Mandatory and voluntary credit information sharing among banks

A thesis submitted for the degree of Doctor of Philosophy in Finance

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September 2023

Abstract

Credit information sharing schemes, which are either mandatory because they are a regulatory requirement of the central bank or voluntary in the sense of being discretionary as a private arrangement among peers, are aimed at reducing asymmetric information in the banking sector. The schemes now exist in many advanced and developing countries. However, although there is increased research on the role and effectiveness of information sharing, the evidence is mixed and inconclusive; indeed, the jury is still out there on identifying the precise effects and mechanisms as to how the effects occur. This thesis aims to contribute to the existing literature by investigating how banking activities are affected when credit information sharing is mandatory, voluntary, and when mandatory and voluntary schemes coexist. The thesis identifies critical gaps in the literature, tracks the theoretical underpinnings of the main research question in each gap, and investigates each research question using a panel dataset of 368 banks from 40 developing countries covering the period 2012-2020. The main findings are threefold. First, it is found that mandatory information sharing reduces credit growth and credit risk when it coexists with stringent capital regulation or a policy that allows banks to apply provisioning rules to a loan net of collateral. Second, the threshold analysis shows that the relationship between bank diversification and excess value is reverse U-shaped. Mandatory information sharing reduces excess value of banks by increasing diversification above the optimal level; consequently, it is associated with a diversification discount. Voluntary information sharing prevents excessive diversification, increases excess value of banks, and it is associated with a premium. Third, information sharing (mandatory or voluntary) reduces procyclicality of bank liquidity creation. The channels supporting the liquidity smoothing role of information sharing are increase in access to interbank liquid funds, increase in the accuracy of default probability estimates, and decrease in bank asset write-offs. Our findings suggest that mandatory information sharing incentivizes bank risk-shifting from lending to non-lending activities, especially when it exists without voluntary scheme. Therefore, the study encourages policymakers to promote the coexistence of both schemes to improve the performance of mandatory information sharing.

Acknowledgements

This work would not have been possible without the support and fellowship of many kind people. First and foremost, I want to thank my PhD supervisor, Professor Victor Murinde, for his support and motivating guidance. I have benefited immensely from his expertise and knowledge during the last three years. I am forever grateful to SOAS University of London for funding my PhD and giving me the opportunity to conduct my research work in an inclusive and supportive environment. I also want to thank members of the Centre for Global Finance (CGF) at SOAS University of London. More specifically, Dr Tolulola Lawal, Professor Hong Bo, and Professor Kemi Yekini for their constructive suggestions at different stages of my research work, and Professor Pasquale Scaramozzino for sharing his expertise on econometrics and data analysis during the first year of my PhD. Finally, I give special thanks to my family and friends for their patience and encouragement over the last three years.

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Chapter 1: Introduction

1.1 Background

The finance literature overwhelmingly supports positive linkages between bank financing and rise in economic productivity and growth.[1] However, the positive effect of bank credit is conditional on the quality of lending (e.g., Jayaratne & Strahan, 1996) and the ability of banks to allocate credit toward more productive firms (e.g., Bai et al., 2018). Banks and firms are differentially informed in many markets about the quality of firms' projects when loan applications are made due to informational asymmetries. Therefore, banks are faced with adverse selection problem since they cannot separate bad borrowers from good ones. Banks also face ex-post moral hazard problem due to their inability to control the behaviour of borrowers or directly influence the outcome of their projects after loans have been granted. Consequently, markets with these imperfections are characterised by either credit rationing (e.g., Stiglitz & Weiss, 1981) or excessive lending that may lead to diminished allocative efficiency and productivity (e.g., de Meza & Webb, 1987; Blek & Liu, 2018). To alleviate the effects of asymmetric information in credit markets, many countries have adopted information sharing schemes which enable lenders to exchange information about their borrowers. Theory suggests that credit information sharing reduces adverse selection and moral hazard problems in credit markets (Pagano & Jappelli, 1993; Flatnes, 2021).

In addition to credit information sharing schemes, lenders in both advanced and developing credit markets use collateral and engage in relationship lending to overcome problems caused by asymmetric information. Relationship lending technique is less costly and can increase access to finance (e.g., Diamond, 1984; DeYoung et al., 2015; Wang et al., 2020). However, it increases adverse selection problem faced by non-relationship lenders (e.g., Detragiache et al., 2000) and encourages lenders to extract higher rents from borrowers (e.g.,

[1] The positive relationship between credit and economic growth is more pronounced with private banks than state-owned banks (Silva et al., 2021); there is positive association between financial intermediary development and economic growth (Beck et al., 2000; Levine et al., 2000); corporate loans (to non-financial institutions) have positive, while household loans have negative impact on growth (Benczur et al., 2019); and productivity growth is more sensitive to external finance when financial frictions increase (see Levine & Warusawitharana, 2021).

Duqi et al., 2018). Similarly, although collateralization helps to reduce adverse selection (e.g., Bester, 1985; Ioannidou et al., 2022) and ex-post issues including moral hazard (e.g., Boot & Thakor, 1994; Ioannidou et al., 2022), it may squeeze collateral-poor borrowers out of the credit market (e.g., Araujo et al., 2019). Moreover, the use of collateral can reduce loan screening incentives (as in Manove et al., 2001). Credit information sharing schemes are designed to address these issues with both lending relationship and the use of collateral. One of the exceptional features of the scheme is that it is the first system designed to address asymmetric information between banks and regulators, banks and their customers, and among banks.

Credit information sharing occurs through public credit registries or private credit bureaus (World Bank, 2016). Credit registries are administered by central banks and participation is mandatory for financial institutions, whereas credit bureaus operate a voluntary participation system which is based on a principle of reciprocity (only members who have shared their information are granted access to information shared by other members). Theory suggests that, by reducing adverse selection and moral hazard problems, credit information sharing can reduce collateral requirements and increase access to credit (Flatnes, 2021). These predictions suggest that information sharing is a valid substitute for the use of collateral in loan screening. In this study, we refer to this as *information-based lending*.

The empirical literature on the effects of information sharing shows that it increases loan quality (e.g., Fosu et al., 2020) and competition in credit markets (e.g., Liberti et al., 2022), reduces borrowers' switching cost (e.g., Sutherland, 2018), and improves financial development (de Moraes et al., 2022). In terms of credit growth, however, evidence is mixed. Credit growth have been reported in studies based on information sharing index (e.g., Fosu, 2014) and credit bureaus (e.g., Liberti et al., 2022), while lending reduction (e.g., De Haas et al., 2021) and insignificant results (e.g., Grajzl & Laptieva, 2016) are associated with credit registries.

The rest of this chapter provides background knowledge on the three empirical chapters of this thesis, the methodological approaches employed in the chapters, and the summary of findings.

1.2 Motivation

The weak relationship between credit registry and credit growth reported in the literature suggests that the mandatory principle of credit registry requires empirical scrutiny. Ability to control when and where to share private information has strategic importance since sharing increases competition and reduces informational rents. As noted by Liberti & Petersen (2019), private information that banks built up over time is valuable to them not only because it informs their own lending decisions but also because it is difficult to replicate outside the banks. Under voluntary system of credit bureau, banks can manage the costs and benefits associated with sharing private information. Liberti et al. (2022) show that the voluntary nature of credit bureau enables lenders to subscribe when it favours their business in terms of access to new markets or when they are concerned about losing their own customers to competitors who have subscribed. Under mandatory system, however, financial institutions are not allowed to subscribe and unsubscribe to credit registries in line with their business needs because participation is a regulatory requirement.

The primary objective of credit registry is to help the government in bank supervision, and this makes the scheme a supervisory tool designed to reduce credit risk. Therefore, its impact on credit growth may vary based on country specific factors. Moreover, it is not clear how information sharing can increase credit growth and reduce credit risk simultaneously as theoretical literature appears to suggest. By reducing opacity and increasing bank monitoring, mandatory information sharing may induce high-quality/low-volume lending strategy among regulated banks. The literature lacks evidence on the differential effects of mandatory information sharing on the volume and quality of credit in markets with features that make lending volume important to banks. The intensity of capital regulation in a country should be considered for this purpose since banks would normally respond to higher capital requirements with higher lending to accumulate more earnings (see Uluc & Wieladek, 2018).

Information sharing is expected to increase credit growth by reducing collateral requirements (Flatnes, 2021). Could the failure of this important mechanism explain the weak relationship between mandatory information sharing and credit growth shown in the literature (e.g., Grajzl & Laptieva, 2016; Loaba & Zahonogo, 2019)? Given that information sharing now exists in over 170 countries due to recent adoption increase (World Bank, 2019), changes are expected in the use of collateral in credit markets. However, recent global survey of collateralized loans across 131 countries shows that over three-quarter of loans issued during the last decade require collateral, and average collateral value is about 167% of loan value (Fan et al., 2022). As a matter of fact, the study shows that these numbers are higher across developing countries. There are no studies on the role of country specific loan classification policies and practices. We do not know whether loan policies in some countries with credit registry favour collateralization and disincentivize the use of information-based lending technique.

A complete view of bank asset portfolios in relation to information sharing can expand the current literature with new knowledge. In many markets, banks diversify their operations by engaging in both lending and non-lending activities. Therefore, these banks have interest income earning assets (lending activities) and non-interest income earning assets (non-lending activities). Information sharing may affect bank diversification through the following channels. First, banks can reuse information about customers in one financial services area to evaluate their behaviour in other areas and offer additonal services to a selected group of customers. Moreover, historical information of credit customers can predict the effectiveness of financial services cross-selling (Thuring et al., 2012). Second, information sharing can influence bank diversification through its effect on lending activities. For example, if mandatory information sharing reduces credit risk-taking and lending volume in countries with intense banking regulation, it may increase bank managers' incentives to invest their free cash flow in non-lending activities that are less monitored and not part of the mandatory reporting system. Moreover, banks are more likely to diversify into non-interest income generating activities (advisory, brokerage, underwriting, and insurance) when lending is less profitable (e.g., de Silva et al., 2022).

There is no recognition in credit information sharing literature that loan may not represent an adequate measure of bank output but liquidity creation measure that incorporates all balance sheet items including long-term and short-term assets and liabilities (see Berger & Bouwman, 2015). This measure of bank output provides opportunity to explore how information sharing affects other key factors determining the ability and willingness of banks to finance the real economy. A complete balance sheet approach such as the three-step measure developed by Berger & Bouwman (2009) permits the inclusion of off-balance sheet financing commitments which, although more likely to suffer from effects of asymmetric information (see Avery & Berger, 1991), are usually excluded when modelling loan growth. Banks create liquidity by converting liquid liabilities such as deposits into illiquid assets (Diamond & Dybvig, 1983). By doing so, however, banks erode their own liquidity position. Consequently, excessive creation of liquidity during good economic times increases the likelihood of experiencing liquidity shortages during downturns when deposit funds dry out and other short-term funding opportunities are either not available or unaffordable. Information sharing has the potential to smooth liquidity creation over the business cycle by reducing moral hazard behaviour which drives excessive creation during upturn of the business cycle when banks have access to surplus deposits (e.g., Acharya & Naqvi, 2012), and by addressing adverse selection problem which prevents access to liquidity during downturn (e.g., Heider et al., 2015).

1.3 Scope and limitations of the study

We start the analysis with a comprehensive review of the literature on credit information sharing among banks using a systematic approach. The literature review enables us to identify patterns in theoretical arguments and empirical evidence, highlight the main sources of data, and discuss methodological approaches used in majority of empirical studies. Importantly, the analysis is used to identify gaps in existing knowledge which we translate into research ideas. The literature review is presented in chapter 2 of the study while three of the research ideas are investigated in chapter 3, 4, and 5.

The first empirical chapter of this thesis investigates whether the direction of impact of mandatory information sharing, that is increase in credit growth or reduction in credit risk, is conditional on loan classification policies or the stringency of capital regulation in a country.[2] Specifically, we investigate the following research question: *How does mandatory credit information sharing affect credit growth and credit quality when it coexists with a policy that permits banks to apply provisioning rules to a loan net of collateral value or stringent capital regulation?* By focusing on a policy that may allow banks to carry a loan at a higher

[2] Section 3.3.1 provides the coverage of variables and data description including the prevalence of loan classification policies and the extent of capital regulation stringency in the sample countries. 63% of banks in the study sample are allowed to provision for loan losses net of collateral while 31% of banks operate in countries with the most stringent capital regulation (the top quartile of the regulation index).

value and recognise lower losses if it is collateralized, the study aims to shed light on the role of country specific policies in the performance of mandatory information sharing system. We extend the analysis to investigate whether the weak relationship between mandatory information sharing and credit growth (as in Grajzl & Laptieva, 2016) is due to lack of incentives to engage in information-based screening or the disciplining effect of mandatory information sharing. If the loan policy and stringent capital regulation incentivize higher credit risk taking due to bank opacity, the introduction of mandatory information sharing system as a disciplinary device is more likely to reduce than to increase credit growth.

In chapter 4, the analysis is extended to non-lending activities of banks. If the prediction in chapter 3 holds that mandatory information sharing prevents banks from engaging in credit risk-taking, it may incentivize higher investment in non-lending activities to improve earnings. To answer our research question "*How does credit information sharing affect bank diversification strategies and excess value?*", we start by estimating the optimal level of bank diversification. This allows us to investigate the differential effects of mandatory and voluntary information sharing schemes on bank diversification below and above the optimal value, and how these relationships affect the *excess value* of diversified banks.

The third empirical chapter, chapter 5, evaluates whether information sharing can reduce the intensity of fluctuations in bank on- and off-balance sheet liquidity creation in the economy. To achieve this objective, the following question has been raised to direct the investigation. *How does credit information sharing shape the cyclicality of bank liquidity creation?* Following the recommendation by Berger & Bouwman (2009), liquidity creation is estimated using all balance sheet items. In addition, we account for the effects of business cycle fluctuations since liquidity creation is highly sensitive to business cycle changes (e.g., Davydov et al., 2018).

The analysis is based on a panel data of 368 banks from 40 developing countries. Developing countries have seen the most growth in the development of credit reporting systems in the last decade (see World Bank, 2019), and emerging studies in the literature reflect this trend. Majority of empirical articles that we have reviewed in chapter 2 are based on developing countries. Moreover, our data shows significant expansion in information sharing systems across 40 developing countries in the sample. *Figure 4.1* shows that the coverage of mandatory information sharing (credit registry) has increased from 13.6% in 2012 to 22.1% in 2020 while the coverage of voluntary information sharing (credit bureau) has increased from 24% to 43.2% during the same period. Unlike OECD countries where credit registries and credit bureaus are well-established and have been in place for several decades, credit information sharing is a recent phenomenon in many developing countries (see Figures 2.4 and 2.5). In addition to growing adoption, developing countries are modifying information sharing systems to meet their specific needs such as lowering the reporting threshold and including microfinance institutions.[3] The inclusion of microfinance institutions is critically important since majority of developing countries promote access to finance for small businesses and households through the microfinance market.

Our study has at least one limitation which is data availability. We have not been able to employ a balanced panel data due to missing observations in the bank-level data. However, we have carefully selected the testing and estimation techniques that are appropriate for our data and we have achieved the best possible outcomes (see section 1.5). Moreover, recommendations have been provided to extend the study in future research when there is improvement in access to data.

1.4 Methodology

To investigate the research questions discussed in section 1.3, we review the relevant literature, develop testable hypotheses from the literature review, define relevant variables, and collect the data required for the empirical estimations. As discussed in section 2.4.2 of the thesis, the majority of empirical studies in credit information sharing literature adopt panel data approach. To follow this method, we construct a panel dataset based on bank-level and macroeconomic data. The source of bank-level data is BankFocus provided by Bureau van Dijk, sources of macroeconomic data are the World Development Indicators (WDI) and the International Financial Statistics database of the International Monetary Fund (IMF), and information sharing data have been collected from the World Bank's *Doing Business* database. In addition to these data sources, chapter 3 of the thesis requires banking sector data from the Bank Regulation and Supervision Database of the World Bank. After some

[3] India and Bosnia & Herzegovina are example of countries with effective information sharing systems that include microfinance institutions (see World Bank, 2019).

adjustments to the original data, the thesis is based on a final unbalanced panel data of 368 banks from 40 countries over the period 2012-2020.

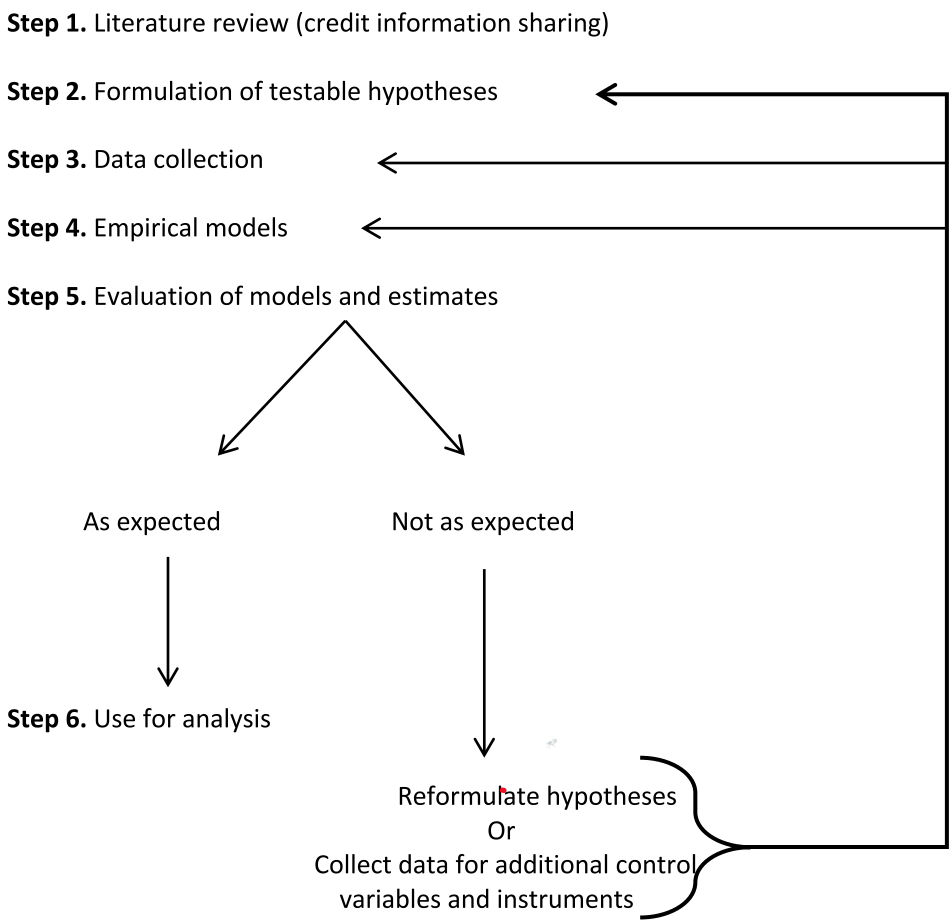


Figure 1. 1 A modified six-step research methodology proposed by Brooks (2008).

In terms of methodology, we adopt a dynamic panel modelling approach because our main dependent variables have dynamic properties (see Fosu, 2014 for credit growth; Yildirim & Efthyvoulou, 2018 for bank value; Davydov et al., 2018 for liquidity creation). A variable is dynamic if its contemporaneous value is affected by its own past value(s). We account for this effect by including the lag of dependent variable as a regressor in each model. However, the inclusion of lagged dependent variable means that the standard estimation techniques used when estimating static model including OLS will bias our estimates due to the endogeneity resulting from the correlation between the lagged dependent variable and the error term. Therefore, we estimate the dynamic models with Generalized Method of Moments (GMM) estimator that uses instruments to address endogeneity problem (e.g., de Moraes et al., 2022). Moreover, this thesis is based on a panel data of 368 banks and 2012-2020 period which satisfy large-*N* and short-*T* criteria for a dynamic model with GMM. In addition to GMM, a modified version of a dynamic panel threshold model introduced by Kremer et al. (2013) is employed in chapter 4 to estimate the optimal value of bank diversification.

We begin the estimation process by eliminating bank fixed effects that might be correlated with explanatory variables. First difference transformation is commonly used in the literature when dealing with fixed effects in a balanced panel data (e.g., Fosu et al., 2020). Given that first differencing subtracts previous observation from the contemporaneous value, any missing value of y_{it}, for instance, would result in both Δy_{it} and $\Delta y_{i,t-1}$ missing in the transformed data. This magnifies gaps in our unbalanced panel data because one period of missing data is replaced with two missing differences. To overcome this problem, Arellano & Bover (1995) recommend the use of forward orthogonal deviations transformation which subtracts the average of all future available observations of a variable from the contemporaneous value rather than subtracting the previous observation as in first differencing. Regardless of gaps in the panel data, all observations are transformed with the orthogonal deviations except the last observation in each panel. This allows us to eliminate the fixed effects without significant reduction in the data.

Next, we estimate our models using GMM estimator that combines levels equation with the orthogonal deviations equation. For more on the combination of equations as a system, see Arellano & Bover (1995) and Blundell & Bond (1998). To evaluate the appropriateness of models, the Hansen test of over-identifying restrictions and the Arellano-Bond tests for autocorrelation of the errors [AR (2)] are used. If both tests have p-values of at least 10%, the model is deemed valid. Otherwise, the process is repeated by reformulating the hypothesis or considering different control variables and instruments, then re-estimate the model.[4]

When a model is successfully estimated, the parameter estimates and arguments supporting the hypothesis tested are evaluated for consistency. Particularly, whether the predicted signs and the level of significance are in line with expectations. If expectations are

[4] For all our results discussed in section 1.5, the lagged dependent variable enters each model at the 1% level of significance, validating our dynamic modelling approach. Importantly, the Hansen and Arellano-Bond AR(2) tests have at least 0.1 p-values confirming that our instruments are appropriate and no second-order serial correlation detected.

not met, the process is repeated as described in the preceding paragraph. If the model and estimates are as expected, the results are formally analysed by outlining the findings, contributions to the extant literature, and the importance of the findings for both policy and practice.

1.5 New findings and contributions to existing knowledge

Several new and interesting findings have been uncovered across the chapters of this thesis, including evidence of risk shifting from highly monitored interest income generating activities to non-interest income activities when information sharing is mandatory. We have carefully summarized the findings in this section covering the three empirical chapters as well as contributions to the extant literature. In the first empirical chapter, chapter 3, the main findings are that mandatory credit information sharing via credit registry is associated with lower credit risk and lower credit growth when it coexists with a loan policy that allows banks to apply provisioning rules to a loan net of collateral value. The findings suggest that mandatory information sharing reduces credit risk by reducing excessive collateralized lending associated with the loan policy. Therefore, the results are more consistent with the disciplinary channel of mandatory information sharing than lower incentives to engage in information-based lending.

Chapter 3 also shows that in countries with stringent capital regulation, mandatory credit information sharing is associated with lower credit risk, lower credit growth, and lower bank profitability. Moreover, an extended analysis in chapter 3 shows that without mandatory information sharing, stringent capital regulation is associated with higher credit growth, higher profitability, and higher credit risk. These findings suggest that by reducing asymmetric information between banks and regulators, mandatory information sharing changes how banks meet stringent capital requirements from “high-volume/high-profits/low-quality” to “low-volume/low-profits/high-quality”. This change in lending policy improves the quality of loan assets in the banking sector but at the expense of credit supply to the real economy and banking sector profitability.

Hence, the main contribution of chapter 3 to the literature is by reconciling existing mixed evidence on the impact of mandatory information sharing via credit registry. The findings indicate that the weak relationship between credit registry and credit growth reported in the literature (e.g., Grajzl & Laptieva, 2016 for insignificant effect; De Haas et al., 2021 for credit reduction) is because existing studies have underestimated the effect of mandatory information sharing by ignoring the role of loan classification policies and the stringency of banking regulations. The new evidence shows that existing loan practices in many countries incentivize higher credit risk-taking especially in the use of collateral. When mandatory information sharing scheme is introduced, however, it restores quality in bank credit screening and reduces the origination of low-quality collateralized loans. This new knowledge should improve policy formulation in developing and emerging countries where the adoption of information sharing system is growing. In addition, chapter 3 complements a growing literature on falling bank lending activities due to higher regulations (e.g., Mirzaei et al., 2021). While capital regulation is important in preventing bank failures, the findings in this chapter show that when the stringency of capital regulation is in the top quartile of the regulation index, its coexistence with mandatory information sharing stifles credit growth and increases profit performance risk in the banking sector.

In chapter 4, the results suggest that both mandatory and voluntary credit information sharing increase diversification in the lower regime (below optimal diversification level), and these relationships increase excess value of banks. These results suggest that both information sharing schemes enable banks to diversify their investments toward optimal level to achieve higher diversification premium. However, there is a positive relationship between mandatory information sharing and diversification in the upper regime which reduces excess value and a negative association between voluntary information sharing and diversification in the upper regime which increases excess value of banks. These are indications of possible overinvestment in relation to mandatory information sharing. In addition, the chapter shows a diversification premium in the overall data, among banks in countries with voluntary information sharing only, and when both schemes of information sharing coexist (see Gulamhussen et al., 2017 for diversification premium). However, a diversification discount is found among banks in countries with mandatory information sharing only, supporting the other half of the literature with evidence of negative net effect of bank diversification (e.g., Laeven & Levine, 2007). These results suggest that the quality of information explains the higher premium associated with voluntary system rather than higher quantity of investments associated with mandatory information sharing. Moreover, the optimal diversification value under mandatory information sharing is significantly lower than the sample average while that of voluntary system is higher than the average value.[5]

Chapter 4 contributes to the literature in several ways. It shows that the role of credit information sharing among banks goes beyond what we already know in the literature. Existing studies generally limit the role of information sharing to lending and other credit market activities (e.g., Sutherland, 2018; Bahadir & Valev, 2021; Liberti et al., 2022). However, our results suggest that information sharing shapes the composition of lending and non-lending activities in bank asset portfolios, and that banks can use credit information sharing schemes to reduce adverse selection when investing in non-lending activities and improve diversification strategies. The complete portfolio view adopted in this study provides better understanding of how information sharing affects investment behaviour of banks. Existing literature agrees that mandatory information sharing via credit registry reduces credit risk (e.g., Fosu et al., 2021; De Haas et al., 2021). However, our study reveals new evidence that the positive effect of credit registry on credit risk is due to risk shifting behaviour of banks. As mandatory information sharing coverage increases, banks reduce credit risk since credit activities are highly monitored but increase risk-taking in less monitored non-lending activities. This is an indication that the mandatory nature of credit registry intensifies agency problems. Chapter 4 also contributes to the literature by shedding light on why the quality of information shared is vital. It suggests that the higher the quality of information shared, the higher the threshold level of diversification, and the higher the excess value of a diversified bank. Voluntary information sharing system is associated with higher quality of diversified investments compared to mandatory system, and banks using voluntarily shared information have higher excess value.

Chapter 5 shows that on- and off-balance sheet liquidity creation are procyclical, suggesting that banks create higher liquidity during upturn and lower liquidity during downturn of the business cycle. However, information sharing reduces procyclicality of both types of liquidity creation by increasing banks' access to interbank liquid funds, improving the accuracy of default probability estimates, and reducing the amount of asset write-offs. The interbank channel is more effective during downturn of the business cycle when many banks experience liquidity shortages. This confirms that by reducing asymmetric information in the

[5] The optimal or threshold value represents the value beyond which the positive effect of diversification starts to fall.

interbank market, credit information sharing reduces liquidity hoarding which causes shortages during downturn. Meanwhile, the last two channels suggest that by improving banks' ability to evaluate customers more accurately and reducing asset deterioration, information sharing helps banks to stabilize their liquidity position and creation across the phases of the business cycle.

Chapter 5 extends the literature on the cyclicality of bank liquidity creation (e.g., Davydov et al., 2018; Niu 2022) with new evidence that credit information sharing can be used as a smoothing device in the banking sector to stabilize liquidity creation over the business cycle. Importantly, the chapter expands the literature on credit information sharing (e.g., Bahadir & Valev, 2021; Fosu et al., 2021) by providing evidence on the linkages between information sharing among banks and the effectiveness of liquidity channelling in the interbank network.

Overall, this thesis casts a brighter light on the role of credit information sharing in the banking sector and the significance of the mandatory principle of credit registries as well as the voluntary model of credit bureaus. Voluntary system is associated with higher quality of information and investments, while mandatory system appears to trigger incentive conflicts and risk shifting behaviour that has not been documented before now. The findings show that by preventing banks from engaging in credit risk-taking, mandatory information sharing incentivizes higher risk-taking in non-lending activities that are not covered by the mandatory scheme and less monitored. Therefore, the thesis raises some important questions about regulators' knowledge of how credit registry affects non-lending activities of banks, and whether sufficient resources are being directed toward monitoring and supervising non-lending activities compared to credit activities. Average diversification of the 368 banks in our study sample is about 0.44,[6] suggesting that banks are highly diversified across developing countries and that non-lending activities of banks should be given sufficient attention. Credit registry should be modified at the country level in line with country specific factors to prevent risk shifting behaviour. For example, where banks hold highly diversified portfolios, there should be a requirement to share information about non-lending activities so that risk relating to non-interest income generating activities can be monitored too. That is, from "credit information sharing" to "banking information sharing". However, such disclosure

[6] Recall that 0.50 represents the highest level of bank diversification. That is when lending and non-lending activities are 50% each in a bank's overall income generating activities.

requirement may intensify bank supervision and reduce liquidity creation in the economy, especially in countries where bank supervisors have significant power. Therefore, the suggestion to extend informational content to non-lending activities may only appeal to policymakers in countries that want to reduce risk in the banking sector rather than those encouraging credit growth and higher bank investment.

1.6 Structure of thesis

The rest of the thesis is structured as follows: Chapter 2 presents the systematic review of literature on credit information sharing covering both theoretical and recent empirical studies. It also provides key methodological approaches and data sources used in majority of empirical studies, and the summary of knowledge gaps in the literature. The following three empirical chapters are based on some of the promising research ideas developed from these knowledge gaps. Chapter 3 investigates how loan classification policies and the intensity of capital regulation in a country affect the effectiveness of mandatory information sharing in the banking sector. Chapter 4 extends the analysis to non-lending activities and voluntary information sharing. It uses a threshold specification to create two regimes of bank diversification and examines the impact of mandatory and voluntary information sharing on bank excess value. Meanwhile, a comprehensive measure of bank output is adopted in chapter 5 to investigate the role of information sharing in smoothing bank liquidity creation over the business cycle, as well as the channels through which information sharing affects bank liquidity. Chapter 6 summarizes the findings, presents the study implications for both policy and banking practice, highlights the limitations of the thesis, and provides suggestions for future research.

Chapter 2: What do we know about credit information sharing among banks? A systematic review of the theoretical and empirical literature

2.1 Introduction

It has been acknowledged that information is a fundamental component of all financial transactions and markets (Liberti & Petersen, 2019). Therefore, it is not surprising that lower asymmetric information is associated with higher access to credit (e.g., Moro et al., 2015) while credit rationing occurs as a consequence of adverse selection problem in markets burdened with asymmetric information (e.g., Ikeda, 2020 for business credit; Distefano et al., 2020 for consumer credit).[7] A significantly large body of literature exists on the effectiveness of techniques used in credit markets to remedy the effects of asymmetric information including collateralization (e.g., Ioannidou et al., 2022) and relationship lending (e.g., DeYoung et al., 2015).[8] Meanwhile, a recent technique which is the focus of this survey is credit information sharing that evolves from the idea that borrowers' past credit performance (credit history) can give a reliable estimate of their future performance. Therefore, when banks exchange information about their borrowers, they can reduce adverse selection and improve the quality of loan screening for all applicants including those that are moving from one bank to another (Pagano & Jappelli, 1993).

In many countries, information sharing systems are made up of credit registries and credit bureaus which are the two main providers of credit reports. There is usually one credit registry in a country which is administered by the central bank to facilitate sharing of credit information among banks (World Bank, 2016). Credit registries are designed to improve the quality of bank lending and assist the government in bank supervision (World Bank, 2019). Banks are required to participate in information sharing via a central credit registry in a

[7] Effects of information asymmetries are not limited to credit markets, other markets with adverse selection problem including insurance may also generate bad trades that would not happen under full information (e.g., de Meza et al., 2021).
[8] However, both lending approaches have several shortcomings. Disadvantages of collateralization include lack of pledgeable assets among many borrowers with good projects, lower screening incentives (Manove et al., 2001), and higher asymmetric information about collateral values (Stroebel, 2016). Reduction in collateral values results in tightening credit limits, increasing interest rates, and increasing loan delinquency due to falling monitoring intensity (Cerqueiro et al., 2016). Similarly, relationship lending technique increases information asymmetries faced by non-relationship banks (Detragiache et al., 2000).

country where they operate. However, this compulsory participation is one of the key issues with credit registry because incentive problems may arise where some banks prefer to manage access to their private information differently.

Credit bureaus are privately owned but regulated by the regulatory authorities (World Bank, 2016). Unlike credit registries which report information shared by banks only, credit bureaus utilize information from multiple sources (including government organizations, financial institutions, and non-financial institutions) to produce more accurate reports. Although subscription is voluntary, members must agree to share their private information to have access to other members' information when joining a credit bureau (see Sutherland, 2018).

Both credit registries and credit bureaus have expanded rapidly in recent years. Over 170 countries now have either one or both information sharing schemes (World Bank, 2019). Figure 2.1 shows that reports based on the combination of information from financial and non-financial institutions have more predictive power than credit reports based on information shared by financial institutions only.

Types of Information / Sources of Information	Positive & Negative Information	Negative Information
"Full" (Information Shared by Banks, Retailers, NBFIs)	High Predictiveness (e.g., U.S., U.K., India)	Lower Predictiveness (e.g., Botswana, Eswatini)
"Fragmented" (e.g., Information Shared Among Banks Only or Retail Only)	Lower Predictiveness (e.g., Mexico, Kuwait)	Lowest Predictiveness (e.g., Malaysia, Botswana)

Source: World Bank (2019)

Figure 2. 1 Types and sources of information and their predictive power

In this literature survey, we review theoretical literature to date and recent empirical evidence on the effects of credit information sharing from the following important research avenues: first, incentive issues associated with information sharing schemes; second, bank lending; third, credit risk and stability in the banking sector. We intend to provoke review of policies with our improvement suggestions and motivate future studies by providing detailed promising research ideas.

The rest of the literature survey is organized as follows: Section 2.2 presents the survey methodology. Section 2.3 presents the review of theoretical literature covering adverse selection, moral hazard, and the use of collateral in markets with information sharing system. Section 2.4 covers information sharing measures and empirical issues in the literature. Section 2.5 presents the evidence on the effects of mandatory and voluntary nature of credit registries and credit bureaus on bank behaviour. Section 2.6 covers empirical evidence on the relationship between credit information sharing and the use of collateral, access to credit, and bank risk. It also presents the knowledge gaps identified in the literature and the related promising research ideas. Section 2.7 presents the conclusion of the analysis.

2.2 Survey methodology

The methodology we adopt for this literature survey is the systematic literature review which is inspired by recent papers including Linnenluecke et al. (2020), Alaeddini et al. (2023), and Adeabah et al. (2023). The systematic approach enables us to search and select articles based on our set criteria, analyse to establish themes, identify knowledge gaps in the literature, and set out some future research ideas.

We start the online search process by entering the keywords “credit information sharing” that represent the survey subject area into finance related databases including ScienceDirect and Wiley Online Library. The initial searches reveal over 300 papers that are related to credit information sharing. However, our intention is to make sure that the analysis and our final conclusions are based on evidence reported in highly ranked papers. Therefore, the search was adjusted to select papers based on journal ranking. We select papers that are published in at least 3-star journals. According to the Chartered Association of Business Schools ranking, we know that papers published in journals that are rated 3 or more have the most citation impact factors in the field of finance. This process reduced the number of articles to 138.

Credit registries and credit bureaus are recent schemes in many developing countries compared to advanced markets where both systems have been in place for several decades. Therefore, the period covered in the survey needed to be adjusted so that sufficient number of studies based on developing credit markets are included. This gives a fair representation of markets at different stages of development which is an important part of the survey objectives. For this, the search is further adjusted to sort the articles by date, and those published in the last ten years (2013 to 2022) are included in the final sample of studies. However, some theoretical papers published before 2013 have been included to create a strong theoretical background for credit information sharing. The final sample provides sufficient evidence to capture the focus of emerging studies in the literature and directly address the survey objectives outlined in section 2.1.

These articles are grouped according to their similarities (study motivation, topic, and findings) and relationship with credit information sharing. For example, studies on the relationship between credit information sharing and access to credit are in one group while those on the impact of information sharing on credit risk are in another group. This survey design allows us to analyse evidence and trends in each group and identify knowledge gaps.

Contrary to other areas of finance literature that are dominated by US-based studies, majority of recent studies on the effects of credit information sharing in the top journals are based on developing credit markets. The main areas of focus include the linkages between credit information sharing and asymmetric information in credit markets, access to credit, and stability in the banking sector. Although the survey covers 2013-2022 period, most of the empirical papers on credit information sharing that we have reviewed were published during the last three years (2020-2022). This is an indication that information sharing has a literature that is rapidly growing in line with the growing adoption of both credit registries and credit bureaus across the world.[9] We have provided a summary of articles on credit information sharing reviewed in the survey. Appendix Table A2.1 presents the summary of theoretical articles while Appendix Table A2.2 summarizes the empirical articles.

2.3 Theoretical literature

The credit information sharing framework is deeply rooted in the theory of asymmetric information which suggests that adverse selection can arise in credit markets where borrowers know more than the lenders about their repayment prospects (as in Akerlof, 1970). Addressing these informational asymmetries is central to the principle of credit information sharing. That is, when banks have greater knowledge of borrowers' credit history and ongoing projects, they are less concerned about the lemons problem of financing bad projects. Therefore, theoretical literature on credit information sharing focuses on how it addresses the effects of asymmetric information (adverse selection and moral hazard) which prevent the efficient allocation of credit and the proper functioning of markets.

2.3.1 Countering adverse selection and moral hazard problems

By reducing asymmetric information in the banking sector, credit information sharing improves the quality of bank lending and eases borrowers' financing constraints. Pagano & Jappelli (1993) argue that borrowers' mobility and heterogeneity can motivate banks to exchange information about their local borrowers to reduce adverse selection problem. Borrowers' mobility increases adverse selection faced by outside banks. However, when inside and outside banks share information about their local borrowers, all banks can accurately evaluate the creditworthiness of all borrowers including those moving to other locality to apply for loans. Pagano & Jappelli (1993) show in their adverse selection model that credit information sharing can increase the volume of lending in markets where adverse

[9] Although empirical studies published in journals that are ranked lower than 3 and those earlier than 2013 have not been included in this survey, we are not by any means suggesting that these papers cannot be used in other survey studies with different motivation or targets. However, because of the specific aim to position our study with the top tier research possible, we believe that the selected sample provides the best opportunity for the survey.

selection is so severe that safe borrowers are priced out of the market. However, two alternative outcomes can equally be argued. First, increase in lending to safe borrowers may only compensate for the reduction in lending to high-risk borrowers in the new transparent credit market with information sharing system. Second, because information sharing enables lenders to set interest rates based on more accurate default probability estimates, high-risk borrowers who are willing to pay higher interest rates may remain in the credit market. These arguments also mean that credit information sharing allows high-quality borrowers to be rewarded with lower interest rates and enables lenders who are risk-takers to finance riskier projects to earn higher returns.

In addition to adverse selection problem faced by outside banks when screening new loan applicants, asymmetric information may also become an issue in relation to own borrowers when banks are not investing in new information about borrowers' ongoing business activities. Because credit information sharing reduces informational rents, it is reasonable to think that it can also reduce inside bank's incentives to invest in collecting new information about own borrowers since it might not be cost effective to do so. However, theoretical literature disagrees with this thinking. For example, Karapetyan & Stacescu (2014a) show that credit information sharing increases banks' incentives to collect more private information. In their adverse selection model, when information is made available to other users by credit information sharing system, banks invest more in acquiring soft information as the new source of rents.

What is interesting about the contribution made by Karapetyan & Stacescu (2014a) is that rent seeking motivates banks' ongoing investment in new information when existing information is shared. There are markets where it might not be cost effective to invest in information that must be shared within the regulated time; therefore, it would be more interesting to investigate the type of information that banks in this position are more likely to invest in. Without empirical evidence it remains unknown how profitable it is to compete with private information in the presence of credit information sharing schemes that are designed to shorten the time that information can be kept private. What we know, however, is that lenders transition from private information (relationship) lending technique to transaction technique with shorter contract maturity when they have shared their borrowers' information (Sutherland, 2018). Informational rents are limited where soft information cannot be kept private for a long time. Another study by Padilla & Pagano (1997) shows that reduction in informational monopoly and rents benefit both banks and their borrowers. Their argument is that the positive effect of credit information sharing is stronger through the competition channel which reduces future interest rates and increases borrowers' incentives to service their loans. Padilla & Pagano (1997) believe that the fear of further exploitation reduces borrowers' incentives to perform when banks have informational monopoly. Therefore, banks can motivate borrowers by sharing their information with other banks to reduce hold-up. While sharing may reduce banks' future interest income, it increases banks' current returns due to increase in borrowers' effort. Moreover, banks are motivated to lend more when borrowers exert greater effort.

Borrowers are more likely to default strategically than not when the benefits derived from defaulting outweigh its costs, especially when banks cannot force repayment (as in Schiantarelli et al., 2020). However, credit information sharing can discipline borrowers by increasing the cost of default. This argument is supported by Padilla & Pagano (2000) who demonstrate how credit information sharing reduces moral hazard and increases borrowers' repayment incentives. In their model, the fear of being punished in the event of default motivates borrowers to service and repay loans. Therefore, banks can discipline their borrowers by exchanging past default (negative) information. As credit markets become more transparent, good credit reputation becomes borrowers' most important credit collateral (as in Albertazzi et al., 2017). Padilla & Pagano (2000) also argue that banks may reduce borrowers' incentives to perform when they share all information about borrowers. However, this second argument is confusing because credit information sharing schemes are not meant to only punish defaulters but also to reward high quality borrowers. Not sharing positive information encourages hold-up of good borrowers and may be perceived as a punishment since it increases cost of switching. Moreover, this argument disagrees with their earlier study [Padilla & Pagano (1997)] which shows that disclosing full information including borrowers' quality increases incentives to perform.

Incentive problems in credit markets are not driven by borrowers only but also by banks. It is shown in Bennardo et al. (2015) that over-indebtedness arises from opportunistic behaviour of borrowers and banks.[10] Borrowers tend to overborrow where creditor rights are

[10] Banks offer more loans to already indebted borrowers to earn higher interest rates. However, this lending behaviour increases the risk associated with borrowers' existing loans.

poorly protected while banks are more likely to engage in opportunistic lending at the expense of their competitors where collateral prices are unstable. Consequently, credit rationing and higher interest rates are common features of markets with these incentive issues. However, Bennardo et al. (2015) show that credit information sharing can disincentivize opportunistic lending and borrowing, prevent over-indebtedness, and reduce credit rationing if collateral values are relatively stable and creditors are moderately protected. These theoretical predictions suggest that the effects of credit information sharing depend on market specific factors. Therefore, their model sheds light on why credit information sharing may have complete opposite effects in different markets.

Overall, theoretical literature covered in this section suggests that by reducing asymmetric information, the effects of credit information sharing are fourfold: it reduces adverse selection in credit markets; it reduces the ability of banks to extract higher rents from borrowers' private information; it reduces moral hazard and increases borrowers' repayment incentives; it increases lenders' knowledge of borrowers' indebtedness and prevents multiple and excessive borrowings. However, we find predictions in the following areas ambiguous. First, it is not clear how credit information sharing impacts credit growth. Increase in lending volume is predicted in markets where safe borrowers were previously priced out of credit markets due to severe adverse selection. However, the opposite can also be argued since there are markets where adverse selection leads to excessive lending rather than rationing. What happens when credit information sharing system is introduced in these markets? We predict credit rationing since information sharing makes it difficult for low quality borrowers to obtain new loans or for defaulters to move from one bank to another for new contracts. Second, one of the predictions in the literature is that sharing all information about borrowers reduces their incentives to perform. While it is clear how sharing default information can motivate currently defaulting borrowers to exert more effort and deter non-defaulting borrowers from future default, it is not clear how sharing detailed information about borrowers' quality can reduce disciplinary effects of credit information sharing. One would have thought the opposite effect is more likely since sharing positive information reduces hold-up and informational monopoly. One way to extend this argument is by investigating the impact of not sharing information about borrowers' quality on the performance of high-quality borrowers as well as the potential cost to banks.

2.3.2 Credit information sharing and collateralization

Banks use both collateralization (e.g., Ioannidou et al., 2022) and credit information sharing (e.g., De Haas et al., 2021) to reduce the effects of asymmetric information. This means the two techniques can be substitutes in which case increase in credit information sharing reduces the use of collateral, or complements meaning that increase in information sharing increases the use of collateral. It is not realistic to think that credit information sharing can replace collateralization but it has the potential to reduce the use of collateral since it also serves the dual purpose (screening and addressing ex post moral hazard) as collateral in credit markets. A recent study in the literature appears to agree with this argument. Flatnes (2021) demonstrates in a two-period model that collateral requirements become significantly lower when credit information sharing reduces adverse selection and increases banks' ability to control ex post borrowers' effort. This outcome is conditional on borrowers' awareness of credit information sharing scheme and how it may impact their future loan terms. This means even when banks have perfect information but cannot enforce high effort of borrowers, collateral requirements may remain high because offering low collateral in this case increases borrowers' incentives to choose low effort.

Flatnes (2021) argues that when banks cannot enforce high effort, contracts (R_{it}, C_{it}) that motivate borrowers to choose high effort should be offered rather than low-collateral/high-interest contracts that induce low effort. That is, moral hazard incentive compatibility constraint ($MHICC$):

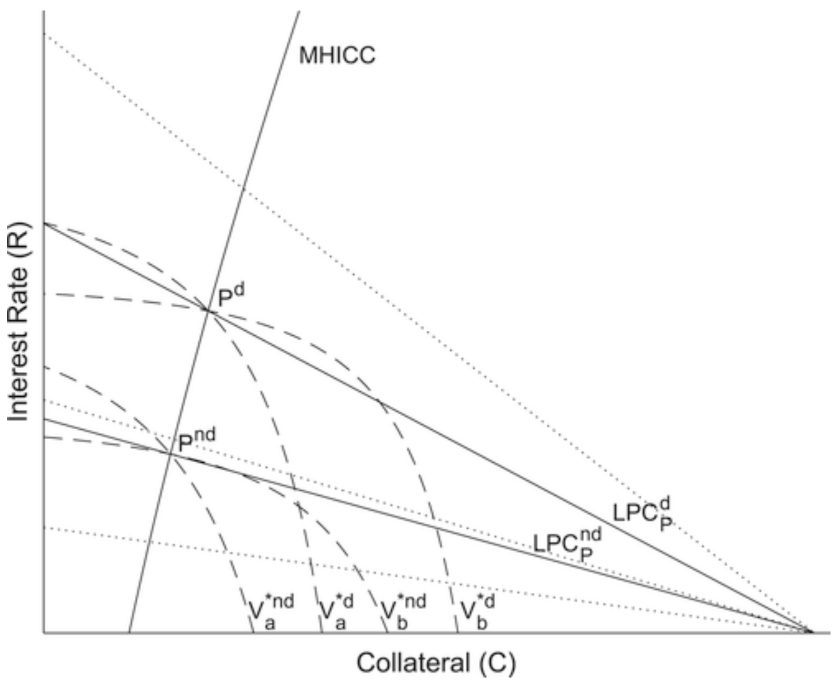
$$U_{it}(R_{it}, C_{it}|H) \geq U_{it}(R_{it}, C_{it}|L) \tag{2.1}$$

Where U is the utility function, a contract is represented by the combination of interest rate and collateral (R_{it}, C_{it}), H and L are high and low effort. When borrowers are not fully informed about credit information sharing, the optimal contract terms offered by banks in period 2 based on information about borrowers' behaviour in period 1 are: non-defaulters receive contract terms that are better than terms received in period 1 while defaulters are offered worse terms than those received in period 1. The two types of contracts are summarized below:

$$\left(R_2^{SUd} > R_1^{SU} > R_2^{SU\overline{d}}, C_2^{SUd} > C_1^{SU} > C_2^{SU\overline{d}}\right) \tag{2.2}$$

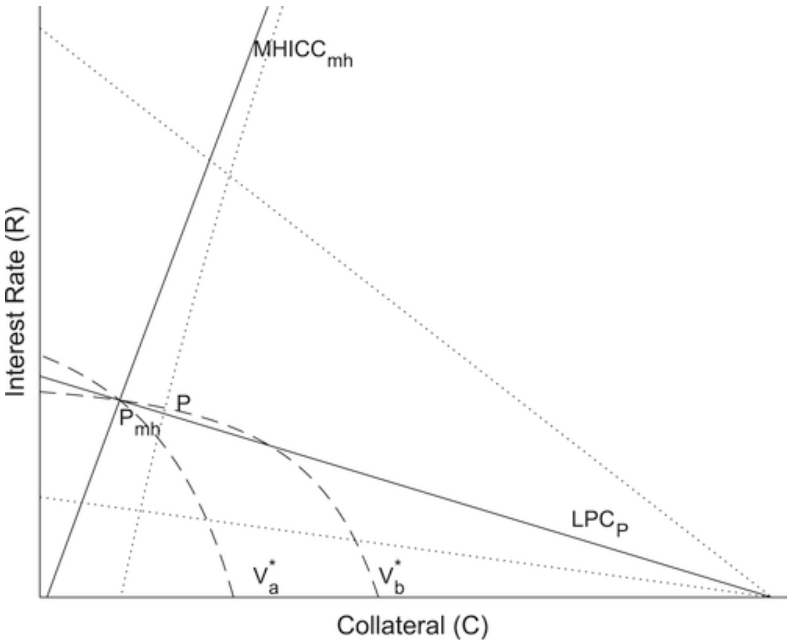
Where SU is information sharing, $\gamma^d = Pr(a|d)$ is the probability that a borrower is high risk (type a) and defaulted in previous period, while $\gamma^{\overline{d}} = Pr(a|\overline{d})$ is low risk borrower with no default in previous period. The optimal contracts for both high and low risk borrowers are illustrated in Figure 2.2, P^{nd} represents better contract terms in period 2 for non-defaulters, while P^d represents higher terms received by defaulters in period 2. The most important line in Figure 2.2 is $MHICC$ which is always to the right of the vertical axis. This means that collateral requirement is always positive because reducing adverse selection through credit information sharing does not reduce collateral requirements when borrowers are not informed about information sharing and its impact.

However, the outcome is different when borrowers are fully informed about the use of default information and the potential impact on their future loan terms. The awareness helps to reduce borrowers' ex post moral hazard behaviour and incentivize higher effort even when banks reduce collateral requirements. Consequently, the $MHICC$ assumption in Flatnes (2021) model that high-interest/low-collateral contracts induce low effort among borrowers is relaxed and the $MHICC$ line is shifted from its position in Figure 2.2 toward the west as illustrated in Figure 2.3.



Source: Flatnes (2021)

Figure 2. 2 Equilibrium contracts when borrowers are not aware that default information is shared by lenders



Source: Flatnes (2021)

Figure 2. 3 Equilibrium contracts when borrowers are aware that default information is utilized and shared by lenders

With lower collateral requirement in the new optimal contract, credit rationing is reduced as more borrowers with insufficient collateral can now borrow more. However, banks have to increase interest rates to avoid loss making or to at least break even. The model clearly demonstrates how sharing of default information among lenders results in equitable contract terms, borrowers without default history receive better contract terms than those with history of defaults. This supports the idea that low-quality borrowers do not have to drop out of the credit market due to credit information sharing but must be willing to accept worse contract terms than those offered to high-quality borrowers.

The conclusion by Flatnes (2021) that credit information sharing reduces collateral requirements suggests that both are substitutes. However, this is in contrast to the increase in collateral requirements shown in Karapetyan & Stacescu (2014b). The explanation for this disagreement is that control of ex post moral hazard behaviour which is the channel supporting lower collateral requirements in Flatness (2021) is not considered by Karapetyan & Stacescu (2014b) in their adverse selection model.

The argument proposed by Karapetyan & Stacescu (2014b) is that credit information sharing and collateral are complements rather than substitutes because information sharing via credit registry and credit bureau may result in the use of collateral in circumstances that collateral would not be required in the absence of information sharing. Credit information sharing makes it easier for banks to separate outside borrowers with good credit history from those with bad history. What follows is that those with bad history are required to provide collateral for loans that would not have required collateral if information sharing was not in place. This argument implies that credit information sharing may lead to credit rationing in markets where firms do not have sufficient collateral as well as where regulations do not permit the use of certain assets (e.g., movable assets) as collateral. However, one of the limitations of their study is its focus on ex ante adverse selection without ex post moral hazard problem. In terms of the disagreement with Flatness (2021), it may be the case that the outcome of the interaction between credit information sharing and collateralization is conditional on other market specific features not considered in both studies. For example, Bennardo et al. (2015) show that the effect of credit information sharing may depend on the stability in collateral prices in a country. They argue that in markets with volatile collateral prices, credit information sharing enables outside banks to identify low-debt customers of other banks and bet on the appreciation of their collateral by granting more loans to them at the expense of inside banks. Bennardo et al. (2015) conclude that this lending behaviour increases credit risk and may result in higher credit rationing or market freeze.

Overall, theoretical literature suggests that credit information sharing and collateralization are substitutes as well as complements. Knowledge in this area of the literature requires significant expansion to clarify the direction of impact of credit information sharing on the use of collateral in credit markets. The focus should be on why it may be difficult for banks to reduce collateralization and whether more country-specific factors should be included when modelling interaction between the two.

2.4 Measurement of credit information sharing among banks

In this section, we cover how credit information sharing is measured in emerging studies and some of the most adopted empirical approaches in the literature.

2.4.1 Credit information sharing measures and sources of data in the empirical literature

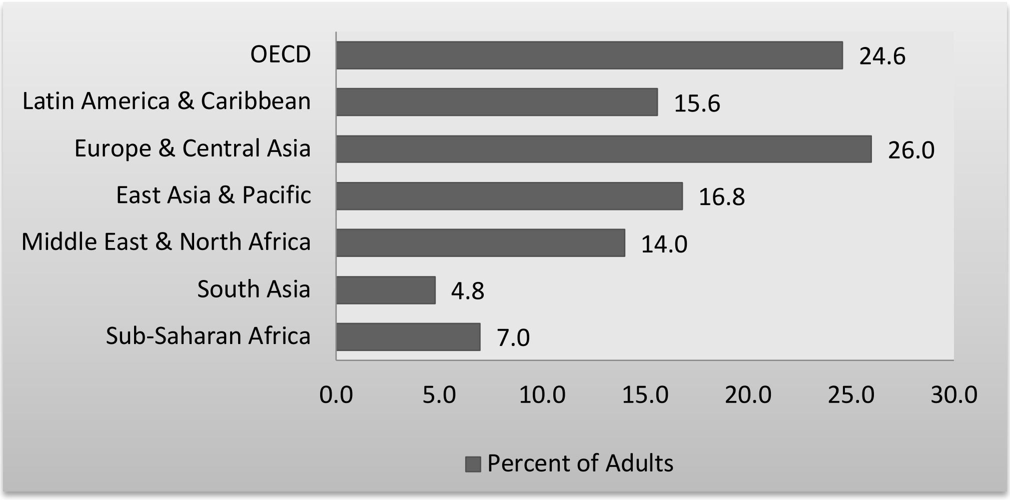
The following three main measures of credit information sharing and source(s) of data are generally used in the literature. First, the depth of information sharing index. The index measures the scope, accessibility, and quality of credit information available through credit registries and credit bureaus (World Bank, 2020a). The index ranges from 0 to 6 between 2004 and 2013 and 0 to 8 after 2013. Higher value indicates higher depth of information scope, accessibility, and quality. For each country, the value of one is added to the index for any of the questions below with a yes answer:

- Are data on both firms and individuals distributed?
- Are both positive and negative credit data distributed?
- Are data from banks, financial institutions, retailers, and utility companies distributed?
- Are at least 2 years of historical data distributed?
- Are data on loan amounts below 1% of income per capital distributed?
- Do borrowers have rights to access their data in the credit registry or credit bureau?
- Do banks and other financial institutions have online access to credit information?
- Are Bureaus and Registries credit scores offered as value-added services to help banks and other financial institutions in assessing the creditworthiness of borrowers?

Positive information includes borrowers' on-time payment history, unused credit capacity and outstanding credits, while negative information includes borrowers' defaults history and material threat to going-concern due to bankruptcy or other risks. Data on the depth of credit information sharing index are generally obtained from the Doing Business database of the World Bank; and the index has been used in many studies in the literature including Fosu et al. (2021), Iakimenko et al. (2022), and Adusei & Adeleye (2022).

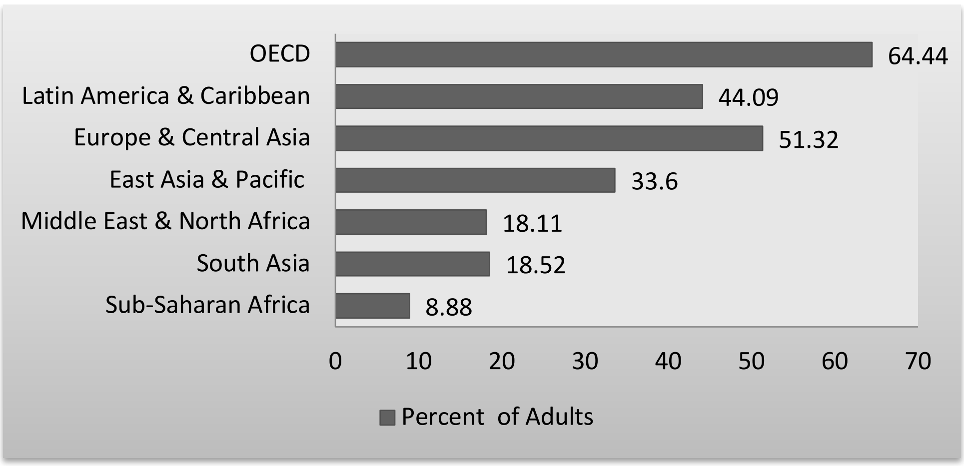
Second, a dummy variable indicating the existence of credit information sharing mechanism has been used in many studies including Giannetti et al. (2017) and De Haas et al. (2021). It takes the value of one if credit registry or credit bureau exists and zero otherwise. This measure is particularly useful in conducting event studies or examining the effects of shock and unexpected announcement of credit information sharing scheme. Data indicating the existence of credit registry or bureau can be obtained from the Doing Business database or directly from individual credit register and credit bureau. Another way that a dummy variable has been used in the literature is to capture when individual lenders adopt credit bureau, as in Darmouni & Sutherland (2021) and Liberti et al. (2022). Data on the staggered entry of lenders into credit bureau scheme can only be obtained from the credit bureau.

Third, the percentage coverage of credit information sharing scheme is another measure that is regularly used in the literature (e.g., Guerineau & Leon, 2019; de Moraes et al., 2022). Credit registry coverage is the percentage of firms and individuals covered in a country’s public credit registry through which financial institutions in the country engage in the mandatory credit information sharing scheme of the central bank. While credit bureau coverage represents the percentage covered by the private credit bureau(s) in a country providing voluntary credit information sharing services. Credit registries and credit bureaus share information such as firm’s name, business address, name of owner(s), field of business, assets and liabilities, tax and income, other financial information on the business and the owner(s), utility records, bad check list, bankruptcies, court judgments, existing credit facilities, default history, and many more (World Bank, 2019). Doing Business database is the primary source of data on coverage of credit information sharing schemes. Figures 2.4 and 2.5 give the percentage breakdown of regional coverage of credit registries and credit bureaus respectively. The figures clearly demonstrate weak coverage of information reporting systems across developing countries compared to advanced nations. For example, Figure 2.5 shows that credit bureau coverage in OECD countries is around 64% compared approximately 9% in Sub Saharan Africa and 18% across Middle East & North Africa. Similar pattern of coverage is observed in Figure 2.4.



Source: World Bank (2019)

Figure 2. 4 Regional Coverage of Credit Registry



Source: World Bank (2019)

Figure 2. 5 Regional Coverage of Credit Bureau

There is a strong link between access to finance and coverage of credit information sharing systems in a particular country since banks can only share information about their existing customers. This has contributed significantly to the low coverage reported in the figures above. It also highlights the need for more policies that support small businesses and individuals to move into the formal credit system for the first time and establish a formal credit record. This line of argument is connected to some of the problems that are embedded in the specific characteristics of developing markets including poor creditor protection, limited contract enforcement, and volatile collateral market (as indicated in Bennardo et al., 2015).

The summary of this section is that credit information sharing coverage is significantly lower across developing and emerging economies compared to advanced nations. The literature shows that credit information sharing is measured in three ways. The depth of information sharing index which measures the scope, accessibility, and quality of credit information; a dummy measure indicating the existence of credit information sharing mechanism or when a lender subscribes to a credit bureau; and the percentage coverage of credit information sharing schemes. Studies in the literature have generally sourced data for the three measures of credit information sharing from the Doing Business database of the World Bank. Since this is an open database, researchers face less complications in accessing data for future studies to expand the current literature.

2.4.2 Empirical issues and common methodological approaches

Existing literature on credit information sharing focuses mainly on credit growth and credit risk. Consequently, endogeneity and how to isolate the effect of information sharing on bank lending are some of the key empirical challenges. For example, we know that banks lend more during good economic times (e.g., Cuestas et al., 2022). However, this might not be due to banks' willingness to lend only, but also because firms are requiring more credit to engage in more activities when economic conditions are good. Therefore, not accounting for this macroeconomic factor that also drives firms' credit demand may bias empirical results. Consequently, we observe that more than half of empirical studies in credit information sharing literature have adopted a panel data approach which permits the combination of macroeconomic and bank or firm characteristics (e.g., Fosu et al., 2020; de Moraes et al., 2022). As stated by Fosu et al. (2020), to explore variations in bank lending over time, panel data approach is appropriate because it allows both bank-level and country-level variables to vary over time. Similarly, Kusi & Opoku-Mensah (2018) indicate that panel method can control for omitted variable biases.

The dynamic nature of both credit growth and credit risk measures is also reflected in the models used in the literature. For example, loan growth targeting is common among banks whereby current year growth targets are conditional on previous period's level of growth and accumulated risk. As a result, dynamic models have been employed in most empirical studies in the literature to account for the dynamic characteristic of credit growth (e.g., Fosu, 2014) or credit risk (e.g., Iakimenko et al., 2022) as endogenous variable. A loan growth dynamic model for the effect of credit information sharing takes the following form:

$$y_{i,t} = \alpha + \phi y_{i,t-1} + \beta info_{j,t} + \varphi bc_{i,t} + \pi cc_{j,t} + \lambda_t + \mathcal{E}_{i,t} \tag{2.3}$$

Where $y_{i,t}$ is the credit growth or the ratio of nonperforming loans for a similar risk model, $info_{j,t}$ represents any of the three measures of credit information sharing described in section 2.4.1, $bc_{i,t}$ represents bank control variables, $cc_{j,t}$ represents country specific variables, and λ_t is the fixed effects. y_{t-1} is included to account for the dynamic effect. However, the presence of this lagged dependent variable as a regressor increases the endogeneity concern in estimating equation 2.3. This also makes conventional estimators such as OLS unreliable. Even fixed effects approach can be problematic in the context of dynamic panel models as within transformation may result in correlation between regressor and the error (as in Nickell, 1981). Consequently, we observe that Generalized Method of Moments (GMM) estimator proposed by Arellano & Bover (1995) and Blundell & Bond (1998) is the most employed estimator in the literature due to its ability to address endogeneity and fixed effects problems (e.g., Fosu et al., 2021; Iakimenko et al., 2022; de Moraes et al., 2022).

Some researchers have gone beyond the application of GMM estimator by employing additional set of external instruments to demonstrate that β in equation 2.3 is unbiased. Omitted variable bias is a genuine concern in this context. For example, it may be the case that there is a variable that drives both credit information sharing expansion and credit growth. Excluding such variable overstates β in equation 2.3 and attributes too much importance to credit information sharing. For further test, secured internet infrastructure was used as external instrument for credit information sharing in Bahadir & Valev (2021). Similarly, population size was used in Fosu et al. (2021) as external instrument. In both studies, the effects of credit information sharing remain the same as their main findings even with the external instruments introduced. Although the appropriateness of a particular IV is always contested. As credit information sharing literature continues to evolve, it will eventually emerge whether instrument related to macroeconomic, regulations, or advances in technology makes a stronger IV.

There are studies based on quasi-experiments in the literature, particularly difference-in-differences (DiD) estimation around the time a credit registry or credit bureau is introduced (e.g., Giannetti et al., 2017). The DiD framework helps to capture the immediate reaction of lenders, borrowers, investors, the banking sector, or the entire credit market when a credit information sharing scheme is introduced. For example, to estimate the effect of a new credit information sharing scheme on credit growth, the following DiD model could be used.

$$y_{i,t} = \eta_0 + \eta_1 T_i + \eta_2 T_i * P_t + \delta X'_{i,t} + \lambda_t + \mu_i + \mathcal{E}_{i,t} \tag{2.4}$$

Where $y_{i,t}$ represents credit growth, T_i $(treated)$ has a value of one for banks located in countries with the new information sharing scheme (credit registry or credit bureau) and zero otherwise. P_t $(Post)$ is an indicator set to one for the period after the introduction of information sharing scheme and zero for the period before. $T_i * P_t$ is the interaction of the treated banks and post registry/bureau period, $\mathcal{E}_{i,t}$ is the error term. A vector of covariates $X_{i,t}$ is included for the time-varying control variables, while λ_t and μ_i are time and bank fixed effects. η_2 estimates the treatment effect on the treated group. η_2 is unbiased if $T_i * P_t$ is uncorrelated with the error term, that is $cov(\mathcal{E}_{i,t}, T_i * P_t) = 0$.[11]

One of the common mechanisms that can undermine this unbiased estimate assumption is that the banks in the treated group and those in the control group were experiencing different trends prior to the introduction of credit information sharing scheme which means the groups are not comparable and the estimated effect is not causal. Therefore, validating this assumption is one of the key challenges associated with the DiD framework. A common practice in the finance literature is to plot the parallel trend lines to demonstrate graphically that the two groups were trending identically before the intervention. However, data availability issues restrict the use of this approach because it requires more than two years of data in the period before an intervention. It is therefore not surprising that

[11] By estimating equation 2.4, it is assumed that the trends of the dependent variable y_{it} were identical between the treated and control groups before credit information sharing scheme was introduced, and that these trends would have remained parallel had information sharing not been introduced, so that the difference experienced in the post period can be attributed to information sharing (the treatment effect [η_2]).

propensity scores matching is commonly used in credit information sharing literature to estimate the comparability of the treated and control groups (e.g., De Haas et al., 2021). Treated banks are matched with those in the control group based on their estimated propensity scores so that a balancing test and DiD estimation can be applied to the matched group of banks.

De Haas et al. (2021) use DiD model to investigate lending behaviour before and after mandatory information sharing via credit registry was introduced in Bosnia and Herzegovina, with nearest-neighbour propensity scores matching as robustness. The framework enables them to carefully examine loan applications made by both old and new borrowers during the two periods**.** Similarly, Giannetti et al. (2017) use a DiD model to investigate bank moral hazard behaviour incentivized by the announcement of credit registry in Argentina. They were able to capture important incentive issues associated with mandatory information sharing including manipulation of borrowers’ information before sharing with other banks.

The role of data type is crucial in the DiD design adopted in both studies. For example, access to data on loan applications enables De Haas et al. (2021) to differentiate between applications approved and those rejected for old and new borrowers and identify how the financial institution reacted to different group of borrowers in the post registry transparent credit market. This unique behavioural aspect of credit information sharing is more likely to be identified with DiD methodology using borrower-based groups rather than bank-level time series data. Identifying with loan applications ensures that the effects of idiosyncratic credit demand and rejected loan applications that are often disregarded in studies based on aggregate bank lending data are accounted for. Where possible, rejected loan applications and discouraged borrowers should be incorporated into credit models to provide a complete knowledge of how credit supply and demand interact, and how this interaction affects market participants and the wider economy. However, these variables are usually not observable and rarely appear in the literature especially discouraged borrowers.

Estimating treatment effect on the treated group is problematic with credit bureau since all users do not subscribe to the scheme at the same time. In Darmouni & Sutherland (2021), staggered DiD design was used to study the behaviour of lenders upon joining a US credit bureau in a staggered pattern. Based on contract terms offered by lenders before and after joining the bureau, the staggered DiD estimates the effects of credit bureau subscription on contract terms. However, staggered DiD poses some econometric complications and may bias the estimated effects. The standard DiD is a two-group and two-period (2x2DiD) estimator which estimates causal effect on the assumption that treatment effects are constant over time (Goodman-Bacon, 2021). However, when treatments occur at different times as in staggered adoption of credit bureau, the data contains several 2x2DiDs, and the estimated effect represents the weighted average of all the 2x2DiDs.

Goodman-Bacon (2021) shows that when there are more than two groups and two periods, the staggered DiD is a two-way fixed effects (TWFE) model that takes the following form:

$$\mathcal{Y}_{it} = \alpha_i + \mu_t + \lambda^{\mathcal{DD}}\mathcal{D}_{it} + \epsilon_{it} \tag{2.5}$$

α_{I} and μ_{t} are cross-sectional units and time periods, and $\mathcal{D}_{\mathrm{it}}$ represents the treatment (the interaction term). Goodman-Bacon (2021) shows that $\lambda^{\mathcal{DD}}$ is the weighted average of several 2x2DiD estimators in the data. Importantly, it is shown that negative weights may arise because "when already-treated units act as controls, changes in their outcomes are subtracted and these changes may include time-varying treatment effects". The possibility of obtaining different signs conditional on treatment timing variation is one of the issues raising questions about the reliability of staggered DiD estimates. Meanwhile, Goodman-Bacon (2021) recommends that if researchers must use staggered DiD, the estimated effects should be interpreted with caution. It is also suggested that decomposing the TWFE DiD estimator may be helpful.

Similarly, Baker et al. (2022) show that staggered DiD may be susceptible to biases due to treatment effect heterogeneity. They encourage researchers to provide an analysis of the likelihood of bias using a plot which shows treatment timing across cohorts so that significant variation in treatment timing suggests the possibility of biases. They also recommend that when biases are likely, alternative estimators should be employed for robustness.

The intuition behind staggered DiD is very clear. However, the significance of the biases associated with the estimated average effect remains unknown, and the appropriate robustness procedure to address them have not been identified. More evidence-based research is required to improve our knowledge of staggered DiD and the associated issues. In terms of the reliability of estimates, Goodman-Bacon (2021) argues that the potential bias discussed above does not imply the failure of staggered DiD but the need to interpret the treatment effects with caution.

Fixed effects model has also been used in some studies in the literature including Bahadir & Valev (2021). A standard fixed effects model is shown below:

$$y_{i,t} = \alpha + \psi info_{j,t} + \beth X'_{i,t} + \lambda_t + \mu_i + \nu_{i,t} \tag{2.6}$$

Where $y_{i,t}$ is the outcome variable (credit growth or credit risk), $info_{j,t}$ represents credit information sharing, $X'_{i,t}$ is a vector of control variables, λ_t and μ_i are time and bank fixed effects, and $\nu_{i,t}$ is the error term. What is common among studies based on fixed effects model in the literature is that additional estimations based on dynamic panel model with GMM estimator are presented in their robustness sections (e.g., Grajzl & Laptieva, 2016 for a single country study; Bahadir & Valev, 2021 for a cross-country analysis). This type of study design confirms the dominance of dynamic panel approach in credit information sharing literature.

Overall, the use of panel data and GMM estimator to address fixed effects and endogeneity problems dominate the literature. Study sample and data type may also have contributed to the methodological choices in the literature. We observe that multi-country studies generally follow the panel approach, while studies based on micro-level data, single credit bureau or credit registry mostly conduct quasi-natural experiments or fixed effects estimation. Meanwhile, the use of GMM remains popular among all studies especially for endogeneity and additional robustness checks. Credit growth which is the focus of most studies in the literature is dynamic in nature, hence the dominance of dynamic estimation technique especially GMM. However, as the literature expands into other areas, we may see more studies conducted at the firm-level, identification with loan applications, randomization, or other methodological approaches in future research.

2.5 Mandatory versus voluntary sharing of private information

Banks obtain private information which is only observable to them through their dealings with borrowers. Private information gives competitive advantage, especially for local and smaller banks that provide the specific needs of local customers. According to Liberti & Petersen (2019), private information is not only important because it informs bank lending decisions but because it is difficult to replicate and transmit outside the bank. Therefore, why would banks voluntarily share private information or share accurately when mandated to participate in formation sharing by regulators? Credit registry is based on the theory that where lenders would not share their private information willingly, government's intervention is needed to request information sharing.[12] This makes it compulsory for financial institutions in a country to register with credit registry and share their borrowers' information. Financial sector regulators use the compulsory registration principle to promote transparency and discipline in the banking sector. In addition, because credit registry is operated directly by the central bank, it gives the authorities direct access to the database to monitor stability in the sector. However, mandatory sharing of private information with other banks may create incentive problems including moral hazard behaviour to protect informational rents.

Giannetti et al. (2017) show that the introduction of mandatory information sharing via credit registry in Argentina provoked data manipulation before sharing. Their findings show that banks downgrade high-quality borrowers and upgrade low-quality borrowers before sharing information with other banks through the registry. They added that manipulating information before sharing allows banks to protect their informational rents and prevent borrowers' multiple borrowings. Banks benefit from protecting information about their high-quality borrowers because doing so prevents overborrowing which impairs borrowers' financial capacity and ability to service or repay existing loans. However, negative manipulation of information before sharing increases adverse selection faced by other banks relying on shared information. Where this behaviour is widespread in the banking sector, it may change the effect of credit information sharing scheme from the intended positive outcome such as risk reduction to adverse results including increase in financial system vulnerability.

Banks may reduce lending following the introduction of credit registry to improve the quality of their loan assets (as in De Haas et al., 2021), to prevent low regulatory ratings

[12] See Bennardo et al. (2015) where this argument is explained in detail.

associated with poor-quality loan portfolios, or to protect reputation among peers since other banks would have access to information shared and know about the quality of their loan assets. However, lending reduction strategy induced by credit registry may create conflict of interest between senior management and loan officers with volume related rewards. This could be another source of incentive problem since the combination of hard information and lending reduction strategy provides a perfect environment for data manipulation by loan officers to increase loan volume and volume-based rewards (as in Berg et al., 2020a).

With voluntary credit information sharing, participation is costly due to reduction in informational rents coupled with the fact that some credit bureaus require subscription fees. Banks are not required to join private credit bureaus by regulators, participation is discretionary. In terms of what incentivizes voluntary sharing of private information, Sutherland (2018) shows that lenders voluntarily subscribe to credit bureau information sharing scheme to have access to other lenders' private information. Similarly, Liberti et al. (2022) show that lenders join voluntary information sharing system to have access to new markets; however, it also increases competition for their own borrowers. The argument that may follow this evidence is that voluntary information sharing scheme encourages lenders to share their information strategically by joining a credit bureau when it favours their business activities and leave when it does not. However, a counter argument would be that there is no harm caused by temporary participation in the voluntary system; moreover, other members continue to benefit from information shared by temporary participants even when they have left the bureau.

Darmouni & Sutherland (2021) find that lenders' reactions upon joining a U.S. credit bureau are shaped by market competition or their own market share. They show that lenders with higher market share or those in concentrated markets react less when it comes to adjusting contract terms toward what others are offering when they join the credit bureau. Meanwhile, Liberti et al. (2022) provide the most recent evidence and convincing explanation as to why it is costly not to participate in voluntary credit information sharing scheme. They find that lenders that do not adopt the voluntary system lose borrowers to their competitors that do; consequently, they are compelled to adopt due to fear of market share decline. Their study quantifies the cost of absence from voluntary scheme which drives the incentives to participate.

In summary, the literature shows that both credit registry and credit bureau increase competition in credit markets. However, the mandatory and voluntary nature of the two informational schemes incentivize different reactions to the growing competition. With credit registry, banks seem to be concerned about losing their informational monopoly and rents. Meanwhile, market share decline is a common concern under voluntary credit information sharing, but banks appear to be able to time their subscription perfectly to prevent it.

While it is not clear whether banking regulators expect mandatory system to drive credit growth in addition to credit risk reduction, one result they certainly do not want is moral hazard behaviour among banks incentivized by the requirement to share their private information for free. Manipulation of information before sharing may reduce the quality of information and increase risk in the banking sector. We review the impact of both informational schemes on loan volume and quality in section 2.6 below.

2.6 Empirical Evidence on the effects of credit information sharing

In this section, we provide empirical evidence on the effects of credit information sharing. Most of the predictions in the theoretical literature have been confirmed empirically. For example, studies have shown that credit information sharing increases competition in credit markets (e.g., Liberti et al., 2022), increases financial system development (e.g., de Moraes et al., 2022), and reduces bank funding costs (e.g., Kusi & Opoku-Mensah, 2018). In Fosu et al. (2021), credit information sharing reduces bank intermediation cost across 27 African countries. Reduction in intermediation cost is particularly interesting because it could be one of the channels through which information sharing increases credit growth, bank profits, and loan quality.[13] Moreover, reduction in intermediation cost is an indicator of reduction in asymmetric information.

On the relationship between credit information sharing and collateral requirements, Doblas-Madrid & Minetti (2013) show in a study based on contract-level data from a U.S. credit bureau that credit information sharing does not reduce the use of collateral. In fact,

[13] A negative relationship between credit information sharing and bank funding cost (as in Kusi & Opoku-Mensah, 2018) may have similar growth effect on credit since increase in bank cost of capital is associated with tightening credit supply (as in Kovner & Tassel, 2022).

increase in collateral was reported for low quality borrowers. Meanwhile, De Haas & Millone (2020) find that credit information sharing leads to a shift from collateral requirement to third-party guarantees among new borrowers, and reduction in both collateral and guarantees for repeat borrowers. In addition, the result for repeat borrowers is proportional to the duration of their lending relationship. The study seems to suggest that the interaction between credit information sharing and relationship lending drives reduction in the use of collateral which is surprising given that credit information sharing is expected to reduce relationship and promote transactional lending (see Sutherland, 2018). These findings highlight the need for more research in this area of the literature to understand which of the lending techniques are substitutes and which are complements, and whehter the effects of any combination are different for credit risk compared to credit growth.

Understanding the relationship between collateralization and credit information sharing is important since many collateral-poor firms are unable to innovate (see Araujo et al., 2019). If more evidence supports the reduction effect of credit information sharing without any harm to the financial system, it can inspire policies to drive further adoption and coverage of information sharing schemes. This will benefit many developing countries with significantly low coverage of credit information sharing schemes (see Figures 2.4 & 2.5).

The mixed evidence on the impact of credit information sharing on collateral requirement could be an indication that individual market characteristics are important and should be explored in future research. If, for instance, it costs more to meet regulatory requirements with credit information sharing than collateralization, banks are less likely to reduce the use of collateral. Knowledge of how a country's regulations influence the relationship between credit information sharing and collateralization is needed to inform policy review when implementing credit information sharing schemes such as credit registry.

2.6.1 Credit information sharing and access to credit

In this section, we review recent evidence on the impact of credit information sharing on credit growth. Credit information sharing is expected to increase the ability and willingness of banks to lend since credit rationing is due to informational and incentive problems in credit markets (e.g., Kirschenmann, 2016). Evidence appears to support this positive relationship even though theoretical literature has not identified a clear link between the two. For example, Fosu (2014) finds that credit information sharing increases bank lending across Africa, with higher impact in less concentrated banking sectors. Similarly, Bahadir & Valev (2021) report that credit information sharing contributes significantly to increase in bank lending to households relative to businesses in 25 European countries. These studies are based on the index measure of credit information sharing that captures the entire information system (the scope, accessibility, and quality of credit information available through credit registry and credit bureau) or a dummy indicating the existence of credit information sharing system. However, the two informational schemes may have differential effects on bank lending decisions since sharing via credit registry is mandatory while credit bureau sharing is voluntary. For this reason, we review evidence on how credit is impacted under each scheme in the rest of this section.

Evidence on credit bureau is generally positive (e.g., Grajzl & Laptieva, 2016), supporting the view that the voluntary system of credit bureau improves lenders' confidence in information-based screening and willingness to lend. A study by Sutherland (2018) which examines the effects of information sharing via a U.S. credit bureau on firms' access to credit finds significant reduction in borrowers' cost of switching from one lender to another within the bureau. This suggests that voluntary credit information sharing improves borrowers' bargaining power and ability to negotiate more favourable credit terms elsewhere. A borrower with good credit reputation and high-quality projects may seek alternative funding arrangement when existing lender joins a bureau, especially in a competitive credit market. Additionally, Sutherland (2018) shows that the impact of credit bureau is higher for firms that are small, young, and those without defaults. Again, these demonstrate that the effect of voluntary information sharing is stronger for opaque borrowers such as SMEs.

In terms of the channel through which credit bureau increases lending, Liberti et al. (2022) identify competition as the driving factor. They find that by increasing competition, voluntary information sharing motivates more lenders to join the scheme and lend more to high-quality borrowers. The study by Sutherland (2018) also supports the competition channel of credit information sharing by showing that having shared borrowers' information, lenders transition from relationship lending to transaction technique with shorter contract maturity and less willingness to fund delinquent borrowers. These findings suggest that the competition channel of voluntary information sharing benefits both high-quality borrowers and lenders through higher lending and access to new markets.

While the literature generally focuses on credit information sharing among lenders, Bird et al. (2019) report that borrowers' voluntary reporting of credit information can increase access to credit, alleviate *hold-up* problem, and improve credit market performance. The study is based on data representing users from across the world and it shows that borrowers who voluntarily share their credit information are 16% more likely to switch to other lenders, experience 4% lower spread, and 8% more loan amount than non-sharing borrowers. For borrowers with positive investment opportunities and without default history, it is more beneficial to voluntarily share their information to expand funding opportunities with lower interest charges. For borrowers with default history, however, it makes business sense to remain in their existing lending relationships and pay relatively higher charges because other lenders may not be willing to finance their projects.

Bird et al. (2019) have started a new strand of the literature that may change how we think about credit information sharing. Generally, credit bureaus are designed to facilitate information sharing among lenders. However, they show that customer-based scheme can be as effective in remedying asymmetric information in credit markets. If more bureaus and platforms exist for borrowers to share their information voluntarily and interact with lenders directly, lenders' strategic reporting and firms' opacity can be reduced. One concern that lenders may have is the reliability of borrowers' voluntarily disclosed information. However, technology development has improved verification of information significantly. There are several online platforms where lenders can obtain further information to assess borrowers' creditworthiness, including easily accessible data from digital footprint with high level of accuracy (see Berg et al., 2020b). Moreover, the positive results reported by Bird et al. (2019) show that lenders have confidence in borrowers' self-reporting.

Meanwhile, evidence on the effect of credit registry on credit growth is not as positive as the literature has shown in relation to credit bureau. For example, in a study based on contract-level data from a microfinance institution, De Haas et al. (2021) find that a new credit registry in Bosnia and Herzegovina results in tightened lending at the extensive margin (higher loan rejections) and at the intensive margin (smaller, shorter, and more expensive loans). The study also shows that these effects apply to both new and existing borrowers. However, lending terms start to improve for new borrowers (that is, lending relationship formed in post registry periods) after demonstrating their quality through good repayment behaviour. Similarly, Loaba & Zahonogo (2019) report that credit information sharing via credit registry does not have significant impact on credit growth in West African Economic and Monetary Union. They relate this finding to low coverage of credit registers across the region.

By comparing the behaviour of voluntary and mandatory information sharing in the same market, Grajzl & Laptieva (2016) confirm the differential effects of the two informational schemes on credit. They find that voluntary information sharing via credit bureau in Ukraine is associated with credit growth whereas credit registry administered by the central bank does not have similar positive impact on bank lending. Credit registry reduces asymmetric information among banks and importantly, between banks and regulatory authorities. Therefore, it is expected to have disciplinary impact on bank credit behaviour. Moreover, banks are aware that regulators use credit registry information for monitoring and risk rating purposes. Evidence shows that following lower regulatory risk ratings, affected banks reduce lending (e.g., Gopalan, 2022). The fear of regulators' actions may deter banks from adopting volume-based lending strategy with a functioning credit registry in place.

The introduction of mandatory information sharing scheme in markets with adverse selection is more likely to have immediate positive impact on lending quality than volume. This argument is consistent with the findings reported by De Haas et al. (2021). Prior to the introduction of credit registry, adverse selection was a problem in Bosnia and Herzegovina credit market, and many low-quality borrowers were able to secure multiple loans at the same time.[14] However, De Haas et al. (2021) discover that improved credit quality and reduced credit growth were the immediate effects of the new credit registry. These findings address the confusion and lack of theoretical clarification on the conditions under which credit information sharing may and may not increase bank lending in markets with adverse selection problem before the introduction of credit information sharing system.

Overall, the relationship between information sharing and access to credit is positive, suggesting that informational schemes should be promoted to improve activities in credit markets and financing for businesses. However, evidence on the effect of mandatory scheme

[14] There is a competitive financial sector in Bosnia and Herzegovina with a mix of 27 banks and 12 microfinance institutions (De Haas et al., 2021). For more on adverse selection and microloans problem in Bosnia and Herzegovina, see De Haas et al. (2021) or "Maurer et al. (2011) Indebtedness of Microfinance Clients in Bosnia and Herzegovina. Results from a Comprehensive Field Study. European Fund for Southeast Europe Development Facility, Mimeo."

of credit registry is not as positive as voluntary system of credit bureau with credit reduction and insignificant results mainly reported. The factors driving the differential effects of the two schemes on credit growth are not known. Therefore, an important knowledge gap in the literature is the lack of evidence on why mandatory information sharing does not have significant effect on bank lending in some host countries. In addition, evidence shows that borrower-based credit bureau can expand firms' funding opportunities. Having multiple credit bureaus or platforms where borrowers can share their credit information with lenders may address some of the shortcomings of lender-based information sharing systems. For example, borrow-based platforms provide funding opportunities for small businesses and individuals that are left out of credit registries and credit bureaus because they do not have historical information to be shared by lenders. Therefore, another gap in the literature is evidence on how borrower-based credit bureaus enable small and opaque firms to innovate by improving their access to competitive credit facilities.

2.6.2 Credit information sharing and bank risk

Credit information sharing increases lenders' knowledge of borrowers' credit behaviour and existing indebtedness (Bennardo et al., 2015).[15] Consequently, borrowers are less likely to default when they are aware that credit information sharing system is in place (Flatnes, 2021). Good coverage of information sharing system increases transparency and reduces risk in the credit market. Moreover, empirical evidence shows that transparent credit markets have higher loan quality, lower default probability, and lower losses upon default (Ertan et al., 2017).

Evidence from 159 countries provided by Guerineau & Leon (2019) shows that credit information sharing reduces fragility in both advanced and emerging financial markets. By reducing adverse selection and moral hazard problems, credit information sharing enables banks to build high-quality loan asset portfolios which suffer less defaults and less likely to increase banking sector vulnerability. In another study of banks domiciled in developing

[15] Credit information sharing prevents multiple borrowings from different banks (Bennardo et al., 2015). This is one of the channels through which information sharing reduces credit rationing since firms with higher number of banking relationships are more likely to be rationed. For multiple-banking and the probability of rationing, see Cenni et al. (2015).

countries, Fosu et al. (2020) find positive impact of credit information sharing on the quality of bank loans. The study is based on a dataset of 879 banks operating in 87 countries. They find that credit information sharing reduces loan default rates, and this effect is conditional on banking market concentration. Adusei & Adeleye (2022) find similar result in their study of the impact of credit information sharing on nonperforming loans and whether creditor rights protection influences this relationship. They show that credit information sharing improves nonperforming loans of banks, and the positive effect is higher in the presence of creditor rights protection.

Meanwhile, a nonlinear relationship between depth of credit information sharing and credit risk was reported by Iakimenko et al. (2022). The relationship found in the study is reverse U-shaped, meaning that credit risk is at its lowest when depth of credit information sharing is at its minimum or maximum. This is an interesting finding because it contradicts both theoretical prediction and evidence in the literature that as information sharing increases, credit risk reduces. However, credit information sharing is a recent scheme with rapidly growing literature, and evidence such as this is the reason that more work is needed in this important topic area to help address issues relating to credit shortages and banking sector vulnerability. Moreover, evidence in this section largely agrees with theoretical predictions that credit information sharing increases the quality of bank loans and reduces financial system fragility. Even at the individual scheme level, evidence on the effects of both mandatory and voluntary information sharing supports risk reduction. For example, Doblas-Madrid & Minetti (2013) find that credit information sharing via credit bureau reduces loan delinquencies and defaults, while De Haas et al. (2021) show that credit registry reduces loan defaults, increases borrowers' repayment and lenders' return on loans.

These findings are consistent with the theoretical argument that credit information sharing disciplines borrowers (e.g., Padilla & Pagano, 2000). The fear of being punished when lenders exchange information about past defaults (negative information) is higher in markets with expanding credit information sharing scheme(s). Credit history creates reputational collateral which is an important component of information-based lending. Consequently, borrowers' effort to create good credit image is understandably higher in the presence of credit information sharing. The possibility of being downgraded helps to discipline borrowers who do not want the stigma of negative credit reputation that may result in higher spreads and tighter screening process in future borrowings (e.g., Freudenberg et al., 2017; Albertazzi et al., 2017). In a study by Liberman (2016), it is shown that borrowers are willing to pay up to 11% of their income to maintain good credit reputation in Chile. In another study by Bos et al. (2018), the findings show that one additional year of negative credit information in Sweden is associated with one-fourth decrease in credit. While Garmaise & Natividad (2017) show that positive actions by borrowers following reduction in their credit ratings do not immediately eliminate the negative effects associated with the initial damage to reputation, and these borrowers may exit credit markets within two to three years. It is clear why borrowers value credit reputation as much as 11% of their income. The impact of being downgraded or not able to secure future funding is material; therefore, the disciplinary effect of information sharing is higher when borrowers are aware of the scheme (as in Flatnes, 2021). This also explains why lower credit default rates are experienced in markets with information sharing schemes (e.g., Fosu et al., 2020).

In summary, evidence reviewed in this section strongly agrees that credit information sharing reduces bank risk. Credit information sharing as a disciplinary device increases borrowers' repayment incentives. It also seems to discipline banks too, especially mandatory scheme that is associated with lower credit risk and lower lending volume. However, it is not known whether banks are engaging in risky non-lending investments because mandatory system prevents credit risk-taking. More evidence is needed to get a complete picture of bank investment behaviour when it becomes mandatory to share private information with other banks via a platform administered by the regulators.

2.6.3 Summary of gaps in the literature and associated promising research ideas

In this section, we summarize the key gaps identified in the literature; the gaps are then used to generate promising research ideas for the empirical chapters of this thesis and for future studies. The first three research ideas below are investigated in the empirical chapters of this thesis, leaving the rest of the ideas for future research.

Mandatory credit information sharing and policy-induced credit constraints: The roles of loan classification policies and capital regulation stringency

The literature generally associates credit bureau with higher credit growth and credit registry with lower credit growth. It is difficult to identify a particular factor which drives the weak relationship between credit information sharing via credit registry and bank lending; however, some key features of the scheme may provide some answers. Credit registries are owned and administered by the regulatory authorities and participation is mandatory for financial institutions in a country. Depending on existing policies in the host country, these features of credit registry can affect bank lending behaviour. Therefore, the first empirical chapter focuses on examining how loan policies and regulations in a country affect the performance of mandatory information sharing scheme.

Loan classification policies allocate risks to loans based on estimated borrowers' ability to meet loan obligations (Song, 2002). Loan policies in each country have direct effects on the balance sheet and income statement of banks through initial loan valuation, loan loss provisioning, and loan asset write-offs. This study investigates how loan classification policies influence the relationship between mandatory information sharing and bank lending. For example, if loan policies allow banks to avoid making provisions for expected losses in relation to loans that are collateralized, banks are more likely to increase collateral requirements to avoid early loss charges and asset write-offs. These policies reduce the cost of collateralized lending relative to uncollateralized lending such as information based. Therefore, mandatory information sharing is more likely to reduce credit risk-taking and overall lending volume in markets with such policies. Moreover, the literature shows mixed theoretical predictions and evidence on the relationship between credit information sharing and the use of collateral in debt contracting. This study is expected to shed light on this relationship, especially the effects of loan policies in individual countries.

The credit information sharing literature predicts increase in credit growth and decrease in credit risk even though higher credit growth is more likely to increase than to reduce credit risk. We have no knowledge of the conditions under which information sharing may drive one of these outcomes at the expense of the other. Therefore, this study will also investigate whether the effect of mandatory information sharing is conditional on the stringency of banking regulation in the host country. We expect lower credit risk-taking and lower lending volume in countries with both mandatory information sharing and stringent capital regulations since these markets are highly transparent and tightly regulated.

Effects of credit information sharing on bank diversification strategies and excess value

In section 2.6.1, empirical evidence shows that mandatory information sharing through credit registry does not increase credit growth in most markets. If mandatory scheme disincentivizes credit risk-taking due to increase in supervision and monitoring of bank credit activities, does it incentivize risk-taking elsewhere? For example, banks may invest significantly more in non-lending activity areas where they have lower expertise to manage risk but because those activities are less monitored. Moreover, when lending becomes less profitable, banks increase diversification into non-lending activities to boost profit, but this also increases instability in banking (e.g., De Silva et al., 2022). The research idea is to examine how credit information sharing affects changes in the composition of interest and non-interest income generating activities in bank asset portfolios. With specific focus on evaluating the quality of diversified investments, possible overinvestment, impact on bank balance sheet and shareholders' wealth creation. Therefore, the study should be placed in the bank diversification literature as well as credit information sharing literature.

Cyclicality of bank liquidity creation and the smoothing role of credit information sharing

While credit information sharing literature generally focuses on the quality and volume of bank lending, Berger & Bouwman (2015) note that lending alone is not an optimal measure of bank output. Liquidity creation measure which accounts for assets and liabilities, long- and short-term, on-balance and off-balance sheet items of banks is generally recommended in the literature (as in Berger & Bouwman, 2009). Moreover, off-balance sheet items are usually left out when studying credit growth even though they are highly prone to manipulation and moral hazard behaviour. This comprehensive measure should be employed in future studies to examine how credit information sharing impact the different components contributing to banks' ability and willingness to create liquidity in the economy. The study should track the behaviour of banks across the stages of the business cycle since cyclical fluctuations may also affect bank behaviour and key financial statement figures (for cyclical liquidity creation, see Davydov et al., 2018). Credit information sharing should have a role in the process of obtaining short-term deposit funds which are liquid liabilities and converting them into illiquid assets. For example, it would be interesting to know if depositors' confidence is higher with an established credit information sharing scheme present, and whether this prevents mass withdrawal of funds during downturn of the business cycle which causes procyclical liquidity creation. Moreover, the literature relates excessive liquidity creation during upturn to moral hazard (e.g., Acharya & Naqvi, 2012) and liquidity shortages during downturn to adverse selection problem (e.g., Heider et al., 2015). By reducing both moral hazard and adverse selection problems, credit information sharing may have a smoothing role in the creation of liquidity.

Credit information sharing and activities in the interbank market

We reveal in section 2.6 that credit information sharing does not increase bank lending in some countries, particularly mandatory scheme of credit registry. It may be the case that, due to heightened monitoring and scrutiny that come with credit registry, banks in these countries increase interbank lending rather than loans to firms and individuals. There is no evidence on the role of credit information sharing in the interbank markets. An investigation of the linkages between mandatory information sharing and activities in the interbank market will expand the current literature with new knowledge. In addition, credit information sharing may remedy moral hazard behaviour among borrowing banks in the interbank markets (as in Boissay et al., 2016).

Does collateral registry help to establish formal credit history?

The literature shows that sharing of credit information by borrowers may ease their financing constraints (Bird et al., 2019), suggesting that borrower-based bureau can remedy frictions in credit markets. This new strand of the literature could be extended by investigating similar platforms that help borrowers without credit history to obtain formal financing for the first time to start building credit history. For this purpose, we have identified collateral registry that has been widely adopted across developing countries in the last decade. The registry is a platform that allows businesses and households to register information about their inventory, receivables, equipment, farm, business operation, other forms of assets or entire self-employed for credit (see Chavez et al., 2018). There are no formalities required, users can easily register online from any part of the country and doing so connects them to lenders on the platform automatically. For instance, a farming firm that is opaque (that is, no historical information) and without physical collateral, may secure first formal credit by registering information about their future farm produce. The platform facilitates the transaction by bringing the farmer and a lender together. Transactions are monitored by the financial sector regulators to prevent multiple contracts on the same piece of information.

The World Bank survey data suggests that collateral registry can improve access to credit (Love et al., 2016). In future research, how individuals and small businesses without credit history become users of formal credit facilities and start to build credit history on the registry platform should be investigated. By employing firm-level data, the study is expected to reveal how the platform addresses opacity among first time users. Alternative lines of investigation include the role of insurance firms in facilitating transactions on the platform, the impact of regulatory constraints since the platform is established and controlled by the financial sector regulators (see Sultanov et al., 2019), and the ability of firms to innovate.[16]

The effectiveness of credit information sharing schemes during COVID-19 pandemic

Another important knowledge gap in the literature is the role of credit information sharing during the COVID-19 pandemic. To fill this gap, a study should be designed to compare the role of information sharing in credit markets before and during the pandemic. The investigation may focus on a single market or two markets that are different in relation to credit information sharing schemes but similar in other areas including key market characteristics. These similarities provide common factors to support comparability of the two markets. The expectation is that banks with undisrupted access to formal credit information sharing system during COVID-19 should rely less on the so called "fake news" that adversely affected market performance in many countries during the pandemic (see Cepoi, 2020). Importantly, these banks should invest more, invest in higher quality projects, and outperform comparable banks in markets without a developed system of credit information sharing. An extension of the study should explore the differential effects of the two

[16] *Can online-based collateral registry drive firms' innovation and entrepreneurship?* Collateral registry is more than just online platform where potential borrowers contact lenders or share their information. Some of the credit products that the platform facilitates give creditors a stake-like interest in a firm's current and future cash flows especially under the secured transactions scheme. One of these common credit arrangements is the revolving line of credit whereby a lender grants a loan that is payable to the borrower over the agreed series of events or products. An agreed percentage of the loan will initially be paid to the borrower which is secured by the finished inventory or harvested crops, further amount is extended when inventory becomes receivable, and the remaining loan amount is paid to the borrower when the receivable is paid into the bank account controlled by the creditor or secured interest creditor in the case of assets with multiple claims, then the cycle restarts (see Sultanov et al., 2019). This revolving line of credit can go on for around 3-5years with renewal options. Knowing that the overall performance of a loan depends on the outcome of future events, lenders help firms to succeed. Interest in future cash flows of firms may also reduce liquidation bias in favour of reorganization in the event of default. This registry platform may only facilitate smaller loans compared to the traditional credit bureau, but because it enables lenders to be involved in borrowers' business or trading activities, it provides opportunities for entrepreneurs to benefit from the expertise of lenders. Therefore, the new registry may also drive firms' innovation and entrepreneurship.

information sharing schemes, and whether the pandemic impacted the effectiveness of credit bureau and credit registry differently in terms of flow and quality of information. COVID-19 may have had less disruptive impact on information sharing via credit registry that is mandatory compared to credit bureaus that are private information providers.

2.7 Conclusion

In this study, we review theoretical literature and recent empirical studies on the effects of credit information sharing. Credit information sharing has a rapidly growing literature which provides several opportunities for further research. The analysis identifies some important themes in the literature and few weaknesses in the current information sharing mechanisms. Importantly, we provide improvement suggestions in the following areas of the literature. First, we highlight the need to expand information sharing coverage across emerging and developing countries to maximize its impact. Second, the role of incentives in sharing private information among banks is highlighted in the analysis to motivate review of policies. Third, we use the analysis to motivate future research by identifying opportunities to expand existing knowledge. We do so by offering several policy-oriented research ideas of which three are investigated in this thesis, leaving the rest for further research.

Appendix

Appendix Table A2. 1 Theoretical articles on credit information sharing among banks

Author(s) and year	**Main Idea**	**Model**	**Main findings**

Bennardo et al. (2015)	Credit information sharing and borrowers' over-indebtedness	Theoretical model (Moral Hazard)	Credit information sharing reduces multiple borrowings and borrowers' over-indebtedness.
Flatnes (2021)	Credit information sharing and lending in credit markets	Theoretical Model (Adverse selection and Moral Hazard)	Credit information sharing reduces adverse selection, moral hazard, collateral requirement, and credit rationing.
Karapetyan & Stacescu (2014a)	Credit information sharing and information acquisition	Theoretical Model	Credit information sharing increases banks' incentives to acquire more private information.
Karapetyan & Stacescu (2014b)	Credit information sharing and the role of collateral	Theoretical Model (Adverse selection)	Credit information sharing increases the role of collateral in credit markets.
Padilla & Pagano (1997)	Information sharing among lenders	Theoretical Model (Moral Hazard)	Sharing borrowers' information can increase their effort.
Padilla & Pagano (2000)	"Sharing default information as a borrower disciplining device"	Theoretical Model (Moral Hazard)	Sharing information about past defaults helps to discipline borrowers.
Pagano & Jappelli (1993)	"Information sharing in credit markets"	Theoretical Model (Adverse selection)	Borrowers' mobility increases banks' incentives to share their borrowers' information. Such sharing may increase lending in markets with sever adverse selection problem.

Source: Compiled by the authors

Appendix Table A2. 2 Empirical articles on credit information sharing among banks

Author(s) and year	**Main Idea**	**Credit information sharing measure**	**Source(s) of information sharing data**	**Empirical model**	**Main findings**
Adusei & Adeleye (2022)	Effects of credit information sharing on NPLs and the moderating role of creditor rights protection	Credit information sharing Index	World Bank Doing Business	Syst-GMM & OLS/Weighted Least Squares	Credit information sharing reduces NPLs, with higher effects in the presence of creditor rights protection.
Bahadir & Valev (2021)	Investigating how increase in information sharing impact household loans compared to business loans	Credit information sharing index and dummy variable	World Bank Doing Business database	Panel data with fixed and random effects	Credit information sharing increases lending to households relative to business loans.
Bird et al. (2019)	The effects of credit information sharing by borrowers on access to credit and holdup	Dummy variable (whether a borrower shares information or not)	LPC Dealscan database	Fixed effect regression	Borrowers that share their information have higher access to loan, higher loan amount, and lower interest rates.
Darmouni & Sutherland (2021)	They examine how lenders react to information about their competitors lending decisions	Dummy variable	PayNet (Credit Bureau)	Regression with fixed effects	Conditional on market share and concentration, lenders adjust their lending terms toward what competitors are offering when they join a bureau.

De Moraes et al. (2022)	The relationship between credit information sharing and financial development	Coverage of credit bureau and credit registry	World Bank Doing Business database	Panel model with Syst-GMM	Credit information sharing improves financial development.
De Haas et al. (2021)	Effects of credit registry in an emerging market	A dummy variable (whether credit registry is in place of not)	The start of credit registry in Bosnia & Herzegovina in 2009	Difference-in-Differences	Credit information sharing reduces defaults, increases return on loans, and results in tightened lending at both extensive and intensive margins. However, lending to new borrowers improves over time.
De Haas & Millone (2020)	Impact of information sharing on the use of collateral versus guarantees	A dummy variable (whether credit registry is in place of not)	Start of Bosnia and Herzegovina credit registry in 2009	OLS	Both collateral and guarantee requirements decline for repeat borrowers, but a shift from collateral to guarantee for new borrowers.
Doblas-Madrid & Minetti (2013)	Relationship between information sharing and firms' performance	A dummy variable (When lenders join a bureau)	PayNet Database (Credit Bureau)	OLS with Probit and Tobit	Credit information sharing reduces loan defaults and increases collateral requirement for lower-quality borrowers.
Fosu (2014)	Effect of information sharing on bank lending	Credit information sharing index and a dummy variable	World Bank Doing Business database	Panel model with GMM	Conditional on market concentration, information sharing increases bank lending.

Fosu et al. (2021)	The relationship between information sharing and credit intermediation cost	Credit information sharing index, coverage of credit bureau and credit registry	World Bank Doing Business database	Panel model with GMM	Credit information sharing reduces credit intermediation cost.
Fosu et al. (2020)	Effect of information sharing on loan default rates in developing countries	Credit information sharing index	World Bank Doing Business database	Panel model with GMM	Conditional on bank market concentration, information sharing reduces loan defaults.
Giannetti et al. (2017)	Effect of information sharing on borrowers' credit ratings	Dummy variable	1998 reform of Argentinian credit registry	Difference-in-Differences	Banks downgrade high-quality and upgrade low-quality borrowers before sharing information with the credit registry.
Grajzl & Laptieva (2016)	Effect of information sharing on the volume of private credit	Dummy variables (bank participation in the national registry and private bureau)	National Bank of Ukraine and a Ukrainian private bureau	Fixed effects	Credit information sharing via private bureau is associated with higher lending, but no volume effect with the public registry.
Guerineau & Leon (2019)	Effect of information sharing on financial stability	Credit information sharing index, coverage of credit	World Bank Doing Business database	Random effect probit model	Credit information sharing reduces financial fragility.

		bureau and credit registry			
Iakimenko et al. (2022)	The relationship between information and banking sector stability	Credit information sharing index	World Bank Doing Business database	Panel model with Syst-GMM	Lowest level of credit risk is observed at minimum and maximum levels of information sharing.
Kusi & Opoku-Mensah (2018)	The link between information sharing and bank funding cost	Coverage and dummy variable measures of both credit registry and credit bureau	World Bank	Panel model with Syst-GMM	Credit information sharing reduces bank funding cost.
Liberti et al. (2022)	How lenders adoption of credit bureau affects access to credit and competition	Dummy variable capturing when a lender adopts the voluntary system of credit bureau	PayNet Database (Credit Bureau)	OLS	Credit information sharing increases competition and access to credit among higher-quality borrowers.
Loaba & Zahonogo (2019)	Linkages between information sharing and bank credit and economic growth	Coverage of credit register	WDI	Two-stage and three-stage least square	There is no obvious indication of credit and economic growth.
Sutherland (2018)	Credit information sharing, firms' access credit, and lenders' lending behaviour	Dummy variable capturing when a lender adopts the	PayNet Database (Credit Bureau)	OLS	Credit information sharing reduces borrowers' cost switching. After sharing their information, lenders

		voluntary system of credit bureau			change to transactional lending approach.

Credit information sharing index measures the scope, accessibility, and quality of credit information sharing via credit registry and credit bureau. The index ranges from 0 to 6 between 2004 and 2013, and 0 to 8 after 2013. Higher value indicates higher depth of information scope, accessibility, and quality. Credit registry coverage and credit bureau coverage represent the percentage of firms and individuals covered in each of the information sharing scheme in countries where they exist.

Source: Compiled by the authors

Chapter 3: Mandatory credit information sharing and policy-induced credit constraints: The roles of loan classification policies and capital regulation stringency

3.1 Introduction

In markets where lenders cannot determine borrowers' creditworthiness due to asymmetric information, credit rationing (e.g., Stiglitz & Weiss, 1981) or excessive lending (e.g., de Meza & Webb, 1987) may occur. Consequently, credit information sharing schemes which enable banks to exchange information about their borrowers have been adopted in many banking sectors across the world to reduce the effects of asymmetric information including adverse selection and moral hazard.[17] However, not all banks with positive private information may disclose it voluntarily since information sharing increases competition.[18] To address this problem, banking regulators in many countries have introduced mandatory credit information sharing scheme that requires financial institutions in a country to participate in a central credit registry administered by the central bank (World Bank, 2019; 2020a).

With credit information sharing scheme in place, the expectation is that a market emerges where loan screening is higher and lending decisions are based on the quality of borrowers' credit history and ongoing projects. Theoretical literature predicts reduction in asymmetric information, collateral requirements, and credit rationing (Flatnes, 2021). These predictions suggest that credit information sharing can benefit both banks and their borrowers by improving the quality and volume of loans. Given that lack of collateral prevents many businesses from using bank credit, small businesses that are more opaque and without physical collateral for loans may benefit even more from credit information sharing schemes.

[17] Information sharing is the most recent of three techniques (including relationship banking and collateralized lending) commonly used in credit markets to reduce the effects of asymmetric information. On relationship lending, banks offer more favourable continuation lending to firms with which they have had stronger credit relationships (Banerjee et al., 2021). However, relationship lending enables banks to extract higher rents from relationship borrowers (Duqi et al., 2018). Additionally, relationship lending is based on private information which increases the cost of information and adverse selection problems faced by non-relationship lenders. These mean that relationship borrowers remain highly opaque and may not be able to find alternative funding when current lenders stop supplying funds. Similarly, collateralization improves credit activities because it plays the vital role of preventing contract's parties from reneging especially in a frictional environment where commitment is weak (as in Awaya et al., 2021). Again, collateralization has several shortcomings including reduction in screening incentives (Manove et al., 2001). This mixed blessing that is associated with relationship and collateralized lending drives the interest in information sharing technique and why its adoption is growing rapidly.

[18] Both theory (e.g., Pagano & Jappelli, 1993) and empirical evidence (e.g., Liberti et al., 2022) agree that credit information sharing increases competition in credit markets.

However, empirical studies have not supported all these claims especially when information sharing is a regulatory requirement rather than voluntary. Existing evidence shows that mandatory credit information sharing is associated with higher loan quality (e.g., De Haas et al., 2021). However, insignificant effect (e.g., Grajzl & Laptieva, 2016) and lower bank lending (e.g., De Haas et al., 2021) have generally been reported in terms of credit growth. As a matter of fact, evidence on credit activities from across the world agrees with lending reduction in recent years. Firms' access to external financing has declined globally during the last decade (Banti & Bose, 2021), and majority of loans are collateralized (Fan et al., 2022).

The key insights from these studies are that access to credit is weak and the use of collateral dominates global credit markets despite the widespread adoption of mandatory information sharing scheme in recent years. It should be noted, however, that banks are only required to share private information under mandatory information sharing system but not required to adopt information-based lending technique. Therefore, information sharing schemes are unlikely to replace relationship lending and collateralization in credit markets, and banks' decision to engage in information-based lending may depend on how it impacts their financial statements in terms of cost and loan valuation. For example, collateralized loans receive lower risk weights when estimating Risk-Weighted Assets (RWA) in many markets (e.g., Degryse et al., 2021). This is an unexplored area of the literature, especially the effects of policies that can disincentivize information-based lending. We have no knowledge of what happens when mandatory credit information sharing coexists with policies determining how loans are recognised in bank balance sheet, and how the interaction affects key regulatory ratios and other important cost components of bank financial statements.

We fill this gap in the literature with specific focus on loan classification policies and banking regulations that may influence how banks lend in a particular market. Loan classification policies allocate risks to loans based on estimated borrowers' ability to meet their loan obligations (Song, 2002). Loan policies and practices vary widely across countries in terms of loan asset categories, number of days in arrears before a loan is classified as nonperforming or written off, and the rate at which provisioning for loan losses is estimated (see World Bank, 2020b). These policies have direct effects on the balance sheet and income statement of banks through provisioning and loan asset write-offs. Accordingly, we expect the existence of policies that reduce the costs associated with collateralization relative to uncollateralized loans to diminish banks' incentives to engage in information-based lending.

We start by investigating the effect of a policy which allows banks to apply provisioning rules to a loan net of collateral value.[19] With this policy present, banks can avoid provisioning cost for a loan with value equals or less than the value of collateral. When mandatory information sharing coexists with this policy, it is unlikely to increase uncollateralized loans and may reduce credit growth by addressing excessive collateralized lending associated with the loan policy.

In addition, we expect the stringency of capital regulation in a country to determine whether mandatory information sharing reduces credit risk and increases credit growth or achieve one at the expense of the other. It is difficult to achieve both credit growth and risk reduction in the same market with one policy tool. Moreover, the bank risk literature shows that higher loan growth is often associated with higher credit risk (e.g., Kandrac & Schlusche, 2021). Given that mandatory information sharing scheme is administered by the central bank, it improves regulatory knowledge of the quality of bank asset portfolios in the banking sector. This also means that the scheme reduces bank opacity and is more likely to reduce credit risk. However, it may be the case that reducing lending volume is one of the channels through which mandatory information sharing reduces credit risk, especially in markets where lending volume is important such as those with stringent capital regulation (see Uluc & Wieladek, 2018 for capital regulation and lending volume). Therefore, we predict that mandatory information sharing reduces credit risk when it coexists with stringent capital regulation but at the expense of credit growth. Understanding this potential trade-off is important for ongoing review of credit information sharing related policies. We also provide further analysis to understand the economic importance of the resulting credit supply shortages by looking at how the coexistence of the two policy tools impacts bank profit performance.

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[19] Initially, we identified the following two standout policies. First, loan classification policy which allows banks to classify a collateralized loan in a better category than uncollateralized loan. Second, a loan policy which allows banks to apply provisioning rules to a loan net of collateral value. The two policies favour collateralization but are different in principles. The first is based on the three-stage (sub-standard, doubtful, and loss) loan loss recognition system of IAS 39, while the second policy applies provisioning rules to a loan value less the value of collateral which is consistent with the expected credit loss (ECL) approach of IFRS 9. Under ECL, credit losses are estimated as the difference between cash flows expected from collateral and other credit enhancements such as guarantee, less the costs of obtaining and selling the collateral (see Caruso et al., 2021 for more on IFRS 9). With IFRS 9 becoming mandatory in many countries in 2018 as a replacement for IAS 39, we want to focus on the second policy to position our study in the future of this literature. Moreover, while the incurred loss model of IAS 39 is being phased out across the world, the application of the second policy is increasing in line with growing adoption of ECL model.

We test our predictions using bank-level panel data of 368 banks from 40 countries. The sample period is from 2012 to 2020, and we employ the system Generalized Method of Moments (GMM) proposed by Arellano & Bover (1995) and Blundell & Bond (1998). Our results show that mandatory information sharing is associated with lower credit growth when it coexists with a policy which allows banks to apply provisioning rules to a loan net of collateral value. The investigation shows that this policy is associated with higher credit growth and higher rate of nonperforming loans without mandatory information sharing, but lower credit growth and lower rate of nonperforming loans with mandatory information sharing present. Therefore, the findings are more consistent with the disciplinary channel of mandatory information sharing than lower incentives to engage in information-based lending. Whether this policy favouring collateralization is designed to increase credit growth or reduce credit risk is hard to know.[20] Regardless, our results suggest that by reducing the costs associated with collateralization, the policy incentivizes moral hazard lending behaviour.

Next, we find that mandatory information sharing reduces both credit risk and credit growth in countries with stringent capital regulation. These results confirm our third prediction that the combination of tight capital regulation and compulsory disclosure of credit information can improve the quality of bank loan assets but at the expense of credit growth. The findings show that without mandatory information sharing, banks generally meet stringent capital requirement by engaging in credit risk-taking to increase loan volume and accumulate higher earnings which are important components of Common Equity Tier 1 (CET1). With mandatory information sharing present, banks appear to change lending policy to low-volume/high-quality to shrink risk-weighted assets and improve capital ratio even though such policy is associated with poor profit performance. It comes as no surprise that many countries combine stringent capital regulation and mandatory credit information sharing scheme since doing so reduces bank opacity and credit risk-taking. However, significant reduction in lending driven by the combination of these policies may increase risk in the banking sector when many banks reduce lending at the same time.

Overall, our findings suggest that mandatory credit information sharing is associated with lower credit growth and lower nonperforming loans when it coexists with a loan policy

[20] While collateral increases firms' access to credit (as in Aretz et al., 2020), there is no conclusive evidence that collateralization reduces credit risk. Reduction in information asymmetries (e.g., Ioannidou et al., 2022) and higher risk-taking (e.g., Costello, 2019) have both been reported.

which allows banks to provision for loan losses net of collateral or stringent capital regulation. Further analysis indicates that the coexistence also reduces bank profit performance.

This study contributes to an expanding literature on the role of credit information sharing in improving credit quality (e.g., Fosu et al., 2020) and credit availability (e.g., Bahadir & Valev, 2021). The findings provide evidence on the role of loan classification policies in the effectiveness of mandatory information sharing in promoting credit growth. One of the key promises of credit information sharing is its potential to reduce the incidence of collateral in credit markets (Flatnes, 2021). Our study shows that existing loan policies in many countries favour collateralization in terms of cost associated with bank loan losses. Consequently, mandatory information sharing scheme cannot drive higher lending in these countries but reduces excessive collateralized lending associated with these loan policies. We are hoping that this paper starts a new strand of the literature which focuses on uncovering issues arising from interaction between credit information sharing and many other policies in different countries.

In addition, the study extends a growing literature on falling bank lending activities due to higher regulations (e.g., Mirzaei et al., 2021 for global evidence; Cehajic & Marko, 2022 for countries in the European Union). We contribute to this literature with new evidence that the cost of credit reduction due to the coexistence of tight capital regulation and mandatory information sharing is material and can cause significant harm to the banking sector through weaker profitability. By doing so, we shed light on the real effect of mandatory information sharing on credit risk, that in the presence of stringent capital regulation, it reduces risk in the banking sector through the lending channel but creates further risk through the performance channel. This new knowledge is critically important because in the event that many banks experience significant profit decline at the same time, risk of failure may increase in the banking sector.

The rest of chapter 3 proceeds as follows: Section 3.2 presents the literature review and development of hypotheses. Section 3.3 covers the description of data used in the study, explanation of variables, and empirical models. Section 3.4 presents the study results and discussion. Section 3.5 presents how we address endogeneity issues as well as additional robustness checks and discussion, while section 3.6 is the study conclusion.

3.2 Literature review and hypotheses development

Theoretical literature on credit information sharing shows that it alleviates effects of asymmetric information in credit markets including adverse selection problem (Pagano & Jappelli, 1993) and moral hazard behaviour (Padilla & Pagano, 1997; 2000). In addition, information sharing increases incentives to collect more private information (Karapetyan & Stacescu, 2014a) and prevents excessive borrowings from multiple lenders (Bennardo et al., 2015). These studies show that information sharing promotes safe lending and risk reduction in credit markets. What is not clear, however, is the channel through which it increases credit growth. It could be argued that the net effect of information sharing on lending volume is immaterial as increase in credit received by borrowers with good credit history only covers the gap created by the reduction in lending to low-quality borrowers.

In one of the most recent studies in the literature, Flatnes (2021) makes two important contributions to this argument. First, the study shows that information sharing results in *equitable credit terms* whereby borrowers with good credit history receive better credit terms while those with bad history get worse credit terms such as higher interest rates. This argument appears credible because many lenders would want to lend more if default probabilities can be estimated more accurately with information sharing present and the expected returns are high enough to reward them in line with the estimated risk. The issue with this argument is that higher interest rates may motivate borrowers to invest in high-risk projects, and banks would ration credit when raising interest rates is expected to incentivize borrowers' risk-taking (as in Stiglitz & Weiss, 1981).

The second argument by Flatnes (2021) is that by increasing the use of shared information, information sharing system reduces collateral requirement. This could be the most important channel through which information sharing increases credit growth since collateral-poor firms are likely to exit the credit market (see Araujo et al., 2019 for firms' access to credit and the use of collateral). However, this prediction is in sharp contrast to previous theoretical work by Karapetyan & Stacescu (2014b) which reports increase in collateral requirement. Their model shows that, by revealing more borrowers with bad credit history, information sharing results in more collateral requirement by new lenders. This implies that the effect of information sharing on collateral requirement is conditional on the quality of borrowers' information revealed by information sharing system. If the system reveals significantly higher proportion of high-quality borrowers, the incidence of collateral may fall below the level experienced before the introduction of credit information sharing scheme(s). If it reveals higher proportion of low-quality borrowers, the role of collateral in credit market may increase.

Overall, theoretical literature suggests that information sharing reduces credit risk. However, the channel through which it increases credit growth remains ambiguous, hence providing a research gap that requires further investigation.

From the empirical perspective, evidence shows that credit information sharing increases access to bank credit (Fosu, 2014), lengthens the maturity of loans (Sorge et al., 2017), and reduces loan default rates (Adusei & Adeleye, 2022). In addition, information sharing is associated with lower financial system fragility in both advanced and emerging markets (Guerineau & Leon, 2019), higher financial system development (de Moraes et al., 2022), and lower intermediation cost of banks (Fosu et al., 2021).

Evidence from studies specifically investigating the effects of mandatory information sharing via credit registry rather than the whole information sharing system is growing but with mixed evidence. Bertrand & Klein (2021) investigate the impact of information sharing by means of credit registry on relationship lending across Europe, they find that banks' long-term credit relationship and investment in collecting private information fall significantly as coverage of credit registry grows. De Haas et al. (2021) show that the introduction of credit registry in Bosnia and Herzegovina results in tightened lending at the extensive and intensive margins. However, the study also shows increase in lending to new borrowers when they have demonstrated their quality; reduction in loan defaults, especially among new borrowers; and increase in returns on loan. Behr & Sonnekalb (2012) study the effect of information sharing through credit registry in Albania on access to credit, cost of credit, and loan performance. They find no impact on access to credit and cost of credit except significant improvement in loan performance. Similarly, Grajzl & Laptieva (2016) use a bank-level panel data to investigate the impact of information sharing on the volume of private credit in Ukraine, they find that information sharing through the central credit registry has no effects on credit growth. Meanwhile, Hertzberg et al. (2011) report that lenders in Argentina reduce credit supply in anticipation of other lenders' reaction to negative information about firms, and this increases firms' financial difficulties.

The evidence so far shows strong support for higher loan quality but the channel for credit growth remains unclear. It appears that credit registry has not increased credit growth by reducing collateral requirements as predicted by Flatnes (2021). Lending reduction and insignificant results have generally been reported. These are consistent with evidence on credit activities across the world. Firms' access to external financing has declined during the last decade (Banti & Bose, 2021), while credit constraints remain the biggest driver of lower firms' capacity utilization especially in developing countries (Zhang, 2022). Regarding the use of collateral in global credit markets, Fan et al. (2022) report in their study of collateralized borrowings across 131 countries that 77% of loans in recent years are collateralized. Evidence from another cross-country study by Banerjee & Blickle (2021) shows that firms' access to credit is conditional on the value of their collateral. It may be the case that, by revealing more borrowers with bad credit history, mandatory information sharing increases collateral requirements and reduces access to credit (as in Karapetyan & Stacescu, 2014b).

An alternative argument is that loan policies and practices in some host countries limit the use of information-based lending approach by favouring collateralization. Loan classification policies allocate risk to loans based on estimated borrowers' ability to meet their loan obligations (Song, 2002). Policies that increase the costs associated with information-based lending approach or reduce the costs associated with other lending techniques relative to information-based, may have adverse impact on the performance of credit registry. Therefore, we start by looking at the role of a particular loan policy that allows banks to deduct collateral value before applying provisioning rules to a loan.

There are at least two possible ways that this policy may impact mandatory information sharing scheme. First, the policy makes collateralization more attractive to lenders than uncollateralized lending. Early recognition of loan losses is important for bank stability (e.g., Gomaa et al., 2021), and inadequate provisioning increases bank risk (e.g., Yang, 2022). Therefore, banks in some countries are required to make 100% provision as soon as a loan is classified as nonperforming (see World Bank, 2020b). However, when there is a loan policy that permits the application of provisioning rules net of collateral value, banks can avoid the costs associated with provisioning by requiring higher collateral from borrowers. This also means that collateral-based lenders would have higher profits and capital ratio than non-collateral lenders who cannot avoid these costs. These arguments are consistent with evidence which shows that higher provisioning is associated with higher net loan charge-offs

(Basu et al., 2020) and lower bank lending (Pool et al., 2015). This cost advantage of collateral-based lending technique reduces the use of uncollateralized lending technique such as information-based screening.

Second, a loan policy that favours collateralization may also incentivize moral hazard behaviour such as excessive lending since the use of collateral reduces screening incentives (e.g., Manove et al., 2001) and increases credit risk-taking (e.g., Costello, 2019). Therefore, mandatory information sharing in markets with this loan policy is more likely to act as a disciplinary device that reduces credit risk-taking than a scheme that increases lending volume. Based on these arguments, we develop the following hypothesis.

Hypothesis 3.1: Mandatory credit information sharing is associated with lower credit growth when it coexists with a policy that allows banks to apply provisioning rules to a loan net of collateral value.

In addition to reducing asymmetric information between banks and borrowers, mandatory credit information sharing also reduces asymmetric information between banks and regulatory authorities since credit registry is administered by the central bank. While the literature focuses entirely on the former, the latter relationship has equal ability to influence bank risk-taking and willingness to lend depending on the stringency of banking regulations in a country.

An important part of Basel III is higher capital requirements (Degryse et al., 2021), and prior studies have emphasized the importance of such higher capital regulation in enhancing efficiency in the banking sector (e.g., Barth et al., 2013).[21] With growing number of countries adopting these stricter regulations, banks are finding ways to satisfy them without falling short of other regulatory requirements. Banks can meet higher regulatory capital requirements by reducing lending to shrink risk-weighted assets, that is the denominator of the capital ratio (e.g., Gropp et al., 2019); by lending more to accumulate higher earnings and increase the numerator of the capital ratio (e.g., Uluc & Wieladek, 2018); or by expanding collateralized loans to reduce Risk-Weighted Assets (RWA) since loans with collateral are assigned lower risk weights (e.g., Degryse et al., 2021). Regulators generally favour capital

[21] Note, the benefit of higher capital regulation, especially operating efficiency, is more pronounced in countries with higher quality institutions (Chortareas et al., 2012).

increase because shrinking assets may result in many banks reducing credit supply at the same time (Hanson et al., 2011). For banks, this presents a dilemma since lending more to boost retained earnings may result in credit expansion to low-quality borrowers while lending reduction policy may result in lower retained earnings. However, mandatory credit information sharing can change these dynamics. For instance, the option to increase capital through earnings accumulation that involves the origination of riskier loans (e.g., Uluc & Wieladek, 2018), relies on the window of time between loan origination and when the associated risk comes to light. However, by requiring all banks to report credit information on a regular basis, mandatory credit information sharing scheme can close this window of opacity that has been described as a necessity for liquidity creation (e.g., Holmstrom, 2015; Dang et at., 2017). This also means that mandatory information sharing scheme can reduce credit risk-taking. Moreover, evidence shows that following disclosure of risk ratings, poorly rated banks reduce credit supply (Kupiec et al., 2017) and improve their risk management practices (Gopalan, 2022).

It appears that having stringent policies such as tight capital regulation without addressing bank opacity may not be sufficient when it comes to safeguarding the banking system from extreme vulnerability. As a matter of fact, the evidence reported by Uluc & Wieladek (2018) seems to suggest that stringent capital regulation incentivizes higher credit risk-taking. The complex nature of banks' operations and regulators' inability to understand them may allow opaque banks to accumulate higher risks even when there are strict regulations in place. For example, Niinimaki (2012) describes how banks effectively hide loan losses from regulators in the immediate term by rolling over defaulted loans or by issuing new loans to defaulting borrowers to repay the previous loans so that new loans are not in arrears. This behaviour is driven by opacity, and it is a good example of why many countries have introduced mandatory credit information sharing in addition to tight capital regulation to ensure that banks are sharing information about the quality of their credit portfolios regularly. However, our prediction is that the combination of mandatory credit information sharing and stringent capital regulation can reduce credit risk but could choke off lending. Therefore, we make the following hypotheses:

Hypothesis 3.2A: where there is stringent capital regulation, mandatory credit information sharing reduces credit risk.

Hypothesis 3.2B: where there is stringent capital regulation, mandatory credit information sharing reduces credit growth.

While credit risk reduction is important, falling credit supply cannot be ignored because it poses material risk too especially when it is policy-induced. The resulting credit constraints can cause devasting effects on both the financial sector and the economy. This argument is consistent with Mankart et al. (2020) model which demonstrates that tighter capital regulations which reduce credit growth are also likely to adversely affect bank profitability and increase the incidence of bank failure. Accordingly, if our data supports hypotheses 3.2A and 3.2B, we also expect the combination of mandatory information sharing and stringent capital regulation to have adverse effect on bank profitability. Therefore, we hypothesize that:

Hypothesis 3.2C: where there is stringent capital regulation, mandatory credit information sharing reduces bank profitability.

The literature clearly shows that the role of opacity in bank risk behaviour is significant. Therefore, having a sound information system such as credit registry to reduce opacity is critically important. We have carefully formulated the above hypotheses to improve our knowledge of the costs and benefits of employing credit registry to reduce opacity in the banking sector.

3.3 Data and Methodology

3.3.1 Data and variables

We use a panel dataset based on bank-level, banking sector, and macroeconomic data. We obtain bank-level data from BankFocus provided by Bureau van Dijk,[22] banking sector data from the Banking Regulation and Supervision Database of the World Bank, macroeconomic

[22] We would have preferred hand-collected data, but it yields a very small dataset.

data from the World Development Indicators (WDI) and the International Financial Statistics database of the International Monetary Fund (IMF), and information sharing data from the World Bank's *Doing Business* database. Initially, we considered all developing countries with sufficient data availability on mandatory information sharing, and we had the original dataset representing 460 banks from 68 countries. We then applied the following adjustments to the dataset. First, bank-level data obtained from BankFocus had significant number of missing observations between 2009 and 2011. Consequently, we reduced our sample period from 2009-2020 to 2011-2020. Second, the dependent variable (loan growth) and changes in deposits are growth rates. For each bank, we lose one year (2011) in estimating growth rates. Third, for our main dependent variable, we follow the literature (e.g., Micco & Panizza, 2006) by excluding observations or banks with loan growth rates that are larger than 100% (in absolute value) to control for outliers. Following these adjustments, we have a final unbalanced dataset of 3,321 observations and 368 banks from 40 countries over the period 2012-2020. To construct the bank-level panel dataset, each bank is assigned the appropriate values of banking sector and macroeconomic variables.

The main dependent variable is the real growth in bank loans (LG). Following Bouvatier & Lepetit (2008), we estimate LG as the change in total loans of a bank scaled by average total assets [$l_{it} - l_{i,t-1}/0.5(ta_{it} + ta_{i,t-1})$]. l and ta are bank-year total loans and total assets. We have excluded bank loans to other banks as financial institutions have different risk structure. Other dependent variables used in the analysis include log of loan growth ($lnLG$) as alternative measure of credit growth, ratio of nonperforming loans to total loans of a bank ($NPLr$) and loan loss provisions to total loans ($PROV$) which are the two measures of credit risk, and *Profitability* which is the return on average total equity of a bank.

Our main explanatory variables are active mandatory information sharing ($AMIS$) and mandatory information sharing coverage ($MISCOV$). $AMIS$ has a value of one if banks in a country actively share borrowers' information in a particular period and zero otherwise. We adopt this definition to avoid assigning the value of one to periods of registry existence before the start of actual information sharing and periods when sharing was on hold. We measure $MISCOV$ as the number of firms and individuals covered in a country's public credit registry with information on repayment history, unpaid debt balances, or outstanding credit from the past five years as a percentage of total adult population (as in Houston et al., 2010). Other explanatory variables are $LoanPolicy$ which equals one if loan classification policies allow banks to provision for loan losses net of collateral and zero otherwise, and stringent capital regulation (SCR) with a value of one if a country has a capital regulation stringency score that is in the top quartile of bank capital regulations index and zero otherwise. SCR is based on the index which measures the stringency of the banking sector capital regulations from 0 to 10, with higher index value indicating higher capital stringency (as in Barth et al., 2013; Deli & Hasan, 2017). In each of the ten questions below, value 1 indicates stringent regulation:

- Is bank capital ratio risk-weighted in line with Basel guidelines?" value of one for yes and zero otherwise.
- Does the ratio vary with bank's credit risk?" value of one for yes and zero otherwise.
- Does the ratio vary with market risk?" value of one for yes and zero otherwise.
- Before minimum capital adequacy is determined, is the market value of loan losses deducted from capital? Value of one for yes and zero otherwise.
- Before minimum capital adequacy is determined, are unrealized securities losses deducted from capital? Value of one for yes and zero otherwise.
- Before minimum capital adequacy is determined, are unrealized foreign exchange losses deducted from capital? Value of one for yes and zero otherwise.
- Is the fraction of revaluation gains allowed as part of capital lower than 0.75? value one for yes and zero otherwise.
- Can the initial disbursement or subsequent injections of capital be done with assets other than cash or government securities?" value of one for no and zero otherwise.
- Are the sources of funds to be used as capital verified by the regulatory/supervisory authorities? Value one for yes and zero otherwise.
- Can initial disbursement of capital be done with borrowed funds?" value of one for no and zero otherwise.

We control for bank characteristics that are likely to affect lending activities and the quality of bank loans by including the following variables: $ROAA$ (return on average total assets of a bank, except where $ROAE$ is used as the dependent variable), $Liquidity$ (liquid assets to total assets ratio of a bank), $Deposits$ (the growth in total deposits of a bank). While banks with higher profitability and deposits may have higher loanable funds and able to lend more, the direction of impact of the other controls remain ambiguous. For example, banks with higher liquidity are able to lend more (e.g., Jeon et al., 2013). However, other studies report that higher liquidity and capital are associated with slower credit growth (e.g., De Haas & van Lelyveld, 2010).

We also consider macroeconomic fundamentals in line with literature (e.g., Adusei & Adeleye, 2022). For instance, improvement in a country's GDP per capital can improve borrowers' ability to borrow, service, and repay their loans due to improvement in their income and business activities. Meanwhile, higher inflation indicates unstable macroeconomic conditions that can exacerbate market frictions and credit rationing (e.g., Boyd et al., 2001). Consequently, we include GDP per capital growth ($GDPPCgr$) and $Inflation$ ($INFL$) as macroeconomic controls. In addition to mandatory information sharing (credit registry) which is the focus of our study, voluntary information sharing system (credit bureau) also exists in some countries. To account for the effect of this, we include CB (Private Credit Bureau) with a value of one if a country has a credit bureau and zero otherwise, and *CBCOV* (Credit Bureau Coverage in percentage). Lastly, we include a banking sector control variable that account for the extent to which banking regulations in a country support the ability of private investors to monitor banks and promote effective bank governance. We include a private monitoring index which ranges from 0 to 10 (definition in Appendix Table A3.1), with higher value indicating higher private monitoring (as in Beck et al., 2006; He et al., 2021). Appendix Table A3.1 summarizes the definition of all variables and the symbols representing them in the empirical sections. It also includes sources of all data used in the study.

Summary statistics

Table 3.1 presents the descriptive statistics of variables used in the study. The dependent variable, loan growth rate (*LG),* has a mean of 3.7%. The second measure of loan growth, log of loan growth (*lnLG*), has approximately 6% mean. The first of the two measures of credit information sharing, the percentage coverage of mandatory information sharing (*MISCOV)* through credit registry has a mean of 18.6%, while the second measure representing periods of active credit information sharing, *AMIS,* has a value of 0.69 or 69%. Meanwhile, Figure 3.1 shows that, during the sample period, *MISCOV* increases from 13.6% to 22.1%. This is an indication that credit registry coverage is expanding across developing and emerging countries. *LoanPolicy* has a mean value of 0.630. That is, on average, 63% of banks in the sample are allowed to provision for loan losses net of collateral. The variable representing the stringency of capital regulation (*SCR*) has a mean value of 0.31, indicating that 31% of banks in our study are in countries with the most stringent capital regulation (the top quartile of the regulation index).

Table 3. 1 Descriptive statistics

Variable	**Obs**	**Mean**	**Std.dev**	**Min**	**Max**
LG	3,312	0.037	0.099	-0.672	0.827
lnLG	3,312	0.061	0.176	-1.422	1.447
MISCOV	3,312	18.561	21.971	0	100
AMIS	3,312	0.689	0.462	0	1
Profitability	3,312	0.175	0.292	-12.342	3.458
LoanPolicy	3,312	0.630	0.483	0	1
SCR	3,312	0.311	0.463	0	1
ROAA	3,302	1.392	1.431	-8.953	9.586
NPLr	2,457	0.055	0.079	0.000	1.000
LIQUIDITY	3,285	25.018	14.22	0.168	90.991
INFL	3,227	4.739	3.261	-2.431	19.629
GDPPCgr	3,312	1.569	3.666	-14.819	14.701
DEPOSITS	3,272	7.691	18.633	-92.339	102.345
PROV	2,640	0.015	0.022	-0.089	0.686
PrivMontr	3,312	7.456	1.921	2	11
CBCOV	3,312	31.876	31.017	0	100
CB	3,312	0.795	0.403	0	1

This table presents the summary statistics of variables used in the study. Obs is the number of observations, Std.dev Is the standard deviation, Min is the minimum value, and Max is the maximum value. The key variables include loan growth (*LG*), log loan growth (*lnLG*), ratio of nonperforming loans to total loans ($NPLr$), return on average total equity (*Profitability*), active mandatory credit information sharing (*AMIS)* which represents periods of actual information sharing, $MISCOV$ is the coverage of mandatory credit information sharing in percentage, *LoanPolicy* which has a value of one if banks in a country can provision for loan losses net of collateral and zero otherwise, and stringent capital regulation (*SCR*) with a value of one if a country has a capital regulation stringency score that is in the top quartile of the index and zero otherwise. The dependent variables (*LG*, *lnLG,* $NPLr$, *Profitability*) are in ratio. All variables, including controls are defined in Appendix Table A3.1.

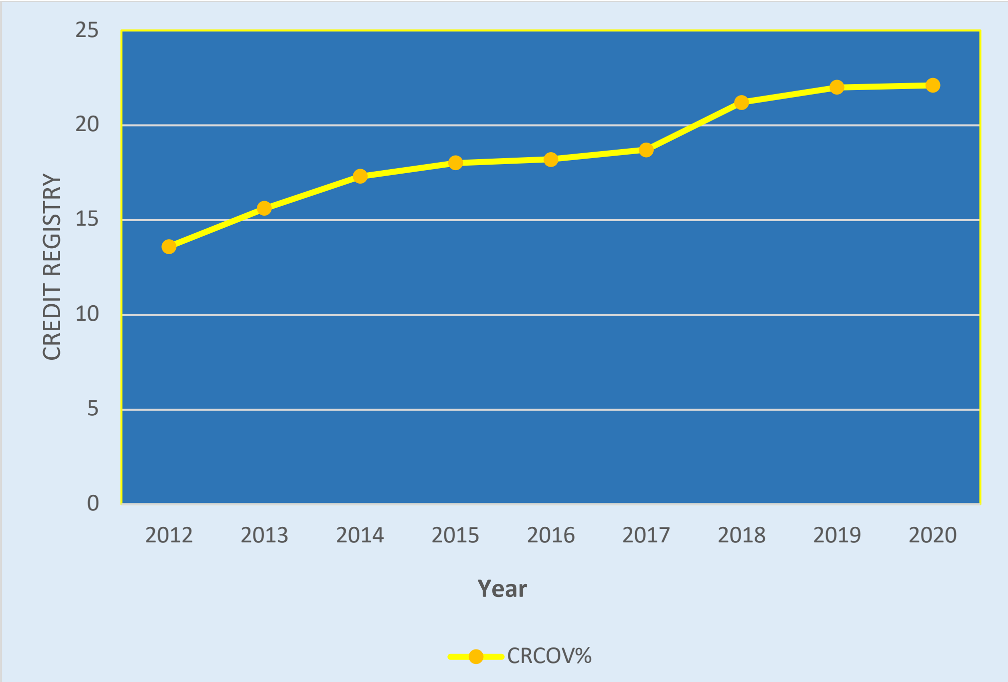

Figure 3. 1 Mandatory credit information sharing (credit registry) coverage in percentage

The correlation matrix is presented in Appendix Table A3.3. We observe that both measures of mandatory credit information sharing, *AMIS* and *MISCOV,* are negatively correlated with *LG* and $NPLr$, suggesting that mandatory credit information sharing may have negative association with both credit growth and nonperforming loans. While we cannot read much meaning to these relationships without empirical testing, we can be sure that our two measures of mandatory credit information sharing have the same signs. This is important because the indicator variable has been carefully coded to represent only periods of active information sharing rather than periods of registry existence. Therefore, *AMIS* having the same sign as the percentage coverage variable, (*MISCOV)*, indicates that we have captured the active sharing periods accurately. Meanwhile, *LoanPolicy* and *SCR* are positively correlated with *LG* and $NPLr$, suggesting possible increase in both credit growth and credit risk when either of the two is present. Regarding multicollinearity, other than alternative variables that will not enter the same regression together, the overall results in the correlation matrix do not show any multicollinearity problem among variables that are used in the same regression.

3.3.2 Estimation and testing procedures

To test hypothesis 3.1 that mandatory credit information sharing is associated with lower credit growth when it coexists with a policy that allows banks to apply provisioning rules to a loan net of collateral value, we adopt a dynamic panel model in line with prior studies which show that past shocks to credit growth directly influence the contemporaneous growth rate (e.g., Fosu, 2014; Allen et al., 2017). Specifically, we estimate the following model:

$$
\begin{aligned}
LG_{i,t} = \; & \alpha + \beta_1 LG_{i,t-1} + \beta_2 LoanPolicy_{j,t} + \beta_3 \left(LoanPolicy_{j,t} * MIS'_{j,t} \right) + \measuredangle\, MIS'_{j,t} \\
& + \pi X'_{i,t} + \varphi Z'_{j,t} + \lambda_t + \mathcal{E}_{i,t} \qquad (3.1)
\end{aligned}
$$

where i, j and t index bank, country, and time. $LG_{i,t}$ represents bank loan growth rate, $MIS'_{j,t}$ represents the two measures of mandatory information sharing ($AMIS$ and $MISCOV$). $AMIS$ (Active mandatory credit information sharing) has the value of one if banks in a country actively share borrowers' information in a particular period and zero otherwise. $MISCOV$ is mandatory credit information sharing coverage in percentage. $LoanPolicy_{j,t}$ is a $(0, 1)$ variable indicating whether loan policies in a country allow banks to provision for loan losses net of collateral value. $X'_{i,t}$ is a vector of bank-level control variables ($ROAA$, $Liquididity$, and $Deposits$). $Z'_{j,t}$ is a vector of country-specific variables that include GDP per capital growth ($GDPPCgr$) and $Inflation$ rate to control for Macroeconomic environment, and CB is included to control for the presence of credit bureau(s) in a country. λ_t represents time fixed effects, $\mathcal{E}_{i,t}$ is the error term which consists of bank fixed effects (μ_i) and zero mean idiosyncratic random disturbance ($v_{i,t}$). $LG_{i,t-1}$ is a period lagged dependent variable to account for the effect of dynamic relationship in loan growth. The main variable of interest is $LoanPolicy_{j,t} * MIS'_{j,t}$ which represents the interaction term of mandatory credit information sharing and $LoanPolicy_{j,t}$. Therefore, $LoanPolicy_{j,t} * AMIS_{j,t}$ and $LoanPolicy_{j,t} * MISCOV_{j,t}$ represent the interaction terms for the two measures of $MIS'_{j,t}$. For $LoanPolicy_{j,t} * AMIS_{j,t}$, the coefficient β_3 measures the average effect of mandatory information sharing on credit growth where $LoanPolicy$ is in place. For $LoanPolicy_{j,t} * MISCOV_{j,t}$, coefficient β_3 measures the percentage point change in credit growth due to the coexistence of mandatory information sharing and $LoanPolicy$. A negative sign is expected for β_3 to confirm our hypothesis.

Next, we test hypotheses 3.2[A], 3.2[B] & 3.2[C] in the three equations below. For hypothesis 3.2A that in countries with stringent capital regulation, mandatory credit information sharing reduces credit risk, we estimate the following model.

$$r_{i,t} = \delta_0 + \delta_1 r_{i,t-1} + \delta_2 SCR_{j,t} + \delta_3 \left(MIS'_{j,t} * SCR_{j,t}\right) + \measuredangle MIS'_{j,t} + \pi X'_{i,t} + \varphi Z'_{j,t} + \lambda_t + \vartheta_{i,t} \quad (3.2)$$

Where $r_{i,t}$ (credit risk) is the dependent variable which is the ratio of bank nonperforming loans to total loans (as in Adusei & Adeleye, 2022), $SCR_{j,t}$ has a value of one if a country has a capital regulation stringency score that is in the top quartile of bank capital regulations index and zero otherwise. $\vartheta_{i,t}$ is the error term. The variable of interest in this estimation is $MIS'_{j,t} * SCR_{j,t}$ which confirms hypothesis 3.2A if the coefficient is negative and significant. We also use the ratio of loan loss provisions to total loans as alternative measure of credit risk.

For hypothesis 3.2B that in countries with stringent capital regulation, mandatory credit information sharing reduces credit growth, we estimate the following model:

$$LG_{i,t} = \Lambda_0 + \Lambda_1 LG_{i,t-1} + \Lambda_2 SCR_{j,t} + \Lambda_3 (MIS'_{j,t} * SCR_{j,t}) + \measuredangle MIS'_{j,t} + \pi X'_{i,t} + \varphi Z'_{j,t} + \lambda_t + \beth_{i,t} \quad (3.3)$$

Where $\beth_{i,t}$ is the error term. We expect a negative sign for $MIS'_{j,t} * SCR_{j,t}$ to validate our prediction. For hypothesis 3.2C that in countries with stringent capital regulation, mandatory credit information sharing reduces bank profitability, we estimate the following model:

$$prof_{i,t} = \prod\nolimits_0 + \prod\nolimits_1 prof_{i,t-1} + \prod\nolimits_2 SCR_{j,t} + \prod\nolimits_3 (MIS'_{j,t} * SCR_{j,t}) + \measuredangle MIS'_{j,t} + \pi X'_{i,t} + \varphi Z'_{j,t} + \lambda_t + ð_{i,t} \quad (3.4)$$

$prof_{it}$ represents bank profitability (return on average total equity) and $ð_{i,t}$ is the error term. We expect the coefficient of $MIS'_{j,t} * SCR_{j,t}$ to be negative and significant to confirm hypothesis 3.2C.

We understand the need to eliminate bank fixed effects that might be correlated with the explanatory variables. To address this issue and endogeneity due to the lag of dependent variable in our models, we follow the literature (e.g., Fosu et al., 2021) by estimating equation 3.1 to 3.4 using the system Generalized Method of Moments (GMM) estimator proposed by Arellano & Bover (1995) and Blundell & Bond (1998). We use the system rather than the difference GMM since the former overcomes the problem of weak instruments associated with the latter (Arellano & Bover, 1995; Blundell & Bond, 1998; Roodman, 2009). Moreover, difference GMM eliminates the fixed effects using first difference transformation (Arellano & Bond, 1991). This would be problematic with our unbalanced panel data. Given that first-differencing subtracts previous observation from the contemporaneous value, any missing value of LG_{it} would result in both ΔLG_{it} and $\Delta LG_{i,t-1}$ missing in the transformed data. Therefore, first difference transformation will magnify gaps in our data. Consequently, we follow Arellano & Bover (1995) recommendation to use the forward orthogonal deviations transformation when working with unbalanced panel data.

Orthogonal deviations transformation eliminates the fixed effects by subtracting the average of all future available observations of a variable from the contemporaneous value rather than subtracting the previous observation (as in Foos et al., 2010). Importantly, orthogonal deviations transformation does not trigger serial correlation of the errors. Meaning that it preserves the orthogonality among the transformed errors. If the original errors $\mathcal{E}_{it}$ are not autocorrelated and have constant variance, so are the transformed errors $\mathcal{E}^*_{it}$. The forward orthogonal deviations transformation of error term is given by:

$$\mathcal{E}^*_{i,t} = \sqrt{\frac{T-t}{T-t+1}}\left[\mathcal{E}_{i,t} - \frac{1}{T-t}(\mathcal{E}_{i(t+1)} + \cdots + \mathcal{E}_{i,T})\right] \tag{3.5}$$

The transformation preserves the uncorrelatedness of the error term, that is:

$$Var(\mathcal{E}_i) = \sigma^2 I_T \ \Rightarrow \ Var(\mathcal{E}^*_i) = \sigma^2 I_{T-1} \tag{3.6}$$

Where $\sqrt{\frac{T-t}{T-t+1}}$ in equation 3.5 represents the weighting introduced to equalize the variance, and σ^2 in equation 3.6 is the variance of the error term.

By combining levels equation and the orthogonal deviations equation (a system of equations), we estimate our models so that lags of predetermined variables are valid instruments in the transformed equation. With the lags of the dependent variable ($LG_{i,t-1}, \dots, LG_{i,t-n}$) used as instruments, estimating the models without restricting the number of lags may introduce large number of instruments that might overfit the endogenous variable (instrumented variable) and bias our estimates.[23] Therefore, we use the lag limits ($n = 2 - 3$) and the collapse options in estimating our models to control the instrument count. We subject all estimations to the Windmeijer (2005) correction to minimize downward bias in standard errors. To evaluate the validity of our instruments and estimations, we use the Hansen test of over-identifying restrictions with the null hypothesis that the instruments are valid. The Arellano-Bond test is used to check for autocorrelation of the errors [AR(2)]. The null hypothesis is that no autocorrelation is present in the transformed residuals. If both Hansen and AR(2) tests have p-values of at least 10%, the model is deemed valid.

3.4 Estimation results and discussion

3.4.1 Mandatory credit information sharing and loan classification policies

We start by testing hypothesis 3.1 that mandatory credit information sharing is associated with lower credit growth when it coexists with a policy that allows banks to deduct the value of collateral before applying provisioning rules to a loan ($LoanPolicy$). We use the two measures of mandatory information sharing. $AMIS$ is a categorical variable capturing periods of active information sharing while $MISCOV$ is the coverage of mandatory information sharing in percentage. In table 3.2, column 1, the coefficient of $AMIS * LoanPolicy$ which is the interaction term of mandatory information sharing and loan policy is -0.0281 and it is significant at the 1% level. The result suggests that, on average, mandatory information sharing reduces bank loans by 2.8 percentage points more in countries where loan policies allow banks to apply provisioning rules net of collateral value than in countries without such

[23] Note, although we have $T < 10$ in our data, estimating our models without controlling the number of lags of the dependent variable may still generate numerous instruments, large enough to cause instrument proliferation (see Roodman, 2009)

policy. The economic significance of this result is large, representing about 75% [0.028/0.037] of the sample average bank loans. Meanwhile, the results for the control variables show that GDP per capital growth, bank deposits, and ROAA are associated with higher credit growth. However, liquidity has negative effect on credit growth.

In terms of model diagnostics, the lag of dependent variable is significant at the 1% level in all the estimations confirming the appropriateness of our dynamic specification. In addition, the Hansen test of over-identifying restrictions and the Arellano-Bond tests for autocorrelation of the errors are at least 10%. These tests validate our instruments used and confirm that our estimations are robust.

Table 3. 2 Mandatory credit information sharing and policy-induced credit constraints: The role of loan policies

MODEL	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE	Loan growth	*NPL_ratio*	Loan growth	*NPL_ratio*
LG_{t-1}	0.1621***		0.1613***	
	(0.0264)		(0.0328)	
$NPLr_{t-1}$		0.6545***		0.7448***
		(0.0778)		(0.0837)
$LoanPolicy$	0.0570***	0.0755***	0.0572***	0.0797***
	(0.0122)	(0.0283)	(0.0121)	(0.0306)
$LoanPolicy * AMIS$	-0.0281***	-0.0302***		
	(0.0095)	(0.0073)		
$LoanPolicy * MISCOV$			-0.0078***	-0.0180***
			(0.0005)	(0.0014)
$AMIS$	-0.0401***	-0.0340***		
	(0.0127)	(0.0132)		
$MISCOV$			-0.0024***	-0.0031***
			(0.0006)	(0.0007)
$GDPPCgr$	0.0050***	-0.0030*	0.0058***	-0.0037**
	(0.0009)	(0.0013)	(0.0015)	(0.0021)
$Deposits$	0.0030***	-0.0016**	0.0030***	-0.0019***
	(0.0002)	(0.0005)	(0.0002)	(0.0008)
$ROAA$	0.0128***	-0.0057***	0.0114***	-0.0056***
	(0.0028)	(0.0021)	(0.0021)	(0.0023)
$INFL$	-0.0001	0.0002	-0.0028	0.0001
	(0.0011)	(0.0001)	(0.0013)	(0.0001)
$Liquidity$	-0.0007***	0.0027**	-0.0009**	0.0029**
	(0.0004)	(0.0009)	(0.0002)	(0.0012)
$CBCOV$			-0.0008	-0.0009***
			(0.0003)	(0.0003)
CB	-0.0330***	-0.0370***		
	(0.0107)	(0.0168)		
$CONST$	0.0604***	0.0834***	0.0021**	0.0819***
	(0.0148)	(0.0238)	(0.0024)	(0.0357)
Time fixed effects	Yes	Yes	Yes	Yes

Observations	2,108	2,022	2,123	2,023
No. of Banks	320	301	325	301
No. of Instruments	41	31	36	31
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.639	0.193	0.364	0.868
Hansen Test	0.535	0.709	0.368	0.532

This table presents the results of two-step system GMM panel regressions. Data represents 368 banks from 40 countries covering 2012-2020 period. The dependent variables are growth rate of bank loans (*LG*) in columns 1 & 3; and nonperforming loan ratio (*NPLr*) in columns 2 & 4. The main independent variables are *active* mandatory information sharing (*AMIS)* representing periods of actual information sharing, mandatory credit information sharing coverage (*MISCOV)*, and *LoanPolicy* which has a value of one if banks in a country can provision for loan losses net of collateral value and zero otherwise. All variables, including controls are defined in Appendix Table A3.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

The coefficient of $LoanPolicy$ in column 1 is positive, large, and significant at the 1% level. This indicates higher lending volume and perhaps the presence of moral hazard behaviour when this policy is in place without mandatory information sharing system. Banks are incentivized to extend more collateralized loans knowing that early provisioning for loan losses can be avoided if the value of loan is covered by the value of collateral. This finding supports recent evidence which shows that average collateral value across 131 countries is almost twice the value of loan and collateral requirements are higher in developing countries (see Fan et al., 2022). With $LoanPolicy$ in place, banks would rather request that borrowers provide higher collateral which provides cost advantage than to engage in uncollateralized lending such as information based. The results in column 2 confirm the implication of this collateral policy for loan quality. $LoanPolicy$ has a positive coefficient of 0.0755 indicating that, on average, the policy increases nonperforming loans of banks by about 7.5 percentage points. However, the negative and significant coefficient of $AMIS * LoanPolicy$ in column 2 suggests that mandatory information sharing reduces credit risk associated with the loan policy by 3 percentage points. These results mean that the credit reduction effect of mandatory information sharing is not only due to lack of incentives to engage in uncollateralized lending but also reduction in excessive collateralized lending associated with the loan policy. In columns [3] & [4], we re-estimate the models using the second measure of mandatory information sharing which is the coverage in percentage. We observe similar results in both estimations but with smaller coefficients because mandatory information sharing measure is in percentage rather than the average.

The results in table 3.2 show that mandatory information sharing is associated with lower credit growth and lower credit risk when it coexists with loan policy that permits banks to make provision for loan losses net of collateral value, suggesting that it plays a disciplining role rather than volume enhancing. The findings support hypothesis 3.1.

3.4.2 Mandatory credit information sharing and stringent capital regulation

This section focuses on hypotheses 3.2A, 3.2B & 3.2C. Our predictions are that mandatory information sharing reduces credit risk, credit growth, and bank profitability when it coexists with stringent capital regulation. We test the validity of these predictions, and the results are in table 3.3. In column 1, *AMIS*SCR* has a coefficient of -0.0217 suggesting that mandatory information sharing reduces nonperforming loans of banks by 2.2 percentage points more in countries with stringent capital regulation than in countries without stringent regulation. Similarly, *AMIS*SCR* has coefficients of -0.0201 and -0.0317 in columns [2] and [3] respectively. These results suggest that mandatory credit information sharing also reduces credit growth by 2 percentage points and bank profitability by 3.2 percentage points more in countries with stringent capital regulation. These results show significantly lower credit risk in banking sectors where stricter capital regulation and mandatory credit information sharing coexist. However, this is achieved at the expense of credit growth and bank profit performance.

Table 3. 3 Mandatory credit information sharing and policy-induced credit constraints and risk reduction: The role of stringent capital regulation

MODEL	(1)	(2)	(3)	(4)	(5)	(6)
DEPENDENT VARIABLE	*NPL_ratio*	Loan Growth	Profitability	*NPL_ratio*	Loan Growth	Profitability
$NPLr_{t-1}$	0.6976***			0.6324***		
	(0.0485)			(0.0459)		
LG_{t-1}		0.1058***			0.1023***	
		(0.0280)			(0.0284)	
$PROF_{t-1}$			0.8191***			0.6281***
			(0.0934)			(0.1134)
SCR	0.0412***	0.0307**	0.0840***	0.0403***	0.0306***	0.0816***
	(0.0110)	(0.0120)	(0.0331)	(0.0136)	(0.0129)	(0.0300)
*AMIS*SCR*	-0.0217***	-0.0201***	-0.0317***			

	(0.0173)	(0.0184)	(0.0098)			
*MISCOV*SCR*				-0.0128**	-0.0026***	-0.0047***
				(0.0005)	(0.0009)	(0.0018)
AMIS	-0.0340***	-0.0405***	-0.0106			
	(0.0107)	(0.0158)	(0.0372)			
MISCOV				-0.0033***	-0.0025***	-0.0010
				(0.0001)	(0.0003)	(0.0004)
GDPPCgr	-0.0030**	0.0055***	0.0040**	-0.0030**	0.0050***	0.0045***
	(0.0008)	(0.0010)	(0.0013)	(0.0005)	(0.0010)	(0.0017)
Deposits	-0.0015***	0.0030***	0.0013***	-0.0015**	0.0031***	0.0012**
	(0.0002)	(0.0001)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
ROAA	-0.0061***	0.0119***		-0.0059***	0.0109***	
	(0.0022)	(0.0033)		(0.0024)	(0.0032)	
INFL	0.0002	-0.0009	0.0039**	0.0002	-0.0042	0.0040**
	(0.0001)	(0.0001)	(0.0015)	(0.0001)	(0.0011)	(0.0027)
Liquidity	0.0021***	-0.0007**	0.0029***	0.0021**	-0.0009**	0.0025***
	(0.0005)	(0.0001)	(0.0011)	(0.0003)	(0.0006)	(0.0005)
Private monitor	-0.0057***	-0.0006	-0.0008	-0.0051***	-0.0005	-0.0007
	(0.0016)	(0.0019)	(0.0045)	(0.0019)	(0.0030)	(0.0008)
CBCOV				-0.0008**	-0.0001	-0.0010
				(0.0001)	(0.0001)	(0.0004)
CB	-0.0358***	-0.0317***	-0.0038			
	(0.0103)	(0.0113)	(0.0023)			
CONST	0.0807***	0.0731***	0.0213	0.0683***	0.0563**	0.0103
	(0.0214)	(0.0249)	(0.0621)	(0.0188)	(0.0260)	(0.0730)
Time fixed effects	Yes	Yes	Yes	YES	Yes	Yes
Observations	2,016	2661	2,786	2,010	2655	2,743
No. of Banks	300	349	365	300	349	361
No. of Instruments	34	53	49	46	42	39
AR (1)	0.000	0.000	0.000	0.000	0.000	0.000
AR (2)	0.102	0.805	0.302	0.190	0.535	0.246
Hansen Test	0.675	0.143	0.212	0.380	0.431	0.166

This table presents the results of a two-step system GMM panel regressions. Data represents 368 banks from 40 countries covering the period 2012-2020. The dependent variables are nonperforming loan ratio (*NPLr*) in columns [1] & [4], Loan Growth (*LG*) in columns [2] & [5], and return on average total equity (*Profitability*) in columns [3] & [6]. The key independent variables are *active* mandatory credit information sharing (*AMIS)* representing periods of actual information sharing, mandatory credit information sharing coverage (*MISCOV),* and stringent capital regulation (*SCR*) which has a value of one if a country has a capital regulation stringency score that is in the top quartile of the index, and zero otherwise. All variables, including controls are defined in Appendix Table A3.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

The estimations presented in columns [4], [5] and [6] are based on our second measure of mandatory information sharing which is the coverage in percentage. The results are consistent with those shown in columns 1 to 3 that mandatory credit information sharing is associated with lower credit risk, lower credit growth, and weaker profitability when it coexists with stringent capital regulation. Therefore, the results in table 3.3 support hypotheses 3.2A, 3.2B & 3.2C.

There are other interesting findings that emerge from the estimations in table 3.3. We observe that SCR is positive and significant in relation to nonperforming loans, credit growth, and profitability in columns [1] to [6]. These results suggest that without mandatory information sharing banks rely on high-volume lending approach to meet stringent capital requirements. By increasing lending volume, banks can increase total earnings and regulatory capital ratio. However, the ratio of nonperforming loans also increases due to reduced lending standards. These demonstrate how regulatory efforts to reduce capital risk can increase bank vulnerability due to higher accumulation of credit risk. Although the results also show that the introduction of mandatory information sharing can successfully reverse the policy induced moral hazard and improve loan quality, but it does so by increasing performance risk in the banking sector (falling profitability). Therefore, the findings reveal a trade-off that seems particularly difficult to balance when it comes to managing risk in the banking sector.

In summary, our findings suggest that the effect of mandatory credit information sharing on credit growth is conditional on loan policies and the stringency of capital regulation. We find significant reduction in both credit growth and credit risk where loan policies allow banks to deduct the value of collateral before applying provisioning rules to a loan, as well as in countries with stringent capital regulation.

3.5 Robustness checks

3.5.1 Endogeneity

In this section, we address potential endogeneity issues. Endogeneity may arise from reverse causality between mandatory information sharing and credit risk or credit growth. For example, it is possible that the decision to adopt mandatory information sharing scheme is induced by falling bank lending to solve adverse selection problem. However, this is unlikely to bias our results since the decision to establish credit registry is made at the country-level (government) rather than bank-level at which both credit risk and credit growth are measured. Nonetheless, we perform robustness tests to confirm that our estimates have not been biased by any endogeneity problem. We do so in line with Buyukkarabacak & Valev (2012) and Fosu et al. (2021) by using population size as external instrument for information sharing. The rationale is that dissemination of information is more effective in less populated countries compared to highly populated countries. Therefore, population size represents a valid external instrument for credit information sharing since it may impact the effectiveness of information sharing without directly affecting credit growth and credit risk. Using this instrument, we re-estimate our models based on one rather than two measures of mandatory credit information sharing to avoid unnecessary repetition because we have observed in the main analysis in section 3.4 that both measures enter all regressions with the same sign. The estimated results are presented in table 3.4.

Table 3. 4 Mandatory credit information sharing, loan policy, and capital regulation stringency: Endogeneity

MODEL	(1) (Instruments: Population size)	(2) (Instruments: Population size)	(3) (Instruments: Population size)	(4) (Instruments: Population size)	(5) (Instruments: Population size)
DEPENDENT VARIABLE	Loan Growth	Loan Growth	NPLr	NPLr	Profitability
LG_{t-1}	0.1817***	0.1069***			
	(0.0505)	(0.0278)			
$NPLr_{t-1}$			0.6676***	0.7105***	
			(0.0905)	(0.0611)	
$PROF_{t-1}$					0.7880***
					(0.1051)
$LoanPolicy$	0.0522***		0.0701***		
	(0.0120)		(0.0271)		
SCR		0.0300***		0.0316**	0.0801***
		(0.0114)		(0.0177)	(0.0387)
$LoanPolicy * AMIS$	-0.0250**		-0.0297***		
	(0.0060)		(0.0078)		
$SCR * AMIS$		-0.0189***		-0.0200***	-0.0301**
		(0.0018)		(0.0299)	(0.0088)
$AMIS$	-0.0383***	-0.0403***	-0.0368***	-0.0358***	-0.0090
	(0.0078)	(0.0156)	(0.0138)	(0.0111)	(0.0437)
GDPPCgr	0.0051***	0.0057***	-0.0032*	-0.0031**	0.0039**
	(0.0008)	(0.0010)	(0.0013)	(0.0007)	(0.0013)
Deposits	0.0030***	0.0030***	-0.0015**	-0.0016***	0.0014*
	(0.0002)	(0.0001)	(0.0005)	(0.0002)	(0.0005)
ROAA	0.0118***	0.0116***	-0.0060***	-0.0058***	
	(0.0022)	(0.0031)	(0.0022)	(0.0024)	
INFL	-0.0017	-0.0010	0.0002	0.0004	0.0042**
	(0.0007)	(0.0007)	(0.0001)	(0.0001)	(0.0019)
Liquidity	-0.0006***	-0.0007***	0.0023**	0.0025**	0.0028**
	(0.0001)	(0.0002)	(0.0007)	(0.0004)	(0.0013)
Private Monitor		-0.0005		-0.0054***	-0.0008
		(0.0019)		(0.0018)	(0.0007)
CB	-0.0326***	-0.0313***	-0.0371***	-0.0387***	-0.0034
	(0.0071)	(0.0114)	(0.0246)	(0.0122)	(0.0027)

CONST	0.0372***	0.0730***	0.0859***	0.0903***	0.0252
	(0.0110)	(0.0249)	(0.0251)	(0.0252)	(0.0793)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2,408	2,661	1,789	1,795	2,786
No. of Banks	320	349	255	256	365
No. of Instruments	43	53	35	34	48
AR (1)	0.000	0.000	0.000	0.000	0.000
AR (2)	0.594	0.807	0.208	0.104	0.298
Hansen Test	0.398	0.141	0.851	0.526	0.172

This table presents the results of a two-step system GMM panel regressions. Data represents 368 banks from 40 countries covering 2012-2020 period. The dependent variables are Loan Growth (*LG*) in columns [1] & [2], nonperforming loan ratio (NPLr) in column [3] & [4], and return on average total equity (*Profitability*) in column [5]. The main independent variables are active mandatory credit information sharing (*AMIS)* representing periods of actual information sharing*, LoanPolicy* which has a value of one if banks in a country can provision for loan losses net of collateral value and zero otherwise, *SCR* (stringent capital regulation) with a value of one if a country has a capital regulation stringency score that is in the top quartile of the index and zero otherwise. All variables, including controls are defined in Appendix Table A3.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

The results for $LoanPolicy * AMIS$ and $SCR * AMIS$ in all the models have negative signs and the coefficients are statistically significant. Columns [1] and [3] confirm our findings in section 3.4 that mandatory credit information sharing is associated with lower credit growth and lower credit risk when it coexists with a loan policy which allows banks to provision for loan losses net of collateral value. Columns [2], [4] and [5] also confirm our previous results that where there is stringent capital regulation, mandatory information sharing reduces credit risk but also reduces credit growth and bank profitability. All the results in table 3.4 are consistent with our findings in section 3.4, and both Hansen and AR(2) tests are satisfied with *p*-values of at least 10% in all five models which validate our choice of instrument and erase any endogeneity concern.

3.5.2 Additional robustness checks

In this section, we provide two additional robustness checks. First, we use alternative measure of credit risk. The quality of bank loan assets is measured as the ratio of nonperforming loans to total loans (*NPLr*) in the main estimations in section 3.4. Potential concern with this measure is that *NPLr* may be affected by the different accounting policies and practices across countries in our study sample. Moreover, loan policies in many countries keep loans in the first stage of default (sub-standard) as performing and not regarded as deteriorated. This means that nonperforming loan ratios only reflect the most severe cases of credit defaults. Therefore, to confirm that our results have not been driven by the differences between *NPLr* and other measures that respond faster to changes in loan quality, we replace *NPLr* with provisions for loan losses (*PROV*) and re-estimate the credit risk models. Loan loss provisions capture credit risk associated with performing loans that is not accounted for by *NPLr* measure (see Cucinelli et al., 2018). Provisioning is required once a loan is classified as sub-standard even though it remains performing, suggesting that provisions may affect bank profitability, capital ratios, and lending behaviour differently. The new results are presented in table 3.5, columns 1 and 2. The coefficients of $LoanPolicy * AMIS$ and $SCR * AMIS$ are negative and significant, indicating that there is reduction in provision for loan losses.[24] These results corroborate our findings in section 3.4 that mandatory information sharing reduces credit risk where loan policies and practices allow banks to apply provisioning rules net of collateral value as well as in banking sectors with stringent capital regulation.

Table 3. 5 Mandatory credit information sharing, loan policy, and capital regulation stringency: Additional robustness checks for credit growth and risk reduction

MODEL	(1)	(2)	(3)	(4)
DEPENDENT VARIABLE	Provision for loan losses	Provision for loan losses	Log Loan Growth	Log Loan Growth
PROV$_{t-1}$	0.3564***	0.3662***		
	(0.0587)	(0.0764)		
lnLG$_{t-1}$			0.2543***	0.0893***
			(0.0659)	(0.0342)
AMIS	-0.0037***	-0.0037**	-0.0491***	-0.0502***
	(0.0018)	(0.0016)	(0.0113)	(0.0349)
*LoanPolicy*AMIS*	-0.0020**		-0.0310***	
	(0.0016)		(0.0097)	
*SCR*AMIS*		-0.0062***		-0.0300**
		(0.0015)		(0.0485)
SCR		0.0103***		0.0466***
		(0.0030)		(0.0303)

24 We acknowledge that a positive sign for *AMIS*LoanPolicy* is possible in a study that is designed to capture only the immediate impact of mandatory information sharing when it is introduced for the first time. This would only reflect the initial increase in provisioning for the accumulated credit risk revealed by the new informational scheme rather than the reduction in subsequent periods when the credit market becomes more transparent with mandatory information sharing system in place. Our study captures the ability of mandatory information sharing system to increase the quality of bank lending over the sample period, hence the reduction in provisioning.

GDPPCgr	-0.0006***	-0.0005***	0.0060***	0.0063***
	(0.0001)	(0.0001)	(0.0014)	(0.0017)
Deposits	-0.0001***	-0.0001**	0.0039***	0.0040***
	(0.0000)	(0.0001)	(0.0003)	(0.0012)
ROAA	-0.0016***	-0.0014*	0.0155***	0.0209**
	(0.0005)	(0.0008)	(0.0042)	(0.0062)
INFL	0.0008***	0.0007***	-0.0025	-0.0017
	(0.0002)	(0.0002)	(0.0011)	(0.0028)
Liquidity	0.0002	0.0003	-0.0004**	-0.0005*
	(0.0001)	(0.0001)	(0.0002)	(0.0004)
CB	0.0014	0.0012	-0.0367***	-0.0375
	(0.0012)	(0.0015)	(0.0105)	(0.0283)
CONST	0.0110***	0.0109**	0.0392***	0.3645***
	(0.0025)	(0.0044)	(0.0190)	(0.0762)
Time fixed effects	YES	Yes	Yes	Yes
Observations	2,174	2,179	2,322	2,320
No. of Banks	293	293	343	343
No. of Instruments	41	60	40	43
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.855	0.765	0.461	0.188
Hansen Test	0.117	0.245	0.491	0.120

This table presents the results of a two-step system GMM panel regressions. The dependent variables are *Provisions* in columns [1] & [2], and Log Loan Growth (*lnLG*) in [3] & [4]. The main independent variables are *active* mandatory credit information sharing (*AMIS)* representing periods of actual information sharing, *LoanPolicy* which has a value of one if banks in a country can provision for loan losses net of collateral value and zero otherwise, and stringent capital regulation (*SCR*) with a value of one if a country has a capital regulation stringency score that is in the top quartile of the index and zero otherwise. All variables, including controls are defined in Appendix Table A3.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

Second, we address any concern that the choice of measure of credit growth influences our findings. We replace loan growth scaled by average total assets with growth in log of loans, and then test the two credit growth hypotheses. The results in columns [3] & [4] in table 3.5 are consistent with our main findings that with $LoanPolicy$ or SCR present, mandatory credit information sharing is associated with lower credit growth.

Overall, we find significant reduction in both credit growth and credit risk with mandatory information sharing scheme. These results are consistent with several studies in credit information sharing literature which show that credit registry has lower credit growth but higher credit quality effects (e.g., Hertzberg et al., 2011; De Haas et al., 2021). Importantly, we show that the effect of mandatory credit information sharing on credit growth is conditional on loan classification policies and the stringency of capital regulation. Significantly lower credit growth and lower credit risk are found when mandatory information sharing coexists with a loan policy that allows banks to deduct the value of collateral before applying provisioning rules to a loan or when it coexists with stringent capital regulation. Therefore, the findings also agree with studies which show that the effects of credit information sharing are conditional on market specific factors (e.g., Fosu et al., 2020;2021). Our findings provide support for the evidence reported by De Haas & Millone (2020) which shows that mandatory information sharing is associated with lower use of collateral in Bosnia & Herzegovina. Bosnia & Herzegovina is one of the countries in our study sample without the collateral policy that permits banks to compute loan loss provisions net of collateral, meaning that there are lower incentives for higher use of collateral compared to where this policy exists. Put differently, the finding implies that information sharing has higher potential to reduce the use of collateral where this policy does not exist compared to where it does.

3.6 Conclusion

In this study we investigate how loan classification policies and the stringency of capital regulation influence the relationship between mandatory credit information sharing in the banking sector and credit growth as well as credit risk. The study is based on a sample of 368 banks from 40 countries. We find that mandatory information sharing is associated with lower credit growth and lower credit risk where banks can apply provisioning rules to a loan net of collateral value. The findings suggest that mandatory information sharing reduces credit risk by reducing excessive collateralized lending associated with the loan policy. In the second part of the analysis, we find that when there is stringent capital regulation, mandatory credit information sharing reduces credit risk but also reduces credit growth. These results suggest that banking regulators in these countries either have uncompromising commitment to promoting stringent policies to lower credit risk even at the expense of credit growth or they have underestimated the impact of combining the two policy tools on banks' ability and willingness to lend. In addition to credit reduction, we find lower bank profit performance in markets where mandatory credit information sharing and strict capital regulation coexist. Overall, our study uncovers new evidence and reconciles existing mixed evidence on the role of credit registry. The findings indicate that the weak relationship between credit registry and credit growth that is largely reported in the literature is because existing studies have underestimated the effect of mandatory credit information sharing by ignoring the role of loan classification policies and the stringency of banking regulations. The results are robust to several checks including the use of external instruments and alternative measures of mandatory information sharing, loan growth, and credit risk.

Appendix

Appendix Table A3. 1 Definition and measurement of variables used in the study

Variables	**Description**	**Observable data**	**Exp Sign**	**Original source(s) of data**
		Dependent Variables		
LG	Real growth rate of bank total loans (Bouvatier & Lepetit, 2008). $LG = {(l_t - l_{t-1})}/{0.5(ta_t + ta_{t-1})}$	l = Total bank loans. ta = Total assets	n.a.	Bank Focus
$lnLG$	$lnLG$ is the log of loan growth rate. $lnLG = log[l_t] - log[l_{t-1}]$	l = Total bank loans.	n.a.	Bank Focus
$NPLr$	Is the credit risk measure as the ratio of non-performing loans to total loans of a bank. $NPLr = {NPL}/{TL}$	NPL = Nonperforming loans of bank. TL = Total bank loans	n.a.	Bank Focus
$PROV$	$PROV$ is the ratio of loan loss provisions to total loans of a bank (Deli & Hasan, 2017)	LLP = Loan loss provision.	n.a.	Bank Focus

	$PROV = {}^{LLP}/_{TL}$	TL = Total loans		
Profitability	*Profitability* Is the return of gross profit on average total equity of a bank.	*ROAE*	n.a.	Bank Focus
	Main Explanatory Variables			
$AMIS$	$AMIS$ takes the value of one if banks in a country actively share borrowers' information in a particular period and zero otherwise.	Period of no active sharing is shown as zero.	$(-)$	World Bank's Doing Business database (2004-2020)
MISCOV	We measure $MISCOV$ as the percentage of firms and individuals covered in a country's public credit registry with information on repayment history, unpaid debt balances, or outstanding credit from the past five years (Houston et al., 2010).	% of Credit Registry coverage in a country	$(-)$	World Bank's Doing Business database (2004-2020)
$LoanPolicy$	$LoanPolicy$ takes the value of one if banks can provision for loan losses net of collateral and zero otherwise.	Data available as Yes=1, No=0	$(+)$	Bank Regulation and Supervision database of the World Bank
SCR	Stringent Capital Regulation (SCR) is assigned the value of one if a country has a capital regulation stringency score that is in the top quartile of bank	Data is available as answers to question 1 to 10.	$(+)$	Bank Regulation and Supervision database of

	capital regulation index, and zero otherwise. The index measures the general capital regulatory stringency of the banking systems from 0 to 10 (Barth et al., 2013). Value 1 indicates stringent regulation in each of the ten questions below: (1) Is bank capital ratio risk-weighted in line with Basel guidelines?" value of one for yes and zero otherwise. (2) Does the ratio vary with bank's credit risk?" value of one for yes and zero otherwise. (3) Does the ratio vary with market risk?" value of one for yes and zero otherwise. (4) Before minimum capital adequacy is determined, is the market value of loan losses deducted from capital? Value of one for yes and zero otherwise. (5) Before minimum capital adequacy is determined, is unrealized securities losses deducted from capital? Value of one for yes and zero otherwise. (6) Before minimum capital adequacy is determined, is unrealized foreign exchange losses deducted from capital? Value of one for yes and zero otherwise. (7) Is the fraction of revaluation gains allowed as part of capital lower than 0.75? value			the World Bank

		one for yes and zero otherwise. (8) Can the initial disbursement or subsequent injections of capital be done with assets other than cash or government securities?" value of one for no and zero otherwise. (9) Are the sources of funds to be used as capital verified by the regulatory/supervisory authorities? Value one for yes and zero otherwise. (10) Can initial disbursement of capital be done with borrowed funds?" value of one for no and zero otherwise. *Higher index value indicates higher capital stringency*.			
		Control Variables			
Bank specific variables	$ROAA$	Return of gross profit on average total assets.	$ROAA$	$(+)$ for LG, $(-)$ for NPL	Bank Focus
	$DEPOSITS$	Is the growth in bank total deposits. $DEPOSITSgr = {TD_t - TD_{t-1}}/{TD_{t+1}}$	TD = Total deposits of bank.	$(+)$ for LG, $(\pm)$ for NPL	Bank Focus
	$Size$	Bank size is the natural log of total assets of banks (Houston et al., 2010, Deli & Hasan, 2017)	Total Assets	$(\pm)$	Bank Focus
	$Liquidity$	Liquidity is the ratio of liquid assets to total assets (Deli & Hasan, 2017) $LIQUID = {LA}/{TA}$	LA= liquid assets of bank. TA= total assets of bank.	$(\pm)$	Bank Focus

Country level variables	$GDPPCgr$	Growth rate of GDP per capital (Sorge et al., 2017). $\Delta GDPpc = \frac{GDPpc_t - DGPpc_{t-1}}{DGPpc_{t-1}}$	*GDPPC* = GDP per capital.	$(+)$ for $LG,$ $(-)$ for NPL	WDI
	$GDPgr$	Real GDP growth rate (Guerineau & Leon, 2019)	GDP growth rate in %	$(+)$ for $LG,$ $(-)$ for NPL	WDI
	$INFL$	Inflation is the annual growth rate of consumer price index (Sorge et al., 2017)	Inflation in %	$(\pm)$	WDI
	CB	*CB* has a value of one for countries with credit bureau and zero otherwise (Houston et al., 2010	Yes = 1, no = 0	$(\pm)$	Doing Business (2004-2020)
	$PrivMontr$	This index variable measures how much regulatory policies in a country support and motivate private investors to monitor and improve the governance of banks (e.g., Beck et al., 2006; He et al., 2021). The index ranges from 0 to 10. A yes answer adds the value of 1 to the index as follows: (1) whether bank officials are legally liable if information disclosure is erroneous or misleading, (2) whether banks disclosure information such as: (2) consolidated accounts of all financial institutions? (3) off-balance sheet items? (4) Accrued, though unpaid interest/principal of NPLs? (5) Risk management	Yes = 1; No = 0 for question 1 to 10	$(\pm)$	Bank Regulation and Supervision database of the World Bank

		procedures to the public? (6) whether banks must be audited by certified international auditors? (7) whether the largest ten banks are rated by international rating agencies? (8) whether the largest ten banks are rated by domestic rating agencies? (9) whether subordinated debt is allowable as part of capital? (10) whether there is no explicit deposit insurance system and no insurance was paid the last time a bank failed? *Higher index value indicates higher private monitoring*			
Variables used as instruments					
Population Size		Population size is the natural log of total population (as in Buyukkarabacak & Valev, 2012; Fosu et al., 2021)	Population size	(±)	WDI

This table summarizes the definition and measurement of variables used in the study. It covers the dependent variables, explanatory and control variables, and their expected signs. It also presents the observable data used in computing each variable, identifies the original sources of all data.

n.a. denotes 'not applicable'; ± indicates indeterminate sign

Appendix Table A3. 2 Study sample by country and number of banks in each country

S/No	Country	Number of banks
1	ANGOLA	2
2	ARGENTINA	6
3	ARMENIA	3

4	AZERBAIJAN	3
5	BANGLADESH	16
6	BOLIVIA	8
7	BOSNIA & HERZEGOVINA	5
8	BOTSWANA	2
9	BRASIL	26
10	CHILE	9
11	DOMINICAN REPUBLIC	5
12	EGYPT	18
13	EL SALVADOR	5
14	INDIA	18
15	INDONESIA	23
16	JORDAN	16
17	KAZAKHSTAN	5
18	KENYA	8
19	MALAWI	3
20	MAURITIUS	5
21	MEXICO	9
22	MOROCCO	10
23	NAMIBIA	4
24	NEPAL	4
25	NICARAGUA	6
26	NIGERIA	13
27	PAKISTAN	22
28	PARAGUAY	13
29	PERU	18
30	PHILIPPINES	12
31	SENEGAL	1
32	SOUTH AFRICA	7
33	SRI LANKA	9
34	TANZANIA	2
35	THAILAND	18
36	TOGO	1
37	TUNISIA	13
38	UGANDA	2
39	VIETNAM	16
40	ZIMBABWE	2
TOTAL	**40**	**368**

Appendix Table A3. 3 Correlation matrix of variables used in the study

Variable		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
LG	1	1.000															
lnL	2	0.949*	1.000														
ROAA	3	0.121*	0.084*	1.000													
Profitability	4	0.093*	0.078*	0.696*	1.000												
PrivMon	5	-0.039*	-0.057*	-0.103	-0.099	1.000											
NPLr	6	-0.187*	-0.179*	-0.193*	-0.233*	-0.180*	1.000										
LIQUIDITY	7	-0.159*	-0.105	0.088*	0.049*	-0.159*	0.100	1.000									
INFL	8	-0.119*	-0.109*	0.128*	0.074*	-0.044	0.099*	0.142*	1.000								
GDPPCgr	9	0.258*	0.260*	0.040*	0.068*	0.032*	-0.083*	-0.145*	-0.036*	1.000							
DEPOSITS	10	0.623*	0.624*	0.087*	0.058*	-0.079*	-0.103*	0.019*	-0.057*	0.122*	1.000						
LoanPolicy	11	0.060*	0.052*	0.004*	0.009*	0.109*	-0.068*	-0.133*	-0.001	0.163*	0.075*	1.000					
MISCOV	12	-0.090*	-0.093*	-0.083*	-0.062*	0.195*	-0.086*	0.077*	-0.165*	-0.102*	-0.084*	-0.092*	1.000				
AMIS	13	-0.056*	-0.042*	-0.080*	-0.009*	0.022	-0.009*	0.136*	-0.128*	-0.071*	-0.053*	-0.089*	0.568	1.000			
CBCOV	14	-0.105*	-0.122*	0.054	0.029	0.264*	-0.135*	0.067*	-0.214*	-0.294*	-0.099*	-0.233*	0.199*	-0.144	1.000		
CB	15	-0.024*	-0.029	0.053*	0.065	0.004	-0.077*	0.148*	-0.064*	-0.083*	-0.030	-0.196*	-0.103*	-0.301*	0.520*	1.000	
SCR	16	0.021*	0.012*	0.002*	0.031*	0.155*	0.031*	-0.089*	0.032*	-0.048*	0.039*	0.125*	-0.096*	-0.032*	-0.056*	-0.086*	1.000

This table presents the correlation matrix of the variables used in the study. The key variables include Loan Growth (*LG*), Log Loan Growth (*lnLG*), *active* mandatory credit information sharing (*AMIS)* which represents periods of actual information sharing, nonperforming loan ratio (NPLr), return on average total equity (*Profitability*), $MISCOV$ is the coverage of mandatory credit information sharing in percentage, *LoanPolicy* which has a value of one if banks in a country can provision for loan losses net of collateral and zero otherwise, *SCR* (stringent capital regulation) with a value of one if a country has a capital regulation stringency score that is in the top quartile of the index, and zero otherwise. All variables, including controls are defined in Appendix Table A3.1.

* indicates 5% level of significance

Chapter 4: How does credit information sharing affect bank diversification strategies and excess value? An investigation into threshold effects

4.1 Introduction

Diversification in banking has received heightened attention in recent years. The focus is on the effects of increasing complexity of banks' operations and business models (e.g., Ho et al., 2022), and whether a diversified bank has higher (premium) or lower (discount) value relative to its undiversified counterpart (e.g., Velasco, 2022). Bank diversification can be motivated by several factors including economic uncertainty such as the recent Covid-19 pandemic (e.g., Taylor, 2022), to achieve economies of scope, or when interest-based products such as loans are less profitable due to economic policy uncertainty (e.g., de Silva et al., 2022). By diversifying into non-interest income generating activities, banks can increase their fee-based and commission-based income.[25] However, these non-traditional activities increase bank risk and instability (de Silva et al., 2022). Therefore, interest in understanding the net effect of diversification on the value of banks has risen and the literature has expanded accordingly. Some studies have reported a diversification premium (e.g., Elsas et al., 2010; Gulamhussen et al., 2017), while others have shown a diversification discount (e.g., Laeven & Levine, 2007; Velasco, 2022).

The difference between the two findings in the literature can be explained by both quality and quantity of diversified investments. If banks can diversify into high-quality non-lending activities, and avoid excessive diversification, a premium is the most likely outcome. Evidence shows that value creation is larger among banks in the middle range of diversification (Gulamhussen et al., 2017), suggesting that keeping diversification below but close to the optimal level is crucial in maximizing the benefits associated with diversification. However, agency problem is the most reported reason why the net effect of diversification changes from a premium to a discount (e.g., Laeven & Levine, 2007).

Diversification increases banks' access to cash flow (Klein & Saidenberg, 2010). Consequently, incentives grow among managers to increase the volume of investment using

[25] In many advanced and developing countries, commercial banks are allowed to diversify into non-lending activities such as advisory, brokerage, insurance, and many more.

the extra funds especially where there is informational gap between central and divisional managers or between managers and investors. Fuente & Velasco (2020) note that even when diversification strategy does not have value enhancing effects, it may still appeal to managers if it serves their own self-interests. As a matter of fact, diversified financial institutions in the U.S. suffered significant adverse selection problem and accumulated more uninformed investments than undiversified institutions prior to the 2007/08 financial crisis (Loutskina & Strahan, 2011). These studies have demonstrated that bank diversification strategies are adversely impacted by the effects of asymmetric information including adverse selection and moral hazard. However, there is no evidence of any institutional arrangement with the potential to alleviate the documented adverse selection and agency problems by making information less costly, easily accessible, and of higher quality. Therefore, in this study we examine how credit information sharing used in reducing asymmetric information in the banking sector influences three important aspects of bank diversification: (I) optimal level of diversification; (II) diversification and excess value of banks in the lower regime (below the optimal level); and (III) diversification and excess value of banks in the upper regime (above the optimal level).

The concept of credit information sharing involves the reporting of private credit information by financial institutions via a central credit registry or the provision of comprehensive reports on individuals and firms by a credit bureau using information collected from both private and public sources. Usually, there is one credit registry in a country for mandatory information sharing among financial institutions in that country, and it is owned and operated by the central bank (World Bank, 2019). In many countries, there are two or more credit bureaus for voluntary information sharing, they are privately owned and regulated by the regulatory authorities in each country. Both credit bureaus and credit registries have expanded greatly during the last two decades with 173 countries having either one or both schemes (World Bank, 2019). Information sharing motivates banks to invest more in new information (Karapetyan & Stacescu, 2014a), and it reduces the effects of asymmetric information such as adverse selection and moral hazard (Flatnes, 2021).

There are several channels through which information sharing may influence bank diversification strategies. First, information reusability whereby existing customer information in one financial services area is reused by banks to overcome asymmetric information when offering other financial products. Both theoretical (e.g., Chan et al., 1986) and empirical (e.g., Chu & Li, 2022) studies have confirmed that banks reuse customers' information in their investment decisions. For example, banks are more likely to offer insurance or advisory service to existing loan customers with high-quality credit information than unknown customers with higher potential for adverse selection. Accordingly, we argue that credit information sharing among banks has a role in financial services cross-selling and diversification strategies of banks.

Second, portfolio monitoring service of credit bureaus can help banks to reduce ex post incentive conflicts associated with diversification. By providing banks with regular updates on changes in their investment units or customers' standing profiles, agency problems can be reduced. Many credit bureaus across the world now employ big data and machine learning to improve the efficiency of large amount of information processing and transforming it into insightful and real-time assessment data (Jiang & Novik, 2021). With these technologies, credit bureaus have expanded into real time value adding services such as customer behavioural scoring, customer profiling, and monitoring services (see World Bank, 2019). Customer profiling and service modelling can increase banks' screening (*ex-ante)* abilities in their cross-sales campaign and predicting the likelihood that additional service offer will be successful.

In addition to commercial banks that are diversifying into non-lending activities, there are investment banks that are diversifying into lending activities. These banks can also rely on credit information shared to improve the quality of their investments. Our measure of diversification in section 4.3 is estimated to capture diversified investments of both types of banks.

We differentiate between mandatory and voluntary credit information sharing. One of the reasons that asymmetric information remains a fundamental problem in the banking sector is because information is not free and it is an important source of competitive advantage. Consequently, when it is mandatory to share private information with other banks, the outcome may be counterproductive for two important reasons. First, it may increase bank managers' incentives to engage in moral hazard behaviour to protect their informational rents (as in Giannetti et al., 2017). Second, mandatory information sharing is expected to increase bank supervision and monitoring of credit portfolios. We know that regulatory pressure can lead to lending reduction (as in Cehajic & Marko, 2022), and lending reduction increases the likelihood of moral hazard behaviour and higher diversification into non-lending activities to increase profits (as in de Silva et al., 2022). Consequently, we expect mandatory credit information sharing via credit registry to drive higher bank diversification than voluntary scheme of credit bureau. We also predict high-quality investments and more excess value of banks in relation to voluntary credit information sharing. These predictions are based on our earlier argument that credit bureaus have technological advantage coupled with the fact that voluntary reporting is driven by genuine business needs rather than regulatory requirement.[26]

We test these predictions using a panel dataset of 368 banks from 40 countries, covering the period 2012-2020. Mandatory information sharing is measured as the percentage coverage of credit registry, while voluntary information sharing is the percentage coverage of credit bureau in a country. Diversification is measured using the adjusted earning assets based Herfindahl Hirschman Index, while excess value is the difference between actual Tobin's q of a diversified bank and the Tobin's q it would have if it was broken into a portfolio of entities with each entity specializing in each activity of the diversified bank (as in Velasco, 2022). In terms of methodology, we employ both dynamic panel threshold model introduced by Kremer et al. (2013), and system Generalized Method of Moments (GMM) proposed by Arellano & Bover (1995) and Blundell & Bond (1998).

We uncover some interesting findings. First, both mandatory and voluntary credit information sharing increase bank diversification in the lower regime (below the optimal value) where diversification premium is certain. Second, we show that mandatory credit information sharing increases diversification in the upper regime (above the optimal value) and this relationship reduces excess value of diversified banks. Third, the findings show that voluntary credit information sharing reduces diversification in the upper regime, and this increases excess value of banks. We find diversification premium in the overall data which is consistent with previous studies in the literature (e.g., Gulamhussen et al., 2017). However, the breakdown of the data shows a diversification discount among banks in countries with mandatory information sharing only, and a diversification premium in countries with voluntary information sharing only. Importantly, we discover that when both schemes of information sharing coexist, voluntary information sharing dominates the quality of non-

[26] According to the World Bank data presented by Jiang & Novik (2021), financial institutions can access credit bureau data online in at least 117 countries through a website interface or system-to-system connection as of 2019. Therefore, we expect the use of real time information to increase screening and monitoring abilities of banks as well as quality of diversification.

lending activities. Therefore, majority of banks in the study sample that use both schemes of credit information sharing have a diversification premium.

In an extended threshold analysis, we directly compare the quality of information and diversified investments associated with the two informational schemes. Under mandatory credit information sharing, diversification starts to erode bank value beyond optimal level of 0.42 compared to 0.48 under voluntary information sharing. Lower quality of diversified investments results in lower optimal value. Therefore, these findings confirm the quality advantage of voluntary credit information system which helps banks to make better investment decisions and diversify up to 48% and still create premium compared to 42% under the mandatory system. This also helps to understand why discount is found where there is mandatory information sharing only, as average diversification of 0.44 is higher than the optimal level of 0.42 in those countries.

The results are robust to several checks. In addition to system GMM approach that is generally used in the literature to control endogeneity issues (e.g., Addai et al., 2022), we conduct further tests using external instruments. We also employ alternative measure of diversification, and all results remain unchanged and continue to agree that by increasing diversification above optimal level, mandatory credit information sharing reduces the market value of diversified banks while voluntary system increases value by reducing diversification above optimal value.

Our study contributes to the literature in several ways. First, to the best of our knowledge, this is the first study to investigate how mandatory and voluntary information sharing affect bank diversification optimal level, and how these in turn affect excess value of diversified banks. We have shown that the dynamic threshold approach helps to capture the differences in the behaviour of mandatory and voluntary credit information sharing in the two regimes created by the optimal value. This approach has not been used in relation to credit information sharing before, and we expect future studies to follow our research design especially those exploring the differences between the two informational schemes.

Second, the study complements the group of studies in the literature that have investigated the quality of information shared (e.g., Giannetti et al., 2017). We document that the quality of diversified investments is higher under voluntary than mandatory information sharing system. Importantly, where both schemes of information sharing coexist, the quality of voluntary system dominates diversified investments. Therefore, the findings suggest that the best practice is to have both informational schemes so that the banking sector can benefit from the protective ability of credit registry and the higher quality information and reports that credit bureaus provide.

Third, the study contributes to the literature by highlighting how the mandatory and protective features of credit registry can cause agency problems. The findings show that mandatory system is associated with lower optimal value (low quality investments), and it increases diversification beyond the optimal value (overinvestment). These are indications of agency problems. The findings support the argument by Guillen (2000) that protectionist policies drive the rise in conglomerates, especially in emerging countries. Mandatory information sharing system is designed to increase monitoring of banks' credit activities and reduce credit risk-taking. Therefore, it increases the incentives of bank managers to invest more in nonlending activities of which many are of lower quality.

The rest of this chapter is structured as follows: Section 4.2 is the literature review and the development of hypotheses. Section 4.3 describes the data used in the study, defines variables, and explains the empirical models and the two estimators employed in this chapter. Section 4.4 presents the study results and discussion. Section 4.5 describes how endogeneity issues are addressed in the study as well as additional robustness checks and discussion. Section 4.6 presents the conclusion of chapter 4.

4.2 Literature review and hypotheses development

4.2.1 Theoretical background

The theoretical literature has identified several benefits and costs associated with bank diversification. Benefits include economies of scope (Teece, 1982) and greater access to internal capital markets (Stulz, 1990). Potential costs of diversification include greater incentives for inefficient rent-seeking by divisional managers (Scharfstein & Stein, 2000), overinvestment especially in lines of business with poor opportunities (Stulz, 1990), and higher overload costs of monitoring expanding number of projects (Cerasi & Daltung, 2000). Regarding value creation, Rajan et al. (2000) show that increase in diversification may lead to inefficient allocation of resources, poor investment, and lower firm value.

Another group of theoretical studies show that asymmetric information plays important role in the formulation of diversification strategies. Diamond (1984) argues that diversification helps an intermediary to reduce overall monitoring costs by reducing asymmetric information. Therefore, delegating the task of producing monitoring information to banks has a net cost advantage. However, this argument assumes an absence of agency conflicts even though this is not often the case. Meanwhile, other theoretical studies have identified material costs associated with information asymmetry between head office and divisional managers (e.g., Harris et al., 1982; Myerson, 1982). As diversification increases, the costs of managing the group and informational gap between the central management and the growing number of divisions are rising too. Myerson (1982) describes a typical principal-agent problem in relation to diversification whereby agents have both private information and private decisions that are unobservable to the principal. Higher diversification leads to increase in interests and informational differences between central and the divisional managers, thereby increasing the potential for moral hazard behaviour.

All the disadvantages of diversification (inefficient rent-seeking, overinvestment, misallocation of resources, agency costs) covered above are due to adverse selection or moral hazard problems associated with asymmetric information. Therefore, using credit information sharing schemes such as credit bureau and credit registry to improve banks' screening and monitoring abilities can alleviate most of these problems. Theoretical studies have shown that credit information sharing can prevent excessive investment (Bennardo et al., 2015), reduce adverse selection and moral hazard problems (Padilla & Pagano, 2000; Flatnes, 2021), and increase banks' incentives to collect more private information (Karapetyan & Stacescu, 2014a). By solving these problems, information sharing can address many of the current issues with diversification caused by asymmetric information.

Information reusability theory provides an important link between diversification and information sharing. Banks utilize existing customer information in one line of service when diversifying into other services. A model by Novo-Peteiro (2000) demonstrates intersectoral information reusability whereby existing information offers factors that are common to different financial services or products. The study conclusion is that historical information on one financial product can be reused partially or totally for another product(s). This is central to the concept of historical information sharing. Information reusability enables banks to evaluate the prospect for financial services cross-selling (Bae & Kim, 2010), which is one of the major causes of diversification in the financial services sector. Overall, the sharing of customer information among banks coupled with the monitoring role of credit bureaus can enhance information reusability, screening and monitoring abilities of banks, and the quality of diversified investments.

4.2.2 Empirical literature on bank diversification and credit information sharing

Empirical studies on bank diversification have mixed evidence. Numerous benefits of diversification have been reported, including increase in bank earnings (Sanya & Wolfe, 2011); value creation (Filson & Olfati, 2014); reduction in funding costs (Levine et al., 2021); access to internal capital markets (Klein & Saidenberg, 2010); stability in the supply of funds during financial scrises (Doerr & Schaz, 2021); and reduction in systemic risk (Maghyereh & Yamani, 2022). Reported disadvantages of diversification include lower earnings and falling bank performance (Stiroh & Rumble, 2006); increasing complexity and higher agency problems (Tran et al., 2020); and diversification discount (Schmid & Walter, 2009). On diversification as an effective monitoring device, Loutskina & Strahan (2011) reported a link between diversification and decline in financial institutions' information production and screening prior to the 2007/08 financial crisis. Their study shows that specialized institutions made informed investments with better performing share prices. Whereas diversified institutions retained higher mortgages due to adverse selection. In another study by Meslier et al. (2016), it is shown that bank diversification increases investment returns. However, as diversification moves further up, its impact becomes negative. Their supporting argument is that positive effect of diversification becomes negative "due to distance-related information and agency costs". Similarly, Avramidis et al. (2018) show that monitoring costs overtake the benefits from scale economies as the size of bank increases. Particularly, costs arising from shareholders' monitoring of managers and the costs of monitoring investments by managers were identified in the study.

Empirical evidence on credit information sharing confirms most of the predictions in the theoretical literature. In an experimental investigation of how asymmetric information and competition affect credit information sharing, Brown & Zehnder (2010) find that the presence of asymmetric information increases the frequency of voluntary information sharing significantly. This finding sugests that the need to overcome adverse selection problem motivates lenders to engage in voluntary information sharing. However, the study also shows that stronger competition between lenders may reduce information sharing. Similarly, Liberti et al. (2022) discover that lenders who do not subscribe to credit bureau information sharing are compelled to do so due to fear of losing market share to competitors and to have access to new markets. De Moraes et al. (2022) examine the effects of information sharing on financial development in 79 countries, and they find increase in financial system development with reduction in asymmetric information identified as a potential channel associated with this effect. Houston et al., (2010) provide a cross country evidence that information sharing reduces bank risk, increases bank earnings and economic growth. Other benefits of information sharing reported in the literature include increase in access to bank credit (Bahadir & Valev, 2021); lower loan default rates, especially in countries with competitive markets (Fosu et al., 2020); lower financial system fragility in both advanced and emerging markets (Guerineau & Leon, 2019); and lower intermediation cost (Fosu et al., 2021).

What we can clearly see in the analysis so far is the role of agency problems in bank diversification fuelled by asymmetric information. On the one hand, there are banks that monitor their diversified investments and end up incurring costs that eventually overwhelm the benefits associated with diversification. On the other hand, there are banks that rely on diversified income as hedging mechanism rather than monitoring and collecting information but suffer value discount caused by adverse selection and agency problems. However, information sharing can control agency costs by reducing asymmetric information. Moreover, evidence supports the information reusability theory that information about past customers' behaviour in one financial services area can predict their performance in other financial services areas (e.g., Thuring et al., 2012). Based on the above evidence on information sharing and bank diversification, we argue that information sharing can play a vital role in improving bank diversification strategies.

However, the two information sharing schemes may impact diversification differently in terms of volume and quality of investment because one is mandatory and free while the other is voluntary and based on business model. Moral hazard behaviour and information manipulation have been reported in relation to mandatory sharing via credit registry (Giannetti et al., 2017). Voluntary information sharing, on the other hand, is driven by the presence of asymmetric information (Brown & Zehnder, 2010) and the need to access new markets (Liberti et al., 2022). As recommended by Nakamura & Roszbach (2018), credit bureau information should be efficiently included in bank ratings because of its ability to predict future movements and improve forecasts.

Mandatory information sharing through credit registry helps regulatory authorities in monitoring credit portfolios and protecting the banking sector. Consequently, we expect this regulatory pressure to reduce bank risk-taking and lending volume (as in Cehajic & Marko, 2022). We also expect this lending reduction to increase bank diversification into non-lending activities for higher income (as in de Silva et al., 2022). The pressure on bank managers to find alternative ways to improve performance may increase incentives to diversify above optimal level to meet their short-term targets. We do not expect similar excessive diversification in relation to voluntary information sharing since there is no regulatory pressure to use credit bureau and share private information. Moreover, credit bureaus utilize latest technologies to improve the quality and timeliness of their reports (Jiang & Novik, 2021). Consequently, we expect voluntarily requested information to be of higher quality which helps banks to make informed diversified investments and create more value than banks using mandatory system. Based on these arguments we make the following hypotheses:

Hypothesis 4.1: *Mandatory and voluntary credit information sharing increase diversification below the optimal value.*

Hypothesis 4.2: *Mandatory credit information sharing increases diversification above optimal value while voluntary credit information sharing reduces diversification above the optimal value.*

Majority of studies in the literature focus on the relationship between diversification and the value of diversified banks. In a study based on data representing large banks from across the world and a system GMM estimation technique, Yildirim & Efthyvoulou (2018) report that diversification affects the value of banks in emerging countries but not in developed countries. Their findings show that intra-regional diversification enhances bank value while inter-regional diversification, although statistically less robust, negatively affects the value of banks. In another study of commercial banks across 56 countries, Gulamhussen et al. (2017) find diversification premium, with higher value created in the middle range of diversification and expansion towards less developed countries. Similarly, Elsas et al. (2010) find diversification premium across 9 developed countries; Filson & Olfati (2014) show that diversification into investment banking, securities brokerage, and insurance in the U.S. banking sector between 2001-2011 result in higher value; while Simoens & Vennet (2022) discover that functional diversification acts as shock absorber that protects European banks' value from declining during the Covid-19 pandemic.

However, there is more evidence of diversification discount in the literature than premium especially in developed countries. Schmid & Walter (2009) show that diversification in the U.S. financial services sector was value-destroying for about two decades (1985-2004), and this applies to all financial services except investment banking. Kim & Kim (2020) report that U.S. banks suffer diversification discount at the early stage due to adjustment costs. However, this discount gradually reduces and disappears at later stage. Meanwhile, Bressan & Weissensteiner (2021) show that diversification reduces value when investors demand higher future returns from diversified banks because they expect these banks to perform worse than undiversified banks. Their findings shed light on how shareholders' perception may influence the outcome of diversification. When shareholders expect the value of their investments to decline due to growing bank diversification, they demand higher future returns. However, such demand signals trouble which affects market value of banks. In an investigation of the value of diversified banks that engage in multiple activities including lending and non-lending services across 43 countries, Laeven & Levine (2007) report diversification discount. The conclusion is that higher agency problems associated with diversification result in higher costs than economies of scope. In another study based on BankScope data covering the period 1998-2013, Guerry & Wallmeier (2017) provide global evidence of significant diversification discount before the financial crisis. However, they show that the discount decreases over time and vanishes after the financial crisis. Similarly, Velasco (2022) finds diversification discount in a study of listed banks across developed countries between 2011 and 2017. The study also finds that regulatory capital restricts the level of diversification which helps to improve bank value.

The literature has shown that the net impact of bank diversification changes from positive to negative when costs arising from agency problems outweigh the benefits of diversification (e.g., Laeven & Levine, 2007; Tran et al., 2020), or when the rising monitoring costs due to bank expansion overtake the benefits from economies of scale (e.g., Avramidis et al., 2018). Therefore, based on the same arguments supporting hypotheses 4.1 and 4.2, voluntary credit information sharing via credit bureau can improve bank market value by increasing their screening and monitoring abilities, alleviating agency problems, and preventing excessive diversification. However, mandatory credit information sharing is expected to be associated with lower excess value than voluntary credit information sharing due to costs arising from agency problems identified in the build up to hypotheses 4.1 and 4.2. For the last two hypotheses below, we use excess value resulting from diversification to capture both premium and discount rather than having one hypothesis for each.

Hypothesis 4.3: *By increasing diversification above the optimal value, mandatory credit information sharing reduces excess value of diversified banks.*

Hypothesis 4.4: *By reducing diversification above the optimal value, voluntary credit information sharing increases excess value of diversified banks.*

4.3 Data and Methodology

4.3.1 Data and variables

We use a panel dataset based on bank-level data from BankFocus provided by Bureau van Dijk, macroeconomic data from the World Development Indicators (WDI) and the International Financial Statistics database of the International Monetary Fund (IMF), and information sharing data from the World Bank's Doing Business database. Initially, we considered all developing countries with sufficient data availability on both bank and credit information sharing and we had the original dataset representing 460 banks from 68 developing countries, with 5520 observations covering the period 2009-2020. We adjusted the data by reducing the sample period to 2011-2020 due to significant number of missing observations in the bank-level data from BankFocus between 2009 and 2011. In addition, the sample period is further reduced by one year when we estimated variables that are growth rates such as deposits. Following these adjustments, we have a final unbalanced panel data of 3,312 observations and 368 banks from 40 countries over the period 2012-2020.

The main dependent variables are $Excess\ Value$ and *Diversification* of banks. $Tobin's\ Q$ has been used in the literature to measure the value of diversified banks (e.g., Guerry & Wallmeier, 2017). However, the use of Tobin's q in assessing the impact of diversification has been criticized because it may not capture all relevant events under which the value of a diversified bank exceeds the sum of the values of its component parts. Therefore, we follow recent studies (e.g., Laeven & Levine, 2007; Bressan & Weissensteiner, 2021) by adopting a modified version of the 'chop shop' approach that was introduced by LeBaron & Speidell (1987). We start by grouping banking activities into commercial banking (lending activities) and investment banking (nonlending activities), then estimate the actual $Tobin's\ Q\ [q]$ as well as the $Activity\ adjusted\ Tobin's\ Q\ [q_j]$ of a bank with the assumption that the bank is "chopped" into different single-activity financial "shops". Therefore, the difference between q and q_j is the $Excess\ Value$ created or lost due to diversification.

We estimate q and q_j using the following equations:

$$q = \left|\frac{market\ value\ of\ equity + book\ value\ of\ assets - book\ value\ of\ equity}{book\ value\ of\ assets}\right| \tag{4.1}$$

$$q_j\ (Activity\ adjusted\ q) = \{\partial_{j1}q^1 + \partial_{j2}q^2\} = \{\partial_{j1}q^1 + (1-\partial_{j1})q^2\} \tag{4.2}$$

Where ∂_{j1} and ∂_{j2} are the proportions of banking activities that are commercial banking and investment banking respectively; therefore, $\partial_{j1} + \partial_{j2} = 1$. Following the literature (e.g., Liang et al., 2016; Velasco, 2022), we estimate q^1 and q^2 using subsample classification of banks as specialized in commercial banking (investment banking) if the ratio of their net loan assets to total assets is greater than 0.90 (less than 0.10). Accordingly, q^1 is the average q of all banks in our sample that specialize in commercial banking, while q^2 is the average q of all banks that specialize in investment banking. To estimate the excess value created or lost due to diversification, we obtain the difference between actual q and $activity\ adjusted\ q$ as follows:

$$Excess\ Value = q - q_j = q - \{\partial_{j1}q^1 + (1-\partial_{j1})q^2\} \tag{4.3}$$

For diversification, it is generally measured in the literature based on income or asset structure of banks. However, greater measurement problems have been identified with the income-based measure (e.g., Laeven & Levine, 2007; Liang et al., 2016). These studies highlight the disadvantage of not having gross income as most banks only report net income. Many databases report net rather than gross income of banks, this is problematic when estimating income-based diversification. The estimated diversification would include negative observations in periods of negative net income (losses). BankFocus provides net rather than gross income; consequently, we adopt asset-based measure of diversification. The measure is estimated using bank assets classified as either interest income generating activities (lending) or noninterest income activities (e.g., securities and foreign exchange trading, advisory services, investments and many other fee and commission-based services). Specifically, we adopt adjusted Herfindahl-Hirschman Index (HHI) in line with the literature (e.g., Velasco, 2022), and compute bank diversification as follows:

$$HHIDiv = 1 - \left| \left\{\frac{NLA}{TEA}\right\}^2 + \left\{\frac{OEA}{TEA}\right\}^2 \right| \tag{4.4}$$

Where $HHIDiv$, NLA, OEA and TEA are HHI based diversification, net loan assets, other earning assets, and total earning assets respectively. By taking the sum of the squares of each earning asset group as a proportion of the square of total earning assets, $HHIDiv$ has a range of 0 to 0.5, with 0.5 representing a balanced mix and equal contribution of interest earning and non-interest earning banking activities. Banks with 0 $HHIDiv$ are specialized banks, while those with 0.5 are highly diversified.

For robustness, we use another measure of asset-based diversification known as L&L measure following its application in Laeven & Levine (2007). This measure has since been used in many studies including Liang et al. (2016) and Gulamhussen et al. (2017). It has minimum and maximum values of zero and one, with lower values representing specialized banks while higher values represent greater diversification. It is estimated as follows:

$$LLDiv = 1 - \left| \frac{(NetLoanAssets - OtherEarningAssets)}{TotalEarningAssets} \right| \tag{4.5}$$

The use of unbalanced panel data is very common in bank diversification literature (e.g., Meslier et al., 2014). However, one of the disadvantages of estimating variables from unbalanced dataset is that it reduces the number of observations, especially when the estimation process involves the combination of several variables. For instance, to estimate Tobin's q we use three different variables. This means we can only use bank-year observations with all three variables matched to avoid outliers. Consequently, some of our variables have observations lower than 3,312. See table 4.1 below.

In addition to diversification that is also used as independent variable in some of the estimations, the coverage of credit information sharing is the main independent variable used in the study. We measure this as the percentage of firms and individuals covered in a country's public credit registry which delivers mandatory credit information sharing scheme (MISCOV), and the percentage of private credit bureau which provides voluntary credit information sharing services (VISCOV). Credit registry and credit bureau share information such as firm's name, business address, name of owner(s), field of business, assets and liabilities, tax and income, other financial information on the business and the owner(s), utility records, bad check list, bankruptcies, court judgments, existing credit facilities, default history, and many more (World Bank, 2019).

We control for bank characteristics and macroeconomic fundamentals that may affect bank value and diversification strategies in line with the literature (e.g., Yildirim & Efthyvoulou, 2018). For bank characteristics, we include the following control variables. $Deposits$ is the growth in total deposits of a bank. $SIZE$ is the natural logarithm of total assets. $Liquidity$ is the ratio of liquid assets to total assets of a bank. For macroeconomic factors, we have included GDP per capital growth ($GDPPCgr$) and $Inflation$ ($INFL$) rates.

Descriptive statistics

Table 4.1 presents the descriptive statistics. The top panel presents the statistics for all variables and the full sample banks used in the study, while the three bottom panels are the statistics for $HHIDiv$ and EV in countries where banks use both mandatory and voluntary information sharing, mandatory information sharing only, voluntary information sharing only respectively. The baseline dependent variable is excess value [EV] of diversified banks, which ranges from -0.206 to 1.648 in the top panel and has a positive mean of 0.015. This provides a prima facie evidence of diversification premium (as in Elsas et al., 2010), suggesting that a diversified bank may have higher market value than a specialized bank. Recall that a diversified bank has a ratio of net loan assets to total earning assets between 0.10 to 0.90 (less than 0.10 is a specialized investment bank while greater than 0.90 is a specialized commercial banks). The two measures of diversification [$HHIDiv$ & $LLDiv$] show average values of 0.44 and 0.43. Based on previous studies, we do not expect significant difference between the values of both measures. For example, Maghyereh & Yamani (2022) use $HHIDiv$ and $LLDiv$ measures of income diversification, and they also observe close average values of 0.44 and 0.45 for the two measures. However, the two measures are not perfectly correlated because one ranges from 0 to 0.5 and the other ranges from 0 to 1. The average coverage of mandatory information sharing [$MISCOV$] is 18.56, while the average coverage of voluntary information sharing [$VISCOV$] is 31.88. Meanwhile, these two measures have increased significantly during the sample period. As shown in Figure 4.1, $MISCOV$ has increased from 13.6% in 2012 to 22.1% in 2020 while $VISCOV$ has increased from 24% to 43.2% during the same period.

Table 4. 1 Descriptive statistics

Variable	Obs	Mean	Std.dev	Min	Max
The full sample					
EV	2,009	0.015	0.135	-0.206	1.648
HHIDiv	3,247	0.441	0.062	0.000	0.499
LLDiv	3,286	0.433	0.178	0.000	0.999
MISCOV	3,312	18.561	21.971	0	100
VISCOV	3,312	31.877	31.014	0	100
GDPPCgr	3,312	1.569	3.666	-14.819	14.701
DEPOSITS	3,272	7.691	18.633	-92.339	102.345
LIQUIDITY	3,285	25.018	14.222	0.168	90.991
INFL	3,227	4.739	3.261	-2.431	19.629
SIZE	3,312	15.271	1.733	9.223	20.306
DOWNTURNS	3,312	0.252	0.434	0	1
EXCH	3,276	4.015	2.830	-0.342	10.052
SCR	3,312	0.311	0.463	0	1
Mandatory and voluntary information sharing					
EV	772	0.018	0.132	-0.183	1.648
HHIDiv	1,910	0.448	0.062	0.001	0.001
Mandatory information sharing only					
EV	578	-0.002	0.103	-0.157	0.672
HHIDiv	621	0.450	0.056	0.001	0.499

Voluntary information sharing only					
EV	658	0.023	0.149	-0.206	1.189
HHIDiv	711	0.439	0.069	0.001	0.499

This table presents the summary statistics for the variables used in the study. Obs is the number of observations, Std.dev is the standard deviation, Min and max represent the minimum and maximum values. The dataset is for 368 banks from 40 countries, and the sample period is 2012-2020. The key variables include *EV* which is the excess value of a bank, it is estimated as the difference between actual q of a diversified bank and its activity-adjusted q ($q - q_j = q - \{\partial_{j1}q^1 + (1-\partial_{j1})q^2\}$). *HHIDiv* is the main measure of diversification estimated as $1 - \left|\left\{\frac{NLA}{TA}\right\}^2 + \left\{\frac{OA}{TA}\right\}^2\right|$. *LLDiv* is the second measure of diversification, estimated as $1 - \left|\frac{(NetLoanAssets - OtherEarningAssets)}{TotalEarningAssets}\right|$. $MISCOV$ is the coverage of mandatory information sharing, while $VISCOV$ represents the coverage of voluntary information sharing. Other variables are defined in Appendix Table A4.1.

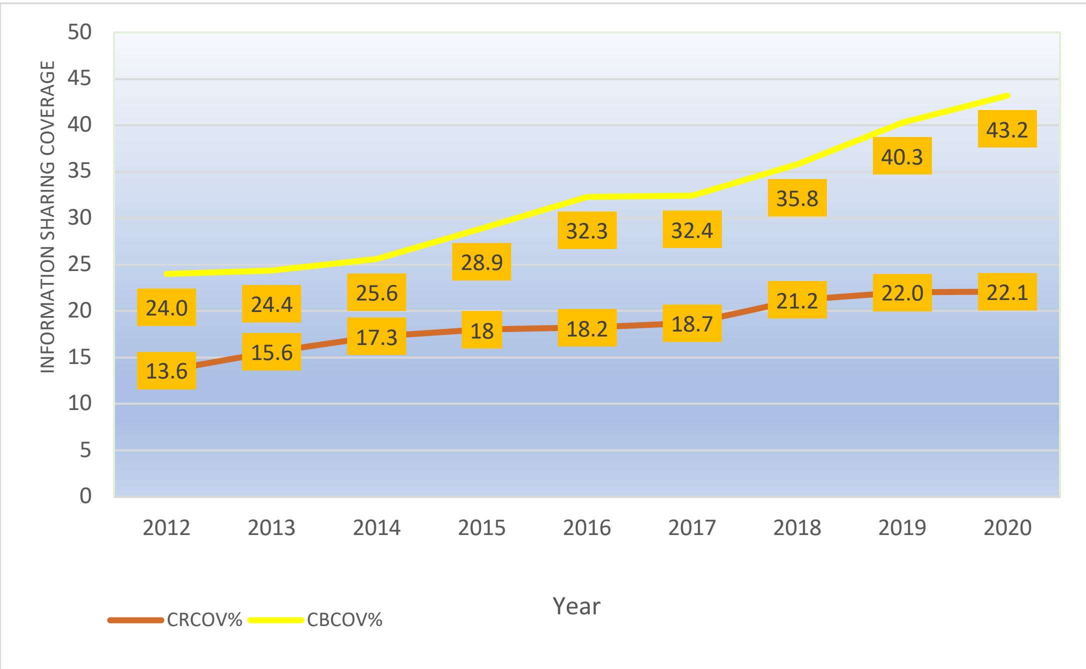

Figure 4. 1 Percentage coverage of mandatory information sharing via credit registry and voluntary information sharing via credit bureau

In the second, third, and fourth panels of table 4.1, the mean values of EV and $HHIDiv$ are 0.018 and 0.44 for banks in countries with both mandatory and voluntary information sharing, -0.002 and 0.45 for banks in countries with mandatory information sharing only, and 0.023 and 0.43 for banks in countries with voluntary information sharing only. These average values show that even though the three groups have similar diversification values, they have significantly different EV values. Importantly, with mandatory information sharing only, EV is marginally negative, suggesting that there is a diversification discount. Another important observation is the larger premium reported for banks operating where there is voluntary information sharing only, especially when compared with 0.015 in the top panel and 0.018 in countries with both schemes of information sharing. These provide initial evidence that voluntary information sharing system has higher quality information which enables diversified banks to trade at a premium, and when it coexists with mandatory information sharing, it improves the quality of diversification from a discount to a premium net value.

The correlation matrix in Appendix Table A4.2 shows that the two measures of diversification [$HHIDiv$ and $LLDiv$] have positive correlation with the excess value of banks [EV]. These positive relationships confirm the average premium shown in table 4.1 since excess value represents the net effect of diversification on market value. Similarly, both $MISCOV$ and $VISCOV$ are positively correlated with both diversification measures and excess value, providing initial indications that, on average, both information sharing schemes increase diversification and excess value of diversified banks. We also observe that large and liquid banks are more likely to diversify for value creation than small and illiquid banks.

4.3.2 Estimation and testing procedures

The first objective is to establish an optimal level of bank diversification beyond which a diversification premium turns into a discount. This is followed by the evaluation of how mandatory and voluntary information sharing influence diversification strategies and excess value below and above the optimal level. Therefore, we start with a test of linearity to establish whether an optimal level or a tipping point exists in the impact of bank diversification. A quadratic specification is generally used in the literature to test whether the effect of bank diversification is linear or not (e.g., Abuzayed et al., 2018). In addition, we follow the literature by specifying a dynamic model for bank value (e.g., Yildirim & Efthyvoulou, 2018). By incorporating these two important components, we have a dynamic quadratic model that includes one period lag of the dependent variable and a squared value of diversification (as in Maghyereh & Yamani, 2022). The model takes the following form:

$$EV_{i,t} = \delta_0 + \delta_1 EV_{i,t-1} + \delta_2 HHIDiv_{i,t} + \delta_3 HHIDiv_{i,t}^2 + \theta X'_{i,t} + \eta Z'_{j,t} + \lambda_t + \zeta_{i,t} \quad (4.6)$$

Where i, j and t index bank, country, and time. $EV_{i,t}$ is the excess value of banks. $HHIDiv_{i,t}$ represents bank diversification, while $HHIDiv^2_{i,t}$ is the squared value of bank diversification. $X_{i,t}$ is a vector of bank-level control variables [$SIZE$, $Liquidity$, and $Deposits$], and $Z_{j,t}$ is a vector of country-specific variables that include GDP per capital growth ($GDPPCgr$) and $Inflation$ rate to control for Macroeconomic environment in line with previous studies (e.g., Velasco, 2022). λ_t represents time effects, $\zeta_{i,t} = (\mu_i + v_{i,t})$ is the composite error term where μ_i represents bank specific fixed effects and $v_{i,t}$ is the independently and identically distributed ($i.i.d$) idiosyncratic error term with zero mean. $EV_{i,t-1}$ is a period lagged dependent variable; therefore, δ_1 captures the effect of excess value of banks in time $t-1$ on the contemporaneous value. δ_2 is expected to be positive to confirm that diversification improves excess value of a bank, a negative sign is predicted for δ_3 to confirm that beyond certain threshold, the positive effect of diversification becomes negative. Hence, the expected relationship mimics an inverted U-curve.

If the relationship between diversification and excess value in equation [4.6] is reverse U-shaped, our next estimation would be to determine the optimal diversification level. To do this, we need a threshold model that is compatible with panel data. Hansen (1999) panel threshold model is generally used in the literature to estimate threshold level directly rather than imposing it.[27] The model is presented as follows.

$$y_{i,t} = \begin{cases} \mu_i + \alpha' x_{i,t} + \beta_1 q_{i,t} + \mathcal{E}_{i,t} \; if \; q_{i,t} \leq \gamma \\ \mu_i + \alpha' x_{i,t} + \beta_2 q_{i,t} + \mathcal{E}_{i,t} \; if \; q_{i,t} > \gamma \end{cases} \tag{4.7}$$

Where $y_{i,t}$ is the dependent variable, $x_{i,t}$ is a vector of explanatory variables, $q_{i,t}$ is the threshold variable, μ_i represents fixed effects, $\mathcal{E}_{i,t}$ is the error term, and $\boldsymbol{\gamma}$ represents the threshold value. By estimating equation (4.7), we can obtain the threshold value and create regimes below and above this value. However, equation (4.7) does not account for potential endogeneity bias. This cannot be ignored in the context of our study because we have endogenous variable that is dynamic in nature. Therefore, we modify equation (4.7) in line with Kremer et al. (2013) recommendation that allows for endogeneity in a dynamic

[27] The panel threshold model is frequently employed in studies based on bank-level data (e.g., Shabir et al., 2022).

framework. The dynamic version estimates threshold level in a specification with endogenous regressors using a two-step approach with instrumental variables to control for endogeneity. This approach has since been employed in several studies including Baum et al. (2013) and most recently by Lay (2020) and Ho & Saadaoui (2022). Our modified version of equation (4.7) in line with Kremer et al. (2013) dynamic approach is presented as follows:

$$EV_{i,t} = \mu_i + \phi EV_{i,t-1} + \measuredangle_1 HHIDiv_{i,t} I(HHIDiv_{i,t} \leq \gamma) + \measuredangle_2 HHIDiv_{i,t} I(HHIDiv_{i,t} > \gamma) + \theta X'_{i,t} + \eta Z'_{j,t} + \mathscr{m}_{i,t} \qquad i = 1, \dots, N; \ \ t = 1, \dots, T \qquad (4.8)$$

Where $I(.)$ is the function indicating that the regime is defined by the threshold variable. $HHIDiv_{it}$ (diversification) is the threshold variable as well as regime dependent variable. $X_{i,t}$ and $Z_{j,t}$ are bank- and country-specific variables as defined in equation (4.6), while $\mathscr{m}_{i,t}$ is the error term. The threshold parameter γ is estimated with 95% confidence interval, and it splits the effects of diversification on excess value into two regimes, below and above the threshold value. $\measuredangle_1$ and $\measuredangle_2$ are the regime dependent coefficients. Accordingly, the coefficient $\measuredangle_1$ is the marginal effect of diversification on bank excess value in the lower regime, that is, below the threshold value γ. $\measuredangle_2$ is the effect of diversification above the threshold value. If the effect of diversification changes from a premium to a discount at γ, we expect a positive sign for the coefficient $\measuredangle_1$, and a negative sign for $\measuredangle_2$.

With both threshold value and the regime dependent coefficients successfully estimated using equation (4.8), the next step is to examine the differential effects of mandatory and voluntary credit information sharing on diversification below and above the threshold level using the following equations.

$$HHIDivBT_{i,t} = \Im_0 + \Im_1 HHIDivBT_{i,t-1} + \psi CIS'_{j,t} + \theta X'_{i,t} + \eta Z'_{j,t} + \lambda_t + \ell_{i,t} \qquad (4.9)$$

$$HHIDivAT_{i,t} = \vartheta_0 + \vartheta_1 HHIDivAT_{i,t-1} + \psi CIS'_{j,t} + \theta X'_{i,t} + \eta Z'_{j,t} + \lambda_t + \varpi_{i,t} \qquad (4.10)$$

Where $HHIDivBT_{i,t}$ measures bank diversification below threshold, and $HHIDivAT_{i,t}$ measures diversification above threshold. $CIS' \in [MISCOV, VISCOV]$ represents credit information sharing measures. $MISCOV$ and $VISCOV$ are the coverage of mandatory and voluntary credit information sharing respectively. $HHIDivBT_{i,t-1}$ and $HHIDivAT_{i,t-1}$ are one period lagged dependent variables in each equation, while $\ell_{i,t}$ and $\varpi_{i,t}$ are the respective error terms. Our predictions are that voluntary credit information sharing increases diversification below the threshold and reduces diversification above the threshold value. Therefore, for $VISCOV$ we expect positive sign for the coefficient ψ in model (4.9) and negative sign in model (4.10). We expect mandatory credit information sharing to increase diversification below and above the threshold value; accordingly, we predict positive sign for ψ in relation to $MISCOV$ in both models (4.9) and (4.10).

Finally, equation (4.11) estimates directly how the relationship between credit information sharing (mandatory and voluntary) and diversification above the threshold affects excess value of banks. The model is presented below:

$$EV_{i,t} = \Omega_0 + \Omega_1 EV_{i,t-1} + \Omega_2 HHIDivAT_{i,t} + \Omega_3 (CIS'_{j,t} * HHIDivAT_{i,t}) + \psi CIS'_{j,t} + \theta X'_{i,t} + \eta Z'_{j,t} + \lambda_t + \tau_{i,t} \tag{4.11}$$

Where the interaction term, $CIS'_{j,t} * HHIDivAT_{i,t}$, represents $MISCOV_{j,t} * HHIDivAT_{i,t}$ and $VISCOV_{j,t} * HHIDivAT_{i,t}$ for the two measures of credit information sharing, and $\tau_{i,t}$ is the error term. A negative sign for $MISCOV_{j,t} * HHIDivAT_{i,t}$ confirms our expectation that by increasing diversification above the threshold value, mandatory credit information sharing reduces excess value of a diversified bank. For $VISCOV_{j,t} * HHIDivAT_{i,t}$, however, we expect a positive sign indicating that by reducing diversification above threshold, voluntary credit information sharing increases the value of a diversified bank.

In terms of estimation techniques, models [4.6] [4.9] [4.10] and [4.11] are estimated with the system Generalized Method of Moments (GMM) estimator proposed by Arellano & Bover (1995) and Blundell & Bond (1998). The literature suggests that GMM helps to address endogeneity and fixed effects issues in dynamic panel models (e.g., Yildirim & Efthyvoulou, 2018; Addai et al., 2022). We use the system rather than the difference GMM since the former overcomes the problem of weak instruments associated with the latter (Arellano & Bover, 1995; Blundell & Bond, 1998; Roodman, 2009). Moreover, difference GMM eliminates the fixed effects using first difference transformation (Arellano & Bond, 1991). This would be problematic with our unbalanced panel data. Given that first-differencing subtracts previous observation from the contemporaneous one, any missing value of $EV_{i,t}$ would result in both ΔEV_{it} and $\Delta EV_{i,t-1}$ missing in the transformed data. Therefore, first difference transformation will magnify gaps in our data. To overcome this problem, we follow Arellano & Bover (1995) recommendation to use the forward orthogonal deviations transformation when working with unbalanced panel data.

Orthogonal deviations transformation eliminates the fixed effects by subtracting the average of all future available observations of a variable from the contemporaneous value rather than subtracting the previous observation (as in Foos et al. (2010). Importantly, orthogonal deviations transformation does not trigger serial correlation of the errors. That is, it preserves the orthogonality among the transformed errors. If the original errors $\mathcal{E}_{it}$ are not autocorrelated and have constant variance, so are the transformed errors $\mathcal{E}_{it}^{*}$. The forward orthogonal deviations transformation of error term is given by:

$$\mathcal{E}_{i,t}^{*} = \sqrt{\frac{T-t}{T-t+1}}\left[\mathcal{E}_{i,t} - \frac{1}{T-t}\left(\mathcal{E}_{i(t+1)} + \cdots + \mathcal{E}_{i,T}\right)\right] \tag{4.12}$$

The transformation preserves the uncorrelatedness of the error term, that is:

$$Var(\mathcal{E}_i) = \sigma^2 I_T \;\Rightarrow\; Var(\mathcal{E}_i^{*}) = \sigma^2 I_{T-1} \tag{4.13}$$

Where $\sqrt{\frac{T-t}{T-t+1}}$ in equation 4.12 represents the weighting introduced to equalize the variance, and σ^2 in equation 4.13 is the variance of the error term.

By combining levels equation and the orthogonal deviations equation (a system of equations), we estimate our models so that lags of predetermined variables are valid instruments in the transformed equation. With the lags of the dependent variable $(LG_{i,t-1}, \dots, LG_{i,t-n})$ used as instruments, estimating the models without restricting the number of lags may introduce large number of instruments that might overfit the endogenous variable (instrumented variable) and bias our estimates. Therefore, we use the lag limits ($n = 2-3$) and the collapse options in estimating our models to control the instrument count. We subject all estimations to the Windmeijer (2005) correction to minimize downward bias in standard errors. To evaluate the validity of our instruments and estimations, we use the

Hansen test of over-identifying restrictions with the null hypothesis that the instruments are valid. The Arellano-Bond test is used to check for autocorrelation of the errors [AR(2)]. The null hypothesis is that no autocorrelation is present in the transformed residuals. If both Hansen and AR(2) tests have p-values of at least 10%, the model is deemed valid.

The dynamic threshold model (equation 4.8) is also estimated with the forward orthogonal deviations transformation to wipe out the fixed effects (as in Kremer et al., 2013; Ho & Saadaoui, 2022). Thanks to Diallo (2020) who developed an estimator specifically for Kremer et al. (2013) dynamic threshold panel model. The estimator is applicable to both balanced and unbalanced panel data. Therefore, it allows us to estimate the threshold effect as well as the slope coefficients together in a two-step dynamic approach with GMM-type instruments. The validity of the dynamic threshold model is tested based on *SupWStar statistic* which uses bootstrap. The null hypothesis for this test is that there is no threshold effect. Therefore, a significant *SupWStar statistic* confirms non-linearity in equation 4.8 and the presence of threshold effect.

4.4. Results and discussion

4.4.1 Optimal diversification value

We start by testing whether an optimal level of bank diversification exists, and if so, establishing the threshold value beyond which the positive effect of diversification becomes negative. In table 4.2, the first two columns present the test of linearity using system GMM, while columns 3 and 4 present the threshold estimations. In columns 1 (without control variables) and 2 (with control variables), $HHIDiv$ has positive coefficients which are significant at the 1% level, suggesting that diversification increases the value of diversified banks. This finding is consistent with prior studies which show that diversifying into non-interest income generating activities creates additional value for banks (e.g., Elsa et al., 2010). However, the results for the squared value of diversification [$HHIDiv^2$] in columns 1 and 2 are negative and significant at the 1 % level. These suggest that as diversification increases further, the excess value of a diversified bank starts to fall. This confirms that the relationship between diversification and excess value is reverse U-shaped.

To establish the optimal diversification value, we estimate the threshold model in equation [4.8]. Columns 3 & 4 present the results with the corresponding 95% confidence interval and the regime-dependent coefficients. Column 3 shows the threshold model results without control variables while column 4 includes relevant control variables. In both columns we have the estimated threshold [γ] value of 0.469. For the sample banks, this represents the optimal diversification level and the point beyond which a diversification premium becomes a discount. Therefore, the threshold value creates two regimes in the form of below and above threshold effects, and these are captured by λ_1 and λ_2 in equation (4.8). Both regime-dependent coefficients are significant at the 1% level in column 3 and at the 5% level in column 4.

In terms of the validity of our estimations, the Hansen test of over-identifying restrictions and the Arellano-Bond tests for autocorrelation of the errors in the GMM models are at least 10% suggesting that our results are robust. To check the validity of the threshold models, we use 300 bootstrap replications in the postestimation test. The *statistic SupWStar* is significant, confirming the threshold effect.

Table 4. 2 Effect of diversification on excess value: test of linearity and optimal value

Model	(1) S-GMM (Test of Linearity)	(2) S-GMM (Test of Linearity)	(3) Dynamic threshold estimation	(4) Dynamic threshold Estimation
Impact of diversification:				
$HHIDiv_{ijt}$	0.0384*** (0.0140)	0.0222*** (0.0083)		
$HHIDiv^2_{ijt}$	-0.0010*** (0.0001)	-0.0004*** (0.0001)		
γ (Threshold)			0.469***	0.469***
95% Confidence Interval			[0.446, 0.498]	[0.406, 0.497]
$\lambda_1(HHIDiv_{ijt} \leq \gamma)$			0.0684*** (0.0230)	0.0379** (0.0203)
$\lambda_2(HHIDiv_{ijt} > \gamma)$			-0.0539*** (0.0142)	-0.0358** (0.0178)
Impact of Covariates:				
EV_{t-1}	0.8151***	0.6995***	0.7972***	0.4642***

	(0.0345)	(0.0568)	(0.0589)	(0.0810)
$GDPPCgr$		0.0061***		0.0051***
		(0.0005)		(0.0001)
$Deposits$		0.0010		0.0012***
		(0.0001)		(0.0003)
$Liquidity$		0.0023***		0.0026***
		(0.0001)		(0.0003)
$Size$		0.0008		0.0006
		(0.0021)		(0.0043)
$INFL$		0.0010		0.0011
		(0.0001)		(0.0013)
$Const$	-0.7373***	-0.5662***	-0.1406**	-0.2476**
	(0.0278)	(0.0155)	(0.0698)	(0.0991)
Diagnostic test:				
Time fixed effects	Yes	Yes		
Obs	1,650	1,590	1,672	1,502
No. of Banks	207	207	208	207
No. of Instruments	26	43	75	90
SupWStar Statistic			12.568***	14.812***
AR (1)	0.000	0.000		
AR (2)	0.747	0.781		
Hansen Test	0.180	0.830		

This table presents the results of dynamic two-step system GMM and the threshold panel regressions. Columns 1 & 2 are system GMM tests of linearity based on quadratic Eq. (4.6), while columns 3 & 4 estimate the optimal diversification value based on threshold Eq. [4.8]. The dependent variable is excess value [*EV*] which is the difference between actual q of a diversified bank and its activity adjusted q ($q - q_j = q - \{\partial_{j1}q^1 + (1 - \partial_{j1})q^2\}$). The main independent variable is bank diversification *HHIDiv,* estimated as $1 - \left|\left\{\frac{NLA}{TA}\right\}^2 + \left\{\frac{OA}{TA}\right\}^2\right|$. γ is the threshold value, $\curlywedge_1(HHIDiv_{it} \leq \gamma)$ and $\curlywedge_2(HHIDiv_{it} > \gamma)$ are the regime-dependent coefficients capturing the marginal effects of diversification on excess value below and above the threshold value. Other variables are defined in Appendix Table A4.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

The coefficient representing the effect of diversification on excess value below the threshold value [$\curlywedge_1$] has a positive sign, while the coefficient capturing the effect above threshold [$\curlywedge_2$] is negative. These results suggest that diversification increases excess value in the lower regime and reduces excess value in the upper regime. In the System GMM in column 2 and threshold model in column 4, we control for bank and country level characteristics by including $Deposits$, $Liquidity$, $Size$, $Inflation$ and $GDPPCgr$. Other than $Size$ and $Inflation$, the control variables have significantly positive association with excess value of diversified banks. However, the inclusion of control variables has not changed our original results, the presence of threshold effect persists in all estimations.

4.4.2 Effects of mandatory and voluntary credit information sharing on diversification below and above the threshold level

Having established the optimal diversification value, we can now turn our attention to testing how mandatory and voluntary credit information sharing affect diversification below and above the threshold value. Estimating the threshold model allows us to generate new variables for diversification below and above the threshold value. These provide continuous measures of bank diversification in two separate regimes. We then use these variables to estimate the effects of both mandatory and voluntary credit information sharing in the two regimes of diversification based on equations (4.9) and (4.10). The results are reported in table 4.3. First, we show the direct linkages between diversification for all banks in the sample and the two measures of information sharing in columns 1 and 2. As expected, both $MISCOV$ and $VISCOV$ have positive and significant coefficients of 0.0024 and 0.0014, suggesting that information sharing increases diversification overall.

Table 4. 3 Effects of mandatory and voluntary credit information sharing on diversification below and above the threshold value

MODEL	(1) S-GMM	(2) S-GMM	(3) S-GMM	(4) S-GMM	(5) S-GMM	(6) S-GMM
DEPENDENT VARIABLE	$HHIDiv$ (All)	$HHIDiv$ (All)	$HIDivBT$ $(HHIDiv_{it} \leq 0.46)$	$HIDivBT$ $(HHIDiv_{it} \leq 0.46)$	$HIDivAT$ $(HHIDiv_{it} > 0.46)$	$HIDivAT$ $(HHIDiv_{it} > 0.46)$
$HHIDiv_{t-1}$	0.7630***	0.7806***				
	(0.0601)	(0.0805)				
$HHIDivBT_{t-1}$			0.6277***	0.6551***		
			(0.0661)	(0.0740)		
$HHIDivAT_{t-1}$					0.7390***	0.5007***
					(0.0612)	(0.0670)
$MISCOV$	0.0024***		0.0030**		0.0013***	

	(0.0000)		(0.0001)		(0.0001)	
$VISCOV$		0.0014***		0.0019**		-0.0005***
		(0.0000)		(0.0000)		(0.0001)
$SIZE$	0.0012**	0.0012***	0.0017*	0.0017*	0.0001	0.0001
	(0.0005)	(0.0005)	(0.0010)	(0.0001)	(0.0001)	(0.0001)
$GDPPCgr$	-0.0014***	-0.0013***	-0.0015**	-0.0015**	-0.0004**	-0.0004***
	(0.0003)	(0.0001)	(0.0008)	(0.0012)	(0.0001)	(0.0001)
$Deposits$	0.0004***	0.0004***	0.0006***	0.0005***	-0.0002***	-0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0000)	0.0001)
$INFL$	0.0022***	0.0023***	0.0016*	0.0015**	-0.0004***	-0.0004***
	(0.0004)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
$Liquidity$	0.0006**	0.0007**	0.0005**	0.0004**	0.0002*	0.0002***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0000)	(0.0001)
$CONST$	0.0681***	0.0532**	0.1057***	0.0963***	0.1193	0.2442***
	(0.0017)	(0.0250)	(0.0261)	(0.0250)	(0.0802)	(0.0321)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,726	2,756	1,198	1,236	1,058	1,008
No. of Banks	357	359	245	245	229	216
No. of Instruments	30	30	44	43	32	34
AR (1)	0.000	0.000	0.000	0.000	0.000	0.000
AR (2)	0.329	0.372	0.705	0.662	0.625	0.831
Hansen Test	0.132	0.439	0.272	0.310	0.528	0.249

This table presents the results of two-step system GMM panel estimates of the effect of mandatory credit information sharing ($MISCOV$) and voluntary credit information sharing ($VISCOV$) on bank diversification. The dependent variable in models 1 & 2 is the diversification of all banks in the study sample [$HHIDiv$], in models 3 & 4 is diversification equals or below the threshold value [$HHIDivBT$], in models 5 & 6 is diversification above the threshold [$HHIDivAT$]. Diversification is measured as $1-\left|\left\{\frac{NLA}{TA}\right\}^2+\left\{\frac{OA}{TA}\right\}^2\right|$. Other variables are defined in Appendix Table A4.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

In columns 3 and 4, $MISCOV$ and $VISCOV$ are positive and significant at the 5% level. In line with our predictions, these results indicate that mandatory and voluntary credit information sharing are positively associated with bank diversification below the threshold value. The results also imply that both credit information sharing schemes help banks to make informed investments and grow their portfolios as close as possible to the optimal level to maximize value creation. Meanwhile, columns 5 and 6 show that the two information sharing schemes behave differently in the upper diversification regime. $MISCOV$ has a positive coefficient which is significant at the 1% level in column 5, suggesting that mandatory credit information sharing increases diversification above the optimal level. In column 6, however, $VISCOV$ is negative and significant at the 1% level, suggesting that voluntary credit information sharing reduces diversification above optimal value. Overall, the results reported in table 4.3 support hypotheses 4.1 and 4.2.

4.4.3 Excess value and the relationship between credit information sharing (mandatory and voluntary) and diversification above the threshold value

In this section, we investigate how the relationship between credit information sharing and diversification above the threshold value affects excess value of diversified banks. We introduce interaction term for each credit information sharing scheme, and the results are shown in table 4.4. In the first column, the interaction term of mandatory credit information sharing and diversification above the threshold, $MISCOV * HHIDivAT$, has a coefficient of -0.0015 which is significant at the 1% level. This suggests that by increasing diversification above the optimal value, mandatory credit information sharing reduces excess value of diversified banks by 0.15 percentage point. In the second column, the coefficient of $VISCOV * HHIDivAT$ is 0.0013, suggesting that the inverse relationship between voluntary credit information sharing and diversification above the optimal level increases excess value by about 0.13 percentage point.

Table 4. 4 Impact of the relationship between credit information sharing and diversification above threshold on excess value of banks

DEPENDENT VARIABLE	(1) S-GMM EV (Excess Value)	(2) S-GMM EV (Excess Value)	(3) S-GMM EV (Excess Value)	(4) S-GMM EV (Excess Value)
EV_{t-1}	0.8114***	0.8125***	0.8320***	0.8230***
	(0.0563)	(0.0370)	(0.0590)	(0.0362)
$HHIDivAT$	-0.0378*	-0.0388***	-0.0300**	-0.0386***
	(0.0051)	(0.0145)	(0.0072)	(0.0125)

$MISCOV$	-0.0015***		-0.0014***	
$* HHIDivAT$	(0.0003)		(0.0003)	
$VISCOV$		0.0013**		0.0012**
$* HHIDivAT$		(0.0002)		(0.0001)
$MISCOV$	0.0012***		0.0012***	
	(0.0002)		(0.0003)	
$VISCOV$		0.0014**		0.0014**
		(0.0002)		(0.0001)
$GDPPCgr$	0.0050***	0.0056***		
	(0.0016)	(0.0021)		
$Deposits$	0.0001	0.0002	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Liquidity$	0.0026***	0.0024***	0.0022***	0.0020***
	(0.0006)	(0.0003)	(0.0007)	(0.0003)
$SIZE$	0.0010	0.0012	0.0013	0.0010
	(0.0010)	(0.0005)	(0.0010)	(0.0016)
$EXCH$			0.0034**	0.0034*
			(0.0016)	(0.0020)
$DOWNTURNS$			-0.0065	-0.0093
			(0.0151)	(0.0083)
$CONST$	-0.0698***	-0.0903***	-0.0671**	-0.0327
	(0.0256)	(0.0301)	(0.0337)	(0.0264)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	1,026	1,212	1,019	1,208
No. of Banks	143	191	143	191
No. of Instruments	34	38	34	41
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.131	0.449	0.168	0.179
Hansen Test	0.379	0.127	0.413	0.365

This table presents the results of two-step system GMM panel estimates. Models 1 & 3 estimate how the relationship between mandatory information sharing and diversification above optimal level affects excess value of diversified banks, while models 2 & 4 present same estimations for voluntary information sharing. The dependent variable in all the models is excess value [*EV*], which is the difference between actual q of a diversified bank and its activity adjusted q ($q - q_j = q - \{\partial_{j1}q^1 + (1 - \partial_{j1})q^2\}$). The independent variables include mandatory credit information sharing ($MISCOV$), voluntary credit information sharing ($VISCOV$), and diversification above the threshold [$HHIDivAT$]. Diversification is measured as $1 - \left|\left\{\frac{NLA}{TA}\right\}^2 + \left\{\frac{OA}{TA}\right\}^2\right|$. Other variables are defined in Appendix Table A4.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

In columns 3 and 4 we introduce two additional control variables that may directly impact the market value of banks. We replace $GDPPCgr$ with $Downturns$ which equals one for a period of negative GDP per capital growth and zero otherwise. This helps to account for bad economic times in line with other studies that have used a dummy to control for economic bad times (e.g., Abuzayed et al., 2018). We also introduce exchange rate $[EXCH]$ to control for the effect of local currency vulnerability on market value of banks diversifying into trading. Foreign exchange is one of the major sources of trading income for all types of banks (Meslier et al., 2014). However, the additional control variables do not change our initial findings, the results in columns 3 and 4 remain significant and consistent with those reported in columns 1 and 2. These findings confirm hypotheses 4.3 and 4.4.

The breakdown of the data in *table 4.1* shows that the difference between average bank diversification in countries with mandatory information sharing only and that of those in countries with voluntary system only is very small compared to the significant difference in their average excess values. These suggest that, beyond the volume of diversification, there is an issue with the quality of diversification in countries with mandatory information sharing only. Lower quality of diversified investments results in lower threshold. Therefore, if voluntary credit information sharing provides banks with higher quality and timely investment information, it is likely to be associated with higher diversification threshold than mandatory credit information sharing. Importantly, the data also shows that diversified banks trade at a discount when there is mandatory information sharing only and a higher premium value when there is voluntary system only. To examine these formally, we estimate the threshold values of the two groups. Reported in table 4.5, columns 1 &2, we discover that diversification threshold in countries with mandatory information sharing only is 0.42, while that of voluntary credit information sharing only is 0.48.

Table 4. 5 Dynamic threshold estimation: optimal diversification level under mandatory and voluntary credit information sharing separated

Model	(1) Dynamic threshold estimation (Banks in countries with mandatory	(2) Dynamic threshold estimation (Banks in countries with voluntary credit	(3) S-GMM (Banks in countries with mandatory information	(4) S-GMM (Banks in countries with voluntary information

	information sharing only)	information sharing only)	sharing only)	sharing only)
Threshold:				
γ	0.424***	0.481***		
95% Confidence Interval	[0.384, 0.498]	[0.379, 0.497]		
Impact of diversification:				
$\measuredangle_1(HHIDiv_{it} \leq \gamma)$	0.0120**	0.0203**		
	(0.0059)	(0.0007)		
$\measuredangle_2(HHIDiv_{it} > \gamma)$	-0.0103**	-0.0164*		
	(0.0034)	(0.0008)		
Impact of Covariates:				
EV_{t-1}	0.6441***	0.4518***	0.8212***	0.8745***
	(0.2021)	(0.1020)	(0.0723)	(0.0704)
$HHIDiv$			-0.0688***	0.09111**
			(0.0330)	(0.0061)
$GDPPCgr$	0.0030*	0.0078**	0.0038***	0.0075**
	(0.0008)	(0.0008)	(0.0012)	(0.0033)
$Deposits$	0.0004	0.0008*	-0.0003	0.0007
	(0.0004)	(0.0005)	(0.0003)	0.0005)
$Liquidity$	0.0022***	0.0025*	0.0020***	0.0026**
	(0.0010)	(0.0012)	(0.0006)	(0.0010)
$Const$	-0.2544**	-0.0079	-0.0304	-0.2476***
	(0.0990)	(0.0080)	(0.0500)	(0.0685)
Fixed effects			Yes	Yes
Observations	551	613	482	453
No. of Banks	69	77	69	77
No. of Instruments	58	74	37	36
SupWStar Statistic	0.023**	8.011***		
AR (1)			0.000	0.000
AR (2)			0.502	0.311
Hansen Test			0.102	0.393

This table presents the results of dynamic threshold and two-step system GMM estimations. Columns 1 & 3 present the threshold and GMM estimations for banks in countries with mandatory information sharing only, while columns 2 & 4 present the same estimations for banks in countries with voluntary information sharing only. The dependent variable is excess value [*EV*] which is the difference between actual q of a diversified bank and its activity adjusted q ($q - q_j = q - \{\partial_{j1}q^1 + (1-\partial_{j1})q^2\}$). The main independent variable is bank diversification *HHIDiv,* which is measured as $1 - \left|\left\{\frac{NLA}{TA}\right\}^2 + \left\{\frac{OA}{TA}\right\}^2\right|$. γ is the threshold value, $\measuredangle_1(HHIDiv_{it} \leq \gamma)$ and $\measuredangle_2(HHIDiv_{it} > \gamma)$ are the regime-dependent coefficients capturing the marginal effects of diversification on excess value below and above the threshold value. Other variables are defined in Appendix Table A4.1.

Robust standard errors are in parentheses, and ***P<0.01, **P<0.05, *P<0.1

These results confirm the quality advantage of credit bureau information over that of credit registry. Banks using information from credit bureaus can diversify up to 48% and still create a premium compared to 42% for credit registries. These are supported by the regression results in columns 3 and 4. In column 3, $HHIDiv$ has a coefficient of -0.0688 which is significant at the 1% level, and 0.09111 in column 4 which is significant at the 5%. These confirm that diversified banks under mandatory credit information sharing only trade at a discount while those with voluntary credit information sharing only trade at a premium. Similarly, *Figure 4.2* shows that mandatory information sharing is associated with actual diversification level that is higher than optimal diversification, while *Figure 4.3* displays the resulting diversification discount. These results suggest that users of credit bureau information make better investment decisions, diversify close to the optimal diversification level to create the highest possible excess value, and avoid overinvestment. Credit registry on the other hand, is seen as another regulatory tool used in monitoring credit portfolios. Moreover, it does not provide specific business information that banks need for specific investments. Even if a model of credit registry exists in any country that does that, dubious reporting (e.g., Giannetti et al., 2017) that is associated with registry's free and mandatory reporting arrangement remains a huge problem when it comes to the quality of information shared.

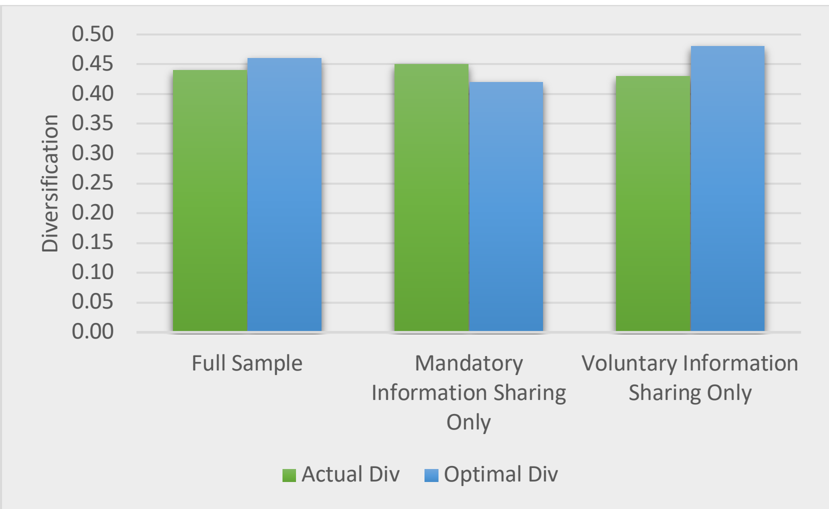

Figure 4. 2 Actual diversification and optimal diversification of banks in countries with both credit information sharing schemes, mandatory scheme only, and voluntary scheme only

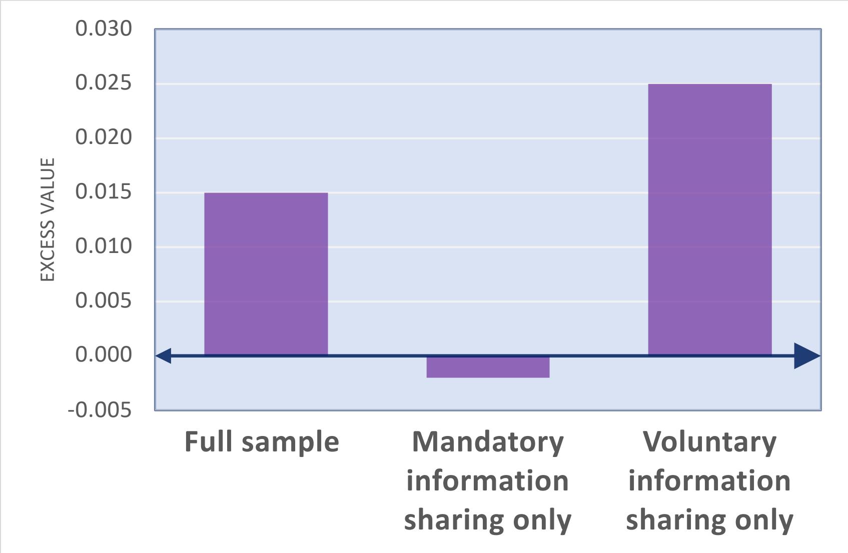

Figure 4. 3 Excess value of diversified banks in countries with both credit information sharing schemes, mandatory scheme only, and voluntary scheme only (premium or discount)

In summary, the findings show that by increasing diversification above optimal level, mandatory credit information sharing reduces excess value of banks, while the inverse relationship between voluntary credit information sharing and diversification above optimal level increases excess value of banks. There is significantly lower threshold beyond which a diversification premium turns into a discount in countries with mandatory credit information sharing only. Consequently, diversified banks in these countries trade at a discount compared to countries with voluntary information sharing only where diversified banks have higher threshold and trade at a premium. The results are consistent with the argument that by making credit information disclosure compulsory, mandatory information sharing system reduces credit risk-taking due to higher monitoring of credit activities but induces risk-taking in non-lending activities that are less monitored. Moreover, by requesting that banks share private information for free, regulators increase incentives for strategic reporting that lowers the quality of information shared. Therefore, users of this information may end up investing in value draining projects due to adverse selection. Banks may manipulate information before sharing to protect their informational rents (as in Giannetti et al., 2017), this results in higher adverse selection problem that information sharing was meant to address. Alternatively, it may be that the current model of credit registry is too credit-focus and lacks quality information in relation to other areas of business which are more relevant to non-lending activities. The most important finding of the study, however, is that when both credit information sharing schemes coexist, voluntary system dominates the quality of diversified investments which helps banks to make informed investments and trade at a premium rather than a discount.

4.5 Endogeneity and additional robustness tests

4.5.1 Endogeneity

The factor(s) driving bank diversification may also affect bank value.[28] Laeven & Levine (2007) argue that because country factors could influence both diversification and market value of banks, estimated effect of diversification on bank value may suffer from simultaneity bias. To address this potential problem, we use an index of regulatory restrictions on banking activities as external instrument for diversification (as in Laeven & Levine, 2007). This addresses any concern that we have incorrectly attributed the cause of a discount or a premium to diversification. The index increases with restrictions on banks' ability to engage in activities such as brokerage, securities, underwriting and many more. The index ranges from 1 to 4, it is 1 for a full range of activities, 2 for a full range of activities but some or all must be carried out in subsidiaries, 3 if less than full range of securities activities can be conducted in the bank or subsidiaries, 4 if securities activities are prohibited (Laeven & Levine, 2007; Barth et al., 2004).

We also want to address any endogeneity problem in relation to credit information sharing. This may arise from reverse causality between information sharing and diversification, especially if the decision to adopt information sharing scheme is influenced by growing diversification in the banking sector. However, this is more likely to affect voluntary than mandatory information sharing given that it is the decision of banks to subscribe to a credit bureau whereas the establishment of credit registry and banks' participation are decided at the country level by the government. Therefore, we use different instruments for the two information sharing schemes since we have less endogeneity concern with

[28] Bank specific factors such as profitability and size could influence diversification and market value (Campa & Kedia, 2002; Laeven & Levine, 2007). However, we have controlled for these bank-specific factors and more in all our estimations in section 4.4.

mandatory information sharing system. Population size is used as an instrument for mandatory information sharing as in Buyukkarabacak & Valev (2012) and Fosu et al. (2021), while internet infrastructure is used as the instrument for voluntary information sharing in line with Bahadir & Valev (2021).

The use of population size is based on the argument that dissemination of information is less effective in countries with large population size compared to less populated countries. While internet infrastructure, measured as the number of secured internet services per one million people, is based on the argument that advanced communication technology makes the process of information sharing easier. Especially for credit bureaus that utilize big data and advances in technology to improve the efficiency of information processing (see Jiang & Novik, 2021). However, Bahadir & Valev (2021) have argued that advanced communication technology should make the process of information sharing easier without directly effecting bank credit. Therefore, it is a good choice of instrument for information sharing.

Table 4. 6 Impact of the relationship between credit information sharing and diversification on excess value of banks: Endogeneity

MODEL	(1) S-GMM (Restrictions on banking activities as Instrument)	(2) S-GMM (Restrictions on banking activities as Instrument)	(3) S-GMM (Restrictions on banking activities as Instrument)	(4) S-GMM (Restrictions on banking activities as Instrument)	(5) S-GMM (Population size as instrument)	(6) S-GMM (Population size as instrument)	(7) S-GMM (Internet infrastructure as instrument)	(8) S-GMM (Internet infrastructure as instrument)
DEPENDENT VARIABLE	$HHIDivAT$	$HHIDivAT$	EV	EV	$HHIDivAT$	EV	$HHIDivAT$	EV
$HHIDivAT_{t-1}$	0.7787***	0.5575***			0.6007***		0.4856***	
	(0.1434)	(0.0740)			(0.0715)		(0.0671)	
EV_{t-1}			0.8235***	0.7988***		0.7456***		0.8222***
			(0.0501)	(0.0345)		(0.0488)		(0.0344)
$MISCOV$	0.0012**		0.0011**		0.0011***	0.0010**		
	(0.0001)		(0.0005)		(0.0000)	(0.0004)		
$VISCOV$		-0.0005**		0.0014***			-0.0005***	0.0013**
		(0.0001)		(0.0001)			(0.0000)	(0.0001)
$HHIDivAT$			-0.0310**	-0.0301***		-0.0350**		-0.0384***
			(0.0001)	(0.0110)		(0.0314)		(0.0134)
$MISCOV$			-0.0016**			-0.0014**		
$* HHIDivAT$			(0.0008)			(0.0007)		
$VISCOV$				0.0012***				0.0012**
$* HHIDivAT$				(0.0001)				(0.0002)
$SIZE$	0.0001	0.0001			0.0001		0.0001	
	(0.0001)	(0.0001)			(0.0001)		(0.0001)	

$GDPPCgr$	-0.0005***	-0.0005***	0.0065***	0.0067***	-0.0004***	0.0067***	-0.0005***	0.0065***
	(0.0001)	(0.0001)	(0.0038)	(0.0019)	(0.0001)	(0.0024)	(0.0001)	(0.0016)
$Deposits$	-0.0002***	-0.0002**	0.0003	0.0003	0.0002***	0.0002	0.0002***	0.0002
	(0.0000)	0.0000)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$INFL$	-0.0004***	-0.0004***			-0.0003***		0.0004***	
	(0.0001)	(0.0001)			(0.0001)		(0.0001)	
$Liquidity$	0.0003**	0.0002**	0.0024***	0.0023***	0.0002**	0.0023***	0.0002***	0.0025**
	(0.0000)	(0.0001)	(0.0016)	(0.0004)	(0.0000)	(0.0017)	(0.0001)	(0.0003)
$CONST$	0.0804	0.2192***	-0.1154***	-0.0667***	0.1901***	-0.1110***	0.2507***	-0.0414***
	(0.0756)	(0.0354)	(0.0405)	(0.0150)	(0.0340)	(0.0356)	(0.0327)	(0.0145)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	996	933	1,036	1,164	1,018	1,154	998	1,212
No. of Banks	218	205	144	183	213	160	216	191
No. of Instruments	31	34	29	40	33	30	35	38
AR (1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR (2)	0.491	0.682	0.180	0.417	0.471	0.133	0.739	0.112
Hansen Test	0.523	0.155	0.670	0.116	0.783	0.757	0.207	0.128

This table presents the results of two-step system GMM panel estimations. The dependent variables include diversification above the threshold value in columns [1] [2] [5] & [7], and excess value [*EV*] in columns [3] [4] [6] & [8]. *EV* is the difference between actual q of a diversified bank and its activity adjusted q ($q - q_j = q - \{\partial_{j1} q^1 + (1 - \partial_{j1}) q^2\}$). The independent variables include mandatory credit information sharing ($MISCOV$), voluntary credit information sharing ($VISCOV$), and diversification above threshold [$HHIDivAT$]. Diversification is measured as $1 - \left| \left\{\frac{NLA}{TA}\right\}^2 + \left\{\frac{OA}{TA}\right\}^2 \right|$. Other variables are defined in Appendix Table A4.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

Using these three external instruments, we re-estimate the effect of credit information sharing on diversification above optimal value and how this in turn affects the excess value of diversified banks. The results are presented in table 4.6. Columns 1 to 4 are estimations with an index of regulatory restrictions on banking activities as external instrument for diversification. The first two regressions show that $MISCOV$ has a positive sign and $VISCOV$ has a negative sign, both results are significant at the 5% level, suggesting that mandatory information sharing has a positive association and voluntary information sharing has a negative association with diversification above threshold ($HHIDivAT$). With these relationships, the results in columns 3 & 4 confirm with the interaction terms that $MISCOV$ reduces excess value while $VISCOV$ increases excess value. Columns 5 and 6 are estimations for mandatory information sharing with population size as external instrument, while columns 7 and 8 are estimations for voluntary information sharing with internet infrastructure as external instrument. Again, the results are consistent with those presented in columns 1 to 4 as well as the original findings in section 4.4.

4.5.2 Additional robustness checks

In this section we conduct additional checks using alternative measure of diversification. Following Laeven & Levine (2007) and Liang et al. (2016), we use a measure of diversification which is defined as 1 minus the absolute value of the difference between net loan assets and other earning assets to total earning assets [$LLDiv$]. It ranges from 0 to 1, and higher value indicates greater diversification. We start by testing whether we can achieve a threshold value similar to what we estimated using the original measure of diversification in section 4.4. We employ a dynamic threshold model in Eq. [4.8], the results are reported in table 4.7. The estimated threshold value in column 1 is 0.466, which is significant at the 1% level. Comparing this result to 0.469 reported under the original measure of diversification in table 4.2, there is no material difference between the two. For the regime dependent coefficients, λ_1 has a positive value of 0.0296, λ_2 has a negative value of 0.0305, and both coefficients are significant at the 5% level.

Table 4. 7 Impact of the relationship between credit information sharing and diversification on excess value of banks: Alternative measure of diversification

Model	(1) Dynamic Threshold	(2) S-GMM	(3) S-GMM	(4) S-GMM	(5) S-GMM
Dependent Variable	EV (Excess Value)	$LLDivAT$ *(Above Threshold)*	$LLDivAT$ *(Above Threshold)*	EV (Excess Value)	EV (Excess Value
Impact of diversification:					
$\boldsymbol{\gamma}$ (Threshold)	0.466***				
95% Confidence Interval	[0.462, 0.487]				
$\lambda_1(LLDiv_{ijt} \leq \gamma)$	0.0296** (0.0136)				
$\lambda_2(LLDiv_{it} > \gamma)$	-0.0305** (0.0123)				
EV_{t-1}	0.7843***			0.7878***	0.7912***

	(0.0952)			(0.0620)	(0.0353)
$LLDivAT_{t-1}$		0.7706***	0.5997***		
		(0.0764)	(0.0837)		
$MISCOV$		0.0010***		0.0011**	
		(0.0002)		(0.0003)	
$VISCOV$			-0.0015***		0.0014**
			(0.0005)		(0.0001)
$MISCOV * LLDivAT$				-0.0015***	
				(0.0005)	
$VISCOV * LLDivAT$					0.0011**
					(0.0004)
$LLDivAT$				-0.0308**	-0.0297**
				(0.0190)	(0.0136)
Impact of Covariates:					
$GDPPCgr$	0.0059***	-0.0010**	-0.0011***	0.0053**	0.0069***
	(0.0007)	(0.0044)	(0.0088)	(0.0024)	(0.0017)
$Deposits$	0.0010	-0.0004**	-0.0003**	0.0002	0.0002
	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
$Liquidity$	0.0023***	0.0004***	0.0005***	0.0024***	0.0021**
	(0.0003)	(0.0009)	(0.0011)	(0.0010)	(0.0003)
$Size$	0.0009	0.0003	0.0002	0.0015	0.0010
	(0.0043)	(0.0037)	(0.0055)	(0.0023)	(0.0018)
$INFL$	0.0018	-0.0006**	-0.0007***		
	(0.0012)	(0.0037)	(0.0074)		
$Const$	-0.1905**	0.1217*	0.1574**	-0.1084**	-0.0740**
	(0.0750)	(0.0707)	(0.0748)	(0.0425)	(0.0310)
Time fixed effects		Yes	Yes	Yes	Yes
Observations	1,503	925	943	1,025	1,198
No. of Banks	207	176	180	143	189
No. of Instruments	96	31	27	33	40
SupWStar Statistic	3.128***				
AR (1)		0.000	0.000	0.000	0.000
AR (2)		0.113	0.108	0.345	0.391
Hansen Test		0.708	0.714	0.382	0.147

This table presents the results of dynamic threshold and two-step system GMM panel regressions. The dependent variables are excess value [*EV*] in columns [1] [4] & [5], and diversification above threshold [$LLDivAT$] in columns [2] & [3]. *EV* is the difference between actual q of a diversified bank and its activity adjusted q ($q - q_j = q - \{\partial_{j1} q^1 + (1 - \partial_{j1}) q^2\}$). The main independent variables are mandatory credit information sharing ($MISCOV$), voluntary credit information sharing ($VISCOV$), and diversification above the threshold [$LLDivAT$]. γ is the threshold value, $\measuredangle_1(LLDiv_{it} \leq \gamma)$ and $\measuredangle_2(LLDiv_{it} > \gamma)$ are the regime-dependent coefficients capturing the marginal effects of diversification on excess value below and above the threshold level. Diversification is measured as $1 - \left|\frac{(NetLoanAssets - OtherEarningAssets)}{TotalEarningAssets}\right|$. Other variables are defined in Appendix Table A4.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.
Significance levels are ***P<0.01, **P<0.05, *P<0.1

In column 2, $MISCOV$ is positive and significant at the 1% level. In column 3, $VISCOV$ is negative and significant at the 1% level. These results confirm earlier findings that $MISCOV$ increases diversification above the threshold, while $VISCOV$ reduces diversification above the threshold value. In column 4, $MISCOV * LLDivAT$ is negative and significant, confirming that mandatory information sharing reduces bank value by increasing diversification above the threshold level. However, the results in column 5 shows that, by reducing excessive diversification, voluntary information sharing is value enhancing.

Overall, the application of instrumental variables (regulatory restrictions on banking activities, Population size, and internet infrastructure) as well as alternative measure of diversification do not appear to affect our findings. The results suggest that the original findings in section 4.4 are free from suspected biases. All results agree that mandatory information sharing is positively associated with diversification above threshold, and this relationship turns a diversification premium into a discount. On the other hand, voluntary information sharing is inversely associated with diversification above the threshold, and this relationship helps diversified banks to create additional value. Our findings agree with other studies in the literature that have documented the differential effects of the two informational schemes. Especially those that have shown that the quality of information shared matters, and that credit bureau has quality advantage and higher positive impact on banking activities (e.g., Grajzl & Laptieva, 2016; Kusi & Opoku-Mensah, 2018). We document that the quality of diversified investments is higher among banks using voluntarily shared information compared to those using information shared under the mandatory system. In addition, our findings are consistent with the evidence which shows that the mandatory nature of credit registry can drive moral hazard behaviour (e.g., Giannetti et al., 2017). We show that, by increasing monitoring and supervision of credit activities, mandatory information sharing drives higher investment in non-lending activities; however, many of these investments are of lower quality.

4.6 Conclusion

Banks continue to leverage advances in technology in their financial product innovation and diversification strategies to create more wealth and to reduce costs of financial distress. However, whether bank diversification has a net premium or discount is the current debate in the literature due to recent reports of both value-enhancing scale economies and value-destroying adverse selection and agency problems. In this study, we use dynamic threshold and GMM models to test our argument that by increasing banks' screening (*ex-ante*) and monitoring (*ex-post*) abilities, credit information sharing can improve bank diversification strategies and excess value. We create lower regime (below optimal value) and upper regime (above optimal value) of bank diversification, then examine the impact of mandatory and voluntary credit information sharing in each regime. Using a panel dataset of 368 banks from 40 countries covering the period 2012-2020, we find the following new results. Diversification increases excess value of banks up to an optimal level beyond which the effect becomes negative, suggesting that the relationship is inverse U-shaped. Mandatory and voluntary credit information sharing increase excess value of banks by increasing diversification in the lower regime. Mandatory credit information sharing reduces excess value by increasing diversification in the upper regime while voluntary credit information sharing increases excess value by reducing diversification in the upper regime. In addition, we investigate the net effects of diversification where there is mandatory scheme only as well as where there is voluntary scheme only. We find that diversification is associated with a discount and significantly lower threshold value (low-quality investments) where there is mandatory information sharing only. Whereas a premium and higher threshold value (high-quality investments) are present where there is voluntary information sharing only or where both information sharing schemes coexist. The findings highlight the importance of having both mandatory and voluntary credit information sharing schemes. We perform several robustness checks including subsample analysis, alternative measure, and use of external instruments.

Appendix

Appendix Table A4. 1 Definition and measurement of variables used in the study

Variables	Description	Observable data	Exp Sign	Original source(s) of data
Dependent Variables				
$Excess\ Value\ (EV)$	Excess value is the difference between a bank's actual Tobin's q and $activity\ adjusted\ q$ (Laeven & Levine, 2007), which is estimated as follows: $EV = q - q_j = q - \{\partial_{j1}q^1 + (1 - \partial_{j1})q^2\}$	Market value and book value of a bank.	n.a.	BankFocus
Main Explanatory Variables				
$HHIDiv$	Is the adjusted Herfindahl-Hirschman Index (HHI) asset-based diversification measure which is estimated as the sum of the squares of each earning asset group as a proportion of the square of total earning assets (Velasco, 2022). $HHIDiv = 1 - \left\lvert \left\{\frac{NLA}{TEA}\right\}^2 + \left\{\frac{OEA}{TEA}\right\}^2 \right\rvert$	NLA, OEA and TEA are net loan assets, other earning assets, and total earning assets	$(+)$	BankFocus
$LLDiv$	is defined as 1 minus the absolute value of the difference between net loan assets and other earning assets to total earning assets (Laeven & Levine, 2007). $1 - \left\lvert \frac{(NetLoanAssets - OtherEarningAssets)}{TotalEarningAssets} \right\rvert$.	Data available as net loan assets, other earning assets, and total earning assets	$(+)$	BankFocus
$MISCOV$	Mandatory credit information sharing coverage $(MISCOV)$ is the	Coverage of registry in %.	$(+)$	World Bank's

		percentage of firms and individuals covered in a country's public credit registry with information on repayment history, unpaid debt balances, or outstanding credit from the past five years.			Doing Business Database (2004-2020)
$VISCOV$		Voluntary credit information sharing coverage $(VISCOV)$ is the percentage of firms and individuals covered in a country's private credit bureau.	Coverage of bureau in %.	$(+)$	World Bank's Doing Business Database (2004-2020)
Control Variables					
Bank Specific Variables	$DEPOSITS$	Is the growth in bank total deposits. $DEPOSITS = {TD_t - TD_{t-1}}/{TD_{t+1}}$	*TD* = Total deposits of bank.	$(+)$	BankFocus
	$Liquidity$	Liquidity is the ratio of liquid assets to total assets. $LIQUID = {LA}/{TA}$	LA= liquid assets of bank. TA= total assets of bank.	$(+)$	BankFocus
	$SIZE$	The natural logarithm of total assets.	*Total assets*	$(+)$	BankFocus
Country level variables	$GDPPCgr$	Growth rate of GDP per capital growth.	*GDPPC* = GDP per capital.	$(+)$	WDI
	$downturns$	Equals one for a period of negative GDP per capital growth and zero otherwise,	GDP per capital.	$(-)$	WDI
	ΔEXCH	This is the change in exchange rate in local currency per dollar (Guerineau & Leon, 2019).	NER= Nominal exchange rate	$(\pm)$	WDI

	$INFL$	Inflation is the annual growth rate of consumer price index (Sorge et al., 2017)	Inflation in %	$(\pm)$	WDI
Variables used as instruments					
Restrictions on banking activities		An index which increases with restrictions on the ability of banks to engage in activities including brokerage, securities, underwriting and many more depending on the country. The index ranges from 1 to 4, it is 1 for a full range of activities, 2 for a full range of activities but some or all must be carried out in subsidiaries, 3 if less than full range of securities activities can be conducted in the bank or subsidiaries, 4 if securities activities are prohibited (Barth et al., 2004; Laeven & Levine, 2007).	An indication that a particular banking activity is restricted in a country	$(\pm)$	Bank Regulation and Supervision database of the World Bank
Population Size		Population size is the natural log of total population (as in Buyukkarabacak & Valev, 2012; Fosu et al., 2021)	Population size	$(\pm)$	WDI
Internet Infrastructure		Internet infrastructure is measured as the number of secured internet services per one million people (as in Bahadir & Valev, 2021)	Internet Infrastructure	$(\pm)$	WDI

This table summarizes the definition and measurement of variables used in the study. It covers the dependent variables, explanatory and control variables, and their expected signs. It also presents the observable data used in computing each variable and identifies the original sources of all data.

n.a. denotes ‘not applicable’; $\pm$ indicates indeterminate sign

Appendix Table A4. 2 Correlation matrix of variables used in the study

Variable		1	2	3	4	5	6	7	8	9	10
EV	1	1.000									
HHIDiv	2	0.033*	1.000								
LLDiv	3	0.045*	0.335*	1.000							
MISCOV	4	0.014*	0.020*	0.059*	1.000						
VISCOV	5	0.114*	0.008*	0.006*	0.199*	1.000					
LIQUIDITY	6	0.081*	0.128*	0.147*	0.077*	0.067*	1.000				
DEPOSITS	7	0.096*	0.008*	0.009*	-0.084*	-0.099*	0.019*	1.000			
SIZE	8	0.132*	0.170*	0.146*	0.061*	0.097*	0.093*	-0.026*	1.000		
GDPPCgr	9	0.031*	-0.007*	-0.105*	-0.102*	-0.295*	-0.145*	0.122*	-0.021*	1.000	
INFL	10	0.026	0.048*	0.234*	-0.165*	-0.214*	0.142*	-0.057*	0.001	-0.036*	1.000

This table presents the correlation matrix of variables used in this study. The key variables include EV which is the excess value estimated as the difference between actual q of a diversified bank and its activity-adjusted q $(\mathrm{q} - \mathrm{q_j} = \mathrm{q} - \{\partial_{j1}\mathrm{q}^1 + (1-\partial_{j1})\mathrm{q}^2\})$. HHIDiv is the main measure of diversification estimated as $1 - \left|\left\{\frac{\mathrm{NLA}}{\mathrm{TA}}\right\}^2 + \left\{\frac{\mathrm{OA}}{\mathrm{TA}}\right\}^2\right|$. LLDiv is the second measure of diversification, measured as $1 - \left|\frac{(\mathrm{NetLoanAssets} - \mathrm{OtherEarningAssets})}{\mathrm{TotalEarningAssets}}\right|$. MISCOV is the coverage of mandatory credit information sharing, while VISCOV represents the coverage of voluntary credit information sharing. Other variables are defined in Appendix Table A4.1.
***** indicates 5% significance level

Chapter 5: How does credit information sharing shape the cyclicality of bank liquidity creation?

5.1 Introduction

Banks create liquidity by issuing illiquid assets financed with liquid liabilities.[29] Liquidity creation is positively associated with economic growth (e.g., Berger & Sedunov, 2017); however, it reduces banks' own liquidity position. The conversion of deposits into illiquid assets increases bank vulnerability because; on the one hand, it increases liquid liabilities with the obligation to provide liquidity to depositors on demand; on the other hand, it increases long-term assets that cannot be liquidated easily to meet the demand.

Existing literature shows that liquidity creation is generally procyclical and can amplify the business cycle fluctuations (e.g., Davydov et al., 2018; Niu, 2022). This is because banks tend to create too much liquidity during upturn of the business cycle and too few during downturn. In addition to excessive liquidity creation during business cycle upturn which causes shortages during downturn, liquidity hoarding by banks attempting to avoid funding difficulties during downturn also increases the cyclicality of liquidity creation.[30] Regardless of the cause of fluctuations in liquidity, it is important to promote its stability because both periods of too much and insufficient liquidity are equally harmful. Excessive liquidity creation can increase systemic risk (e.g., Zhang et al., 2021) while liquidity shortages can amplify the impact of uncertainty shocks on the economy (Breitenlechner et al., 2022).

Empirical studies have not identified how banks can stabilize liquidity creation; however, theoretical literature seems to offer useful insight into the linkages between fluctuations in liquidity and asymmetric information. Using a counterparty risk model, Heider et al. (2015) explain how asymmetric information among banks, particularly adverse selection associated with their assets, causes liquidity shortages. On moral hazard, Acharya & Naqvi (2012) who model liquidity and risk-taking over the business cycle show that higher liquidity creation during deposits surplus is driven by moral hazard behaviour of managers who lower

[29] Banks create liquidity on-balance sheet as well as off-balance sheet (Diamond & Dybvig, 1983; Kashyap et al., 2002).

[30] Note, during bad economic times banks may reduce the creation of liquidity to avoid funding difficulties or the need to raise funds through fire-sales of illiquid assets during downturn when prices are significantly lower (as in Diamond & Rajan, 2011).

their standards to create more illiquid assets in the form of loans. Despite these theoretical arguments, empirical work has largely ignored the role of asymmetric information in the interaction between liquidity creation and business cycle fluctuations.[31]

Therefore, what constitutes an important gap in this literature is identifying a scheme that can address incentive conflicts and adverse selection during both turns of the business cycle. More specifically, the challenge is to identify a liquidity smoothing device that can reduce moral hazard behaviour among banks in their conversion of depositors' liquid funds into illiquid assets during good economic times, reduce opacity of banks' illiquid assets which hinders banks' access to liquid funds during downturns, and enhance banks' access to customer information during good times to improve screening.[32]

In this paper, we fill the above gap by investigating whether credit information sharing in the banking sector can reduce the intensity of fluctuations in bank liquidity creation. We expect the existence of advanced information sharing systems to address the key causes of fluctuations in bank liquidity position and creation including moral hazard which drives excessive creation of liquidity during good economic times (e.g., Acharya & Naqvi, 2012) and adverse selection in the interbank market which causes liquidity shortages during downturn (e.g., Heider et al., 2015).

The literature shows that information sharing among banks can reduce adverse selection and moral hazard problems (Flatnes, 2021), increase information collection (Karapetyan & Stacescu, 2014a), and reduce loan default rates (Fosu et al., 2020).[33] By solving these problems caused by asymmetric information, we predict that information sharing can stabilize liquidity creation over the business cycle either through countercyclical effect or reduction in procyclicality. We also predict the channels through which information sharing may reduce fluctuations in bank liquidity creation, including higher access to interbank liquidity especially during downturn when customer deposits are insufficient to cover bank

[31] In thinking about why this is the case, we do not rule out issues relating to data availability especially in developing countries where access to data is often limited. Moreover, multiple factors contribute to the process through which banks create liquidity, including banks' own liquidity position, depositors' willingness to keep their liquid funds with their banks, the behaviour of customers who receive illiquid assets created by banks, changes in the business cycle, and many more. Therefore, it is not surprising that the literature has not identified a particular factor that connects many of these components and with the potential to address information asymmetries causing disconnection among them.

[32] Moreover, theory shows that poor screening is observed during good economic times because information production during economic expansion is less profitable for banks (Ruckes, 2004). Therefore, the introduction of informational scheme that increases access and use of up to date and less costly information about external applicants can improve banks' screening and asset creation. This may also help to control the volume of liquidity during upturn of the business cycle.

[33] We cover the literature on both information sharing among banks and liquidity creation in section 5.2.

liquidity shortages.[34] In a frictionless interbank market, coinsurance against idiosyncratic liquidity risk whereby funds are reallocated from liquidity-rich banks to liquidity-poor banks helps to cope with shortages (e.g., Castiglionesi & Eboli, 2018). However, asymmetric information among banks can induce a rationing equilibrium whereby banks with surplus hoard liquidity and reduce supply to banks in need of liquidity (e.g., Freixas & Jorge, 2008). Our prediction is that by facilitating regular exchange of information among banks about their illiquid assets, information sharing can reduce liquidity hoarding caused by adverse selection problem in the interbank market. Other predicted channels of information sharing are by improving the accuracy of default probability estimates and reducing bank asset write-offs over the business cycle. These two channels are based on our suspicion that if information sharing can help banks to estimate default probabilities more accurately when converting deposits into illiquid assets, it must also improve the quality of assets originated in the process. We expect these assets to suffer less deterioration and lower write-offs.

We test the baseline prediction and the three channels using a panel dataset of 368 banks from 40 countries, covering the period 2012-2020. Liquidity creation is estimated using Berger & Bouwman (2009) 3-step methodology. This approach allows us to classify items on both asset and liability sides of bank balance sheet based on their level of liquidity, assign weight to each item, and then estimate on- and off-balance sheet liquidity creation measures for each bank. We use two-step system Generalized Method of Moments (GMM) proposed by Arellano & Bover (1995) and Blundell & Bond (1998) as estimator, and Windmeijer (2005) correction to minimize the downward bias in standard errors. We find that both on- and off-balance sheet liquidity creation are procyclical, meaning that banks create higher liquidity during economic expansions and lower liquidity during recessions. However, we discover that information sharing reduces procyclicality of both types of liquidity creation significantly. The results suggest that with greater scope, accessibility and quality of credit information, bank liquidity creation is significantly more stable over the business cycle.

[34] The literature on liquidity risk suggests that during period of uncertainty such as financial crisis, deposit funding channel is likely to be broken and this may increase bank liquidity risk to the extent that government supports are required (e.g., Acharya & Mora, 2015). However, our study focuses on business cycle fluctuations rather than financial crises. The interbank market is not expected to be in a financial crisis because of changes in the business cycle. Therefore, even though depositors and other investors reduce the inflow of funds into banks during downturn of the business cycle because they anticipate trouble, there should be efficient reallocation of liquidity within an interbank market with lower level of asymmetric information. There should be higher level of trust among banks in a market with advanced system of information sharing such as credit registry. We expect this to help in channelling liquidity to institutions experiencing shortages.

We extend the baseline investigation to examine whether the predicted channels are valid. We find that information sharing increases the flow of liquidity among banks, particularly during downturn of the business cycle when many banks suffer liquidity shortages. We also discover that by doing so, information sharing reduces procyclical liquidity creation. Given that asymmetric information prevents the flow of liquidity from banks with surplus to those experiencing shortages (as in Heider et al., 2015), our findings show that having an established system of information sharing whereby banks regularly exchange data about their assets helps to ease liquidity shortages and stabilize creation across the different phases of the business cycle. The results for the two quality channels show that information sharing reduces procyclical liquidity creation by improving the accuracy of default probability estimates and reducing the amount of bank asset write-offs. The first part of these results is consistent with the view that information sharing reduces procyclicality by improving banks' ability to evaluate their customers and predict future performance of illiquid assets more accurately; while the second part suggests that information sharing reduces deterioration in assets which helps to stabilize liquidity position and creation over the business cycle. We can also interpret our findings from the disciplinary perspective. With information sharing scheme in place, especially credit registry, regulators and other banks are regularly updated with information about the quality of illiquid assets created by banks. This increase in transparency reduces the incentives to create low-quality assets due to fear of reputational damage that may discourage potential investors or provoke regulators' disciplinary actions.

Overall, the findings suggest that bank liquidity creation is procyclical. However, information sharing reduces procyclicality by increasing the flow of liquidity among banks which helps liquidity-poor banks to cope with shortages, improving the accuracy of default probability estimates, and reducing asset write-offs. The results are robust to several checks, including alternative measures and additional instruments.

This study contributes to the literature on the cyclicality of bank liquidity creation (e.g., Davydov et al., 2018). We provide evidence that procyclical liquidity creation can be reduced significantly using information sharing schemes to address the effects of asymmetric information. The study also expands the growing literature on credit information sharing which promotes information availability, reduces adverse selection and moral hazard problems (e.g., De Haas et al., 2021). We provide evidence on the linkages between information sharing and the efficiency of interbank liquidity reallocation from banks with surplus to those experiencing shortages during downturn of the business cycle.

The chapter proceeds as follows: Section 5.2 covers the literature review and the development of hypotheses. Section 5.3 presents the description of data, variables and empirical models used in the study. Section 5.4 presents the study results and discussion. Endogeneity and additional robustness checks are presented in section 5.5, while section 5.6 presents the study conclusion.

5.2 Literature review and hypotheses development

5.2.1 Liquidity creation

Bank liquidity creation is critically important for the financing of economic activities (Diamond & Dybvig, 1983). However, banks may be unwilling or unable to create equal level of liquidity over the entire business cycle. Consequently, more liquidity is often created when economic conditions are good and less liquidity when conditions are bad (Niu, 2022). Theoretical literature explains this behaviour in several ways. An argument provided by Allen & Gale (1998) in their business-cycle-based model is that when depositors have information about impending economic downturn, they are likely to withdraw their funds in anticipation of financial difficulties in the banking sector. When this happens, banks suffer significant liquidity shortages, and may be forced to sell their assets even at a loss to settle depositors (as in Diamond & Dybvig, 1983). Jacklin & Bhattacharya (1988) explain how this outcome can be driven by a two-sided asymmetric information, whereby banks cannot observe the true liquidity needs of depositors and depositors are asymmetrically informed about the quality of assets held by banks. This is consistent with the argument that liquidity shortages during downturn may not be due to bank insolvency as informational gap between banks and their investors can trigger a number of liquidity problems including force liquidation of high-quality assets. In another theoretical model of liquidity over the economic cycle, Acharya & Naqvi (2012) demonstrate the effect of moral hazard behaviour on the volume and quality of liquidity creation by banks. They show that when banks have access to abundant deposit funds, they lower their standards to increase liquidity creation. Thakor (2005) shows that banks that are concerned about their reputation may create excessive liquidity off their balance sheets during booms.

From empirical standpoint, evidence shows that both bank lending (e.g., Behr et al., 2017) and liquidity creation (e.g., Davydov et al., 2018) are generally procyclical. However, it has been acknowledged that liquidity creation is superior to bank lending in capturing the complete output of a bank because it reflects both asset and liability sides of the balance sheet (Berger & Bouwman, 2015). Davydov et al. (2018) report that liquidity creation is more procyclical than bank lending in their study of cyclical behaviour of liquidity creation among Russian banks during 2004 to 2015 period. They also discover that procyclical behaviour is common among all banks including state-owned, foreign-owned, and domestic private banks. In another study of cyclicality of bank liquidity creation, Niu (2022) use panel data on U.S. banks and find that more liquidity is created during economic expansion while less is created during recession. The study also shows that both on- and off-balance sheet liquidity creation are procyclical regardless of bank size. Similarly, Tang et al. (2021) report procyclical liquidity creation among Chinese banks between 2012 and 2018.

The problem with procyclical liquidity creation is that it can amplify business cycle fluctuations. Lower liquidity creation can harm economic growth,[35] while excessive liquidity creation can increase systemic risk (e.g., Zhang et al., 2021) and the probability of bank failure (e.g., Fungacova et al., 2021). As a matter of fact, financial crisis tends to follow a period of high liquidity creation, particularly off-balance sheet liquidity creation (Berger & Bouwman, 2017). Off-balance sheet financing commitments are more problematic than spot loan contracts since banks have less information about future performance of borrowers' projects when commitment contracts are signed. This asymmetric information increases both adverse selection and moral hazard problems associated with off-balance sheet commitments (see Avery & Berger, 1991).

Overall, bank liquidity creation is procyclical. Banks create higher liquidity when economic conditions are good, particularly when bank managers have access to abundant deposit funds which aggravates the risk-taking moral hazard behaviour (as in Acharya & Naqvi, 2012). These banks may suffer liquidity shortages during downturn due to mass

[35] Fidrmuc et al. (2015) and Berger & Sedunov (2017) show that liquidity creation is positively associated with economic growth, demonstrating its importance and suggesting that not creating enough may have adverse impact on both businesses and the conomy.

withdrawal of funds by depositors who anticipate difficulties in the banking sector (e.g., Allen & Gale, 1998), because of insufficient funding from external sources (e.g., Acharya & Mora, 2015), or because they have limited access to liquidity in the interbank market due to asymmetric information (e.g., Heider et al., 2015). Consequently, these banks do not create sufficient liquidity during downturn because they are either unable to do so due to liquidity shortages or reducing liquidity creation to manage the expected losses as a precautionary measure.

5.2.2 Literature on credit information sharing

Credit information sharing occurs when banks exchange private information about their borrowers with one another to reduce informational asymmetries. Credit information can be shared via public credit registry administered by the central authorities, or credit bureaus which are privately owned but regulated by the regulatory authorities in individual country (World Bank, 2016). Credit registry information comes from financial institutions only, while credit bureaus collect information from both financial and non-financial institutions. Information sharing system enables banks to learn about applicants' recent performance, existing projects, and their dealings with other banks. Theoretical literature shows that credit information sharing reduces adverse selection (Pagano & Jappelli, 1993) and moral hazard (Flatnes, 2021) problems. In addition, information sharing increases banks' incentives to collect more information (Karapetyan & Stacescu, 2014a), and it prevents excessive lending (Bennardo et al., 2015).

Empirical evidence is consistent with the above theoretical predictions. Houston et al. (2010) provide a cross-country evidence that credit information sharing reduces bank risk, increases bank earnings and economic growth. Similarly, Liberti et al. (2022) find in a study of a U.S. credit bureau that credit information sharing increases competition in credit markets, motivates lenders' subscription, and it enables lenders to access new markets. Meanwhile, Fosu et al. (2021) report that credit information sharing reduces credit intermediation cost in 27 African countries, while de Moraes et al. (2022) find that credit information sharing increases financial development across 79 countries. On the effects of credit information sharing on bank lending activities, higher lending volume has been reported by some studies including Fosu (2014) and Bahadir & Valev (2021), while other studies have reported higher loan quality (e.g., Fosu et al., 2020). Other benefits of credit information sharing reported in the literature include lower financial system fragility in both advanced and emerging markets (Guerineau & Leon, 2019); lower borrowers' switching cost (Sutherland, 2018); reduced adverse selection and higher returns on loan (De Haas et al., 2021).

The literature on credit information sharing provides several possible channels through which some of the causes of procyclical liquidity creation discussed in section 2.1 may be addressed. For example, credit information sharing can reduce moral hazard behaviour during good economic times and adverse selection problem during downturns, and it can prevent underestimation of investment risk during upturns and overestimation of risk during downturns. These effects have the potential to reduce fluctuations in bank liquidity creation. Based on the above evidence and arguments, we make the following hypothesis:

Hypothesis 5.1: *Credit information sharing reduces procyclical on- and off-balance sheet liquidity creation.*

It is important to point out that one of the reasons that liquidity creation is procyclical is because banks' access to funds is procyclical. That is, banks create more liquidity when they have access to higher liquid funds which is usually during upturn of the business cycle and create less during downturn when they have limited access to funds. Where there is a functioning interbank market, deposit network can channel liquidity flows among banks to cope with liquidity shortages (Castiglionesi & Eboli, 2018). However, this is not often the case because many interbank markets malfunction due to the presence of asymmetric information (e.g., Freixas & Jorge, 2008). Heider et al. (2015) show that banks are privately informed about the quality of their assets, and this create adverse selection that results in liquidity hoarding. Recall that credit information sharing has been made mandatory by regulators of banks in many developed and developing countries to reduce information asymmetry among banks particularly in relation to their assets. Because credit information sharing is now well-established in at least 173 countries (World Bank, 2019), all banks within the same regulatory system are expected to have good knowledge of the quality of assets of other banks through the mandatory sharing system. Therefore, by reducing asymmetric information among banks, information sharing can facilitate the flow of funds from banks with surplus to others to cope with shortages, and boost liquidity creation overall. Based on these arguments we make the hypothesis that:

Hypothesis 5.2: *Credit information sharing reduces procyclical liquidity creation by increasing access to interbank liquid funds.*

Both higher liquidity creation caused by underestimation of risk during business cycle upturns and lower liquidity creation caused by overestimation of risk during downturns are effects of asymmetric information and can be addressed by having a well-established credit information sharing system. Moreover, evidence from risk and loss recognition literature shows that if banks can estimate and recognize portfolio risk and future losses early, both risk and procyclicality are lower (e.g., Beatty & Liao, 2011; Bhat et al., 2019). We believe that by improving the accuracy of risk assessment, credit information sharing can reduce adverse selection problem and reduce opacity which drives moral hazard behaviour in bank liquidity creation. Moreover, information sharing can reduce the amount of asset write-offs and stabilize bank liquidity position over the business cycle by improving the quality of assets originated by banks in their liquidity creation. Through these channels, information sharing can reduce the intensity of fluctuations in bank liquidity creation. Accordingly, we formulate the following hypotheses:

Hypothesis 5.3: *Credit information sharing reduces procyclical liquidity creation by improving the accuracy of default probability estimates.*

Hypothesis 5.4: *Credit information sharing reduces procyclical liquidity creation by reducing bank asset write-offs.*

5.3 Data and Methodology

5.3.1 Data and variables

We construct a panel dataset using bank-level data from BankFocus provided by Bureau van Dijk, macroeconomic data from the World Development Indicators (WDI) and the

International Financial Statistics database of the International Monetary Fund (IMF), and credit information sharing data from the World Bank's Doing Business database. The original dataset represents 460 banks from 68 developing countries, with 5520 observations covering 2009-2020 period. However, we adjusted the dataset by reducing the sample period to 2011-2020 due to significant number of missing observations in the bank-level data from BankFocus between 2009 and 2011. In addition, we lose one year (one observation) in estimating growth rate variables. Following these adjustments, we have a final unbalanced panel data of 3,312 observations and 368 banks from 40 countries over the period 2012-2020.

The main dependent variable is bank liquidity creation. Following recent papers (e.g., Niu, 2022), our measure builds on a three-step approach proposed by Berger & Bouwman (2009). In step one, we classify all balance sheet items as liquid, semi-liquid, and illiquid based on the ease, cost, and time for customers to withdraw their funds from banks and for banks to meet the liquidity needs of customers.[36] In step two, we assign weights to the items in each category "cat". The theory behind the weighting system is based on the definition of liquidity as the ease, cost, and time necessary for customers to withdraw their funds and for banks to liquidate their assets and provide the funds. Therefore, when liquid funds such as demand deposits with which depositors face less difficulty, cost, and time to withdraw are used to finance *illiquid assets* such as business loans with which banks face greater difficulty, cost, and time to liquidate, liquidity is created. This is because the substance of such transaction is

[36] **Illiquid Assets:** Corporate loans and other assets have been classified as illiquid because they cannot be sold quickly without incurring significant losses. **Semi-liquid Assets:** Loans to individuals, Loans to other banks, Loans to government, and Residential Mortgages are classified as semi-liquid because individual and residential mortgage loans are generally securitized while governments and other banks are large and informationally transparent which make these loans easier to sell compared to highly illiquid assets. **Liquid Assets:** Cash and government securities are classified as liquid because banks are able to use these items to meet liquidity needs as quickly as possible without incurring significant losses. In addition to this categorical 'cat' classification used in this study, Berger & Bouwman (2009) also discuss classifications based on maturity 'mat" measures which generally classify short term loans of up to one year as semi-liquid and long-term loans over one year as illiquid. See their measures for more on these differences. **Liquid Liabilities:** Savings deposits, demand deposits, debt securities, and other short-term borrowings are classified as liquid liabilities because customers can withdraw them easily without penalties. **Semi-liquid Liabilities:** Premature withdrawal of time deposits may require significant notice and/or penalty. Therefore, time deposits are slightly less liquid than demand deposits and are classified as semi-liquid. This group also includes other borrowed funds from financial institutions with short- and medium-terms maturity. **Illiquid Liabilities:** Capital, subordinated debt, and other liabilities are classified as illiquid because they are long-term liabilities that cannot be withdrawn quickly. We acknowledge that equity of many banks can be traded publicly which enables the investors to retrieve their liquid funds easily. However, this liquidity is created by the capital market rather than the bank. **Illiquid guarantees:** Loan commitments (guarantees) are classified as illiquid because they are similar to business loans under the on-balance sheet above. **Semi-liquid guarantees:** Net guarantee represents the amount guaranteed less the beneficiary amount (i.e., credit derivative). It is classified as semi-liquid since it can be participated or sold. **Liquid Derivatives:** All derivatives (except credit derivatives which are classified are semi-liquid guarantees) are classified as liquid because they can easily be bought and sold, and are similar to liquid securities.

that banks obtain risky funds, keep the risk in their balance sheet, and give stable long-term funds to the public. Following same logic, liquidity is destroyed when *illiquid liabilities* such as long-term debt or *equity* is used to finance *liquid assets* such as treasury securities or cash holdings. Meanwhile, when the source and usage of funds have the same level of liquidity, such as using semi-liquid time deposits to finance semi-liquid loans to individuals, liquidity is neither created nor destroyed because the ease, cost, and time necessary for customers to withdraw their funds are approximately the same as that necessary for banks to liquidate the corresponding assets.

Assigning weights to the classified items is based on the dollar-for-dollar principle, meaning that \$1 of liquidity is created when a bank finance \$1 of illiquid assets with \$1 of liquid liabilities. Since liquid liabilities and illiquid assets jointly determine the creation of maximum liquidity of \$1, each is assigned the value of $+\,{}^{1}/_{2}$ so that liquidity created is ${}^{1}/_{2} * \$1 + {}^{1}/_{2} * \$1 = \$1$. Similarly, since illiquid liabilities or equity and liquid assets jointly destroy \$1 of liquidity, each is assigned $-\,{}^{1}/_{2}$ so that liquidity destroyed is $-\,{}^{1}/_{2} * \$1 + \left[-\,{}^{1}/_{2} * \$1\right] = -\$1$. Zero is assigned to semi-liquid assets and liabilities based on the assumption that semi-liquid activities approximately equal liquid activities as well as illiquid activities since they fall halfway between the two groups. Weights are assigned to illiquid, semi-liquid, and liquid off-balance sheet items based on the same principles as on-balance sheet items.

Table 5. 1 Bank liquidity creation measure

Illiquid Assets (1/2)	**Semi-liquid Assets (0)**	**Liquid Assets (-1/2)**
Corporate loans Other assets	Loans to individuals Loans to other banks Loans to government Residential mortgages	Cash Government securities
Liquid Liabilities (1/2)	**Semi-liquid Liabilities (0)**	**Illiquid Liabilities (-1/2)**
Debt securities Savings deposits Demand deposits Other short-term borrowings	Time deposits Borrowings from banks	Capital Subordinated debt Other liabilities
Illiquid guarantees (1/2)	**Semi-liquid guarantees (0)**	**Liquid Derivatives (-1/2)**
	Net guarantees	Derivatives

Loan commitments (guarantees)		

Source: Prepared by the authors based on Berger & Bouwman (2009) liquidity classification of bank activities

This table categorizes all on- and off-balance sheet items used in the study based on the level of liquidity. The values in parentheses represent the weights assigned to the categories, and these weights have been used in estimating equations 5.1 and 5.2.

In the third step, we estimate liquidity creation for each bank, using the above on- and off-balance sheet items and their corresponding weights. For this, we use the following equations:

$$\begin{aligned} Liquidity\ Creation\ (cat\ non-fat) &= [1/2 \times Illiquid\ Assets + 0 \times Semi-Liquid\ Assets \\ &- 1/2 \times Liquid\ Assets] + [1/2 \times Liquid\ Liabilities + 0 \times Semi \\ &- Liquid\ Liabilities - 1/2 \times Illiquid\ Liabilities] - 1/2 \times Capital \end{aligned} \quad (5.1)$$

$$\begin{aligned} Liquidity\ Creation\ (cat\ fat) &= [1/2 \times Illiquid\ Assets + 0 \times Semi-Liquid\ Assets \\ &- 1/2 \times Liquid\ Assets] + [1/2 \times Liquid\ Liabilities + 0 \times Semi \\ &- Liquid\ Liabilities - 1/2 \times Illiquid\ Liabilities] - 1/2 \times Capital \\ &+ [1/2 \times Illiquid\ Guarantees + 0 \times Semi-Liquid\ Guarantees \\ &- 1/2 \times Liquid\ Derivatives \end{aligned} \quad (5.2)$$

Equation 5.1 is a measure described by Berger & Bouwman (2009) as “cat non-fat” because off-balance sheet items have been excluded. Equation 5.2 is the “cat fat” because it includes off-balance sheet items. The use of these two measures have been validated in the literature. Theory highlights the potential for moral hazard behaviour in relation to off-balance sheet activities, including excessive liquidity creation (e.g., Thakor, 2005). Recent empirical evidence has also highlighted the importance of employing both on- and off-balance sheet measures of liquidity creation (e.g., Niu, 2022). Accordingly, we adopt these two measures by, first, estimating equation 5.1 as the weighted sum of on-balance sheet liquidity creation, and equation 5.2 as the weighted sum of on- and off-balance sheet liquidity creation for each bank. Second, we estimate the year-over-year change in liquidity creation in line with the literature (e.g., Davydov et al., 2018). Based on the above estimations, we have the two main dependent variables used in the study, on-balance sheet liquidity creation ($\Delta LiqCreOn$) as well as on- and off-balance sheet liquidity creation ($\Delta LiqCreOff$).

Our main explanatory variables are GDP per capital growth ($GDPPCgr$) and credit information sharing (CIS). $GDPPCgr$ measures changes in the business cycle (as in Davydov et al., 2018), and bank liquidity creation is expected to react strongly to these changes. A positive coefficient for $GDPPCgr$ indicates procyclical liquidity creation while negative sign indicates countercyclical behaviour. We also use alternative indicator of the business cycle, the real GDP growth rate (as in Niu, 2022), and separate measures representing periods of economic upturns and downturns (as in Bertay et al., 2015). $DOWNTURNS$ equals one for a period of negative GDP per capital growth and zero otherwise, while $UPTURNS$ equals one if GDP per capital growth is positive and zero otherwise. CIS is a measure of the level of credit information sharing in a country. The depth of credit information sharing is an index measuring the scope, accessibility, and quality of credit information (World Bank, 2020a). The index ranges from 0 to 8, with 8 representing the highest level of credit information availability. For each country, the value of one is added to the index for each question below with a yes answer:

- Are data on both firms and individuals distributed?
- Are both positive and negative credit data distributed?
- Are data from banks, financial institutions, retailers, and utility companies distributed?
- Are at least 2 years of historical data distributed?
- Are data on loan amounts below 1% of income per capital distributed?
- Do borrowers have rights to access their data in the credit registry or credit bureau?
- Do banks and other financial institutions have online access to credit information?
- Are bureaus and registries credit scores offered as value-added services to help banks and other financial institutions in assessing the creditworthiness of borrowers?

Note, positive information includes borrowers' on-time payment history, unused credit capacity and outstanding credits, while negative information includes borrowers' defaults history and material threat to going-concern as a business or bankruptcy.

There was a methodological change to credit information sharing index in 2013. The range of the index between 2004 and 2013 is 0 - 6, while from 2014 to present date is 0 - 8.

To ensure consistency in measurement, some researchers have restricted their sample period to either not later than 2013 (e.g., Fosu et al., 2021), while others have applied the old index of 0 to 6 to periods before and after 2013 (e.g., Guerineau & Leon, 2019). Our sample period includes before and after the change, and we want to ensure that our measure of credit information sharing index incorporates both ranges. The only measure that allows us to do so, is the approach used by Calomiris et al. (2017) in their measure of the collateral laws index. They assign the value of one to a country with an index score that is above the median value in a any year and zero otherwise. We follow this approach by individually verifying the values assigned to each country before and after 2013/14 to make sure that no country has received the value of one before 2014 but zero in any year between 2014 and 2020 without any fall in their actual information index. We name this Credit Information Sharing (CIS). In addition, we adopt a measure used by Campello & Larrain (2016) in their application of the movable collateral laws index by assigning the value of one to a country in the top quartile of credit information sharing index in the periods before and after 2014, and zero otherwise. We name this Higher Credit Information Sharing (HCIS) index.

We also investigate the channels through which credit information sharing impacts cyclicality in bank liquidity creation. First, we look at banks' access to liquid funds especially during downturns when customer deposits are likely to shrink. Interbank deposit network is an important source of funds that can help banks to cope with liquidity risk (e.g., Castiglionesi & Eboli, 2018). However, such flow of liquidity within the interbank network is prevented by adverse selection associated with banks' assets (Heider et al., 2015). We expect information sharing among banks about the quality of their illiquid assets such of loans to reduce asymmetric information and unlock liquidity hoarding within the interbank network. We measure interbank funding ($InterbnkF$) as the growth in interbank deposits of a bank.

Second, we consider the quality channel of credit information sharing. We expect banks in countries with credit information sharing to be more informed to estimate customers' default probabilities more accurately. Therefore, we measure the accuracy of default probability estimates ($AccDPEst$) of each bank as the ratio of total loss reserves in time t to problem loan assets in time $t+1$. As explained by Akins et al. (2017), this measure represents the extent to which reserves in current period account for the current year and the predicted future changes in the performance of these assets. The idea Is that a value of 1 represents a perfect predictive ability. A value that is significantly higher than 1 may be regarded as self-insurance precautionary approach or poor risk modelling that may result in liquidity hoarding and lower liquidity creation. Whereas if the value is significantly lower than 1, it could be a sign of higher risk-taking or poor risk modelling which may result in higher liquidity creation. Therefore, a value closer to one represents good prediction.

Third, higher asset write-offs resulting from adverse selection and excessive risk-taking due to moral hazard reduce banks' liquidity position and ability to create more liquidity when economic conditions are bad. We expect information sharing to reduce asymmetric information as well as asset write-offs. Therefore, the last predicted channel ($WriteOffs$) is the ratio of asset write offs to total assets of a bank (as in Behr et al., 2017).

We include bank characteristics and macroeconomic control variables in line with the literature (e.g., Niu, 2022). $Profitability$ is the return on average total equity. $SIZE$ is the natural logarithm of total assets, $Provision$ is the ratio of loan loss provisions to total loans, while $Equity$ is the ratio of equity to total assets. For macroeconomic factors, in addition to $GDPPCgr$, we control for inflation ($INFL$) because higher inflation is an indication of unstable macroeconomic conditions that can exacerbate market frictions and liquidity shortages.

Appendix Table A5.1 summarizes the definition of all variables and the symbols representing them in the empirical section. It also includes sources of all data used in this chapter.

Summary statistics

Table 5.2 presents descriptive statistics of the variables used in the study. The mean values of our two dependent variables, $\Delta LiqCreOn$ and $\Delta LiqCreOff$, are 0.021 and 0.008. These values show that we have average year-over-year change in on-balance sheet liquidity creation of 2.1%, and on- and off-balance sheet liquidity creation of approximately 1%. Regarding our business cycle measures, the statistics show that GDP per capital growth, *GDPPCgr,* has a mean value of 1.57, which is around 1.6% over the sample period. The second measure of business cycle, GDP growth rates has a mean value of 2.96. Our primary measure of credit information sharing (*CIS)* has a mean value of 0.83, meaning that around 83% of banks in the sample operate in countries with depth of information system that is above the median value of credit information sharing index. The mean of *HCIS,* which is the second measure of credit information sharing is 0.79 or 79%, representing banks in countries that are in the top quartile of credit information sharing index.

Other key variables used in the study to investigate the channels through which information sharing stabilizes liquidity creation are interbank funding, $InterBnkF$, which has a mean value of 0.40, accuracy of default probability estimates, $AccDPEst$, with a mean value of 1.7, and change in bank asset write-offs, $WriteOffs$, which has a mean value of -0.012.

Table 5. 2 Descriptive statistics

Variable	**Obs**	**Mean**	**Std.dev**	**Min**	**Max**
$\Delta LiqCreOn$	2,920	0.021	0.430	5.462	9.102
$\Delta LiqCreOff$	2,881	0.008	0.368	-4.794	9.882
CIS	3,312	0.834	0.371	0	1
$HCIS$	3,312	0.790	0.406	0	1
GDPPCgr	3,312	1.569	3.666	-14.819	14.701
$GDPgr$	3,312	2.959	3.710	-15.8	16.665
$InterBnkF$	2,836	0.401	5.104	-8.641	94.829
$AccDPEst$	3,290	1.766	3.784	0.001	63.324
$WriteOffs$	2,256	-0.012	0.540	-9.185	1.295
$Profitability$	3,291	17.692	15.628	-89.321	98.412
$INFL$	3,227	4.739	3.261	-2.431	19.629
$SIZE$	3,312	15.271	1.733	9.223	20.306
$Equity$	3,312	11.434	4.932	-15.781	51.701
DOWNTURNS	3,312	0.252	0.434	0	1
$PROV$	2,640	0.015	0.022	-0.089	0.686

This table presents the summary statistics for the variables used in the study. Obs is the number of observations, Std.dev is the standard deviation, Min and max represent the minimum and maximum values. The dataset is for 368 banks from 40 countries, and the sample period is from 2012 to 2020. The key variables include on-balance sheet liquidity creation ($LiqCreOn$), on- and off-balance sheet liquidity creation ($LiqCreOff$), GDP per capital growth (*GDPPCgr*), Credit Information Sharing (*CIS*) index which takes the value of one if a country has an index value that is above the median value of the index range and zero otherwise, Higher Credit Information Sharing (*HCIS*) which takes the value of one if a country is in the top quartile of credit information sharing index, interbank funding ($InterbnkF$), change in asset write-offs scaled by total assets of a bank ($WriteOffs$), and the accuracy of default probability estimates ($AccDPEst$). All variables, including controls are defined in Appendix Table A5.1.

We also check the correlation between variables, the matrix is presented in Appendix Table A5.2. $\Delta LiqCreOn$ and $\Delta LiqCreOff$ have positive correlations with both measures of the business cycle, *GDPPCgr* and *GDPgr*, indicating that both on- and off-balance sheet liquidity creation may be procyclical. However, $\Delta LiqCreOn$ and $\Delta LiqCreOff$ are negatively correlated with the two measures of information sharing (CIS and $HCIS$), $AccDPEst$, and $WriteOffs$, but positively correlated with $InterBnkF$. Meanwhile, CIS and $HCIS$ are positively correlated with $InterBnkF$ and $AccDPEst$, and negatively correlated with

$WriteOffs$. Overall, the correlation matrix does not show any multicollinearity problem among variables, and the initial signs for the key variables are consistent with our arguments supporting the channels through which information sharing may stabilize liquidity creation over the business cycle.

5.3.2 Estimation and testing procedures

To test our hypotheses, we adopt a dynamic regression model that is used in the literature to study cyclicality in bank liquidity creation (e.g., Bertay et al., 2015; Davydov et al., 2018). For hypothesis 5.1 that credit information sharing reduces procyclical on- and off-balance sheet liquidity creation, the following baseline model is used:

$$\Delta LiqCre_{i,t} = \phi \Delta LiqCre_{i,t-1} + \beta GDPPCgr_{j,t} + \eta CIS_{j,t} + \psi\left(GDPPCgr_{j,t} * CIS_{j,t}\right) + \Pi' X_{i,t} + \Lambda infl_{j,t} + \lambda_t + \mathcal{E}_{i,t} \qquad (5.3)$$

Where i, j and t index bank, country, and time. $\Delta LiqCre \in \{\Delta LiqCreOn, \ \Delta LiqCreOff\}$ represents the growth rate of bank liquidity creation. $\Delta LiqCreOn_{i,t}$ is the growth rate of on-balance sheet liquidity creation while $\Delta LiqCreOff_{i,t}$ represents the growth rate of on-balance and off-balance sheet liquidity creation of banks. $GDPPCgr_{j,t}$ is the growth rate of GDP per capital in a country. $CIS_{j,t}$ represents the depth of credit information sharing in a country. $X_{i,t}$ is a vector of bank specific variables (as in Niu, 2022). These are $Profitability$, $SIZE$, $Equity$, and $Provision$. For macroeconomic factors, in addition to GDP per capital growth, $Inflation$ $(infl)$ rates have been included. λ_t represents time fixed effects, $\mathcal{E}_{i,t}$ is the error term consisting of bank fixed effects (μ_i) and zero mean idiosyncratic random disturbance ($v_{i,t}$). $LiqCre_{i,t-1}$ is the lag of dependent variable to account for the dynamic relationship in bank liquidity creation. The coefficient of *GDPPCgr* shows the behaviour of bank liquidity creation over the business cycle without information sharing, a positive sign indicates procyclical while negative sign suggests countercyclical behaviour. The focus of our study is to examine how credit information sharing impact the behaviour of bank liquidity creation over the business cycle, and the interaction term, $GDPPCgr_{j,t} * CIS_{j,t}$, captures this effect. We expect banks in countries with higher availability of credit information to be less procyclical; therefore, we predict a negative sign for ψ.

Next, we test hypothesis 5.2 that by increasing banks' access to interbank liquid funds, credit information sharing reduces cyclicality in liquidity creation. We do so by introducing a triple interaction term in the baseline model. We employ the triple interaction term in line with Bertay et al. (2015) and Behr et al. (2017) who apply it in their study of procyclicality in the banking sector. The estimated equation is presented below:

$$LiqCre_{i,t} = \phi LiqCre_{i,t-1} + \beta GDPPCgr_{j,t} + \eta CIS_{j,t} + \aleph InterbnkF_{i,t} + \psi\left(GDPPCgr_{j,t} * CIS_{j,t}\right) + \gamma\left(GDPPCgr_{j,t} * CIS_{j,t} * InterbnkF_{i,t}\right) + \Pi' X_{i,t} + \Lambda infl_{j,t} + \lambda_t + \text{ƀ}_{i,t} \qquad (5.4)$$

Where $InterbnkF_{i,t}$ (interbank liquidity) represents the growth in interbank deposits of a bank, and $\text{ƀ}_{i,t}$ is the error term. The triple interaction term, $GDPPCgr_{j,t} * CIS_{j,t} * InterbnkF_{i,t}$, is our variable of interest, and a negative sign is predicted for γ to confirm that by increasing banks' access to interbank liquidity, credit information sharing reduces procyclical liquidity creation. For hypothesis 5.3 that credit information sharing reduces procyclical liquidity creation by improving the accuracy of default probability estimates, we estimate equation 5.5.

$$LiqCre_{i,t} = \phi LiqCre_{i,t-1} + \beta GDPPCgr_{j,t} + \eta CIS_{j,t} + \beth AccDPEst_{i,t} + \psi\left(GDPPCgr_{j,t} * CIS_{j,t}\right) + \xi\left(GDPPCgr_{j,t} * CIS_{j,t} * AccDPEst_{i,t}\right) + \Pi' X_{i,t} + \Lambda infl_{j,t} + \lambda_t + \varrho_{i,t} \qquad (5.5)$$

Where $AccDPEst_{i,t}$ (accuracy of default probability estimates) is the ratio of total loss reserves in time t to actual problem loan assets in time $t+1$ (as in Akins et al., 2017), and $\varrho_{i,t}$ is the error term. $GDPPCgr_{j,t} * CIS_{j,t} * AccDPEst_{i,t}$ is the triple interaction term of GDP per capital growth, credit information sharing indicator and the accuracy of default probability estimates. The coefficient of the interaction variable is expected to have a negative sign, indicating countercyclical or reduction in procyclical bank liquidity creation. Lastly, we test hypothesis 5.4 that credit information sharing reduces procyclical liquidity creation by reducing bank asset write-offs. We estimate equation 5.6 for this test.

$$LiqCre_{i,t} = \phi LiqCre_{i,t-1} + \beta GDPPCgr_{j,t} + \eta CIS_{j,t} + \delta WriteOffs_{i,t} + \psi\big(GDPPCgr_{j,t} * CIS_{j,t}\big) + \Im\big(GDPPCgr_{j,t} * CIS_{j,t} * WriteOffs_{i,t}\big) + \Pi' X_{i,t} + \Lambda infl_{j,t} + \lambda_t + \tau_{i,t} \quad (5.6)$$

Where $WriteOffs_{i,t}$ is the change in asset write offs scaled by total assets of a bank, and $\tau_{i,t}$ is the error term. $GDPPCgr_{j,t} * CIS_{j,t} * WriteOffs_{i,t}$ is the triple interaction term of GDP per capital growth, credit information sharing, and asset write-offs. We expect the coefficient of the interaction variable to have a negative sign which indicates countercyclical or reduction in procyclical bank liquidity creation.

With the lag of dependent variable in our models, we understand the need to address endogeneity and fixed effects problems. To do this, we follow the literature (e.g., Behr et al., 2017; Davydov et al., 2018) and apply the system Generalized Method of Moments (GMM) estimator proposed by Arellano & Bover (1995) and Blundell & Bond (1998). We use the system rather than the difference GMM since the former overcomes the problem of weak instruments associated with the latter (Arellano & Bover, 1995; Blundell & Bond, 1998; Roodman, 2009). Moreover, difference GMM eliminates the fixed effects using first difference transformation (Arellano & Bond, 1991). This would be problematic with our unbalanced panel data. Given that first-differencing subtracts previous observation from the contemporaneous value, any missing value of $LiqCre_{it}$ would result in both $\Delta LiqCre_{it}$ and $\Delta LiqCre_{it-1}$ missing in the transformed data. Therefore, first difference transformation magnifies gaps in our data. To overcome this problem, we follow Arellano & Bover (1995) recommendation to use the forward orthogonal deviations transformation when working with unbalanced panel data.

Orthogonal deviations transformation eliminates the fixed effects by subtracting the average of all future available observations of a variable from the contemporaneous value rather than subtracting the previous observation (as in Foos et al., 2010). Importantly, orthogonal deviations transformation does not trigger serial correlation of the errors. Meaning that it preserves the orthogonality among the transformed errors. If the original errors $\mathcal{E}_{it}$ are not autocorrelated and have constant variance, so are the transformed errors $\mathcal{E}_{it}^{*}$. The forward orthogonal deviations transformation of error term is given by:

$$\mathcal{E}_{i,t}^{*} = \sqrt{\frac{T-t}{T-t+1}}\,[\mathcal{E}_{i,t} - \frac{1}{T-t}(\mathcal{E}_{i(t+1)} + \cdots + \mathcal{E}_{i,T})] \quad (5.7)$$

The transformation preserves the uncorrelatedness of the error term, that is:

$$Var(\mathcal{E}_i) = \sigma^2 I_T \;\Rightarrow\; Var(\mathcal{E}_i^*) = \sigma^2 I_{T-1} \tag{5.8}$$

Where $\sqrt{\frac{T-t}{T-t+1}}$ in equation 5.7 represents the weighting introduced to equalize the variance, and σ^2 in equation 5.8 is the variance of the error term.

By combining levels equation and the orthogonal deviations equation (a system of equations), we estimate our models so that lags of predetermined variables are valid instruments in the transformed equation. With the lags of the dependent variable $(LG_{i,t-1}, \ldots, LG_{i,t-n})$ used as instruments, estimating the models without restricting the number of lags may introduce large number of instruments that might overfit the endogenous variable (instrumented variable) and bias our estimates.[37] Therefore, we use the lag limits ($n = 2 - 3$) and the collapse options in estimating our models to control the instrument count. We subject all estimations to the Windmeijer (2005) correction to minimize downward bias in standard errors. To evaluate the validity of our instruments and estimations, we use the Hansen test of over-identifying restrictions with the null hypothesis that the instruments are valid. The Arellano-Bond test is used to check for autocorrelation of the errors [AR (2)]. The null hypothesis is that no autocorrelation is present in the transformed residuals. If both Hansen and AR (2) tests have p-values of at least 10%, the model is deemed valid.

5.4 Results and discussion

5.4.1 The baseline results

We start with the baseline estimations which test hypothesis 5.1 and the results are reported in table 5.3. In column 1, we observe a positive coefficient for *GDPPCgr* which is significant at

[37] Note, although we have $T < 10$ in our data, estimating our models without instrument control may still generate numerous instruments, large enough to cause instrument proliferation (see Roodman, 2009).

the 1% level. Consistent with the literature (e.g., Niu, 2022), this result suggests that bank liquidity creation is procyclical. The estimated coefficient of 0.0135 indicates that 1 percentage point increase (decrease) in GDP per capital growth results in approximately 1.4 percentage point increase (decrease) in on-balance sheet liquidity creation. The interaction term of GDP per capital growth and credit information sharing, *GDPPCgr*CIS*, has a coefficient of -0.0123 which is significant at the 1% level. This provides evidence that bank liquidity creation is 1.2 percentage point less procyclical in countries with an established credit information sharing system than in countries without or with underdeveloped credit information sharing system. The sum of the base and interaction results can be interpreted as 0.12% [0.0135+(-0.0123)=0.0012] procyclicality in countries with credit information sharing system compared to 1.4% in countries without or with underdeveloped credit information sharing system. The results suggest that credit information sharing is not countercyclical but reduces procyclicality significantly. The low level of procyclicality of 0.12% is not unexpected since business activities are higher in the real economy during upturn of the business cycle compared to a period of economic downturn. When compared with the average liquidity creation, the effect of the result is about 57% (1.2%/2.1%) reduction in liquidity creation.

The lag of the dependent variable is significant at the 1% level, while Hansen and AR (2) tests are 0.10 or more. These results show that we have specified our models correctly, and appropriate instruments have been employed in the estimations.

Table 5. 3 Cyclical behaviour of bank liquidity creation and the effects of credit information sharing: The baseline estimations

Model	[1]	[2]	[3]	[4]
	S-GMM	S-GMM	S-GMM	S-GMM
DEPENDENT VARIABLE	$LiqCreOn$	$LiqCreOn$	$LiqCreOff$	$LiqCreOff$
$LiqCreOn_{t-1}$	0.4023***	0.4479***		
	(0.1377)	(0.1530)		
$LiqCreOff_{t-1}$			0.5356***	0.3261***
			(0.1861)	(0.1647)
$GDPPCgr$	0.0135***	0.0132***	0.0101***	0.0103**
	(0.0043)	(0.0043)	(0.0027)	(0.0038)

$GDPPCgr * CIS$	-0.0123***	-0.0117**	-0.0083***	-0.0082**
	(0.0047)	(0.0051)	(0.0030)	(0.0039)
CIS	-0.0104	-0.0103	-0.0059	-0.0050
	(0.0144)	(0.0188)	(0.0110)	(0.0010)
$Profitability$		0.0020**		0.0011**
		(0.0005)		(0.0003)
$Size$		-0.0075*		-0.0010
		(0.0032)		(0.0021)
$INFL$		-0.0035**		-0.0034**
		(0.0016)		(0.0014)
$Provision$		-0.0036		-0.0006
		(0.0049)		(0.0026)
$CONST$	0.0141	0.1360**	0.0108	0.0343
	(0.0290)	(0.0680)	(0.0274)	(0.0423)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	2,167	2,240	2,007	1,932
No. of Banks	332	342	330	348
No. of Instruments	57	51	38	42
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.162	0.442	0.441	0.782
Hansen Test	0.609	0.678	0.757	0.732

This table presents the results of the impact of credit information sharing on the cyclical behaviour of bank liquidity creation based on two-step system GMM panel regression method. The dependent variables are the growth rate of on-balance sheet liquidity creation ($LiqCreOn$) in columns [1 & 2], growth rate of on- and off-balance sheet liquidity creation ($LiqCreOff$) in columns [3 & 4]. The main independent variables are GDP per capital growth (*GDPPCgr*) and Credit Information Sharing (*CIS*) index which takes the value of one if a country has an index value that is above the median value of the index range, and zero otherwise. All variables, including controls are defined in Appendix Table A5.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

In column (2), we include relevant control variables in the model and the results are consistent. $GDPPCgr$ has a coefficient of 0.0132 which is significant at the 1% level while $GDPPCgr * CIS$ coefficient of -0.0117 is significant at the 5% level. For the control variables, profitability is positive and significant, indicating that profitable banks create more liquidity. Bank size is negative and significant, which is consistent with prior findings (e.g., Davydov et al., 2018). Similarly, the result for inflation is negative and significant, while provision is insignificant. In column [3], we re-estimate equation 5.3 using an alternative measure of liquidity creation that includes off-balance sheet items. Again, $GDPPCgr$ is positive with a coefficient of 0.0101 which is significant at the 1% level. This suggests that both on- and off-balance sheet liquidity creation are procyclical. Meanwhile, the interaction term, $GDPPCgr * CIS$, has a negative coefficient of -0.0083 and it is significant at the 1% level. Combining both results, credit information sharing reduces procyclical liquidity creation from 1.01% to 0.18%. In column [4], we add control variables to this estimation and the results are consistent with the findings for control variables in columns [2]. In all estimations, the baseline results confirm hypothesis 5.1 that credit information sharing among banks significantly reduces fluctuations in bank on- and off-balance sheet liquidity creation over the business cycle. Next, we explore some channels through which the smoothing role of credit information sharing is possible.

5.4.2 Channels: Credit information sharing and access to liquidity in the interbank market

In this section, we investigate whether access to interbank liquidity is one of the channels through which credit information sharing reduces fluctuations in liquidity creation over the business cycle. One of the major causes of procyclical liquidity creation is that banks raise higher customer deposits during upturn of the business cycle which they convert into illiquid assets. However, when the cycle turns downward, banks suffer liquidity shortages due to customer withdrawal of funds, inability to secure short-term borrowings, and liquidity hoarding in the interbank market. Interbank deposit network would normally channel funds to banks in liquidity difficulties (Castiglionesi & Eboli, 2018). However, the flow of liquidity within the interbank network is often prevented by asymmetric information associated with bank assets (Heider et al., 2015). The primary objective of information sharing scheme is to facilitate the exchange of information among banks about the quality of their assets, especially illiquid assets in the form of loans which form majority of banks' assets. Accordingly, we expect significant decrease in asymmetric information and increase in the flow of liquidity in interbank markets with credit information sharing schemes. We test this argument for our second hypothesis and the results are in table 5.4.

Table 5. 4 Cyclical behaviour of bank liquidity creation and the effects of credit information sharing: The interbank market liquidity channel

Model	[1]	[2]	[3]	[4]
	S-GMM	S-GMM	S-GMM	S-GMM
DEPENDENT VARIABLE	$InterbnkF$	$InterbnkF$	$LiqCreOn$	$LiqCreOff$
$InterbnkF_{t-1}$	0.3639***	0.3250***		
	(0.0988)	(0.0386)		
$LiqCreOn_{t-1}$			0.3454***	
			(0.1741)	
$LiqCreOff_{t-1}$				0.3637***
				(0.1210)
$GDPPCgr$	-0.0888**		0.0131***	0.0101***
	(0.0418)		(0.0045)	(0.0023)
$Downturns$		-0.3445**		
		(0.1512)		
$Downturns * CIS$		0.5156**		
		(0.2280)		
$GDPPCgr * CIS$			-0.0099**	-0.0071***
			(0.0049)	(0.0026)
$GDPPCgr * CIS$			-0.0017**	-0.0013**
$* InterbnkF$			(0.0007)	(0.0006)
$InterbnkF$			0.0065**	0.0063**
			(0.0029)	(0.0030)
CIS	0.2701***	0.2512	-0.0106	-0.0053
	(0.1257)	(0.0189)	(0.0139)	(0.0102)
$Profitability$	0.0950**	0.0781**	0.0021**	0.0010*
	(0.0037)	(0.0386)	(0.0004)	(0.0003)
$Size$	-0.0210	-0.0495***	-0.0078**	-0.0011
	(0.0424)	(0.0182)	(0.0040)	(0.0022)
$Equity$	0.0445			
	(0.0373)			
$INFL$	-0.0550***	-0.0419**	-0.0033**	-0.0031**
	(0.0195)	(0.0185)	(0.0017)	(0.0010)
$CONST$	0.1707	0.9365***	0.1855**	0.0307
	(0.0262)	(0.3440)	(0.0796)	(0.0373)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	1,662	1,191	1,843	1,979
No. of Banks	315	225	306	325

No. of Instruments	34	127	56	56
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.392	0.390	0.248	0.412
Hansen Test	0.789	0.140	0.815	0.713

This table presents the results of the impact of credit information sharing on the cyclical behaviour of bank liquidity creation based on two-step system GMM panel regression method. The dependent variables are interbank funding ($InterbnkF$) in columns [1 & 2], on-balance sheet liquidity creation ($LiqCreOn$) in column [3], and on- and off-balance sheet liquidity creation ($LiqCreOff$) in column [4]. The main independent variables are GDP per capital growth (*GDPPCgr*), $Downturns$ which takes the value of one if GDP per capital growth is negative and zero otherwise, and Credit Information Sharing (*CIS*) index which takes the value of one if a country has an index value that is above the median value of the index range, and zero otherwise. All variables, including controls are defined in Appendix Table A5.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

We start by testing the relationship between credit information sharing and access to interbank liquidity. In column [1], CIS enters the regression with a positive sign suggesting that credit information sharing increases access to interbank liquidity. Next, we test whether this result holds during downturns when banks are more likely to suffer liquidity shortages and when interbank markets experience liquidity hoarding. The sum of the coefficients of $Downturns$ and $Downturns * CIS$ in column [2] is +0.171, suggesting that credit information sharing significantly increases banks' access to interbank liquidity during downturns. Lastly, we estimate the liquidity creation model using the two measures. In columns [3 & 4], the triple interaction variables of credit information sharing, GDP per capital growth, and Interbank funding, $GDPPCgr * CIS * InterbnkF$, are negative and significant. These results suggest that by increasing access to interbank liquid funds, credit information sharing reduces procyclical on-balance and off-balance sheet liquidity creation.

5.4.3 Additional channels of credit information sharing: Accuracy of default probability estimates and asset write-offs

In this section we consider two quality channels of credit information sharing. First, we examine whether credit information sharing reduces procyclical liquidity creation by improving the accuracy of default probability estimates. Adverse selection problem can cause underestimation of risk and higher liquidity creation in good economic times, and overestimation of risk and lower liquidity creation during downturns. We expect banks in countries with established system of credit information sharing systems to be more informed and able to estimate default probabilities more accurately. Accordingly, we test the relation between credit information sharing and the accuracy of default probability estimates, $AccDPEst$. Column [1] in table 5.5 shows the estimation, and CIS has a positively significant result suggesting that credit information sharing increases the accuracy of default probability estimates. Next, we investigate whether the link between CIS and $AccDPEst$ is a channel through which credit information sharing affects cyclical behaviour of liquidity creation. We estimate this by introducing a triple interaction term, $GDPPCgr * CIS * AccDPEst,$ in the liquidity creation model, and the results are in columns [2 & 3] for the two measures of liquidity creation. The triple interaction variables have highly significant negative coefficients in the two regressions, confirming our hypothesis that by improving the accuracy of default probability estimates, credit information sharing reduces cyclical fluctuations in bank on- and off-balance sheet liquidity creation.

Table 5. 5 Cyclical behaviour of bank liquidity creation and the effects of credit information sharing: Accuracy of default probability estimates and asset write-offs channels

Model	[1]	[2]	[3]	[4]	[5]	[6]
	S-GMM	S-GMM	S-GMM	S-GMM	S-GMM	S-GMM
DEPENDENT VARIABLE	$AccDPEst$	$LiqCreOn$	$LiqCreOff$	$WriteOffs$	$LiqCreOn$	$LiqCreOff$
	0.5589***					
$AccDPEst_{t-1}$	(0.1046)					
		0.3439***			0.1690**	
$LiqCreOn_{t-1}$		(0.1634)			(0.2908)	
			0.3263*			0.4440***
$LiqCreOff_{t-1}$			(0.2011)			(0.0639)
				-0.2601***		
$WriteOffs_{t-1}$				(0.0479)		
	-0.0728***	0.0130***	0.0100***	0.0264**	0.0133**	0.0110**
$GDPPCgr$	(0.0277)	(0.0041)	(0.0034)	(0.0111)	(0.0065)	(0.0061)
		-0.0089**	-0.0077**		-0.0122**	-0.0101*
$GDPPCgr * CIS$		(0.0051)	(0.0046)		(0.0077)	(0.0061)
$GDPPCgr * CIS$		-0.0025***	-0.0018**			
$* AccDPEst$		(0.0011)	(0.0008)			

$GDPPCgr * CIS$					-0.0005***	-0.0002***
$* WriteOffs$					(0.0002)	(0.0000)
	0.3372**	-0.0110	-0.0041	-0.1358***	-0.01102	-0.0040
CIS	(0.0152)	(0.0107)	(0.0010)	(0.0679)	(0.0266)	(0.0173)
					-0.0100***	-0.0001
$WriteOffs$					(0.0009)	(0.0000)
		-0.0084**	-0.0059**			
$AccDPEst$		(0.0040)	(0.0026)			
	-0.0006	0.0021**	0.0012**	-0.0076***	0.0022**	0.0010**
$Profitability$	(0.0001)	(0.0003)	(0.0006)	(0.0029)	(0.0004)	(0.0003)
	-0.1477***	-0.0073***	-0.0012	0.0292**	-0.0071**	-0.0010
$Size$	(0.0537)	(0.0032)	(0.0026)	(0.0146)	(0.0053)	(0.0026)
	-0.0724***	-0.0034***	-0.0033*	0.0298**	-0.0034**	-0.0032**
$INFL$	(0.0192)	(0.0015)	(0.0018)	(0.0129)	(0.0019)	(0.0010)
	-0.0248**			-0.0041		
$Equity$	(0.0119)			(0.0101		
	0.1126***	0.1460***	0.0316	-0.4072	0.0273	0.0187
$CONST$	(0.0167)	(0.0525)	(0.0535)	(0.2906)	(0.0814	(0.0481)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,041	2,211	2,260	994	1,569	831
No. of Banks	328	342	354	233	260	218
No. of Instruments	39	44	34	49	53	64
AR (1)	0.000	0.000	0.000	0.000	0.000	0.000
AR (2)	0.298	0.365	0.563	0.827	0.898	0.117
Hansen Test	0.277	0.762	0.609	0.376	0.898	0.595

This table presents the results of the impact of information sharing on the cyclical behaviour of bank liquidity creation based on two-step system GMM panel regression method. The dependent variables are the accuracy of default probability estimates ($AccDPEst$) in column [1], on-balance sheet liquidity creation ($LiqCreOn$) in columns [2 & 5], on- and off-balance sheet liquidity creation ($LiqCreOff$) in columns [3 & 6], and bank asset write-offs ($WriteOffs$) in columns [4]. The main independent variables are GDP per capital growth (*GDPPCgr*) and Credit Information Sharing (*CIS*) index, which takes the value of one if a country has an index value that is above the median value of the index range, and zero otherwise. All variables, including controls are defined in Appendix Table A5.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

Second, we test hypothesis 5.4 that credit information sharing reduces procyclical liquidity creation by reducing bank asset write-offs. Again, we start by examining the relationship between credit information sharing and asset write-offs, and then test how this relationship impact liquidity creation over the business cycle. We use the ratio of asset write-offs to total assets, and the results are in table 5.5. In column [4], CIS has a coefficient of -0.1358 and it is significant at the 1% level. This indicates that credit information sharing reduces asset write-offs by up to 13%. In columns [5] and [6], we introduce the triple interaction term of GDP per capital growth, credit information sharing, and asset write-offs, *GDPPCgr*CIS*WriteOff,* to investigate their combined impact on the two measures of liquidity creation. In both regressions, we observe negative coefficients and 1% significance level. These findings are consistent with our hypothesis that by reducing asset write-offs, credit information sharing reduces procyclical on- and off-balance sheet liquidity creation.

In summary, we do not find countercyclical effect of credit information sharing, but significant reduction in procyclical on- and off-balance sheet liquidity creation. We identify three important channels through which the smoothing role of credit information sharing takes place. First, by reducing asymmetric information in the interbank market, credit information sharing increases the flow of liquid funds among banks which helps to reduce fluctuations in bank liquidity position and creation. Second, by improving the accuracy of default probability estimates, credit information sharing reduces fluctuations in liquidity creation. Third, by reducing the amount of asset write-offs, credit information sharing stabilizes bank liquidity position and creation. These findings support both quality and disciplinary channels of credit information sharing. Banks want to be trusted by other banks and regulatory authorities, especially where there is an advanced credit registry that distributes information about bank asset portfolios. Moreover, banks are aware that banking regulators oversee credit information sharing systems and are able to monitor the quality and volume of liquidity creation at each stage of the business cycle.

5.5. Endogeneity and additional robustness tests

5.5.1 Endogeneity

Following the literature (e.g., Davydov et al., 2018; Tang et al., 2021), we use the two-step system GMM in the study because of its ability to address endogeneity and fixed effects problems. In this section, we perform further endogeneity tests. The decision to adopt credit information sharing scheme by the government or banks could be induced by existing or impending liquidity shortages to reduce effects of asymmetric information. Therefore, endogeneity may arise from the reverse causality between credit information sharing and liquidity creation. We conduct robustness tests using three external instruments for credit information sharing. The first two are population size (as in Buyukkarabacak & Valev, 2012; Fosu et al., 2021) and internet infrastructure measured as the number of secured internet services per one million people (as in Bahadir & Valev, 2021). The arguments for these two instruments are that dissemination of information is more effective in less populated countries as well as in countries with advanced technology. While we expect these factors to improve the effectiveness of credit information sharing, we do not expect them to have direct impact on liquidity creation. We re-estimate our models using the two instruments, and the results are reported in table 5.6.

Table 5. 6 Cyclical behaviour of bank liquidity creation and the effects of credit information sharing: Endogeneity

Model	(1) S-GMM (Instruments: population size and internet infrastructure)	(2) S-GMM (Instruments: population size and internet infrastructure)	(3) S-GMM (Instruments: population size and internet infrastructure)	(4) S-GMM (Instruments: population size and internet infrastructure)	(5) S-GMM (Instruments: population size and internet infrastructure)	(6) S-GMM (Instruments: population size and internet infrastructure)	(7) S-GMM (Instruments: population size and internet infrastructure)	(8) S-GMM (Instruments: population size and internet infrastructure)
DEPENDENT VARIABLE	$LiqCreOn$	$LiqCreOff$	$LiqCreOn$	$LiqCreOff$	$LiqCreOn$	$LiqCreOff$	$LiqCreOn$	$LiqCreOff$
$LiqCreOn_{t-1}$	0.3404***		0.3381***		0.2292**		0.3833***	
	(0.1589)		(0.1742)		(0.2942)		(0.2120)	
$LiqCreOff_{t-1}$		0.3478*		0.3990***		0.4243***		0.1036*
		(0.1902)		(0.1507)		(0.0514)		(0.0199)
$GDPPCgr$	0.0130***	0.0102***	0.130***	0.0101**	0.0134**	0.0112**	0.0133***	0.0104***
	(0.0048)	(0.0046)	(0.0044)	(0.0033)	(0.0065)	(0.0059)	(0.0062)	(0.0036)
$GDPPCgr * CIS$	-0.0111**	-0.0088**	-0.0100**	-0.0070**	-0.0122*	-0.0102*	-0.0099*	-0.0080**
	(0.0006)	(0.0047)	(0.0047)	(0.0032)	0.0075)	(0.0060)	(0.0041)	(0.0009)
$GDPPCgr * CIS * InterbnkF$			-0.0018**	-0.0010**				
			(0.0008)	(0.0004)				

$GDPPCgr$ $*CIS$ $*WriteOffs$					-0.0005**	-0.0002**		
					(0.0002)	(0.0000)		
$GDPPCgr$ $*CIS$ $*AccDPEst$							-0.0022***	-0.0018**
							(0.0006)	(0.0009)
$InterbnkF$			0.0063**	0.0061**				
			(0.0032)	(0.0022)				
$WriteOffs$					-0.0101**	-0.0002		
					(0.0011)	(0.0002)		
$AccDPEst$							-0.0029	-0.0059**
							(0.0031)	(0.0029)
CIS	-0.0105	-0.0041	-0.0101	-0.0041	-0.0100	-0.0040	-0.0106	-0.0040
	(0.0192)	(0.0105)	(0.0132)	(0.0132)	(0.0274)	(0.0160)	(0.0178)	(0.0010)
$Profitability$	0.0021***	0.0010*	0.0020**	0.0010**	0.0021**	0.0010*	0.0023	0.0011***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0043)	(0.0005)
$Size$	-0.0078**	-0.0010	-0.0075***	-0.0015	-0.0062**	-0.0010	-0.0062**	-0.0018
	(0.0036)	(0.0022)	(0.0040)	(0.0022)	(0.0052)	(0.0021)	(0.0036)	(0.0025)
$INFL$	-0.0033**	-0.0036**	-0.0034*	-0.0030*	-0.0037**	-0.0032**	-0.0030**	-0.0038**
	(0.0015)	(0.0015)	(0.0017)	(0.0010)	(0.0019)	(0.0009)	(0.0015)	(0.0014)
$Provision$	-0.0037	-0.0011						
	(0.0060)	(0.0022)						
$CONST$	0.1187**	0.0329	0.1986**	0.0374	0.0224	0.0162	0.1176**	0.0312
	0.0591)	(0.0440)	(0.0794)	(0.0376)	(0.0786)	(0.0457)	(0.0501)	(0.0477)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,133	1,932	1,843	1,984	1,569	831	2,168	2,259
No. of Banks	333	348	306	325	260	218	339	354
No. of Instruments	51	40	54	53	54	99	44	39
AR (1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR (2)	0.652	0.756	0.256	0.388	0.794	0.123	0.320	0.694
Hansen Test	0.714	0.621	0.792	0.367	0.827	0.798	0.821	0.408

This table presents the results of the impact of credit information sharing on the cyclical behaviour of bank liquidity creation based on two-step system GMM panel regression method, population size and internet infrastructure as instrumental variables. The dependent variables are on-balance sheet liquidity creation ($LiqCreOn$) in columns [1, 3, 5 & 7], and on- and off-balance sheet liquidity creation ($LiqCreOff$) in columns [2, 4, 6 & 8]. The main independent variables are GDP per capital growth (*GDPPCgr*), Credit Information Sharing (*CIS*) index which takes the value of one if a country has an index value that is above the median value of the index range and zero otherwise, interbank funding ($InterbnkF$), bank asset write-offs ($WriteOffs$), and the accuracy of default probability estimates ($AccDPEst$). All variables, including controls are defined in Appendix Table A5.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.
Significance levels are ***P<0.01, **P<0.05, *P<0.1

Columns 1 and 2 re-estimate the baseline model testing the impact of credit information sharing on the cyclicality of liquidity creation using both on- and off-balance sheet measures. Columns 3 and 4 estimate interbank funding channel, 5 and 6 estimate the asset write-offs channel, while 7 and 8 show the results for the accuracy of default probability estimates. All results are consistent with those reported in section 5.4 that on- and off-balance sheet liquidity creation are procyclical but significantly reduced by credit information sharing. The results in table 5.6 also confirm that by increasing access to interbank liquidity, reducing asset write-offs, and increasing the accuracy of default probability estimates, credit information sharing helps to smooth bank liquidity creation over the business cycle.

For the third instrument, we specifically target countercyclical capital buffer of Basel III. Basel III could influence both the decision to adopt credit information sharing as well as liquidity creation; therefore, lead to simultaneity bias. However, we do not expect our estimates to suffer from this bias because most countries in our study sample have not adopted Basel III. We want to be sure that our results are free from this bias since few countries in the sample have already adopted or in the process of implementing Basel III. Therefore, we employ an instrument which takes the value of one if a bank operates in a country where countercyclical capital buffer is in place and zero otherwise. We re-estimate the baseline specification using both measures of liquidity creation, and the results are presented in Appendix Table A5.3. The results confirm that credit information sharing has no countercyclical effect on bank liquidity creation but reduces procyclicality significantly, and that our findings are not due to the existence of Basel III and its countercyclical requirement.

5.5.2 Additional robustness checks

To add credence to our findings, we also perform additional robustness tests using alternative measures. First, we check whether our main results remain unchanged when an alternative measure of the business cycle is used. In all estimations so far, we have used GDP per capital growth rate as a measure of the business cycle. In the estimations in columns [1] and [2] in table 5.7, we use the real GDP growth rate to capture changes in the business cycle in line with Niu (2022). The results show that on- and off-balance sheet measures of liquidity creation are highly sensitive to changes in the business cycle in a procyclical direction. However, the difference between $GDPgr$ and $GDPgr * CIS$ shows that information sharing significantly reduce procyclicality in liquidity creation from 1.22% to 0.18% for on-balance sheet liquidity creation in column [1], and from 1.16% to 0.21% in column [2] where the combination of on- and off-balance sheet liquidity creation is used. The results in both columns fully agree with our findings in the main analysis.

Table 5. 7 Cyclical behaviour of bank liquidity creation and the effects of credit information sharing: Alternative measures of business cycle and credit information sharing

Model	[1]	[2]	[3]	[4]
	S-GMM	S-GMM	S-GMM	S-GMM
DEPENDENT VARIABLE	$LiqCreOn$	$LiqCreOff$	$LiqCreOn$	$LiqCreOff$
$LiqCreOn_{t-1}$	0.5496***		0.4501***	
	(0.1452)		(0.1670)	
$LiqCreOff_{t-1}$		0.3325**		0.3314**
		(0.1678)		(0.1846)
$GDPgr$	0.0122**	0.0116***		
	(0.0053)	(0.0037)		
$GDPPCgr$			0.0138***	0.0103**
			(0.0047)	(0.0036)
$GDPgr * CIS$	-0.0104*	-0.0095**		
	(0.0062)	(0.0045)		
$GDPPCgr * HCIS$			-0.0122**	-0.0073**
			(0.0056)	(0.0038)
CIS	-0.0100	-0.0050		
	(0.0251)	(0.0028)		
$HCIS$			-0.0096	-0.0052
			(0.0169)	(0.0110)
$Profitability$	0.0022***	0.0009**	0.0021**	0.0010**
	(0.0002)	(0.0003)	(0.0005)	(0.0004)
$Size$	-0.0071**	-0.0012	-0.0075**	-0.0010
	(0.0022)	(0.0002)	(0.0032)	(0.0021)
$INFL$	-0.0038***	-0.0034***	-0.0038**	-0.0035***

	(0.0011)	(0.0034)	(0.0016)	(0.0015)
$Provison$			-0.0043	-0.0011
			(0.0053)	(0.0026)
$CONST$	0.1038	0.0652	0.1126**	0.0106
	(0.0450)	(0.0700)	(0.0642)	(0.0390)
Time fixed effects	Yes	Yes	Yes	Yes
Observations	2,061	1,741	2,241	1,928
No. of Banks	320	333	342	347
No. of Instruments	46	36	51	38
AR (1)	0.000	0.000	0.000	0.000
AR (2)	0.112	0.910	0.478	0.783
Hansen Test	0.695	0.892	0.895	0.511

This table presents the results of the impact of credit information sharing on the cyclical behaviour of bank liquidity creation based on two-step system GMM panel regression method. The dependent variables are on-balance sheet liquidity creation ($LiqCreOn$) in columns [1 & 3], and on- and off-balance sheet liquidity creation ($LiqCreOff$) in columns [2 & 4]. The main independent variables are GDP per capital growth (*GDPPCgr*), real GDP growth rate (*GDPgr*), Credit Information Sharing (*CIS*) index which takes the value of one if a country has an index value that is above the median value of the index range and zero otherwise, and Higher Credit Information Sharing (*HCIS)* which takes the value of one if a country is in the top quartile of the credit information index and zero otherwise. All variables, including controls are defined in Appendix Table 5.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

Second, we replace CIS with $HCIS$ (Higher credit information sharing) that takes the value of one if a country is in the top quartile of credit information sharing index, and zero otherwise. We then re-estimate the liquidity creation model and the results are shown in columns [3] and [4]. The sum of the coefficients of $GDPPCgr$ and $GDPPCgr * CIS$ in both columns are consistent with our main findings that liquidity creation is significantly less sensitive to cyclical change in countries with sound system of information sharing compared to countries without or with underdeveloped credit information sharing scheme(s).

Overall, the above endogeneity tests and robustness exercises have not changed our original findings. All results agree that credit information sharing reduces cyclical fluctuations in bank liquidity creation. Increase in access to interbank liquid funds, especially during downturn, is one of the channels supporting this effect. This helps banks to avoid the higher cost of obtaining funds from external sources during downturn of the business cycle. Therefore, the finding is consistent with prior studies which show that information sharing reduces bank funding cost (e.g., Kusi & Opoku-Mensah, 2018) or intermediation cost (e.g., Fosu et al., 2021). Increase in the accuracy of default probability estimates and reduction in bank asset write-offs are the other channels through which information sharing reduces fluctuations in bank liquidity creation over the business cycle. These findings confirm the ability of information sharing to improve the quality of bank assets by reducing adverse selection problem in banking. Again, the findings support many studies in the literature including Fosu et al. (2020), De Haas et al. (2021), and Adusei & Adeleye (2022) which show that information sharing increases the quality of bank loan assets.

5.6 Conclusion

Liquidity creation is one of the key functions of banks that help to finance the real economy, and the fluency of creation is crucial for financial system stability. Where bank liquidity creation is procyclical, it can amplify the business cycle fluctuations. We argue that credit information sharing used in the banking sector to reduce asymmetric information can stabilize on- and off-balance sheet liquidity creation over the business cycle. We test this argument using Berger & Bouwman (2009) comprehensive measure of liquidity creation and data based on 368 banks from 40 countries, covering the period 2012-2020. The two-step system Generalized Methods of Moments (GMM) proposed by Arellano & Bover (1995) and Blundell & Bond (1998) is employed in our dynamic methodological approach. Our main findings are, first, on- and off-balance sheet liquidity creation are procyclical, meaning that banks create higher liquidity during upturn of the business cycle and lower liquidity during downturn. Second, information sharing reduces procyclicality of on- and off-balance sheet liquidity creation significantly. This suggests that with greater scope, accessibility and quality of credit information, bank liquidity creation is more stable across the stages of the business cycle. Third, the channels through which credit information sharing reduces procyclical liquidity creation are access to interbank liquid funds which helps liquidity-poor banks to cope during shortages, increase in the accuracy of default probability estimates, and reduction in asset write-offs. Given that credit information sharing system is currently underdeveloped or does not exist in many developing countries, our findings highlight its smoothing role in liquidity creation and the need for its expansion. The results are robust to instrumental variables and alternative measures.

Appendix

Appendix Table A5. 1 Definition and measurement of variables used in the study

Variables	Description	Observable data	Exp. Sign	Original Source(s) of data
Endogenous Variable				
$\Delta LiqCreOn$	Measures the growth rate of on-balance sheet liquidity creation (Niu, 2022). $cat\ nonfat_{it} - cat\ nonfat_{i,t-1} \big/ cat\ nonfat_{i,t-1}$	All components of "cat nonfat" described in section 5.3.	n.a.	BankFocus
$\Delta LiqCreOff$	Measures the growth rate of on-balance and off-balance sheet liquidity creation (Niu, 2022). $catfat_{it} - catfat_{i,t-1} \big/ catfat_{i,t-1}$	All components of "catfat" described in section 3.	n.a.	BankFocus
Key Explanatory Variables				
GDPPCgr	GDP per capital growth rate (Bertay et al., 2015)	Growth rate in %	$(+)$	WDI

$InterbnkF$	$InterbnkF$ represents growth in interbank deposits.	Deposits from other banks	$(+)$	BankFocus
$AccDPEst$	$AccDPEst$ (Accuracy of Default Probability Estimates) is the ratio of total loss reserves in time t to actual problem loan assets in time $t+1$ (as in Akins et al., 2017).	Reserves and problem loans	$(-)$	BankFocus
$WriteOffs$	$WriteOffs$ is the change in asset write-offs scaled by total assets of a bank.	Total assets and assets written off	$(-)$	BankFocus
$GDPgr$	Real GDP growth rate (Niu, 2022)	Growth rate in %	$(+)$	WDI
$DOWNTURNS$	Equals one for a period of negative GDP per capital growth and zero otherwise	GDP per capital	$(-)$	WDI
CIS & $HCIS$	CIS has a value of one if a country has an index score that is above the median value in a any year and zero otherwise. $HCIS$ is assigned the value of one if a country is in the top quartile of credit information sharing index and zero otherwise. The *Depth of credit information index* captures the variation in information contents across countries (Houston et al., 2010). The index ranges from 0 to 8, with 8 representing the highest level of information availability and 0 is an indication of absence of both public credit registry and private credit bureau. For each country, the value of one is added to the index for each of the following questions with a yes answer: • Are data on both firms and individuals distributed? • Are both positive and negative credit data distributed?	Data available in the form of Yes = 1; No = 0 for question 1 to 8.	$(-)$	World Bank's Doing Business Database

	• Are data from banks, financial institutions, retailers, and utility companies distributed? • Are at least 2 years of historical data distributed? • Are data on loan amounts below 1% of income per capital distributed? • Do borrowers have rights to access their data in the credit registry or credit bureau? • Do banks and other financial institutions have online access to credit information? • Are Bureaus and Registries credit scores offered as value-added services to help banks and other financial institutions in assessing the creditworthiness of borrowers? *Higher (lower) index value indicates higher (lower) credit information availability.*			
Control Variables				
$SIZE$	Log of total assets of bank. $SIZE = Log(TA)$	TA = Total assets of bank.	$(\pm)$	BankFocus
$Profitability$	Return on total equity. $PROF = {}^{PBT}/_{[0.5(TE_t + TE_{t-1})]}$	PBT = Profits before tax of bank. TE= Total equity of bank.	$(+)$	BankFocus
$PROV$	$Provisions$ is the ratio of loan loss provisions to total loans. $PROV = {}^{LLP}/_{TL}$	LLP = Loan loss provision.	$(\pm)$	BankFocus

		TL = Total loans		
$EQUITY$	Equity is the ratio of equity capital to total assets $$EQUITY = {}^{EC}/_{TA}$$	EC = Equity capital of bank. TA= Total assets of bank	$(\pm)$	BankFocus
$INFL$	Inflation is the annual growth rate of consumer price index	Inflation in %	$(-)$	WDI
Variables used as instruments				
Population Size	Population size is the natural log of total population (as in Buyukkarabacak & Valev, 2012; Fosu et al., 2021)	Population size	$(\pm)$	WDI
Internet Infrastructure	Internet infrastructure is measured as the number of secured internet services per one million people (as in Bahadir & Valev, 2021)	Internet Infrastructure	$(\pm)$	WDI
Countercyclical Capital Buffer (Basel III)	It takes the value of one if a bank operates in a country where countercyclical capital buffer of Basel III is in place and zero otherwise	Answer= yes/no	$(\pm)$	Bank Regulation and Supervision database of the World Bank

This table presents the summary of variables used in chapter 5 of the thesis. It covers the description of each variable, expected signs for the explanatory and control variables, and the observable data for the computation of each variable. It also identifies the original sources of all data used in the study.

n.a. denotes 'not applicable'; $\pm$ indicates indeterminate sign

Appendix Table A5. 2 Correlation matrix of variables used in the study

Variable		1	2	3	4	5	6	7	8	9	10	11	12	13

$\Delta LiqCreOn$	1	1.000												
$\Delta LiqCreOff$	2	0.358*	1.000											
$GDPPCgr$	3	0.028*	0.007*	1.000										
$GDPgr$	4	0.026*	0.006*	0.968*	1.000									
CIS	5	-0.027*	-0.006*	-0.115*	-0.230*	1.000								
$HCIS$	6	-0.022*	-0.005*	-0.135*	-0.234*	0.867*	1.000							
$InterBnkF$	7	0.005*	0.002*	-0.003*	-0.005*	0.010*	0.015*	1.000						
$AccDPEst$	8	-0.013*	-0.015*	-0.185*	-0.200*	0.042*	0.060*	0.015*	1.000					
$WriteOffs$	9	-0.012*	-0.026*	0.028*	0.031*	-0.012*	-0.010*	-0.011*	-0.025*	1.000				
$Profitability$	10	0.004*	0.002*	0.068*	0.084*	-0.039*	-0.035*	0.012*	-0.011*	-0.012*	1.000			
$SIZE$	11	-0.005*	-0.014*	-0.021*	-0.036*	0.159*	0.159*	-0.049	-0.007*	0.006*	0.018*	1.000		
$Inflation$	12	-0.014*	-0.007*	-0.036*	-0.048*	-0.133*	-0.141*	-0.019*	-0.076*	0.015*	0.074*	0.001	1.000	
$Equity$	13	0.007*	0.015	-0.102*	-0.082*	-0.005*	0.018	0.006	-0.027*	-0.013*	0.018*	-0.332	-0.038*	1.000

This table presents the correlation matrix of the variables used in this study. The key variables include on-balance sheet liquidity creation ($LiqCreOn$), on- and off-balance sheet liquidity creation ($LiqCreOff$), GDP per capital growth (*GDPPCgr*), Credit Information Sharing (*CIS*) index which takes the value of one if a country has an index value that is above the median value of the index range and zero otherwise, Higher Credit Information Sharing (*HCIS*) which takes the value of one if a country is in the top quartile of credit information sharing index, interbank funding ($InterbnkF$), bank asset write offs ($WriteOffs$), and the accuracy of default probability estimates ($AccDPEst$). All variables, including controls are defined in Appendix Table A5.1.
***** indicates 5% significance level

Appendix Table A5. 3 Cyclical behaviour of bank liquidity creation and the effects of credit information sharing: Endogeneity (Basel III as instrument)

Model	[1] S-GMM (Instrument: Basel III)	[2] S-GMM (Instrument: Basel III)
DEPENDENT VARIABLE	$LiqCreOn$	$LiqCreOff$
$LiqCreOn_{t-1}$	0.5096***	
	(0.1696)	
$LiqCreOff_{t-1}$		0.3607**
		(0.1787)
$GDPPCgr$	0.0130***	0.0111**
	(0.0046)	(0.0036)
$GDPPCgr * CIS$	-0.0103**	-0.0080**
	(0.0051)	(0.0037)
CIS	-0.0090	-0.0020
	(0.0184)	(0.0107)
$Profitability$	0.0021**	0.0010*
	(0.0007)	(0.0003)
$Size$	-0.0070**	-0.0009
	(0.0032)	(0.0020)
$INFL$	-0.0034***	-0.0032**

	(0.0015)	(0.0015)
$Provision$	-0.0052	-0.0011
	(0.0051)	(0.0023)
$CONST$	0.1234*	0.0220
	0.0746)	(0.0455)
Time fixed effects	Yes	Yes
Observations	2,240	1,938
No. of Banks	342	349
No. of Instruments	49	36
AR (1)	0.000	0.000
AR (2)	0.619	0.689
Hansen Test	0.722	0.857

This table presents the results of the impact of credit information sharing on the cyclical behaviour of bank liquidity creation based on two-step system GMM panel regression method and Basel III adoption as instrumental variable. The dependent variables are on-balance sheet liquidity creation ($LiqCreOn$) in column [1], and on- and off-balance sheet liquidity creation ($LiqCreOff$) in column [2]. The main independent variables are GDP per capital growth (*GDPPCgr*), Credit Information Sharing (*CIS*) index which takes the value of one if a country has an index value that is above the median value of the index range and zero otherwise. All variables, including controls are defined in Appendix Table A5.1.

Robust standard errors based on Windmeijer (2005) finite sample correction are reported in parentheses.

Significance levels are ***P<0.01, **P<0.05, *P<0.1

Chapter 6: Conclusion

6.1 Summary of results

Credit information sharing schemes now exist in many countries following decades of significant adoption of both credit registries (mandatory scheme) and credit bureaus (voluntary scheme) to strengthen the flow of information so that effects of asymmetric information among economic agents are reduced and the banking system can efficiently carry out its intermediation role in the economy. This thesis provides an analysis of the effects of both mandatory and voluntary schemes of credit information sharing. The study is presented in one survey chapter and three empirical chapters; the main findings are summarised below.

Chapter 2 provides a comprehensive review of theoretical predictions and recent empirical evidence on credit information sharing. The literature agrees that where credit information is shared and used accurately, it reduces information asymmetries and loan default rates, and it increases bank lending and competition in credit markets. The positive effect on bank lending is conditional on the coverage and type of credit information sharing scheme in a country. Credit information sharing as a regulatory requirement via credit registry shows weaker relationship with credit growth than voluntary sharing via credit bureau. Credit information sharing has a rapidly growing literature which provides opportunities for further research. We have identified important knowledge gaps and several promising research ideas have been provided to fill some of these gaps.

The objectives in chapters 3, 4, and 5 are to provide answers to the research questions that we have formulated from three of the gaps and research ideas identified in chapter 2. To achieve these objectives, we use a panel data of 368 banks from 40 countries covering the period 2012-2020 and dynamic panel models estimated with two-step system GMM. Chapter 3 investigates the following research question: *How does mandatory credit information sharing affect credit growth and credit quality when it coexists with a policy that permits banks to apply provisioning rules to a loan net of collateral value or stringent capital regulation?* The aim is to establish the extent to which a country's specific loan classification practices and capital regulations determine whether mandatory information sharing scheme increases credit growth and reduces credit risk or achieve one at the expense of the other. The results show that mandatory information sharing reduces both credit growth and credit risk when it coexists with a policy that allows banks to apply provisioning rules to a loan net of collateral. Similarly, when mandatory information sharing coexists with stringent capital regulation, it reduces credit risk, credit growth, as well as bank earnings.

Chapter 4 investigates the second research question: *How does credit information sharing affect bank diversification strategies and excess value?* Our dynamic threshold investigation shows that diversification increases excess value of banks up to an optimal level beyond which the effect becomes negative. We also find that voluntary information sharing increases excess value of banks by increasing diversification in the lower regime but preventing excessive diversification beyond the optimal level. Mandatory information sharing increases diversification beyond the optimal level, and this reduces excess value of banks. In addition, majority of banks in the sample have positive net effect of diversification (i.e., a premium). However, we discover that diversified banks operating in countries with mandatory but without voluntary information sharing trade at a value lower than they would have without diversification (i.e., a discount). These findings highlight the quality advantage of voluntary information sharing scheme and shed light on how agency problem may arise when sharing of private information with other banks is mandatory. Banks' inability to invest in high-risk high-return lending opportunities due to the presence of mandatory system increases the incentives to invest their free cash flow in lower quality non-lending activities that are more profitable and less monitored.

In chapter 5, we investigate the following research question: *How does credit information sharing shape the cyclicality of bank liquidity creation?* It focuses on the role of credit information sharing in smoothing on- and off-balance sheet liquidity creation over the business cycle. We measure liquidity creation using Berger & Bouwman (2009) three-step approach. The study finds procyclical on- and off-balance sheet liquidity creation and the stabilizing effect of information sharing. Significant reduction in procyclicality is found rather than countercyclical effect, suggesting that bank liquidity creation is more stable across the stages of the business cycle where information sharing schemes are well-established. The channels through which information sharing reduces procyclical liquidity creation are by increasing access to interbank liquid funds, reducing bank asset write-offs, and improving the accuracy of default probability estimates when originating illiquid assets.

Overall, the thesis identifies knowledge gaps in the credit information sharing literature and provide new empirical evidence to fill some of these gaps. It highlights some differences between the two information sharing schemes, and the importance of country specific factors. Conditional on loan policies and practices in a country, mandatory information sharing may reduce credit growth to improve credit quality. The thesis also shows that mandatory and voluntary information sharing schemes affect bank diversification and excess value differently, and that bank liquidity creation is significantly more stable over the business cycle with greater scope, accessibility, and quality of information. The results are robust to several checks including alternative measures of key variables and the use of external instruments.

6.2 Study implications

6.2.1 Implications for policy

Contrary to the general expectation that credit information sharing increases bank lending, findings in chapter 3 of this thesis suggest that the effect of mandatory information sharing on credit growth is conditional on loan classification policies. When it coexists with loan policies that incentivize risk-taking, mandatory information sharing functions as a disciplinary device that reduces credit risk-taking and the overall lending volume. The study clarifies why mandatory information sharing may reduce credit growth under certain loan policies and practices. Therefore, it should help policymakers in deciding the timing of credit registry adoption depending on existing loan policies and whether they are promoting credit growth or credit risk reduction. In addition, chapter 3 suggests that regulators can achieve significantly lower credit risk in the banking sector by combining mandatory information sharing with stringent capital regulation. Therefore, the study supports the adoption of credit registry and expansion of its coverage especially in markets with higher level of information asymmetries. However, the chapter also highlights the need to be cautious when combining these two policy tools because supply of credit to the real economy and earnings performance in banking sector may fall when mandatory information sharing is combined with the highest level of capital regulation.

Findings in chapter 4 suggest that voluntary information sharing should be promoted by authorities in countries without or with underdeveloped credit bureau because it produces higher quality of information, higher diversification premium, and greater excess value of diversified banks. These results are particularly relevant to many developing and emerging countries where legal and regulatory constraints prevent internationally established credit bureaus from operating in a country. By reforming strict regulations and providing business support, policymakers can attract credit bureaus with the capabilities to improve the speed and quality of reporting using latest technologies. While the study highlights the difference between the business model of credit bureau and the supervisory principle of credit registry in relation to informational quality and incentive issues, it also shows that diversification premium can be achieved if mandatory information sharing coexists with voluntary system. Therefore, chapter 4 recommends that both informational schemes should be operated together so that the banking sector benefits from the protective ability of credit registry and the real-time high-quality reports that credit bureaus produce.

Findings in chapter 5 of the thesis support the view that expanding credit information sharing coverage should form part of policies promoting stability in the banking sector. The chapter shows that by reducing asymmetric information in the interbank market, information sharing allows liquidity to be channeled from banks with surplus to those experiencing shortages. This is an important finding since asymmetric information among banks drives liquidity shortages in the interbank market (e.g., Heider et al. (2015), and these shortages exacerbate the effects of economic uncertainty (e.g., Breitenlechner et al., 2022). We expect the findings in this chapter to induce policies to promote the expansion of credit registry and credit bureau especially across developing countries where both schemes do not exist or remain underdeveloped (see Figures 2.4 and 2.5 in chapter 2). It is possible that policymakers in these countries have no adequate knowledge of information sharing and its ability to improve the entire financial system due to lack of evidence.

6.2.2 Implications for banking practice

For bank managers in countries that are in the process of adopting or implementing credit registry, findings in chapter 3 show how mandatory information sharing scheme may affect their lending strategies and ability to fulfil regulatory requirements. For bank managers who rely on high lending volume to accumulate higher earnings and capital may have to reassess such lending policy since it involves credit risk-taking. Our results show that mandatory information sharing system limits banks' ability to engage in credit risk-taking because it reduces opacity that supports such lending strategy. The findings are more consistent with lending reduction approach that reduces risk weighted assets (RWA) to improve capital ratio. Chapter 3 also suggests that banks with volume-based reward system for loan officers may have to re-evaluate such system when mandatory information sharing scheme is introduced because such reward system may incentivize higher credit risk-taking.

Unlike mandatory system, it is the decision of bank managements to subscribe to credit bureau(s). Chapter 4 of the thesis shows why it is important that banks subscribe to the voluntary system of credit bureau because it improves the quality of diversified investments as well as the value of banks. In addition, the findings identify how the high costs of information documented in the literature can be managed. Costs arising from two-sided informational asymmetry in banking (shareholders' monitor of bank management and management's monitor of investments) erode value as the size of banks grow (Avramidis et al., 2018). The study suggests that bank managers can reduce these costs by agreeing with key investors on a particular credit bureau. If key investors have confidence in the services of a particular credit bureau, subscribing to their services can reduce the intensity of investors' monitoring of managers and overall cost of information.

Meanwhile, chapter 5 shows that it is important that a bank participate in information sharing scheme(s) to increase the level of confidence that other banks have in its operations and avoid being rationed in the event of liquidity shortages. Banks are more willing to join a credit bureau when it favours immediate business activities or when they are concerned about heightened competition for their own borrowers (Liberti et al., 2022). The results that have been uncovered in chapter 5 recommend participation in information sharing system because it boosts the trust of investors, regulators, and other banks.

In addition to implications for both policymakers and practitioners, chapter 4 of the thesis also has implications for investors because it focuses on how and where banks invest their funds. Laeven & Levine (2007) state that "markets attach a discount to financial institutions that engage in diverse activities". While Bressan & Weissensteiner (2021) explain that because investors expect diversified banks to perform poorly, they demand huge future reward, thereby lowering the value of diversified banks. These suggest that investors' perception of diversification significantly affect the value of diversified banks. Our findings show that diversification can create shareholders' value when banks subscribe to the right quality of information. Therefore, rather than seeking higher returns due to fear of future poor performance, investors should work with bank managers to promote market discipline and higher quality of diversification. Volume of diversification is not a sufficient indicator of overinvestment. As the results in chapter 4 have shown, there is little difference between the volume of diversification under the two information sharing schemes, but there is significant difference in the two threshold values due to the quality advantage of voluntary information system. Our findings should motivate large institutional investors in countries without credit bureau to engage with policymakers and regulators to facilitate the entry of credit bureaus to improve the quality of diversified investments.

6.3 Study limitations and suggestions for future research

The thesis is not without some limitations. Data availability is the key determinant of the study sample; consequently, it has not been possible to have a systematic selection or equal representation of countries in all regions or continents covered in the study. Future research may extend the study by utilizing firm-level data sources to build a more structured representation or a balanced dataset. Using such rich firm-level data can extend the findings in chapter 3 with some regional differences and shed light on alternative funding sources that are available to firms in each region when bank loans are not available. Firm-level data may also allow future research to quantify the impact of credit shortages arising from the coexistence between mandatory information sharing and existing policies on the real activities of different business sizes in the economy. Chapter 3 may also be extended by shedding light on how mandatory information sharing interact with loan and regulatory policies that are not covered in the chapter such as deposit insurance policies.

Findings in chapter 4 show that voluntary information sharing via credit bureau is associated with higher quality information and diversified investments. Future research may investigate whether the composition of credit bureau in a country is important. For example, higher number of different bureaus versus fewer numbers but higher coverage, foreign versus local, or financial institution ownership versus non-financial institution ownership. Chapter 4 could also be extended by employing a breakdown of diversified investments into brokerages, securities, advisory services, and so on. This helps to understand which activity lines are more likely to be associated with a particular scheme of information sharing. For instance, it may be the case that mandatory information sharing is associated with investment in government securities to reduce the intensity of regulators' scrutiny.

The role of information sharing system in bank diversification decisions during COVID-19 pandemic should be investigated in future studies by looking at both volume and quality effects. Depressed economic activities and lower demand for many types of loans during COVID-19 pandemic increased banks incentives to invest more in non-lending activities to boost their overall income (e.g., Li et al., 2021). However, the disruption caused by the pandemic may have affected banks' ability to screen diversified investments thoroughly. Moreover, the literature highlights the role of information flow during COVID_19 pandemic, particularly the quality of information sources. For example, Cepoi (2020) shows significant reliance on unconventional sources of information such as "fake news" and "media coverage" which affected market performance negatively in some countries most affected by the pandemic. Cepoi (2020) suggests that COVID-19 related financial turmoil could be mitigated by using proper information channels. By focusing on the different features of the two information sharing mechanisms in terms of information quality and incentive issues, the new study should evaluate cross-country variation in the quality of bank diversification strategies and shareholders' wealth creation during COVID-19 pandemic.

Allocative efficiency associated with liquidity smoothing role of information sharing is not investigated in chapter 5 due to data limitation. This could be investigated in future research by looking at whether information sharing enables banks to direct liquidity toward industries with higher value adding or those with more growth opportunities. Additionally, this chapter focuses on liquidity creation over the business cycle when liquidity can be reallocated within interbank markets if asymmetric information is reduced. It would be interesting to investigate the role of information sharing during financial crises when interbank markets may suffer liquidity shortages and cannot reallocate funds.

Moreover, it has not been possible to empirically investigate all the gaps and promising research ideas highlighted in chapter 2 of the thesis. For example, future research may use firm-level data to track the long-term impact of modern collateral registry on individuals and small businesses without previous credit history and physical collateral. This will provide evidence on whether, in addition to helping SMEs to establish formal credit history for the first time, it can also provide sustained funding opportunities. Similarly, the role of information sharing in interbank markets is highlighted in chapter 2 as important gap in the current information sharing literature. Even though information sharing systems are designed to reduce information asymmetries among banks, there is no empirical evidence relating to this area. This thesis only investigates the role of information sharing in improving banks' access to interbank liquidity by reducing asymmetric information within the same interbank market. Future research may look at the position and reputation of interbank markets with well-established information sharing system relative to other interbank markets without or with underdeveloped information sharing system. This may also examine the differential impact of information sharing on borrowing and lending banks, since theory predicts that borrowing banks may behave in a moral hazard manner when investing funds obtained within the interbank markets (e.g., Boissay et al., 2016).

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