter all regressions with statistically significant coefficients, justifying the use of a dynamic model approach in our estimation. The Hansen test *p*-values are all above 0.1, suggesting that the over-identification restrictions are valid. Finally, we cannot reject the absence of second-order serial correlation in our models, which is further evidence that our use of a dynamic model is appropriate.

4.1 Credit information sharing and loan default rates

We present our main findings as follows. First, our baseline results, presented in Table 3, suggest that credit information sharing reduces loan default rate. In Models 1 to 3, we use the depth of credit information index as our main measure of credit information sharing. We then control alternately for governance indicators of rule of law (*Law*), regulatory quality (*Regulation*) and control of corruption (*Control*). It is important to highlight that the governance indicators are not jointly included in the model since they are highly correlated.[8] The depth of credit information index enters each of the regressions with a negative sign and a

[8]The correlation among the governance indicators is at least 0.83 and this could cause multicollinearity problems when they are included in the model together. On the contrary, the correlations among the other country-level variables (*Depth, Concentration, Governance, GDP Growth, and Inflation*) are moderate (less than 0.21) and could thus be included together in the model without serious econometric concerns. The results remain qualitatively similar when the country-level variables (other than the governance indicators) are also included alternately in the model. These results are available upon request.

statistical significance at the 1% level. In fact, the effect of credit information sharing is economically significant.

[Table 3 about here]

Applying Eq. (2) and (3), we present the short-run and long-run marginal effects of the depth of credit information sharing in Table 4. The results suggest that a one standard deviation change (2.41) in the depth of credit information sharing will reduce loan default rate by up to 0.92 percentage points in the short run and 3.35 percentage points in the long run.[9] Practically, for an average firm in our sample with a credit information sharing index (*Depth*) of 3.54, a one standard deviation increase would bring credit information sharing index to 5.95 (i.e., almost the maximum of 6). With a near-maximum credit information sharing index, one can expect a significant reduction in the average banks' default risk from 6% to 2.65% in the long run.

[Table 4 about here]

We confirm our findings of the negative relationship between information sharing and loan default rates in the next six models of Table 3 using alternative measures of information sharing, namely, credit registry coverage (Models 4-6) and credit bureau coverage (Models 7-9). The coefficients of the credit registry (*Registry*) and private bureau (*Bureau*) coverage are both negative and statistically significant. The marginal effect analyses presented in Table 4 suggest that a one standard deviation (13.01) increase in credit registry coverage is associated with between 0.51 and 0.53 percentage points reduction in loan default in the short run and between 1.92 and 1.95 percentage points in the long run. On private bureau, the results suggest that a one standard deviation (31.42) change in the coverage of private bureau is associated with up to a 1.19 and 3.98 percentage points reduction in loan default in the short and long run, respectively.

Overall, these findings provide support for Hypothesis 1 and thus are broadly consistent with previous literature, which suggests that credit information sharing improves bank lending (Jappelli, and Pagano, 2002; Brown et al., 2009; Fosu, 2014) and credit quality (Jappelli, and Pagano, 2002; Behr and Sonnekalb, 2012). Our findings also suggest that prior studies such as De Janvry et al. (2010) that found information sharing to be associated with only marginal

[9]The magnitude of the economic significance that we find is similar to the findings of Vazquez et al. (2012) who examine the impact of GDP on default rate in Brazil (see page 76 of their paper).

improvements in loan repayments may have underestimated the potential benefit of information sharing on loan default rates. It is also plausible that the average gain for information sharing in developing countries is higher than that which is observed in Guatemala (see, De Janvry et al., 2010). Interestingly, our long-run estimates of 3.12 to 3.98 percentage point reductions in default rates resulting from information sharing (based on depth and bureau measures) are similar to the estimated improvements in loan repayments of 3 percentage points in Albania (see Behr and Sonnekalb, 2012). Our findings also support the theoretical view that the benefits of reduced adverse selection and moral hazard problems associated with credit information sharing among lenders may result in improvement in banks' loan quality (Pagano and Jappelli, 1993; Vercammen, 1995; Padilla and Pagano, 2000).

Second, the coefficients on banking market concentration in Table 3 offer an important insight: they are positive and statistically significant at the 1% level in all models, suggesting that banking market concentration increases loan default. The effect of concentration on loan default rate is also economically significant. For instance, a one standard deviation increase in concentration increases loan default by as much as 1.24 (based on Model 3) percentage points in the short run. Similarly, based on Model 5, the same increase in concentration can increase loan default by 4.71 percentage points in the long run.[10] These results are to some extent in contrast with the strand of literature which suggests that banking market concentration fosters relationship building, hence, enabling the acquisition of soft credit information. For instance, contrary to Petersen and Rajan (1995) and Cetorelli and Peretto (2000), our findings seem to suggest that banks in concentrated markets may not have any screening informational advantage from their long-term relationships with their borrowers. Therefore, they are unable to reduce the adverse selection problem to consequently improve their loan quality. In fact, it is plausible that default rates may rise in concentrated banking markets if the borrowers take advantage of their longstanding relationships with the banks to renege on their repayment commitments.

Further, it is plausible for there to be informational advantage for the few top banks in concentrated markets, but for the banks to disregard the information and lend inefficiently (Bonaccorsi and Dell'Ariccia, 2004), which may be due to the absence of competition (Berger and Hannan, 1998) or the presence of governments' 'too-big-to-fail' bailout arrangements (Acharya et al., 2013). In fact, consistent with our findings, Berger et al. (2009) provide

[10]A separate table for the marginal effect of concentration is not reported for brevity but is available upon request.

evidence in support of this line of argument – they show a significant positive impact of banking market concentration on loan default rates. Given the conflicting theoretical predictions regarding the real effect of banking market concentration, we provide further analysis in subsection 4.2.

We draw further insights into what drives bank loan default rate from the coefficients on other control variables. The coefficients on *Lending* is negative and largely statistically significant. This finding is consistent with Berger et al. (2009,) and Jiménez et al. (2013) and suggests that banks with higher lending specialisation have lower loan defaults. Contrary to Jiménez et al. (2013), however, but consistent with Ghosh (2015), we find that banks that are efficient have lower loan defaults, as shown by the statistically significant negative coefficient on *Profit* across all models. *Size* and *Capital* are positive, but often insignificant. In line with previous studies (e.g., Berger et al., 2009; Buncic and Melecky, 2013; Jiménez et al., 2013), the results further suggest that GDP growth reduces loan defaults. Consistent with Ghosh (2015), we find some evidence that inflation reduces default rate, albeit not robustly.

Third, the governance indicators of the rule of law (*Law*), regulatory quality (*Regulation*) and control of corruption (*Control*) all have a negative impact on loan default rate. However, the coefficients on rule of law are statistically insignificant across all models. The negative impact of governance quality on loan default suggests that the macro-level governance infrastructure of a country either helps banks to effectively enforce their loan contracts at minimal costs or incentivise borrowers to willingly commit to loan repayments. Hence, loan defaults appear to be lower in better-governed regimes.

4.2 Information sharing, loan default and banking concentration

The results presented in the preceding section conditioned bank loan default on the level of credit information sharing. However, to the extent that banking market concentration reduces the dispersion of credit information (Marquez 2002; Fosu, 2014) and increases the degree of credit market screening (Cetorelli and Peretto, 2000) and the acquisition of soft credit information through relationship banking (Petersen and Rajan, 1995), we now proceed to condition the relationship between credit information sharing and loan default rate on banking market concentration. We present the findings in Table 5.

[Table 5 about here]

In Models 1 to 3 of Table 5, we confirm the negative relationship between credit information sharing and loan default rate. We also find evidence for the moderating role of banking market concentration on the credit information sharing–loan default rate nexus. The coefficients on the depth of credit information sharing remain negative and statistically significant. Interestingly, the coefficients on the interaction terms between credit information sharing and banking market concentration are positive and statistically significant, suggesting that the reduction in loan default rate arising from credit information sharing is lower in concentrated banking markets.

We confirm the moderating effect of banking market concentration on the relationship between credit information sharing and loan default rate in Models 4 to 9 of Table 5. In Models 4 to 6, the coefficients on the credit registry (*Registry*) coverage remain negative and statistically significant at the 1% level, whilst the coefficients on the interaction term between this variable and banking market concentration (*Concentration* X *Registry*) are positive and statistically significant at the 1% level. The same is true for the coefficients on private bureau (*Bureau*) and the interaction between this variable and concentration (*Concentration* X *Bureau*) in Models 7 to 9. These findings suggest that, although an increase in credit registry and private bureau coverage is associated with a reduction in loan default rate, the reduction in loan default rate decreases with banking market concentration.

[Table 6 about here]

To show the moderating role of banking market concentration, we evaluate the statistical and economic significance of the above findings by presenting the marginal effect of the depth of information sharing evaluated at the sample mean of default and at the relevant levels of banking market concentration (see Table 6). The results suggest that the effect of credit information sharing on loan default is also economically significant. For instance, based on Models 1 to 3 of Table 5, the marginal effect analysis in Table 6 shows that, at the 25th percentile of concentration, a one standard deviation increase in the depth of credit information sharing could reduce loan default by about 2.23-2.27 percentage points in the short run (Panel 1). This effect reduces to 1.95-1.99 percentage points at the 75th percentile of banking market concentration. Thus, the change in the reduction in loan default for a country moving from the 25th percentile to the 75th percentile of banking market concentration is approximately 0.3 percentage points, which is statistically significant at the 1% level. In the long run (Panel 2), the same shift in banking market concentration (from the 25th to the 75th percentiles) could reduce the effect of credit information sharing by approximately 1 percentage point. Similar

results are obtained from the marginal effect analysis based on credit registry (Models 4-6) and private bureau (Models 1-9) coverage, although the moderating role of concentration is relatively small for a one standard deviation change. Overall, the foregoing suggests that banking market concentration moderates the effect of credit information sharing on loan default, providing support for our second research hypothesis (*H2*).

As in Table 3, the coefficients on *Concentration* in Table 5 remain positive and largely significant indicating that banking market concentration, on average, increases loan default rate. Moreover, the interaction terms between *Concentration* and the credit information sharing variables are positive and significant, suggesting that banking market concentration increases loan default, especially in an environment where credit information is shared. Thus, it seems banks in concentrated markets tend to benefit less from credit information sharing. This may be explained by the view that information sharing reduces the informational rent and the resulting competitive advantage a bank derives from its private investment in collecting information about its borrowers (Cetorelli and Peretto, 2000). Information sharing, therefore, seems to end up weakening the private incentive for banks in concentrated markets to invest in screening technologies to accumulate credible borrower information. This then leads to the generation and sharing of low quality information among lenders, which in turn results in poor lending decisions and higher default rates. Another plausible interpretation is that lending in concentrated markets may be driven more by personal and close ties between lenders and borrowers developed over time than by the economic dictates of the available credit information. Banks, therefore, choose to lend to a long-standing client even when available information requires credit to be denied.

4.3 Information sharing, loan default and governance quality

In this section, we focus on the moderating role of governance quality – rule of law (*Law*), regulatory quality (*Regulation*) and control of corruption (*Control*) – underpinning the extent of creditor protection in banking markets. The results in Table 7 show that the coefficients on the credit information sharing variables remain negative and statistically significant. However, the moderating role of the governance indicators on the credit information sharing–loan default rate link is mixed. For instance, when we consider the rule of law, its moderating impact is statistically insignificant in two out of our three proxies for information sharing (i.e., *Depth* and *Bureau*). It is only when information sharing is measured by the number of people and

firms covered by a public credit registry (i.e., *Registry*) that we observe a positive and statistically significant interaction effect. Again, inconclusive results are observed for the regulatory quality indicator with the information sharing measure, *Depth* (*Registry*), showing a statistically negative (positive) interaction effect, while the *Bureau* measure had an insignificant interaction effect. Finally, the control of corruption indicator (*Control*) consistently shows an insignificant interaction effect across all models. Overall, our results for the moderating role of governance quality[11] are inconclusive, but they seem to largely tilt towards the conclusion that the role of credit information sharing in reducing loan default rates is not systematically higher or lower in better-governed countries, relative to poorly-governed countries. Therefore, Hypothesis 3 (*H3*) does not seem to be supported by our results, or, at least, *H3* is only weakly supported in the rule of law and regulatory quality dimensions.

[Table 7 about here]

4.4 Information sharing, loan default, banking market concentration and governance quality

In this section, we control jointly for the interaction effects of banking market concentration and national governance quality on the relationship between credit information sharing and loan default rate. The results in Table 8 show that the coefficients on the credit information sharing variables remain negative across all models. Also, the coefficients remain statistically significant at the 1% level across all models. These results confirm our prior findings, suggesting that the depth of credit information sharing, credit registry coverage, as well as private bureau coverage, all reduce loan default rate, and thus providing support for Hypothesis 1. Further, the coefficient on the interaction terms between *Concentration* and the information sharing variables remains positive and statistically significant at the 1% level. This strengthens our previous findings that provided support for Hypothesis 2, suggesting that the effect of credit information sharing on loan default decreases with banking market concentration. We also provide support for the mixed role of governance indicators in the relationship between

[11] When we utilise Principal Component Analysis to construct a single composite governance quality measure from the three governance variables (rule of law, regulatory quality, and the control of corruption) and re-run regressions with the composite measure of governance quality, the results remain mixed. These results are untabulated to save space. We are grateful to an anonymous reviewer for suggesting this robustness testing.

information sharing and loan default, although the evidence seems to point more to a lack of statistically significant moderating role of governance.

[Table 8 about here]

4.5 Credit information sharing and loan default rate – The endogeneity issue

In this section, we address the potential of endogeneity problems that may plague our findings. Such problems may arise from possible simultaneous determination of credit information sharing and loan default rate. For instance, it is likely that a move towards facilitating lending decisions may lead to a decision to establish credit information sharing schemes. Also, it is possible that relevant omitted variables could jointly determine both lending and default rates, as well as the degree of information sharing. These may, however, not be a problem in our set-up for two main reasons. First, we instigate loan default rate at the bank level in relation to credit information sharing mechanism at the country level; individual bank-level lending decisions are less likely to be directly influenced by country-level information sharing mechanism. Further, our econometric set-up – the dynamic systems GMM technique – simultaneously estimates the model in first-differences and in levels in order to eliminate the potential bias from omitted unobserved bank- and country-specific factors that are invariant across time (Bond et al., 2001). This notwithstanding, we explicitly attempt to address this concern by extending our analysis to control for factors that may influence the decision to set up credit information schemes. We present the results in Table 9.

Consistent with Büyükkarabacak (2012) and Houston et al. (2010), who identify urbanisation, ethnic fractionisation and geographical latitude as potential determinants of information flow, we control for these additional factors in our GMM set-up. As argued in Büyükkarabacak (2012), a high rate of urbanisation impedes the dissemination of information in a country and could, lead to increased default rates. However, urbanisation can also increase lending concentration and improve the acquisition of soft information, and thereby, improving loan quality. Consistent with the latter argument, we observe that urbanisation is associated with lower loan defaults. Moreover, it is argued that geography defines overall institutional development, and consequently financial development (Acemoglu et al., 2005; Beck, et al., 2009). It could, thus, impact the financial system and default rates. Consistently, we find that geographic latitude is associated with lower loan default. Further, ethnic fractionisation could be associated with high degree of agency problems (Djankov, et al., 2007), which could worsen

credit risk. Consistent with this argument, we find that ethnic fractionisation increases loan default.

[Table 9 about here]

The results in Table 9 confirm the negative effect of credit information sharing on bank loan default rate. The coefficients on the depth of credit information as well as credit registry and private bureau coverage enter all the models with a negative sign and are statistically significant. Additionally, the interaction term between credit information sharing variables and banking market concentration remains positive and significant at the 1% level. The coefficients on the interactions between the governance indicators and information sharing remain qualitatively similar to those reported earlier. Overall, these findings corroborate our earlier findings suggesting that credit information sharing reduces loan default but less so in more concentrated banking markets.

4.6 Further robustness tests

Thus far, our measure of loan default rate has been non-performing loans rates. We now consider the robustness of our findings to an alternative dependent variable - net charge-offs rates (defined as net charge-offs / average gross loans), which reflects the actual loan write-offs. As seen from Table 10, the results that credit information sharing improves loan quality remain unchanged. The moderating effect of banking market concentration is also robust to using the net charge-offs measure of loan default rates. In untabulated results, we also use country-level loan default rates (instead of firm-level measures) as our dependent variable and find qualitatively similar results.

[Table 10 about here]

Second, we replace our broad country-level regulation variable with a narrowly-defined set of variables (i.e., *Activity Restriction*, *Capital Stringency*, and *Supervisory Power*) reflecting different banking regulatory regimes (Barth et al., 2013). The results reported in Table 11 support our main conclusions on the effect of credit information sharing on loan default rates and the interaction role of concentration. With respect to the banking regulatory variables, both

capital stringency and supervisory power impact default rates negatively, while activity restriction has a positive, but insignificant effect on loan default rates.

[Table 11 about here]

5. Conclusion

The findings of prior studies suggest that credit information sharing can have a number of positive effects, including reducing loan default rates, enhancing access to private credit and improving credit market performance (Jappelli, and Pagano, 2002; Brown et al. 2009; Fosu, 2014). However, the extent to which credit information sharing influences loan default rate has rarely been examined, particularly in developing countries. Consequently, in this paper, we offer fresh perspectives to the growing literature on credit information sharing by empirically examining the relationship between credit information sharing and loan default in developing countries, where information asymmetry problems are acute. In particular and motivated by the growing attention being paid to banking market concentration and credit information mechanisms in developing countries, we provide first-hand evidence using a sample of 879 banks from 87 countries from every continent over a nine-year period (i.e., over 6,300 observations). Notably, evidence presented in this paper indicates that credit information sharing leads to a reduction in banks' loan default rate. However, the extent to which credit default reduces in response to credit information sharing is moderated by banking market concentration and, to some extent, national governance quality. These findings are new and robust to alternative econometric specifications.

Our study, therefore, contributes to the literature by incorporating bank heterogeneity across markets, as well as providing a more generalizable findings than prior studies. We further offer a more focused analysis by not merely considering the presence or absence of information sharing schemes, but rather examining how the nature and quality of the information sharing schemes may impact actual loan default rates, not the probability of default, as used in some prior research (e.g., Behr and Sonnekalb, 2012). Moreover, we make an additional contribution to the literature by distinctively investigating the potential moderating roles that industry (banking market) concentration and national governance quality (rule of law, regulatory quality and control of corruption) may play in the information sharing-loan default nexus. By this, we recognise that the extent of competitive forces and special long-term lender-borrower

relationships in concentrated banking markets may limit or enhance the value of information sharing in such markets. Similarly, country-level governance issues such as the rule of law, the quality of regulations enacted and the levels of corruption prevailing in an environment may also shape the extent to which information sharing impacts loan default rates. Besides contributing to the information sharing literature, these analyses allow us to add to the literature on the effect of market concentration and national governance quality on corporate outcomes (e.g., Marquez, 2002; Hauswald and Marquez, 2006; Lian, 2018).

A major implication of the findings of our study is that greater information sharing leads to a lower loan default rate for borrowers in developing countries, where institutional voids make adverse selections and moral hazards severe problems for banks. Therefore, the promotion of credit information sharing schemes across developing economies seems to be a step in the right direction since it has the potential to improve the balance sheets of banks, boost lending and even make the financial system more stable. However, in order to reap greater benefits from information sharing, countries with highly concentrated banking markets may need to take steps to increase competition, and perhaps reduce the risk of inefficient lending.

Although our study employs a large dataset comprising bank-level data from BankScope and country-level data from the World Bank with highly robust results, our findings may, however, be limited by the errors and omissions of these data sources. For instance, Bhattacharya (2003) points out that the BankScope database suffers from selectivity bias, and particularly in its coverage of firms in developing countries in that it almost completely omits rural and foreign banks. Given the focus of our analysis on developing countries, it is likely that our results apply more to domestic and commercial banks in urban centres, and generalisation to other banks should be carried out with caution. Future studies can, however, extend our analysis specifically to rural and foreign banks to see how information sharing influences the lending outcomes of such banks. Similarly, as with archival studies of this nature, our measures for credit information sharing, loan default rates, banking market concentration and governance quality, amongst others, may or may not reflect practice. Future research can offer additional and nuanced insights by conducting in-depth interviews and surveys with bankers and regulatory bodies regarding these issues.

Appendix 1

[Figure 1 about here]

Appendix 2

[Table 12 about here]

Appendix 3

[Table 13 about here]

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Table 1: Descriptive statistics

		Standard deviation					Percentile			
	Mean	Overall	Between	Within	Min	Max	25th	50th	75th	Obs
NPL	0.06	0.07	0.06	0.04	0.00	0.28	0.01	0.03	0.08	6323
Depth	3.54	2.41	2.13	1.12	0.00	6.00	0.00	5.00	6.00	6323
Registry	9.37	13.01	11.54	6.81	0.00	63.80	0.00	1.40	16.40	6323
Bureau	29.00	31.42	29.13	11.77	0.00	100.00	0.00	18.40	52.10	6323
Size	6.82	1.86	1.81	0.40	3.76	10.38	5.41	6.63	8.19	6323
Lending	0.61	0.17	0.16	0.07	0.27	0.93	0.49	0.61	0.73	6323
Profit	0.02	0.02	0.02	0.01	-0.02	0.06	0.01	0.02	0.03	6318
Capital	0.15	0.09	0.09	0.03	0.06	0.43	0.09	0.12	0.17	6323
Concentration	0.56	0.15	0.13	0.06	0.23	1.00	0.45	0.56	0.68	6317
GDP growth	4.77	4.49	2.45	3.82	-17.95	34.50	2.48	5.00	7.30	6294
Inflation	6.63	5.33	4.28	3.73	-4.86	59.22	3.18	5.50	8.89	5868
Law	-0.22	0.72	0.70	0.09	-1.79	1.77	-0.76	-0.35	0.18	6323
Regulation	0.06	0.70	0.69	0.11	-1.64	2.00	-0.40	0.09	0.43	6323
Control	-0.17	0.76	0.73	0.11	-1.52	2.42	-0.72	-0.34	0.13	6323

This table presents the descriptive statistics for all variables used in this study. NPL is the ratio of non-performing loans to total loans; Depth is the depth of credit information, an index that captures the depth of credit information; Registry is credit registry coverage, measured as the number of individuals and firms listed by a public credit registry concerning the information on their borrowing history for the past five years, expressed as a percentage of the adult population. Bureau is credit bureau coverage and measures the number of individuals and firms listed in a private credit bureau concerning the information on their borrowing history for the past five years, expressed as a percentage of the adult population; Size is the logarithm of the total bank assets; Lending is lending specialisation and is measured as total loans as a ratio of total assets; Profit is the ratio of operating profit to total assets; Capital is the ratio of book value of equity to total assets; Concentration is the three-bank concentration ratio, measured as the share of assets of the largest three banks as a percentage of total banking assets; GDP growth is the annual percentage change in real GDP; Inflation is the annual percentage change in the consumer price index; Law, Regulation and Control are respectively Rule of law, Regulatory quality and Control of corruption, indicators capturing the quality of governance, all of which are defined in detail in subsection 4.2.

Table 2: Correlations matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. NPL	1.00													
2. Depth	-0.09[a]	1.00												
3. Registry	0.04[a]	0.45[a]	1.00											
4. Bureau	-0.13[a]	0.67[a]	0.24[a]	1.00										
5. Size	-0.16[a]	0.13[a]	-0.07[a]	0.10[a]	1.00									
6. Lending	0.06[a]	0.17[a]	0.12[a]	0.03	-0.08[a]	1.00								
7. Profit	-0.25[a]	-0.09[a]	-0.08[a]	-0.06[a]	-0.03	0.01	1.00							
8. Capital	0.11[a]	0.09[a]	0.02	0.07[a]	-0.34[a]	0.05[a]	0.25[a]	1.00						
9. Concentration	0.06[a]	-0.19[a]	-0.01	-0.16[a]	-0.20[a]	-0.15[a]	0.00	-0.09[a]	1.00					
10. GDP Growth	-0.13[a]	-0.17[a]	-0.13[a]	-0.13[a]	-0.04[a]	-0.10[a]	0.19[a]	-0.00	0.14[a]	1.00				
11. Inflation	-0.01	-0.27[a]	-0.13[a]	-0.22[a]	-0.12[a]	-0.08[a]	0.15[a]	0.01	-0.03	0.08[a]	1.00			
12. Law	-0.05[a]	0.13[a]	-0.05[a]	0.23[a]	0.40[a]	0.04[a]	-0.08[a]	0.02	-0.11[a]	-0.07[a]	-0.33[a]	1.00		
13. Regulation	-0.09[a]	0.21[a]	-0.06[a]	0.24[a]	0.36[a]	0.07[a]	-0.10[a]	0.03	-0.17[a]	-0.12[a]	-0.38[a]	0.88[a]	1.00	
14. Corruption	-0.12[a]	0.19[a]	-0.04[a]	0.34[a]	0.38[a]	0.01	-0.05[a]	0.02	-0.08[a]	-0.06[a]	-0.32[a]	0.92[a]	0.83[a]	1.00

This table presents the unconditional correlation coefficient between any pair of variables. Variables are as described in Table 1. [a] indicates significance at 1% or better.

Table 3: Information sharing and loan default

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Lagged Logit(NPL)	0.726***	0.725***	0.711***	0.739***	0.738***	0.725***	0.702***	0.704***	0.698***
	(0.054)	(0.054)	(0.055)	(0.050)	(0.049)	(0.050)	(0.053)	(0.052)	(0.053)
Size	0.044	0.049*	0.059**	0.019	0.028	0.038	0.023	0.031	0.037
	(0.027)	(0.027)	(0.028)	(0.026)	(0.026)	(0.027)	(0.029)	(0.029)	(0.030)
Lending	-0.315	-0.304	-0.357	-0.411*	-0.386*	-0.442*	-0.522**	-0.500*	-0.529**
	(0.231)	(0.228)	(0.238)	(0.232)	(0.228)	(0.239)	(0.260)	(0.256)	(0.262)
Profit	-9.570***	-9.633***	-9.832***	-8.962***	-9.098***	-9.268***	-9.880***	-9.906***	-9.973***
	(1.982)	(1.978)	(2.017)	(1.833)	(1.843)	(1.874)	(2.044)	(2.036)	(2.052)
Capital	0.293	0.325	0.387	-0.062	0.014	0.072	0.053	0.119	0.150
	(0.540)	(0.530)	(0.559)	(0.509)	(0.500)	(0.530)	(0.595)	(0.584)	(0.598)
GDP Growth	-0.029***	-0.029***	-0.030***	-0.027***	-0.027***	-0.027***	-0.028***	-0.028***	-0.028***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Inflation	-0.007	-0.010*	-0.011**	-0.002	-0.006	-0.007	-0.006	-0.008*	-0.009*
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Concentration	1.255***	1.225***	1.366***	1.358***	1.316***	1.463***	1.359***	1.336***	1.406***
	(0.335)	(0.328)	(0.349)	(0.336)	(0.327)	(0.349)	(0.348)	(0.343)	(0.354)
Depth	-0.074***	-0.071***	-0.073***						
	(0.018)	(0.017)	(0.018)						
Registry				-0.007***	-0.007***	-0.008***			
				(0.002)	(0.002)	(0.002)			
Bureau							-0.008***	-0.007***	-0.007***
							(0.002)	(0.001)	(0.002)
Law	-0.073			-0.067			-0.004		
	(0.050)			(0.049)			(0.054)		
Regulation		-0.135***			-0.151***			-0.064	
		(0.050)			(0.051)			(0.049)	
Control			-0.163***			-0.182***			-0.085*
			(0.047)			(0.047)			(0.049)
Constant	-1.380***	-1.382***	-1.588***	-1.449***	-1.367***	-1.678***	-1.300***	-1.342***	-1.462***
	(0.397)	(0.382)	(0.413)	(0.370)	(0.373)	(0.391)	(0.402)	(0.389)	(0.414)
Observations	4995	4995	4995	4995	4995	4995	4995	4995	4995
Hansen test p-value	0.126	0.134	0.194	0.200	0.207	0.290	0.299	0.285	0.313
AR(1)test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test p-value	0.782	0.785	0.796	0.777	0.778	0.788	0.825	0.824	0.831

This table shows the dynamic system GMM estimation results for the effect of credit information on bank credit default rate. Time fixed effects are included in all estimations. All variables are as described in Table 1. Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses. *, **, *** indicate significance at 10%, 5% and 1% respectively.

Table 4: Marginal effect of information sharing on non-performing loans (NPL)

	(1) Rule of law	(2) Regulatory quality	(3) Control of corruption
Panel 1: Short-run effect			
Depth	-0.919***	-0.888***	-0.909***
	(0.204)	(0.199)	(0.204)
Registry	-0.510***	-0.510***	-0.529***
	(0.161)	(0.161)	(0.162)
Bureau	-1.185***	-1.134***	-1.098***
	(0.216)	(0.209)	(0.219)
Panel 2: Long-run effect			
Depth	-3.352***	-3.229***	-3.147***
	(0.534)	(0.533)	(0.524)
Registry	-1.952***	-1.946***	-1.920***
	(0.559)	(0.559)	(0.546)
Bureau	-3.981***	-3.836***	-3.638***
	(0.623)	(0.625)	(0.647)

This table shows the marginal effect of one standard deviation change in credit information on NPL. All variables are as described in Table 1. Standard errors are in parentheses. *** indicates 1%.

Table 5: Information sharing and loan default rates – Interaction with banking market concentration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged Logit(NPL)	0.740***	0.740***	0.729***	0.747***	0.747***	0.736***	0.735***	0.737***	0.733***
	(0.050)	(0.050)	(0.050)	(0.046)	(0.046)	(0.047)	(0.052)	(0.051)	(0.053)
Size	0.045*	0.053**	0.061**	0.014	0.024	0.034	0.031	0.034	0.044
	(0.026)	(0.025)	(0.026)	(0.025)	(0.025)	(0.026)	(0.027)	(0.027)	(0.028)
Lending	-0.317	-0.303	-0.347	-0.413*	-0.385*	-0.432*	-0.390	-0.375	-0.394
	(0.221)	(0.218)	(0.226)	(0.222)	(0.219)	(0.229)	(0.239)	(0.236)	(0.242)
Profit	-9.239***	-9.332***	-9.468***	-8.713***	-8.828***	-8.968***	-9.076***	-9.062***	-9.082***
	(1.858)	(1.860)	(1.887)	(1.742)	(1.754)	(1.781)	(1.911)	(1.901)	(1.912)
Capital	0.348	0.403	0.467	-0.124	-0.038	0.024	0.123	0.153	0.211
	(0.512)	(0.503)	(0.529)	(0.488)	(0.480)	(0.506)	(0.555)	(0.544)	(0.556)
GDP Growth	-0.026***	-0.026***	-0.026***	-0.025***	-0.026***	-0.026***	-0.026***	-0.026***	-0.025***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Inflation	-0.009	-0.011**	-0.013**	-0.002	-0.005	-0.007	-0.006	-0.008	-0.009*
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Concentration	0.161	0.118	0.200	0.798***	0.768***	0.891***	0.532**	0.515**	0.536**
	(0.161)	(0.160)	(0.164)	(0.253)	(0.248)	(0.266)	(0.211)	(0.208)	(0.213)
Depth	-0.274***	-0.274***	-0.281***						
	(0.069)	(0.068)	(0.068)						
Registry				-0.042***	-0.041***	-0.041***			
				(0.010)	(0.010)	(0.010)			
Bureau							-0.021***	-0.021***	-0.021***
							(0.005)	(0.005)	(0.005)
Concentration X Depth	0.344***	0.349***	0.359***						
	(0.098)	(0.097)	(0.098)						
Concentration X Registry				0.064***	0.062***	0.061***			
				(0.016)	(0.016)	(0.016)			
Concentration X Bureau							0.026***	0.025***	0.027***
							(0.007)	(0.007)	(0.007)
Law	-0.050			-0.049			-0.025		
	(0.046)			(0.047)			(0.051)		
Regulation		-0.122***			-0.130***			-0.061	
		(0.046)			(0.048)			(0.047)	

Control			-0.151***			-0.164***			-0.108**
			(0.043)			(0.044)			(0.048)
Constant	-0.670**	-0.687**	-0.850***	-1.067***	-1.099***	-1.295***	-0.836**	-0.844***	-0.969***
	(0.298)	(0.279)	(0.304)	(0.333)	(0.323)	(0.352)	(0.338)	(0.323)	(0.346)
Observations	4995	4995	4995	4995	4995	4995	4995	4995	4995
Hansen test p-value	0.136	0.143	0.197	0.392	0.379	0.452	0.240	0.231	0.243
AR(1)test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test p-value	0.735	0.737	0.746	0.741	0.742	0.753	0.761	0.761	0.766

This table shows the dynamic system GMM estimation results for the effect of credit information on bank credit default rate. Time fixed effects are included in all estimations. All variables are as described in Table 1. Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses. *, **, *** indicate significance at 10%, 5% and 1% respectively.

Table 6: Marginal effect of depth of credit information sharing on loan default at specified levels of banking market concentration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Depth of credit information			Credit registry			Private bureau		
	Rule of law	Regulatory quality	Control of corruption	Rule of law	Regulatory quality	Control of corruption	Depth of law	Regulatory quality	Control of corruption
Panel 1 – Short-run analysis									
25th percentile	-2.230***	-2.225***	-2.268***	-2.283***	-2.233***	-2.224***	-2.691***	-2.652***	-2.681***
	(0.415)	(0.410)	(0.407)	(0.418)	(0.417)	(0.419)	(0.427)	(0.426)	(0.430)
50th percentile	-2.096***	-2.089***	-2.130***	-2.259***	-2.209***	-2.200***	-2.683***	-2.643***	-2.672***
	(0.394)	(0.389)	(0.387)	(0.415)	(0.414)	(0.416)	(0.426)	(0.425)	(0.429)
75th percentile	-1.956***	-1.946***	-1.985***	-2.234***	-2.185***	-2.177***	-2.674***	-2.635***	-2.663***
	(0.371)	(0.367)	(0.365)	(0.412)	(0.411)	(0.413)	(0.425)	(0.424)	(0.428)
Change	0.274***	0.279***	0.284***	0.049***	0.048***	0.047***	0.017***	0.017***	0.018***
	(0.050)	(0.049)	(0.048)	(0.006)	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)
Panel 2 – Long-run analysis									
25th percentile	-8.588***	-8.542***	-8.361***	-9.008***	-8.824***	-8.421***	-10.160***	-10.090***	-10.025***
	(1.142)	(1.134)	(1.104)	(1.584)	(1.606)	(1.563)	(1.587)	(1.611)	(1.592)
50th percentile	-8.071***	-8.019***	-7.850***	-8.913***	-8.730***	-8.332***	-10.128***	-10.058***	-9.991***
	(1.067)	(1.060)	(1.033)	(1.570)	(1.591)	(1.549)	(1.582)	(1.606)	(1.586)
75th percentile	-7.531***	-7.472***	-7.315***	-8.816***	-8.635***	-8.242***	-10.095***	-10.025***	-9.958***
	(0.989)	(0.982)	(0.959)	(1.556)	(1.577)	(1.535)	(1.576)	(1.601)	(1.581)
Change	1.057***	1.070***	1.046***	0.192***	0.189***	0.179***	0.064***	0.065***	0.067***
	(0.180)	(0.178)	(0.173)	(0.032)	(0.032)	(0.031)	(0.012)	(0.012)	(0.012)

This table shows the marginal effect of one standard deviation change in credit information on NPL. All variables are as described in Table 1. Standard errors are in parentheses. *** indicates 1%.

Table 7: Information sharing and loan default – Interactions with governance variables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Lagged Logit(NPL)	0.729***	0.723***	0.711***	0.725***	0.729***	0.722***	0.707***	0.705***	0.704***
	(0.054)	(0.054)	(0.054)	(0.050)	(0.050)	(0.050)	(0.052)	(0.052)	(0.053)
Size	0.044	0.051*	0.058**	0.023	0.029	0.038	0.024	0.031	0.038
	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)	(0.027)	(0.029)	(0.029)	(0.029)
Lending	-0.312	-0.324	-0.376	-0.446*	-0.421*	-0.453*	-0.501**	-0.507**	-0.501*
	(0.229)	(0.229)	(0.240)	(0.239)	(0.235)	(0.241)	(0.253)	(0.256)	(0.256)
Profit	-9.489***	-9.505***	-9.722***	-9.251***	-9.352***	-9.352***	-9.842***	-9.824***	-9.907***
	(1.973)	(1.962)	(2.011)	(1.899)	(1.899)	(1.896)	(2.037)	(2.047)	(2.041)
Capital	0.285	0.272	0.353	-0.017	0.041	0.068	0.064	0.107	0.165
	(0.539)	(0.530)	(0.562)	(0.530)	(0.518)	(0.533)	(0.589)	(0.584)	(0.592)
GDP Growth	-0.029***	-0.029***	-0.030***	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Inflation	-0.007	-0.008	-0.010*	-0.005	-0.007	-0.008	-0.006	-0.007	-0.009*
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Concentration	1.234***	1.224***	1.339***	1.500***	1.379***	1.495***	1.326***	1.338***	1.355***
	(0.340)	(0.326)	(0.350)	(0.351)	(0.334)	(0.351)	(0.333)	(0.335)	(0.336)
Depth	-0.074***	-0.075***	-0.078***						
	(0.016)	(0.018)	(0.017)						
Registry				-0.007***	-0.009***	-0.007***			
				(0.002)	(0.002)	(0.002)			
Bureau							-0.007***	-0.007***	-0.007***
							(0.002)	(0.002)	(0.002)
Law X Depth	-0.003								
	(0.017)								
Regulation X Depth		-0.041**							
		(0.017)							
Control X Depth			-0.017						
			(0.016)						
Law X Registry				0.011***					
				(0.003)					
Regulation X Registry					0.006***				
					(0.002)				
Control X Registry						0.005			
						(0.003)			
Law X Bureau							0.001		
							(0.001)		

Regulation X Bureau								-0.001	
								(0.001)	
Control X Bureau									0.001
									(0.001)
Law	-0.060			-0.170***			-0.026		
	(0.090)			(0.056)			(0.075)		
Regulation		0.031			-0.197***			-0.037	
		(0.084)			(0.056)			(0.077)	
Control			-0.093			-0.208***			-0.119
			(0.085)			(0.050)			(0.077)
Constant	-1.357***	-1.364***	-1.535***	-1.571***	-1.405***	-1.605***	-1.283***	-1.344***	-1.441***
	(0.407)	(0.381)	(0.420)	(0.384)	(0.380)	(0.408)	(0.397)	(0.388)	(0.412)
Observations	4995	4995	4995	4995	4995	4995	4995	4995	4995
Hansen test p-value	0.127	0.178	0.227	0.324	0.272	0.313	0.290	0.294	0.296
AR(1)test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test p-value	0.781	0.791	0.803	0.782	0.787	0.788	0.818	0.826	0.823

This table shows the dynamic system GMM estimation results for the effect of credit information on bank credit default rate. Time fixed effects are included in all estimations. All variables are as described in Table 1. Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses. *, **, *** indicate significance at 10%, 5% and 1% respectively.

Table 8: Information sharing and loan default – Interaction with banking market concentration and governance quality

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Lagged Logit(NPL)	0.742***	0.738***	0.727***	0.739***	0.739***	0.733***	0.734***	0.736***	0.732***
	(0.050)	(0.050)	(0.050)	(0.047)	(0.047)	(0.048)	(0.051)	(0.051)	(0.052)
Size	0.045*	0.054**	0.062**	0.018	0.024	0.033	0.031	0.035	0.044
	(0.026)	(0.026)	(0.027)	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)	(0.028)
Lending	-0.318	-0.315	-0.376	-0.427*	-0.425*	-0.441*	-0.398*	-0.384	-0.401*
	(0.220)	(0.219)	(0.229)	(0.227)	(0.227)	(0.230)	(0.237)	(0.236)	(0.241)
Profit	-9.177***	-9.217***	-9.367***	-8.805***	-9.031***	-9.041***	-9.078***	-9.021***	-9.081***
	(1.853)	(1.855)	(1.884)	(1.793)	(1.809)	(1.802)	(1.922)	(1.916)	(1.925)
Capital	0.340	0.363	0.434	-0.065	-0.007	0.017	0.119	0.139	0.207
	(0.512)	(0.504)	(0.532)	(0.503)	(0.499)	(0.508)	(0.558)	(0.545)	(0.560)
GDP Growth	-0.026***	-0.026***	-0.026***	-0.027***	-0.027***	-0.027***	-0.025***	-0.026***	-0.025***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Inflation	-0.008	-0.010*	-0.011**	-0.005	-0.007	-0.008	-0.006	-0.007	-0.008*
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Concentration	0.144	0.137	0.141	0.813***	0.735***	0.905***	0.534**	0.531**	0.538**
	(0.166)	(0.156)	(0.170)	(0.261)	(0.251)	(0.268)	(0.211)	(0.206)	(0.212)
Depth	-0.275***	-0.271***	-0.297***						
	(0.067)	(0.068)	(0.068)						
Registry				-0.046***	-0.049***	-0.041***			
				(0.010)	(0.011)	(0.010)			
Bureau							-0.021***	-0.020***	-0.021***
							(0.005)	(0.005)	(0.005)
Concentration X Depth	0.344***	0.340***	0.371***						
	(0.097)	(0.097)	(0.098)						
Concentration X Registry				0.073***	0.073***	0.064***			
				(0.017)	(0.017)	(0.016)			
Concentration X Bureau							0.026***	0.025***	0.027***
							(0.007)	(0.007)	(0.007)
Law X Depth	-0.007								
	(0.016)								
Regulation X Depth		-0.029*							
		(0.015)							
Control X Depth			-0.025*						
			(0.015)						
Law X Registry				0.013***					
				(0.003)					

Regulation X Registry					0.009***				
					(0.002)				
Control X Registry						0.006*			
						(0.003)			
Law X Bureau							-0.000		
							(0.001)		
Regulation X Bureau								-0.001	
								(0.001)	
Control X Bureau									-0.000
									(0.001)
Law	-0.021			-0.161***			-0.014		
	(0.081)			(0.053)			(0.070)		
Regulation		-0.006			-0.196***			-0.035	
		(0.080)			(0.054)			(0.073)	
Control			-0.050			-0.195***			-0.096
			(0.076)			(0.047)			(0.071)
Constant	-0.646**	-0.686**	-0.767**	-1.117***	-1.070***	-1.298***	-0.837**	-0.854***	-0.967***
	(0.307)	(0.279)	(0.313)	(0.344)	(0.329)	(0.354)	(0.340)	(0.323)	(0.350)
Observations	4995	4995	4995	4995	4995	4995	4995	4995	4995
Hansen test p-value	0.141	0.173	0.249	0.517	0.498	0.484	0.237	0.231	0.241
AR(1)test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test p-value	0.736	0.742	0.757	0.749	0.757	0.751	0.762	0.764	0.767

This table shows the dynamic system GMM estimation results for the effect of credit information on bank credit default rate. Time fixed effects are included in all estimations. All variables are as described in Table 1. Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses. *, **, *** indicates significance at 10%, 5% and 1% respectively.

Table 9: Information sharing and loan default – Additional control variables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Lagged Logit(NPL)	0.731***	0.733***	0.729***	0.748***	0.741***	0.740***	0.792***	0.789***	0.788***
	(0.065)	(0.065)	(0.066)	(0.068)	(0.069)	(0.069)	(0.070)	(0.071)	(0.069)
Size	0.024	0.029	0.030	0.008	0.012	0.013	0.021	0.019	0.024
	(0.035)	(0.036)	(0.035)	(0.035)	(0.037)	(0.036)	(0.033)	(0.035)	(0.033)
Lending	-0.411	-0.373	-0.407	-0.466	-0.477*	-0.465	-0.263	-0.281	-0.260
	(0.270)	(0.261)	(0.273)	(0.286)	(0.286)	(0.287)	(0.261)	(0.267)	(0.260)
Profit	-5.866***	-5.789***	-5.866***	-5.585**	-5.742**	-5.749**	-5.178**	-5.238**	-5.360**
	(2.209)	(2.196)	(2.246)	(2.254)	(2.307)	(2.281)	(2.189)	(2.239)	(2.207)
Capital	-0.453	-0.428	-0.373	-0.638	-0.626	-0.613	-0.306	-0.358	-0.290
	(0.657)	(0.651)	(0.663)	(0.681)	(0.694)	(0.682)	(0.655)	(0.672)	(0.649)
GDP Growth	-0.034***	-0.033***	-0.033***	-0.037***	-0.036***	-0.036***	-0.031***	-0.031***	-0.030***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Inflation	-0.007	-0.008	-0.009	-0.004	-0.005	-0.004	-0.004	-0.003	-0.006
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Concentration	0.338*	0.456**	0.325*	0.895***	0.944***	0.945***	0.465**	0.543**	0.485**
	(0.188)	(0.182)	(0.187)	(0.345)	(0.356)	(0.347)	(0.230)	(0.236)	(0.231)
Depth	-0.259***	-0.236***	-0.277***						
	(0.082)	(0.079)	(0.085)						
Registry				-0.034***	-0.035***	-0.034***			
				(0.011)	(0.011)	(0.011)			
Bureau							-0.017***	-0.016***	-0.017***
							(0.006)	(0.006)	(0.005)
Concentration X Depth	0.331***	0.298***	0.342***						
	(0.117)	(0.112)	(0.119)						
Concentration X Registry				0.061***	0.059***	0.057***			
				(0.018)	(0.018)	(0.018)			
Concentration X Bureau							0.021***	0.020**	0.021***
							(0.008)	(0.008)	(0.008)
Law X Depth	-0.033								
	(0.020)								
Regulation X Depth		-0.045**							
		(0.022)							
Control X Depth			-0.055**						
			(0.022)						
Law X Registry				0.005*					
				(0.003)					
Regulation X Registry					0.003				

					(0.003)				
Control X Registry						-0.002			
						(0.003)			
Law X Bureau							-0.001		
							(0.001)		
Regulation X Bureau								-0.002*	
								(0.001)	
Control X Bureau									-0.001
									(0.001)
Law	0.183*			0.048			0.124		
	(0.099)			(0.049)			(0.076)		
Regulation		0.174*			0.008			0.161**	
		(0.098)			(0.049)			(0.076)	
Control			0.186*			0.035			0.056
			(0.103)			(0.051)			(0.076)
Ethnic fractinisation	0.506**	0.534**	0.585**	0.384*	0.432*	0.443**	0.363*	0.380*	0.377*
	(0.226)	(0.233)	(0.240)	(0.214)	(0.226)	(0.220)	(0.208)	(0.218)	(0.209)
Latitude	-0.924*	-0.844*	-0.859*	-0.886*	-0.809*	-0.763	-0.923*	-0.937*	-0.884*
	(0.480)	(0.466)	(0.475)	(0.475)	(0.473)	(0.467)	(0.491)	(0.489)	(0.486)
Urbanisation	-0.002	-0.001	-0.000	-0.006**	-0.005**	-0.005**	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Constant	-0.629*	-0.864**	-0.782**	-0.755*	-0.918**	-0.932**	-0.656*	-0.741*	-0.750**
	(0.372)	(0.372)	(0.373)	(0.417)	(0.457)	(0.425)	(0.371)	(0.385)	(0.370)
Observations	3703	3703	3703	3703	3703	3703	3703	3703	3703
Hansen test p-value	0.893	0.887	0.905	0.835	0.845	0.868	0.306	0.309	0.359
AR(1)test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test p-value	0.788	0.791	0.798	0.711	0.712	0.712	0.721	0.716	0.722

This table shows the dynamic system GMM estimation results for the effect of credit information on bank credit default rate. Time fixed effects are included in all estimations. All variables are as described in Table 1. Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses. *, **, *** indicates significance at 10%, 5% and 1% respectively.

Table 10: Information sharing and loan default – Using net charge offs as an alternative dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.Logit(net charge offs)	0.295***	0.298***	0.299***	0.290***	0.293***	0.308***	0.290***	0.301***	0.297***
	(0.073)	(0.074)	(0.073)	(0.073)	(0.075)	(0.070)	(0.074)	(0.073)	(0.074)
Size	0.155*	0.128	0.138*	0.161**	0.117	0.142*	0.158*	0.128	0.134*
	(0.081)	(0.079)	(0.077)	(0.081)	(0.080)	(0.077)	(0.081)	(0.079)	(0.078)
Lending	-2.064***	-2.095***	-2.235***	-2.222***	-2.279***	-2.199***	-2.001***	-2.047***	-2.126***
	(0.697)	(0.701)	(0.707)	(0.710)	(0.709)	(0.705)	(0.700)	(0.694)	(0.705)
Profit	-10.784**	-11.137**	-10.166*	-12.452**	-11.480**	-10.837**	-10.991**	-10.654*	-10.516*
	(5.481)	(5.550)	(5.590)	(5.559)	(5.607)	(5.498)	(5.473)	(5.509)	(5.535)
Capital	1.625	1.365	1.528	1.909	1.245	1.785	1.720	1.473	1.528
	(1.440)	(1.421)	(1.443)	(1.485)	(1.437)	(1.484)	(1.443)	(1.408)	(1.442)
GDP Growth	-0.017	-0.020	-0.015	-0.010	-0.023	-0.009	-0.018	-0.019	-0.017
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)	(0.015)
Inflation	-0.006	-0.002	-0.003	-0.013	-0.005	-0.009	-0.009	0.006	-0.009
	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.012)	(0.013)	(0.012)
Concentration	2.893***	3.017***	2.913***	-0.459	1.921**	0.756	3.014***	3.154***	2.849***
	(0.931)	(0.946)	(0.934)	(0.603)	(0.893)	(0.719)	(0.939)	(0.951)	(0.928)
Depth	-0.085*			-0.616***			-0.089*		
	(0.045)			(0.169)			(0.047)		
Registry		-0.014*			-0.094**			-0.023**	
		(0.007)			(0.038)			(0.010)	
Bureau			-0.006			-0.047***			-0.008*
			(0.004)			(0.013)			(0.005)
Concentration X Depth				0.919***					
				(0.270)					
Concentration X Registry					0.149**				
					(0.062)				
Concentration X Bureau						0.073***			
						(0.020)			
Regulation X Depth							0.087*		
							(0.052)		
Regulation X Registry								0.025**	
								(0.011)	
Regulation X Bureau									0.005
Regulation	-0.103	-0.133	-0.046	-0.124	-0.095	-0.081	-0.459*	-0.191	-0.250
	(0.120)	(0.119)	(0.138)	(0.123)	(0.124)	(0.139)	(0.237)	(0.121)	(0.195)
									(0.004)
Constant	-5.503***	-5.433***	-5.441***	-3.496***	-4.611***	-4.049***	-5.660***	-5.567***	-5.382***
	(1.119)	(1.163)	(1.131)	(0.936)	(1.203)	(1.028)	(1.135)	(1.165)	(1.135)

Observations	1908	1908	1908	1908	1908	1908	1908	1908	1908
Hansen test p-value	0.748	0.690	0.754	0.843	0.776	0.939	0.739	0.603	0.742
AR(1)test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test p-value	0.652	0.644	0.670	0.609	0.659	0.664	0.596	0.712	0.615

This table shows the dynamic system GMM estimation results for the effect of credit information on bank net charge off rate. Time fixed effects are included in all estimations. All variables are as described in Table 1. Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses. *, **, *** indicates significance at 10%, 5% and 1% respectively.

Table 11: Information sharing and loan default - With bank regulation variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged Logit(NPL)	0.780***	0.774***	0.772***	0.787***	0.790***	0.784***	0.774***	0.764***	0.775***
	(0.054)	(0.067)	(0.057)	(0.053)	(0.061)	(0.054)	(0.055)	(0.069)	(0.057)
Size	0.043	0.033	0.035	0.046	0.037	0.040	0.045	0.027	0.036
	(0.032)	(0.031)	(0.034)	(0.031)	(0.029)	(0.031)	(0.033)	(0.033)	(0.034)
Lending	-0.266	-0.441	-0.430	-0.249	-0.432	-0.403	-0.275	-0.434	-0.380
	(0.268)	(0.304)	(0.287)	(0.260)	(0.290)	(0.267)	(0.272)	(0.309)	(0.280)
Profit	-7.651***	-7.734***	-7.117***	-7.252***	-7.397***	-6.943***	-7.748***	-8.088***	-7.321***
	(2.079)	(2.237)	(2.019)	(2.008)	(2.081)	(1.919)	(2.098)	(2.336)	(2.058)
Capital	0.277	0.195	0.129	0.288	0.312	0.181	0.247	0.142	0.119
	(0.567)	(0.528)	(0.573)	(0.554)	(0.492)	(0.531)	(0.579)	(0.545)	(0.565)
GDP per capita	-0.053	-0.033	-0.025	-0.055	-0.019	-0.022	-0.060	-0.032	-0.016
	(0.042)	(0.042)	(0.041)	(0.041)	(0.038)	(0.038)	(0.043)	(0.044)	(0.041)
GDP Growth	-0.037***	-0.040***	-0.034***	-0.036***	-0.038***	-0.032***	-0.037***	-0.042***	-0.033***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)	(0.006)
Inflation	-0.007	-0.003	-0.006	-0.008	-0.004	-0.007	-0.007	-0.005	-0.008
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Concentration	0.871***	1.342***	0.997***	0.082	0.307	-0.218	0.828**	1.487***	1.131***
	(0.326)	(0.434)	(0.344)	(0.194)	(0.232)	(0.216)	(0.328)	(0.468)	(0.371)
Depth	-0.077***	-0.100***	-0.097***	-0.214***	-0.264***	-0.304***	-0.190***	0.129**	0.073
	(0.021)	(0.028)	(0.025)	(0.066)	(0.088)	(0.086)	(0.060)	(0.057)	(0.058)
Concentration X Depth				0.247**	0.298**	0.356***			
				(0.103)	(0.122)	(0.120)			
Activity restrict X Depth							0.015**		
							(0.007)		
Capital stringency X Depth								-0.044***	
								(0.014)	
Supervisory power X Depth									-0.015**
									(0.006)
Activity restrict	0.040			0.029			-0.016		
	(0.025)			(0.023)			(0.030)		
Capital stringency		-0.127***			-0.130***			0.043	
		(0.045)			(0.045)			(0.027)	
Supervisory power			-0.036**			-0.048***			0.027
			(0.016)			(0.018)			(0.017)
Constant	-0.859*	-0.116	-0.282	-0.301	0.379	0.569	-0.361	-1.118***	-1.177**
	(0.440)	(0.319)	(0.374)	(0.361)	(0.357)	(0.393)	(0.495)	(0.401)	(0.466)
Observations	3633	3486	3697	3633	3486	3697	3633	3486	3697
Hansen test p-value	0.106	0.103	0.262	0.098	0.105	0.263	0.104	0.099	0.231
AR(1)test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test p-value	0.917	0.980	0.819	0.931	0.971	0.824	0.914	0.957	0.839

This table shows the dynamic system GMM estimation results for the effect of credit information on bank credit default rate. Time fixed effects are included in all estimations. All variables are as described in Table 1. Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses. *, **, *** indicates significance at 10%, 5% and 1% respectively.

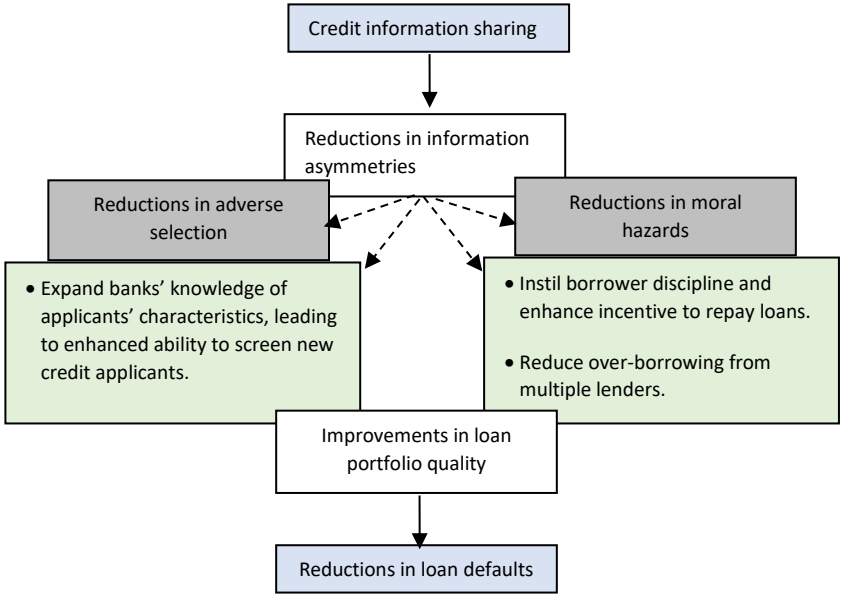

Figure 1: The key channels through which credit information sharing reduces loan default rates

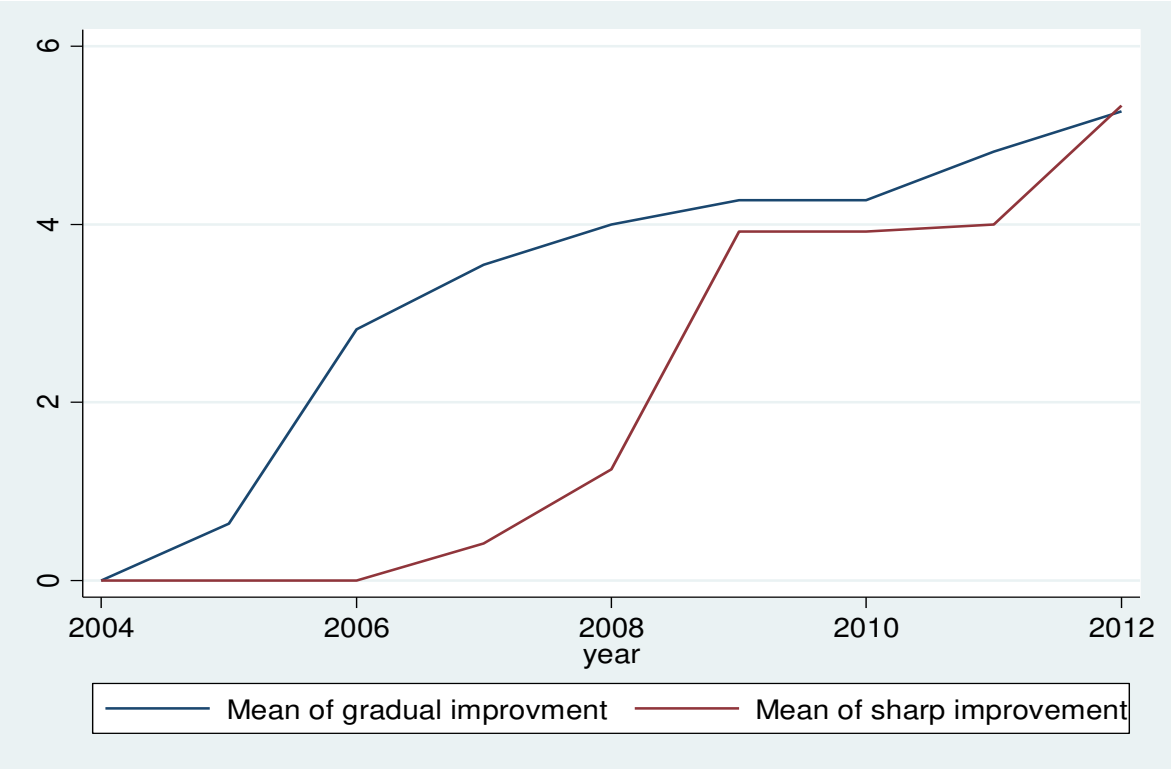

Figure 2: Trends in depth of credit information index for the group of countries with sharp and those with gradual improvements.
Note: The list of countries showing major improvements in information sharing include: *Costa Rica, Croatia, Kazakhstan, Lithuania, Macedonia (Fyrom), Mauritius, Mongolia, Oman, Romania, Saudi Arabia, Serbia,* **Albania, Armenia, Azerbaijan, Belarus, Egypt, Georgia, Ghana, Latvia, Morocco, Rwanda, United Arab Emirates, Zambia**. Please note that the countries in *italics* (**bold**) experienced *gradual* (**sharp**) improvements in information sharing during the sample period.

Table 12: List of countries and cross-sectional sample distribution

Country	No of banks	Percentage	Country	No of banks	Percentage	Country	No of banks	Percentage
Albania	8	0.91	Guyana	2	0.23	Peru	17	1.93
Algeria	2	0.23	Haiti	3	0.34	Philippines	15	1.71
Angola	5	0.57	Honduras	13	1.48	Qatar	7	0.8
Argentina	33	3.75	Hong Kong	32	3.64	Republic of Moldova	3	0.34
Armenia	11	1.25	Jamaica	8	0.91	Romania	9	1.02
Azerbaijan	14	1.59	Jordan	14	1.59	Rwanda	2	0.23
Bahamas	5	0.57	Kazakhstan	19	2.16	Saudi Arabia	12	1.37
Bahrain	13	1.48	Kenya	28	3.19	Senegal	3	0.34
Belarus	4	0.46	Kuwait	13	1.48	Serbia	6	0.68
Benin	2	0.23	Kyrgyzstan	3	0.34	Sierra Leone	2	0.23
Bolivia	10	1.14	Latvia	14	1.59	Singapore	7	0.8
Bosnia and Herzegovina	9	1.02	Lithuania	7	0.8	South Africa	27	3.07
Botswana	6	0.68	Macedonia (Fyrom)	8	0.91	Swaziland	4	0.46
Bulgaria	14	1.59	Malawi	3	0.34	Syrian Arab Republic	3	0.34
Cambodia	6	0.68	Malaysia	6	0.68	Tajikistan	2	0.23
Colombia	7	0.8	Maldives	2	0.23	Thailand	6	0.68
Costa Rica	10	1.14	Mali	3	0.34	Togo	2	0.23
Cote D'Ivoire	2	0.23	Mauritius	7	0.8	Trinidad And Tobago	4	0.46
Croatia	17	1.93	Mongolia	3	0.34	Tunisia	15	1.71
Cyprus	7	0.8	Montenegro	2	0.23	Turkey	50	5.69
Dominican Republic	9	1.02	Morocco	9	1.02	Uganda	12	1.37
Ecuador	24	2.73	Mozambique	6	0.68	Ukraine	13	1.48
Egypt	3	0.34	Namibia	9	1.02	United Arab Emirates	22	2.5
El Salvador	17	1.93	Nepal	14	1.59	United Republic of Tanzania	14	1.59
Ethiopia	2	0.23	Nicaragua	8	0.91	Uruguay	14	1.59
Georgia	10	1.14	Niger	2	0.23	Uzbekistan	5	0.57
Ghana	10	1.14	Oman	11	1.25	Venezuela	24	2.73
Grenada	2	0.23	Panama	25	2.84	Vietnam	6	0.68
Guatemala	22	2.5	Paraguay	9	1.02	Zambia	6	0.68

This table shows the cross-sectional distribution of the sample.

Table 13: Cross-sectional loan default and depth of credit information (mean)

Country	NPL	Depth	Country	NPL	Depth	Country	NPL	Depth
Albania	0.09	3.64	Guyana	0.09	0	Peru	0.02	6
Algeria	0.06	0	Haiti	0.02	0	Philippines	0.08	1.54
Angola	0.06	0	Honduras	0.03	5.58	Qatar	0.02	1.02
Argentina	0.05	6	Hong Kong	0.01	5	Republic of Moldova	0.09	0
Armenia	0.03	4.43	Jamaica	0.06	0	Romania	0.11	4.53
Azerbaijan	0.09	2.75	Jordan	0.10	0	Rwanda	0.15	1.09
Bahamas	0.06	0	Kazakhstan	0.12	4.3	Saudi Arabia	0.03	4.91
Bahrain	0.10	3	Kenya	0.10	0	Senegal	0.06	0
Belarus	0.17	3.13	Kuwait	0.07	4.75	Serbia	0.10	4.03
Benin	0.10	0	Kyrgyzstan	0.02	2.67	Sierra Leone	0.24	0
Bolivia	0.08	5.57	Latvia	0.12	3	Singapore	0.02	3.32
Bosnia and Herzegovina	0.08	4.88	Lithuania	0.09	5.37	South Africa	0.08	5.78
Botswana	0.05	4	Macedonia (Fyrom)	0.09	2.63	Swaziland	0.05	5
Bulgaria	0.08	4.82	Malawi	0.04	0	Syrian Arab Republic	0.08	0
Cambodia	0.06	0.43	Malaysia	0.05	5.39	Tajikistan	0.10	0
Colombia	0.05	5	Maldives	0.13	1.45	Thailand	0.07	4.95
Costa Rica	0.05	4.7	Mali	0.11	0	Togo	0.09	0
Cote D'Ivoire	0.10	0	Mauritius	0.03	2.83	Trinidad And Tobago	0.04	3.75
Croatia	0.10	3.1	Mongolia	0.04	3	Tunisia	0.11	3.06
Cyprus	0.09	1.2	Montenegro	0.13	2.67	Turkey	0.02	4.88
Dominican Republic	0.03	5.98	Morocco	0.06	3.24	Uganda	0.03	0
Ecuador	0.09	5.14	Mozambique	0.04	0	Ukraine	0.12	1.36
Egypt	0.06	3.6	Namibia	0.03	4	United Arab Emirates	0.05	3.01
El Salvador	0.03	5.85	Nepal	0.03	0	United Republic of Tanzania	0.07	0
Ethiopia	0.09	0	Nicaragua	0.03	5.49	Uruguay	0.06	5.59
Georgia	0.06	3.16	Niger	0.05	0	Uzbekistan	0.10	1.21
Ghana	0.12	0.79	Oman	0.06	2.21	Venezuela	0.02	1.85
Grenada	0.04	0	Panama	0.01	6	Vietnam	0.03	3.29
Guatemala	0.04	5.5	Paraguay	0.01	6	Zambia	0.04	0.60

This table shows the cross-sectional mean loan default and depth of information sharing index.