Essays on Credit Scoring and Credit Risk Data for Small and Medium Enterprise (SME) Lending

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Abstract

This thesis includes four essays describing and investigating different aspects of small and medium enterprise (SME) credit scoring, which is associated with expansion of credit to SMEs, a group with historically restricted access to finance. Chapter 1 introduces SMEs and their importance and historical challenges with accessing finance, SME lending and its characteristics, and credit scoring and its foundation, readily available data predictive of borrower likelihood of loan repayment. Chapter 2 focuses on evaluating the quality of credit reporting systems, a key source of data of an effective credit score. Chapters 3 and 4 focus on credit scoring uses and the credit risk data and methods used for the models. Through different approaches, each study seeks to contribute to successful application and advancement of the credit scoring technology.

Credit reporting systems are the foundation of an effective credit score. Chapter 2 introduces a method for formal evaluation of indices of credit reporting system quality. I assess the correlation of lender perceptions of the usefulness of the credit reporting systems (private credit bureaus and public credit registries) in their country and the only globally available measurement of credit reporting infrastructure quality, the World Bank's Doing Business Credit Information Index (CII). In the analysis I combine bank-level responses from the European Bank for Reconstruction and Development's (EBRD's) second Banking and Performance Environment Survey (BEPS II) and country-level CII data. I find that the CII is somewhat correlated with lender perceptions of credit reporting system utility but could be improved by incorporating credit information system adult coverage rates and distinguishing between private credit bureaus and public credit registries.

Chapter 3 identifies factors associated with lender success with use of credit scoring for SME lending. I conduct a global survey of financial institutions (FIs) across 19 countries and correlate success levels with a variety of factors (e.g., credit reporting infrastructure, size of the institution, data sources, customer type, usage, FI's model and credit risk management and reporting). The FIs reporting the highest levels of success were more likely to use credit scoring models with data sources related to repayment history and deposit information and more likely to rely on credit scores for existing customers. On average, lenders considered credit performance with the institution to be the data source with the highest predictive value.

Chapter 4 examines the diffusion of recent credit scoring innovations (incorporation of alternative data and/or use of new credit scoring methods, such as machine learning) among lenders providing Retail and SME lending. For this analysis I incorporate bank-level data from a variety of data sources, including the BEPS III (2020), FI balance sheet and income statement metrics with country level data (credit reporting infrastructure, lender protections, extent of alternative finance, micro business and SME number and financing gap). Larger, more profitable FIs are more likely to be using alternative data and/or new credit scoring methods, as are FIs that have an ongoing relationship with a Fintech company. Country-specific factors such as financial and credit infrastructure, population size, and the prevalence of alternative finance in the market are also instrumental and correlated with usage. Majority foreign-bank owned FIs are less likely to be currently using these innovations.

Collectively, the three studies contribute to the literature by presenting a method to facilitate improvement of credit reporting systems and by identifying factors associated with credit scoring success and innovation.

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1.1 Introduction to credit scoring for MSME Lending

Credit scoring models, built primarily with credit bureau data, have fundamentally changed the lending process to Micro, Small and Medium enterprises (MSMEs) over the past three decades. For small business loans, credit decision-making has transformed from being a time consuming, documentation-intensive, manual, and subjective process to one that is quick, largely automated in data retrieval and processing, and standardized, benefiting small businesses and lenders. Small businesses have gained expanded access to credit, faster decision and funding turn-around times, and pricing more in line with risk. Lenders have expanded lending and increased profitability. Consequently, financial institutions (FIs) across the world have implemented credit scoring for MSME lending. However, not all lenders have achieved the same success. Identification of key success factors can help lenders and development institutions direct resources to programs with a greater likelihood of success.

MSMEs (also referred to as SMEs) account for over 95 percent of businesses worldwide and are key drivers of the economy (IFC 2010). In the 30 high-income countries of the Organization for Economic Cooperation and Development (OECD), MSMEs account for over two-thirds of formal employment, although this percentage drops by half in lower income countries (Ayyagari, Beck and Demirguc-Kunt, 2003). Often referred to as one group, MSMEs vary significantly in size and credit needs, as shown in Table 1.

Table 1.1 World Bank Definition of Micro, Small and Medium Enterprises (MSMEs)

Segment	% of businesses	# of employees	Assets	Annual revenue	Loan size proxies
Micro	65-75%	< 10	< $100,000	< $100,000	< $10,000
Small	20%	< 50	< $3,000,000	< $3,000,000	< $100,000
Medium	5-10%	< 300	< $15,000,000	< $15,000,000	< $1,000,000-$2,000,000

Source: International Finance Corporation, SME Banking Knowledge Guide, 2009.

MSME's, particularly the smaller ones, have historically had limited access to formal credit. In developing countries, about 45-55 percent of MSMEs identify access to finance as an operational constraint (IFC, 2010). Commercial banks have been reluctant to lend to smaller MSMEs, due to inherent challenges in efficiently and effectively measuring and managing MSME credit risk and a perceived lack of profitability of small loans. Micro and small businesses have in turn been reluctant to seek bank financing because of difficult bank underwriting requirements, slow turn-around times, high interest rates and fees, inadequate collateral, and fear of decline. Small MSMEs, and the upper end of Micro have had challenges, as microfinance institutions have focused on the smallest micro businesses, and banks have concentrated on lending to larger SMEs and corporations (IFC, 2010).

Traditionally, commercial lenders have underwritten businesses, regardless of size, by assessing the 5 C's (Character, Capacity, Collateral, Capital, Conditions) through an information, documentation, and labor-intensive process. There is some variation by bank size. Larger banks have been more likely to require "hard" data (i.e., audited financial statements) for making an approval, whereas smaller, "community" banks may be more likely to factor in "soft" qualitative information obtained from close contact with the borrower over an extended period (Berger and Udell, 2006). Providing "hard" data for the loan decision is a challenge for smaller businesses, who are less likely to have audited financial statements (Allee and Yohn, 2009). Thus, community banks, through their local knowledge of the small business, have served an important role for credit access.

The traditional bank underwriting approach is not cost-effective for smaller loans. Risk assessment is typically conducted by a credit officer, who will require a visit to the place of business, and who will perform an extensive qualitative and quantitative analysis of the applicant, including review of the borrower's financial statements, repayment history and collateral. The time and cost of review do not vary proportionally to loan size. Therefore, the smaller the loan, the more relatively costly the operational expense. The primary source of lender revenue is interest income, which is determined by a loan's interest rate and size. The average SME loan greater than $100,000 is 36 times larger than the average small business loan between $10,000-$100,000 (source: IFC REACH database, 2019). Without efficient means of measuring and managing small loan credit risk, lenders will tend to prioritize larger loans.

The traditional approach is also not always effective. The lack of reliable financial statements creates information asymmetry, as lenders may not have verifiable information about the borrower's ability and willingness to repay. Additionally, inadequate collateral becomes even more important in the absence of high-quality financial statements. To ensure profitability, banks often require at least 100 percent collateral coverage or charge high interest rates for small business loans, limiting the availability and demand for formal small business credit.

Credit scoring helps address the challenge of profitably lending to MSMEs. For small, standardized loans credit scoring provides several key benefits that are instrumental to cost-effective, profitable lending. Most importantly, credit scoring can automate the information retrieval and analysis process and quantify credit risk through determination of a borrower's relative risk and/or probability of default, which permits risk-based pricing and risk-ranking of applicants into decision-process segments: automatic declines; automatic approvals; and "gray-area" applications which require more in-depth underwriter scrutiny. This can result in quick, cost-effective, profitable credit decisions. Credit scores also reduce subjectivity in the loan approval and management process, through standardization of credit decision-making; the credit decision is based on the borrower's quantified default risk. Credit scores are used across the full spectrum of credit origination and portfolio risk management, including loan pre-screening, underwriting, account management, early warning processes, loss forecasting, and capital assessment. Similar models are also used for fraud screening. Thus, credit scores make the entire credit risk management process more standardized and efficient.

Credit scoring for consumer lending was first introduced in the United States in the 1950s.

By the late 1970s most of the largest banks in the United States used credit scoring for personal ("consumer") lending (Federal Reserve, 2011).[1] Credit scores were based on data reported to the three major credit bureaus, Experian, Equifax, and Transunion. In 1989 an industry-standard score, the FICO score, was developed by Fair, Isaac, and Company (now called FICO).[2] Credit scoring began being used on a wide scale for small business lending in the 1990s (Mester, 1997, Miller and Rojas, 2004), used primarily for unsecured loan amounts up to $100,000 (Berger and Udell, 2006). The breakthrough for using credit scoring for small business lending came when it was recognized that the risk of small business loan default was strongly correlated with the personal credit risk of the small business owner (Mester, 1997). Lenders identified that industry consumer credit scores like the FICO score were predictive of small business credit risk, as well. Scores specific for small businesses were also developed which incorporated the owner's consumer credit history with additional firmographic variables about the small business.

The early research on credit scoring for small business lending was conducted in the United States. The research was conducted amid an ongoing trend towards fewer, larger banks, due to bank mergers and acquisitions. Between 1990 and 2010, the number of banks in the United States declined 50 percent, and through 2020 the number continued to decline.[3] Banks were also becoming less local and more geographically distant (DeYoung, Glennon and Nigro, 2007). As mentioned previously, in the U.S., larger banks historically tended to lend to larger businesses with strong financial ratios, measured through audited financial statements, whereas smaller "community" banks were more likely to factor in "soft" qualitative information, acquired through local knowledge of the borrower (Berger and Udell, 2006). Thus, community banks were an important source of financing for small businesses without audited financial statements. Given the consistent trend towards fewer, larger, more geographically distant banks, there were concerns that access to finance for small businesses could decline, as small businesses did not have the "hard" data required for loan approval by larger banks.

Credit scores became recognized as a new form of "hard" data (Berger and Udell, 2006). In place of audited financial statements, the "hard" information was the credit history of the business and business owner reported to credit bureaus. Several key studies focused on describing the usage of credit scoring among large institutions and the resulting impact on credit availability for small businesses. Frame, et al. identified that use of credit scoring expanded credit access for small businesses (Frame, et al., 2001, Frame, et. al, 2004) Berger, et al. found that the adoption of credit scoring was associated with an expansion of the quantity, risk, and price for small business loans up to $100,000 (Berger, et al., 2007). The preceding studies were based on one 1998 Federal Reserve survey of 99 of the largest banks in the United States. Subsequent research identified that in the U.S., 46 percent of community banks were using the personal credit scores of business owners for decisioning small business loans up to $50,000 (Berger, Cowan, and Frame, 2011). Over the next decade, use of credit scoring for small business lending expanded to banks in developing countries (Wendel and Harvey, 2006, Beck, Demirguc-Kunt, Peria , 2011, De la Torre, Peria and Schmukler, 2010). International development organizations began promoting the use of credit scoring across the world. (IFC, 2010, USAID, 2006, Vidal and Barbon, CGAP, 2019).

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[1] https://www.federalreserve.gov/boarddocs/rptcongress/creditscore/general.htm
[2] https://www.myfico.com/credit-education/blog/history-of-the-fico-score
[3]https://banks.data.fdic.gov/explore/historical/

Although the literature has documented the use of credit scoring and its benefits for small business lending, there remains an information gap, which is a description of the characteristics of financial institutions that are more likely to succeed in its development and use. This topic is of practical importance because credit scoring is not equally effective everywhere. For example, for several reasons credit scoring is likely most appropriate for use by lenders with large unit volumes of small, standardized loans, a risk appetite permitting controlled higher loss rates while pricing for risk, using data sources that include borrower repayment history and cash-flow. High quality credit bureau/registry data may be an essential data source. Therefore, in a country without a well-developed credit reporting system, it is unclear whether a lender can develop an effective credit score. The scientific literature does not provide this level of detail on success factors or differentiate use by level of success. One study found that banking firms with more branches and those located in New York were more likely to adopt credit scoring earlier than other institutions (Akhavein, Frame and White, 2005). A similar study in Italy found that banks with large branch networks and those with large market shares in concentrated markets were more likely to be successful early adopters of credit scoring (Bofondi and Lotti, 2006). Berger, et al. identified that banks that used credit scores as substitutes for existing lending practices were more likely to expand credit and have increased loan pricing and risk than banks that used credit scoring as a complement to the judgmental assessment of credit risk (Berger, et al., 2007). Nevertheless, as indicated by Frame and White, studies on the diffusion of innovations across the financial services industry are relatively lacking (Frame and White, 2004). This is particularly the case for developing country contexts. The literature does not include research providing detailed characteristics of banks, including their size, approaches to small business lending and credit risk management and data sources used, that succeed and fail at using credit scoring. More information on this topic would help financial institutions and development organizations target credit scoring to programs that would have the most likelihood of success.

More in detail, a credit score is a statistical model that is designed to rank-order the risk of credit applicants and existing borrowers. The most common statistical method for building a traditional credit score is logistic regression (Mays, 2011), which is a generalized linear model appropriate for binary outcomes. The model is built using thousands or even millions of records of borrower repayment history. Importantly, to build an effective statistical application scoring model may require up to 2,000 defaulted accounts in the development sample (Siddiqi, 2006). Each record analyzed contains an outcome variable indicating whether the borrower has defaulted on credit or paid as agreed. The borrower's record also contains potentially many predictive variables, which are used to differentiate borrower risk.

A credit scoring model's effectiveness is measured by its ability to distinguish between borrowers that will default on a loan versus those that will pay as agreed. The Area Under the Receiver Operating Characteristic (AUROC) Curve is a commonly used metric for measuring screening tools' (including a credit score) ability to discriminate between binary (i.e., default versus no default) outcomes (Hanley and McNeil, 1982, Mays, 2011). The AUROC Curve is produced by calculating and charting the true positive rate against the false positive rate for a classifier at a variety of decision cut-offs. An inherent limitation of credit scores (and all credit screening processes) is that the tools are imperfect and there will inevitably be false negatives and false positives. Thus, lenders and modelers continuously seek to develop or acquire ever more predictive models, reducing the misclassification rate.

A credit score can be either generic, built with a broad spectrum of industry data reported to a credit bureau/registry (e.g., the FICO score), or it can be custom, which is built using data customized to an institution's own customer base (Mays, 2011). In large financial institutions it is likely that custom scores would be more predictive than generic scores, as they have sufficient loan volume and incorporate data from both the credit bureau and internal relationship. Credit scores are categorized into those used for loan underwriting (i.e, an application score) versus those applied for uses once a loan has been booked and the lender has sufficient internal repayment history (i.e., a behavior score). Typically, it takes about six months of performance history to build a predictive behavior score. Behavior scores tend to be significantly more predictive than application scores because they may incorporate updated data from the credit bureau and data on recent credit and deposit history with the lender.

Credit scoring model data sources are classified into four categories: loan application data, the lender's internal data, credit bureau data, and "alternative" data (Mays, 2011). Application data are those which are obtained at the time of the loan application. For small businesses, predictive application data include the type of business and its industry, the amount of time the business has been operating, variables related to cash-flow, liquidity, leverage and profitability, collateral type, value, and lien position, among others. Key internal data are the applicant's credit performance on existing or previous credit with the lender, and customer deposits and/or other assets held by the institution. Credit bureau data are the foundation for credit scores and ideally provide extensive information on a borrower's credit history (e.g., type of credit, amount, performance). Business credit bureaus obtain similar information as well as firmographic (e.g., date business established, annual sales) data on the business. Credit bureaus receive information from banks, finance companies, major retailers, and potentially utility companies.

Alternative data for this purpose can be defined as information not routinely captured by the preceding three data sources (application, internal and credit bureau). There are many types of alternative data. In the United States sources include loan information not reported to the major credit bureaus, "quasi" credit data such as payment records to energy, cable and telecom companies, home and apartment rental, information on property ownership, and bank account, property, and asset data (Mays, 2011, Bradford, 2023).

Of all the credit scoring data sources, credit reporting system data are the foundation of traditional credit scoring models. The FICO score is built with credit bureau data, with the primary determinants of the score being payment history, amounts owed, length of credit history, new credit, and credit mix.[4] These data rely on the existence of a well-established credit reporting system. Credit reporting systems have been fundamental to reducing information asymmetry between borrowers and lenders, improving credit markets, and contributing to expansion of access to credit. Sharing of information on borrower performance reduces information asymmetry (Pagano and Japelli, 1993). Information sharing can have a credit disciplining effect on borrowers, improving their performance (Padilla and Pagano, 2000). Bank lending to the private sector is higher in countries with more established information sharing systems (Japelli and Pagano, 2002). Businesses in countries with credit bureaus experience lower financing constraints (Love and Mylenko, 2003). Credit information sharing is associated with expanded access to credit, particularly in transition countries (Brown, et al, 2009). Information

[4] https://www.myfico.com/credit-education/whats-in-your-credit-score

sharing among lenders reduces contract delinquencies and defaults (Doblas-Madrid and Minetti, 2013).

Given the potential benefits of well-developed credit reporting systems, their quality should be formally evaluated, which would permit improvement of these systems over time. In many countries, credit bureaus or registries may not exist, or may be underdeveloped. The quantity, quality, and type of data in these systems varies throughout the world, which can differentially impact risk assessment and credit access. The World Bank's Doing Business Report developed and employed a methodology, based on the work of Djankov, et al. (2007), to produce a country-level Credit Information Index (CII), which was reported from 2003-2020. After a pause of a few years, the World Bank will implement a similar assessment in 2024. Implied by the report is that the higher the level of the CII, the better the quality and usefulness of the credit reporting system. However, the effectiveness of the CII has not been validated, and the CII did not factor in the opinions of lenders, the key credit reporting system users. Development of methods to improve the evaluation of credit reporting systems can lead to improvement of system quality, more predictive and accessible data, and better risk decisions.

Credit reporting systems typically only have data on borrowers who already have a formal credit history, an inherent limitation of this "traditional" credit scoring data source. To improve risk predictions and expand lending, alternative data sources are being tested and applied. Alternative data sources include mobile phone usage, social media usage, geographic location, psychometric tests, demographic data, and "digital footprints", among others (Owens and Wilhelm, 2017, Arraiz, Ortega and Stucci, 2018, Berg, et al., 2019, Jagtiani and Lemieux, 2019). Scores based on these data sources, however, have generally been applied for credit risk assessment of very small, short term loans, ranging in average sizes from about \$300 (Berg, et al., 2019, Agarwal, et al., 2020) to between \$2,000-\$6,000 (Gambacorta, 2019, Arraiz, et al., 2016, Frost, et al., 2019) and at the higher end \$13,000 (Frost, et al., 2019) and less than \$18,000 (Jagtiani and Lemieux, 2019). Hence, these alternative scores are being applied primarily for short-term consumer and microbusiness lending.

Credit scoring methods are continuously evolving, as modelers aim to create more predictive models. Logistic regression requires assumption of a linear relationship between the predictor variables and the logarithm of the odds of the outcome variable (e.g., loan default). In recent years, new methods, such as machine learning, are increasingly being applied and in some contexts potentially improve upon traditional regression models by factoring in non-linear information from variables (Gambacorta, et al., 2019), thus improving predictive power. Gambacorta, et al. compared performance of machine learning versus logistic regression models at a Fintech lender in China and found that the machine learning models outperformed traditional models and that incorporation of non-traditional (i.e., alternative) data improved model performance. Of note, the comparative advantage of the new models and data sources declined as the length of the relationship between the borrower and lender increased (Gambacorta, et al., 2019).

Use of more predictive data sources and modeling methods should ultimately lead to improved risk predictions and lender profitability. Lenders that can successfully apply these innovations will eventually have a competitive advantage. There are several different machine learning algorithms being applied, including Support Vector Machines, k-Nearest Neighbor, Random Forests, Decision Trees, AdaBoost, Extreme Gradient Boosting (XGBoost), Stochastic Gradient Boosting, Bagging, Extreme Learning Machine, Genetic Algorithm, and Deep Learning methods (Shi, 2022). The characteristics and relative value of these methods is beyond the scope of this introduction. For predicting consumer credit risk, Marceau, et al. found that XGBoost outperforms logistic regression, Support Vector Machines and Random Forest (Marceau, et al., 2019), thus, Extreme Gradient Boosting may become an important alternative to logistic regression models for micro and small business lending.

1.2 Structure of the thesis

This thesis aims to expand upon the existing literature related to credit scoring and its recent innovations by providing the detailed characteristics of financial institutions that are using and succeeding with this technology, as well as those that are innovating further by using alternative data and/or new credit scoring methods. The thesis also introduces a new concept aimed at assisting in the improvement of credit reporting systems: validation and improvement of indices of credit reporting system quality. The validation is done by correlating levels of index quality with an outcome variable, in this case, lenders' perceptions of the utility of credit reporting data for credit decision-making.

The three studies in this thesis seek to contribute to successful application and advancement of credit scoring for MSME lending, particularly in developing and transitioning economies.

Chapter 2 introduces a method for formal validation of indices of credit reporting system quality. I assess the correlation of lender perceptions of the usefulness of the credit reporting systems (private credit bureaus and public credit registries) in their country and the World Bank's Doing Business CII. In the analysis I combine bank-level responses from the European Bank for Reconstruction and Development's (EBRD's) second Banking and Performance Environment Survey (BEPS II) and country-level CII data. I find that the CII is somewhat correlated with lender perceptions of credit reporting system utility but could be improved by incorporating credit information system adult coverage rates and distinguishing between private credit bureaus and public credit registries.

Chapter 3 identifies factors associated with lender success with use of credit scoring for SME lending. I conduct a global survey of financial institutions (FIs) across 19 countries and correlate success levels with a variety of factors (e.g., credit reporting infrastructure, size of the institution, data sources, customer type, usage, FI's model and credit risk management and reporting). My hypothesis on key determinants of success and survey questions were developed based on my professional experience and literature review. Some of these assumed key prerequisites were an appropriate lender business model (large unit volume of small, standardized credit products that meet customers' business needs, centralized underwriting, and credit risk management), risk appetite (acceptance of controlled higher losses while pricing for risk), high-quality, predictive data, a scoring strategy that prioritizes existing customers (credit and/or deposit) of the financial institution, well developed and effective credit scores, and strong credit and model risk management. The FIs reporting the highest levels of success were more likely to use credit scoring models with data sources related to repayment history and deposit information and more likely to rely on credit scores for existing customers. On average, lenders considered credit performance with the institution to be the data source with the highest predictive value.

Chapter 4 examines the diffusion of recent credit scoring innovations (incorporation of alternative data and/or use of new credit scoring methods, such as machine learning) among lenders providing Retail and SME lending. For this analysis I incorporate bank-level data from a variety of data sources, including the European Bank for Reconstruction and Development's third Banking and Performance Environment Survey (BEPS III, 2020), FI balance sheet and income statement metrics with country level data (credit reporting infrastructure, lender protections, extent of alternative finance, micro business and SME number and financing gap). I find that larger, more profitable financial institutions (FIs) are more likely to be using alternative data and/or new credit scoring methods, as are FIs that have an ongoing relationship with a Fintech company. Country-specific factors such as financial and credit infrastructure, population size, and the prevalence of alternative finance in the market are also instrumental and correlated with usage. Majority foreign-bank owned FIs are less likely to be currently using these innovations.

Collectively, the studies contribute to the literature by presenting a method to facilitate improvement of credit reporting systems and by identifying factors associated with credit scoring success and innovation.

2 Evaluation of the Predictive Value of the Doing Business Credit Information Index

2.1 Introduction

Sharing of borrower credit information among lenders improves credit markets and is associated with expansion of access to credit. Well established credit reporting systems help promote credit repayment discipline, improving borrower performance (Japelli and Pagano, 2002, Doblas-Madrid and Minetti, 2013). Several studies have identified associations between credit information sharing and credit availability. The literature shows that bank lending to the private sector is higher in countries with more established information sharing systems (Japelli and Pagano, 2002); firms in countries with credit bureaus experience lower financing constraints (Love and Mylenko, 2003); better creditor rights and the presence of credit registries are associated to higher credit (Djankov, et al., 2007), and credit information sharing is associated with better and cheaper access to credit, particularly in transition countries (Brown, et al, 2009).

As stated in International Finance Corporation's (IFC) Credit Reporting Knowledge Guide, "When comprehensive credit infrastructures are available, efficient, and reliable, the cost of financial intermediation falls; financial products and services become accessible to greater numbers of borrowers; and lenders and investors have greater confidence in their ability to evaluate and price risk" (IFC 2020). Given the potential benefits of well-developed credit reporting systems, their quality should be formally evaluated, which would facilitate their improvement.

Globally, there has been one standardized evaluation of credit reporting systems, the World Bank's Doing Business Credit Information Index (CII), which has been a component of the World Bank's Doing Business Report (DBR). Until 2020 the DBR was used by governments to benchmark their regulatory environments against other countries and identify areas for improvement. It was also used by researchers for studies on economic development, the impact of regulations, and comparative analysis of regulatory practice. International development organizations used the DBR in identifying priority areas for technical assistance and policy advice. In 2021 the World Bank discontinued the DBR with plans to create a new report with revised methodologies.[5,6,7]

The initial CII methodology was developed by Djankov, et al. (2007) based on the following six reporting system characteristics the researchers identified that encourage private credit: 1) data

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[5] https://archive.doingbusiness.org/en/about-us/faq

[6] https://www.doingbusiness.org/en/data/exploretopics/getting-credit. As this study was being conducted, in September 2021 the World Bank discontinued publication of the Doing Business Report and initiated a series of reviews and audits of the report and its methodology. (https://www.worldbank.org/en/news/statement/2021/09/16/world-bank-group-to-discontinue-doing-business-report). The World Bank plans on creating a new report with revised methodology within two years. (https://www.reuters.com/business/world-bank-aims-replace-canceled-doing-business-report-two-years-2021-11-10/)

[7] World Bank's revised report, Business Ready, is scheduled to be produced in September 2024. https://www.worldbank.org/en/businessready

on firms and individuals are distributed; 2) both "positive" and "negative" information is collected; 3) in addition to credit data from financial institutions, data from retailers or utility companies are distributed; 4) at least two years of historical data are maintained; 5) data on loan amounts below 1% of income per capita are distributed, and 6) by law, borrowers have the right to access their data in the largest credit bureau or registry in the economy.

From 2004 to 2020 the CII provided a measurement of the quality of credit reporting systems in economies throughout the world. As of 2020, the CII provided ratings for 202 economies, with CII values ranging from '0' (20.8% of the total) to '8' (29.2%), with a mean CII value of 5.3. Implied is that the higher the CII value, the more available and useful credit information is for lending decisions.

The CII has not been empirically validated. As World Bank revises its benchmarking methodologies, it would be opportune to empirically validate the usefulness of this index. Validation would include comparing levels of the CII with an outcome variable measuring credit reporting system effectiveness and utility. Higher levels of the index should equate to higher quality credit reporting systems.

The purpose of this study is to propose a method for validating and improving the CII. The proposed method is to use lender feedback to validate the effectiveness of the CII. I use survey data of financial institution credit reporting system users, link that data to CII data, define outcomes of interest, and seek to determine the level of correlation between CII values and levels of credit reporting system utility. I assess whether lenders perceive a higher utility of credit reporting systems in those countries with higher scores from the Doing Business Reports. Specifically, I analyze the correlation between the CII and the results from a financial institutions survey which asked lenders about their perceptions of the availability and usefulness of credit reporting system information. I assess whether CII levels and/or sub-components of the CII are correlated with lender perceptions of reporting system utility.

I use data from a year 2011 European Bank for Reconstruction and Development (EBRD) survey.[8] The survey asked lenders about their use of credit bureau/registry information for Retail, SME, and Large enterprise lending. For years 2007 and 2011, the survey asked whether the lender used private credit bureau (PCB) and public credit registry (PCR) information, how frequently the PCB or PCR was able to provide the bank with information about their applicants' credit histories, and how frequently the obtained information was accurate and reliable. Hence, the survey provides a useful data source to assess correlations between the CII for years 2007 and 2011 and actual lender use and perceptions of credit reporting system information in those years. I therefore assess the degree of correlation between the CII and lender uses and perceptions of credit reporting system information.

[8] https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance -survey.html. The EBRD, in conjunction with World Bank, conducted the Banking Environment and Performance Survey (BEPS) on a random sample of banks in 32 EBRD countries. The survey, which covered details on bank credit and deposit, as well as risk management practices, perceptions of the security rights of lenders, bankruptcy law and its application and effectiveness of government regulatory policy, was completed by senior bank officers from over 500 banks.

My evaluation hypothesis is that the CII is correlated with lender perceptions of credit reporting utility but that the index's predictive value could be improved by directly factoring in the type of credit reporting system (PCB, PCR, both) available in the country, the credit reporting coverage rate, and the number of years the credit reporting system has been in operation. Differentiating the CII by type of credit reporting system would seem logical, given that PCBs and PCRs serve different purposes (IFC, 2012, Djankov, 2007) and have different effects on credit markets (Love and Mylenko, 2003, Djankov, 2007). The CII does not distinguish between whether the country has a PCR, PCB, or both. The credit reporting system coverage rate is directly related to the availability of information that lenders need to inform the credit decision. The CII does not directly factor in the coverage rate. The number of years the credit reporting system has been in operation would be a valid additional component to the CII, as it is a measure of system maturity and depth of information.

I find that the CII is somewhat positively associated with lender perceptions of credit reporting system utility, but the CII can become more predictive by incorporating a few changes. First, by taking into separate consideration the presence and characteristics, including adult coverage rates, of PCB and PCR makes the CII significantly more predictive. The institutions with the largest percentage of perceived credit reporting system utility are in countries with both types of reporting systems. I find that the higher the reporting system adult coverage rates, the higher the perceived credit reporting system utility. I also find that after controlling for other factors, lenders were more likely to perceive credit reporting utility in 2011 than in 2007, supporting my hypothesis that the number of years a credit reporting system has been in operation is correlated with utility. Additionally, as will be discussed further, the above variables do not explain all the variability of perceptions of credit reporting system utility; therefore, other to be determined data sources and variables likely could be explored and added to improve the CII.

This paper contributes to the literature by introducing a simple method for validating indices of reporting system quality. Assessment of the association between index values and lender perceptions of credit reporting system utility could lead to further refinement of indices and improved reporting systems.

The rest of the paper is organized as follows. Section 2.2 describes the data used in the analysis and presents descriptive statistics. Section 2.3 presents the methods. Section 2.4 presents descriptive and multivariate analysis. Section 2.5 concludes.

2.2 Literature Review

To facilitate understanding the importance of the CII, and evaluation of the CII, it is useful to understand the importance of credit reporting systems and their impact on credit markets. Stiglitz and Weiss (1981), Pagano and Japelli (1993) and Padilla and Pagano (2000) presented theoretical support for credit reporting's role in reducing information asymmetry, adverse selection, and moral hazard. In the context of lending, information asymmetry essentially means that a credit applicant knows more about their degree of credit worthiness than the lender. Stiglitz and Weiss (1981) described how asymmetric information can result in adverse selection and moral hazard, leading to credit rationing. Effective credit reporting systems reduce information asymmetry, resulting in increased access to credit. Pagano and Jappelli (1993) demonstrate that by sharing information on borrower performance, lenders can reduce adverse selection by better distinguishing between high-risk and low-risk borrowers. Padilla and Pagano (2000) articulated that credit information sharing reduces moral hazard by making borrowers' credit histories available to multiple lenders, creating an incentive for borrowers to repay their loans to maintain future credit access.

Empirically, several studies have identified benefits of credit reporting systems and credit information sharing among lenders. Jappelli and Pagano (2002) conducted a multi-country study which identified that information sharing is associated with higher levels of lending and lower default rates. The authors found that countries with PCBs or PCRs have higher ratios of private credit to GDP. Love and Mylenko (2003) identified that businesses in countries with more comprehensive credit reporting systems face fewer financing constraints. Djankov, McLeish and Shleifer (2007) analyzed data from 129 countries and found that the presence of credit registries is associated with higher levels of private credit. Brown, Jappelli, and Pagano (2009) studied the impact of credit information sharing in transition countries and identified that businesses in countries with credit registries are more likely to receive credit access and at better terms. Houston et al. (2010) analyzed 2,400 banks across 69 countries and found that credit information sharing results in lower bank risk, higher profitability, reduced likelihood of financial crises and higher economic growth.

In constructing the CII, Djankov referenced findings from the research of Djankov, McLeish and Shleifer (2007) on credit reporting system factors associated with more private credit. Djankov, et al. found that credit reporting systems that distributed a broader range of data and provided legal incentives to ensure information quality were associated with greater private credit. The six factors identified in their study included: 1) data on firms and individuals are distributed; 2) both “positive” and “negative” information is collected; 3) in addition to credit data from financial institutions, data from retailers or utility companies are distributed; 4) at least five years of historical data are maintained; 5) data on loan amounts below 1% of income per capita are distributed, and 6) by law, borrowers have the right to access their data in the largest credit bureau or registry in the economy. The above six factors comprised the original components of the CII. It would seem logical that the more of these factors present in a credit reporting system, the greater the lender utility derived from the system. However, this assumption should be validated. If, for example, there was no correlation between levels of the CII and lender utility derived from the credit reporting system, then it would be valid to question whether the factors comprising the CII provide an effective assessment of the quality of the credit reporting system.

2.3 Data

The study was conducted by merging datasets from three different sources. One dataset contains responses from the year 2011 European Bank for Reconstruction and Development (EBRD) Banking Environment and Performance Survey (BEPS II) of a random sample of banks in 32 EBRD countries.[9] The survey, which covered details on bank credit and deposit activities in 2007 and 2011, as well as risk management practices, perceptions of the security rights of

[9] https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html

lenders, bankruptcy law and its application and effectiveness of government regulatory policy, was completed by senior bank officers from over 500 banks.

Among many questions, the BEPS II survey asked lenders about their use of PCB and PCR information for Retail, SME, and Large Enterprise lending in 2007 and 2011. Specific to this analysis, the survey asked whether the lender used PCB/PCR information, if the bank didn't use the information, the primary reason for not doing so, how frequently the PCB/PCR was able to provide the bank with information about borrower credit histories, how frequently the PCB/PCR information was accurate and reliable, and how often the lender declined loan applications because of inadequate information about the firm's credit history. Because these questions were asked for years 2007 and 2011, for each responding institution there are two responses (records), one for year 2007 and one for 2011.

The second dataset contains detailed country-level World Bank Doing Business Getting Credit and CII data for the years 2007 and 2011. The CII is developed using data from surveys of banking supervision authorities and credit reporting service providers. The CII is a sub-component of the Doing Business Getting Credit indicator, which is composed of two sub-indicators, the Legal Rights Index, which measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders, and the CII, which measures the strength of a country's credit reporting systems. The initial methodology was developed by Djankov, et al. (2007) and has been adopted with minor changes over time.[10]

In 2007 and 2011, a credit reporting system was evaluated based on six features, with a score of 1 assigned for each feature present. The CII ranges from '0' to '6', with higher values indicating the availability of more credit information, from either a PCB or PCR. Table 1.1 describes the reporting system characteristics that comprised the CII in 2007 and 2011. The dataset contains 12 dummy variables (six for PCB and six for PCR) that equal '1' to indicate the presence of each of those characteristics in either a PCB or PCR.

[10] https://www.doingbusiness.org/en/methodology/getting-credit

Table 2.1. The six components of the Credit Information Index in 2007 and 2011

Credit reporting system characteristic
Data on firms and individuals are distributed
Both "positive" and "negative" information is collected
In addition to credit data from financial institutions, data from retailers or utility companies are distributed
At least two years of historical data are maintained
Data on loan amounts below 1% of income per capita are distributed
By law, borrowers have the right to access their data in the largest credit bureau or registry in the economy

This table shows the six components of the Credit Information Index in 2007 and 2011.
Source: World Bank, Doing Business Project (www.doingbusiness.org).

Of note, the value of the CII is indifferent to whether the country has a PCB, PCR, or both. The CII treats these different systems as equivalents and does not assign additional value if a country has both types of systems. For example, the CII will assign a value of '1' to the variable, "Both positive and negative information is collected" if in each country a PCB or PCR has this characteristic, or if the country has both types of reporting systems and both systems have the characteristic. Therefore, even though there are 12 dummy variables, the maximum CII value is '6'. Additionally, if the PCB or PCR was not operational or covered less than five percent of the adult population, the CII value is '0'.

The third dataset used in the analysis comes from the research of Djankov, et al. (2007) for their article *Private Credit in 129 Countries*.[11] This dataset has a dummy variable to indicate countries with a legal origin in French civil law and has variables to indicate the date of establishment of PCB and PCR.

I merge the datasets by country and reporting year. The BEPS II survey dataset was obtained from EBRD. The Doing Business Getting Credit Data was obtained from the Doing Business website (https://www.doingbusiness.org/en/custom-query).

The analysis is limited to the 514 responding financial institutions that provided both Retail and SME credit. The BEPS II survey defines an SME as an enterprise with between 10 and 250 employees, therefore, using this definition many small businesses would be classified as Retail. Each responding institution has two observations, one from 2007 and the other from 2011. Therefore, the analysis dataset has a total of 1028 observations.

2.4 Methodology

The primary question posed is whether an increase in the level of the CII is correlated with an increase in the percentage of institutions that found credit bureau/registry information available

[11] https://scholar.harvard.edu/shleifer/publications/private-credit-129-countries

and useful for Retail and SME lending decision-making. To assess associations, I construct a binary outcome variable (to be referred to as "**Credit Reporting Utility**") equal to 1 if all the following conditions were met:

the financial institution:

1) had obtained information from PCR or PCB for Retail and SME borrowers.
2) indicated that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and
3) "frequently" or "very frequently" the information provided was accurate and reliable.

Otherwise, Credit Reporting Utility equals 0.

The primary explanatory variable evaluated is the CII. In 2007 and 2011 the CII was derived through a summation in each country of the presence or absence in PCB or PCR of the six reporting system characteristics listed in Table 2.1 and described in Section 2.2. Additionally, if the PCB or PCR was not operational or covered less than five percent of the adult population, the CII value was '0'. In 2007 and 2011, the minimum CII score possible was '0' and the maximum possible score was '6'. The primary question investigated is, as the level of the CII increases, does the percentage of Credit Reporting Utility increase?

I then create and test potential replacements for the CII. I create two new sub-indices, one for PCB and the other for PCR. The value of the CII is indifferent to whether the country has a PCB, PCR, or both. The CII treats these different systems as equivalents and does not assign additional value if a country has both types of systems. I can create these sub-indices, because the CII dataset contains binary indicators for the presence or absence of the six measured reporting system characteristics for both PCB and PCR. I create these sub-indices for PCB and PCR, because historically these systems have served different purposes and are not necessarily equivalents. A PCB is a private or non-profit organization that collects information on borrowers from financial institutions and makes the information available to lenders for credit monitoring and decisioning purposes. PCBs may collect information from a variety of credit granting entities and may be more designed to assess and monitor the creditworthiness of individual borrowers. PCRs historically have focused on larger credit exposures and were created by a country's central bank to identify systemic risk within the lending portfolios of regulated financial institutions (IFC, 2012, Djankov, 2007). Studies have identified different effects of these systems. Love and Mylenko (2003) find that the existence of PCBs, but not PCR, is associated with lower financing constraints and a higher share of bank financing. PCR are more likely to exist in French civil law countries and benefit private credit markets in developing economies (Djankov, 2007). In 2011, of 183 tracked economies, 57 (31%) had at least one PCB but no PCR, 49 (27%) had at least one PCR but no PCB, and 34 (19%) had at least one of each. In each economy, the maximum possible CII value was '6'. In constructing these sub-indices, I did not apply the CII rule that the index value would be '0' if the coverage rate was less than five percent. Hence, Armenia, for example, in 2007 did not have a PCB but had a PCR with an adult coverage rate of 1.5 percent, which assigned it a CII of '0'; however, the PCR had the following characteristics: 1) data on firms and individuals are distributed; 2) both "positive" and "negative" information is collected, and 3) by law, borrowers have the right to access their data in the largest credit bureau or registry in the economy. Thus, for Armenia for 2007, I assigned a PCB sub-index value of ‘0’ and PCR index value of ‘3’. I did not apply the CII five percent coverage rule, because I wanted to directly assess the effect of several levels of coverage rate on the percentage of Credit Reporting Utility.

Another explanatory variable included in logistic regression models 3, 6 and 12 is the adult population coverage rate. The coverage rate, defined as the number of borrowers in the credit reporting system divided by the economically active population, is a fundamental indicator of credit reporting system effectiveness (IFC, 2020). All else equal, higher coverage rates should lead to greater system utility. However, above the five percent coverage rate threshold below which a CII value of ‘0’ is assigned, the CII is indifferent to the credit registry/bureau coverage rate, which can vary greatly between countries. In 2011, among 80 countries with private coverage rates exceeding five percent of the adult population, the coverage rate varied from 5.3 percent to 100 percent, with a mean of 52.6 percent (source: Doing Business Credit Information Index dataset). Of 49 countries with public credit registry coverage rates exceeding five percent of the adult population, the coverage rates ranged from 5.6 percent to 67.1 percent (mean: 25.4 percent). For the regressions, I include categorical variables describing the percentage of the adult population covered by the PCB and PCR.

The CII also does not take into consideration the length of time the CII factors have been present. For example, one of the factors is whether at least two years of historical data are maintained in the registry/bureau. However, the source research which informed the development of the CII identified that reporting systems with at least five years of credit history were associated with more private credit (Djankov, et al., 2007). The more years of historical data a registry or bureau contains, the more useful it should be. Based on Doing Business data going back to 2005, several countries reached the two-plus years of credit history threshold for the first time in 2011, whereas many other countries already had this much seasoned data in 2005. In logistic regression models 4, 5 and 6 I replace the simple PCB and PCR indices with new PCB and PCR indices that take into consideration the number of years the reporting system has had the specific characteristic since 2005. For example, for the characteristic, “both positive and negative data are distributed”, if a country’s credit reporting system had that characteristic as far back as 2005, for 2007, the new value for that characteristic would be ‘3’, and for 2011 the value would be ‘7’. However, if a country’s credit reporting system first had that characteristic in 2011, for 2007 the value would be ‘0’, and for 2011 the value would be ‘1’.

In this analysis I seek to test the incremental value of the above factors, which are all derivations of actual CII components. In the regression analysis I control for other potential explanatory variables, such as whether the financial institution had majority foreign ownership, whether the country had a legal system based on French civil law, the country in which the institution is located, and whether the year was 2011 versus 2007.

I include foreign ownership as a potential explanatory factor based on research which identified that foreign-owned banks can overcome distance-related informational disadvantages by using credit ratings and credit scoring (Beck, et al., 2017). Credit repayment history is typically a significant component of credit scoring models and credit ratings. Foreign-owned financial institutions may be more likely to rely on credit reporting information than domestic institutions, which likely have more access to “soft” (personal knowledge of the borrower) information for making their lending decisions. Therefore, I assume that all else equal, foreign-owned institutions should have a higher percentage of perceived Credit Reporting Utility. Using BEPS II survey data, I created a categorical variable that combined whether the bank was more than 50 percent owned by a foreign bank with a variable describing the influence of the bank’s foreign parent bank in shaping credit risk assessment of clients. Thus, there were three categories of foreign ownership: 1) < 50 percent foreign-owned; 2) >= 50 percent foreign-owned, where the bank’s foreign parent bank did not have significant influence on shaping client credit risk assessment; 3) >= 50 percent foreign-owned, and the influence of the bank’s foreign parent bank in shaping credit risk assessment of clients is “important” or “very important”.

I include whether the country had a legal system based on French civil law based on research by Djankov, et al. (2007) which identified that countries with a legal system based on French civil law were much more likely than other countries to have and gain utility from PCR and to have weaker creditor rights against defaulting borrowers. Essentially, in these countries credit reporting systems become even more important for lenders in the absence of strong creditor rights (Djankov, et al., 2007). Therefore, all else equal, French civil law countries may have higher rates of lender perceived credit reporting system utility.

I include the income group (High, Upper Middle, Middle, Lower Middle, Low) based on the findings of Djankov, et al. (2007) that PCBs and PCRs are strongly associated with private credit in poorer, but not richer countries (Djankov, et al., 2007). This would imply that, all else equal, lenders may perceive greater utility of credit reporting systems in poorer countries.

In conducting the analysis, I observed that there are different percentages of perceived Credit Reporting Utility by country, even after adjusting for several other predictor variables. I therefore created two country dummy variables, which included all countries with significantly higher and lower rates of Credit Reporting Utility than would be predicted, after controlling for other factors. This was determined using multiple logistic regression analysis. A separate multiple logistic regression (not shown in the tables) was conducted for each country, with a dummy variable created for that country. Other explanatory variables included in the regression are the derived PCB and PCR indices, the PCB and PCR adult coverage rates, a dummy variable for year 2011, whether the country's legal system has an origin in French civil law and a categorical variable indicating the extent of foreign-ownership and influence on credit risk assessment. After controlling for these other variables, countries with associations at a less than .10 level of statistical significance were classified as either "High Credit Reporting Utility" or "Low Credit Reporting Utility" countries, depending on the direction of the beta coefficient. To be classified as a “High” country, the beta coefficient must be positive, and the p-value must be less than .10. “Low” countries must have a negative beta coefficient, and a p-value less than .10. Armenia, Estonia, Georgia, Kazakhstan, Kyrgz Republic, Serbia and Tunisia are “High Credit Reporting Utility” countries, and Belarus, Bulgaria, Egypt, Jordan, Latvia, Poland, Russia, Slovenia, and Ukraine are “Low”. These variables were included to capture variation in Credit Reporting Utility not explained by the other variables, and to highlight that there are likely significant country-specific factors influencing the perceived utility of a credit reporting system that could potentially be identified to further refine the indices.

The dummy variable for 2011 versus 2007 was included based on the BEPS II results. Credit Reporting Utility increased significantly between these years, from 37.3 percent to 68.5 percent. This variable therefore is added to explain time-related variation not potentially captured by other variables included in the models.

In Table 2.3, I describe the percentage of Credit Reporting Utility for each credit reporting characteristic, stratified by year. I could not effectively test the independent association of individual components of each sub-index, because the individual factors were highly correlated, (see Table 2.6) causing potential multi-collinearity issues with the analysis. I attempted to conduct a multiple logistic regression analysis that included all 12 of the individual reporting characteristics; however. some of the resulting coefficients did not look directionally correct, reversing the direction of their effect on an individual basis. I therefore concluded that multicollinearity was likely going to create instability in the model. To investigate multi-collinearity further, I used a variable reduction technique[12] to cluster these individual reporting system component variables into groups that are as correlated as possible among themselves and as uncorrelated as possible with other clusters. From the analysis two distinct groups were formed, one which contained all the PCB variables and another that contained all the PCR variables. Therefore, I concluded that using the two sub-indices was sufficient to explain the variation due to these underlying characteristics.

To measure the diagnostic accuracy of the CII and other potential indices, I used multiple logistic regression to determine the direction, level, and statistical significance of associations, and to compute the Area Under the Receiver Operating Characteristic Curve (ROC AUC). The ROC AUC is a standard measurement of screening tool effectiveness and is used in a wide variety of fields and applications (Hanley and McNeil, 1982, Swets, 1988, Mays, 2011). In the credit industry, it is a common measurement for validation of credit scoring models (Siddiqui, 2006, Mays, 2011, Anderson, 2007). An ROC curve plots the true positive rate (y-axis) versus the false positive rate, (x-axis) of a binary classification tool as its discrimination threshold is varied. The greater the Area Under the Curve (AUC), the better the tool's diagnostic ability. An ROC AUC of 0.5 indicates that the diagnostic tool (e.g., the CII) is worthless for predicting the presence of the outcome variable, whereas an ROC AUC of 1.0 indicates perfect predictive power. For example, with the CII, my assumption is that the higher the CII value, the higher the percentage of Credit Reporting Utility. In this context, the ROC AUC represents the probability that a randomly selected bank experiencing Credit Reporting Utility would have a higher CII value than a randomly selected bank that did not experience Credit Reporting Utility.

Logistic regression uses a logistic function to model a binary dependent variable. The model assumes a linear relationship between the predictor variables and the natural logarithm of the odds of the outcome:

$$ln\frac{p}{1-p} = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

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[12] The variable reduction analysis was conducted with PROC VARCLUS using SAS software. Copyright, SAS Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA.

where p is probability of the outcome, X_1 is an explanatory variable such as the CII, and X_2 is another explanatory variable such as the reporting year or other variables.

In logistic regression, the beta coefficient indicates the change in the expected log odds of the outcome relative to a one unit change in the X variable, holding all other explanatory variables constant. A positive beta coefficient indicates that an increase in the level of the independent variable is associated with an increase in the odds of the outcome. Conversely, a negative beta coefficient indicates that an increase in the level of the independent variable is associated with a decrease in the odds of the outcome.

The analysis was conducted in SAS, using the PROC LOGISTIC procedure.[13] The ROC AUC is part of the standard output from the PROC LOGISTIC procedure.

2.5 Descriptive Analysis and Results

2.5.1 Overall index

Table 2.2 describes the percentage of Credit Reporting Utility by levels of various indices, stratified by year. As can be seen, comparing 2007 with 2011, the total percentage of Credit Reporting Utility increased from 37.3 percent to 68.5 percent. The CII also increased over those four years: in 2007, 59.7 percent of responding banks were in a country with a CII value of ‘0’, versus 10.5 percent of responding banks in 2011. As can be seen in Table 2.2 and Figure 2.1, the biggest noticeable difference in the percentage of Credit Reporting Utility is between institutions in countries with a CII of ‘0’ and institutions in countries with CII above ‘0’ (1-6). In 2007, among lenders residing in countries with a CII value of ‘0’, only 20.7 percent perceived Credit Reporting Utility (versus 37.3 percent overall), and in 2011 that figure was 29.6 percent (versus 68.5 percent overall). However, for CII values above ‘0’, there does not seem to be any clear rank-ordering between levels of the CII and the percentage of Credit Reporting Utility. For example, for 2007 and 2011 combined, 77.6 percent of institutions in countries with CII values of ‘3’ perceived Credit Reporting Utility, higher than the 71 percent of institutions in countries with CII values of ‘5’.

[13] Copyright, SAS Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA.

Table 2.2. Distribution of Observations and Credit Reporting Utility Percentage, by Index Level, Years 2007 and 2011.

	Total		Year 2007		Year 2011	
Index	N	Utility%	N	Utility%	N	Utility%
CII						
0	361	21.6%	307	20.2%	54	29.6%
1	14	78.6%	14	78.6%	0	0.0%
2	0	0.0%	0	0.0%	0	0.0%
3	49	77.6%	16	56.3%	33	87.9%
4	184	67.9%	99	73.7%	85	61.2%
5	345	71.0%	78	47.4%	267	77.9%
6	75	62.7%	0	0.0%	75	62.7%
Total	1028	52.9%	514	37.3%	514	68.5%
PCBI						
0	475	37.5%	321	23.1%	154	67.5%
1	0	0.0%	0	0.0%	0	0.0%
2	0	0.0%	0	0.0%	0	0.0%
3	16	50.0%	16	50.0%	0	0.0%
4	209	69.9%	114	74.6%	95	64.2%
5	264	66.3%	63	39.7%	201	74.6%
6	64	57.8%	0	0.0%	64	57.8%
Total	1028	52.9%	514	37.4%	514	68.5%
PCRI						
0	510	38.9%	258	22.5%	252	55.6%
1	33	51.5%	20	55.0%	13	46.2%
2	114	46.4%	77	51.9%	37	35.1%
3	135	65.2%	70	41.4%	65	90.8%
4	183	78.2%	89	60.7%	94	94.7%
5	53	84.9%	0	0.0%	53	84.9%
6	0	0.0%	0	0.0%	0	0.0%
Total	1028	52.9%	514	37.4%	514	68.5%

Table 2.2, continued. Distribution of Observations and Credit Reporting Utility Percentage, by Index Level, Years 2007 and 2011

	Total		Year 2007		Year 2011	
Index	N	Utility%	N	Utility%	N	Utility%
PCBI+PCRI						
0	204	16.6%	180	14.4%	24	33.3%
1	20	55.0%	20	55.0%	0	0.0%
2	71	31.0%	41	34.1%	30	26.7%
3	97	51.5%	64	32.8%	33	87.9%
4	117	53.0%	39	38.5%	78	60.3%
5	249	61.9%	62	37.1%	187	70.1%
6	66	60.6%	29	75.9%	37	48.6%
7	28	64.3%	15	80.0%	13	46.2%
8	112	84.8%	56	75.0%	56	94.6%
9	43	93.0%	8	75.0%	35	97.1%
10	21	85.7%	0	0.0%	21	85.7%
Total	1028	52.9%	514	37.3%	514	68.5%

Data sources: Credit Information Index data: World Bank, Doing Business project (http://www.doingbusiness.org). "Credit Reporting Utility" is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html).

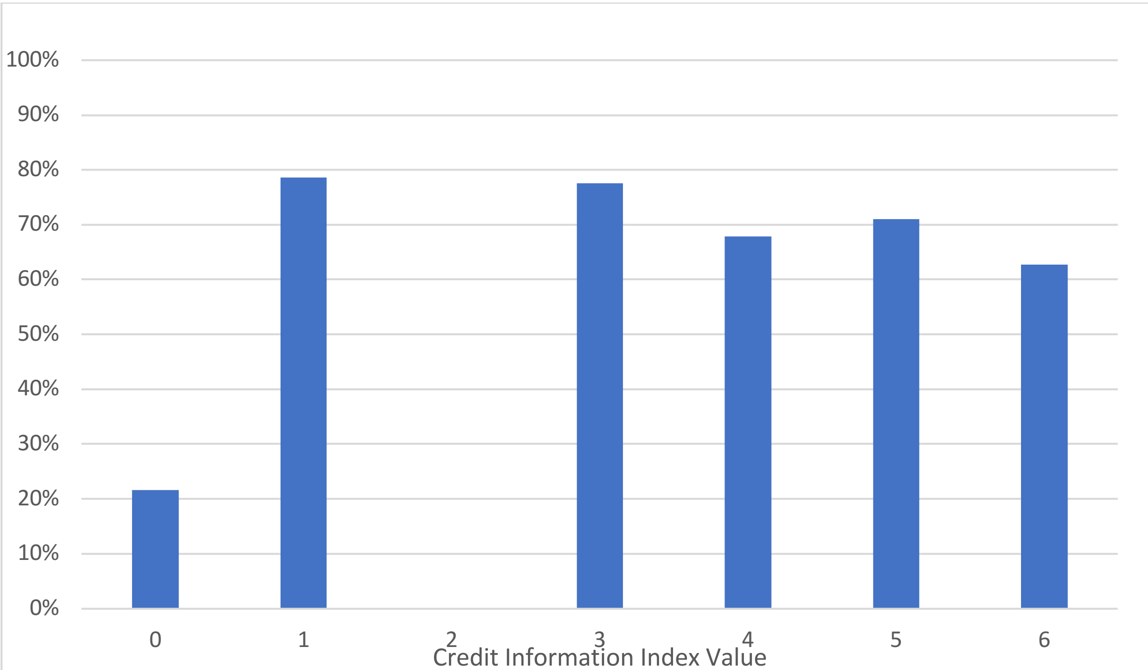
This table shows Credit Reporting Utility by different levels of the Credit Information Index (CII), and other derived indices. Table key: CII: Doing Business Credit Information Index. PCBI: Derived private credit bureau index. PCRI: Derived public credit registry index. "Utility %"represents the percentage of institutions reporting "Credit Reporting Utility", which equals 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and 3) the information provided was "frequently" or "very frequently accurate and reliable. Otherwise Credit Reporting Utility equaled 0.

As can be seen in Table 2.2 and Figure 2.2, the pattern of Credit Reporting Utility by derived PCB index level follows a similar pattern to that of the CII. The lowest percentage of Credit Reporting Utility is among institutions in countries with a derived PCB index of '0'. Above a PCB sub-index level of '0', there is no strong pattern of rank-ordering of Credit Reporting Utility, although in general, the higher the PCB index level, the lower the percentage of perceived Credit Reporting Utility.

For the derived PCR index, the pattern is somewhat different from the other two indices. Among institutions in countries with a PCR index of '0', the percentage of perceived Credit Reporting Utility was 22.5% in 2007 and 55.6% in 2011. The percentage of perceived Credit Reporting Utility is significantly higher among institutions in countries with derived PCR index levels of '3' or greater than among banks in countries with derived PCR index values less than '3'.

Table 2.2 and Figure 2.4 show that the best rank-ordering occurs when the two derived sub-indices are used together and combined into one index. With some variation which could be due to small sample sizes, for years 2007 and 2011 combined, the higher the combined index value, the higher the percentage of perceived Credit Reporting Utility.

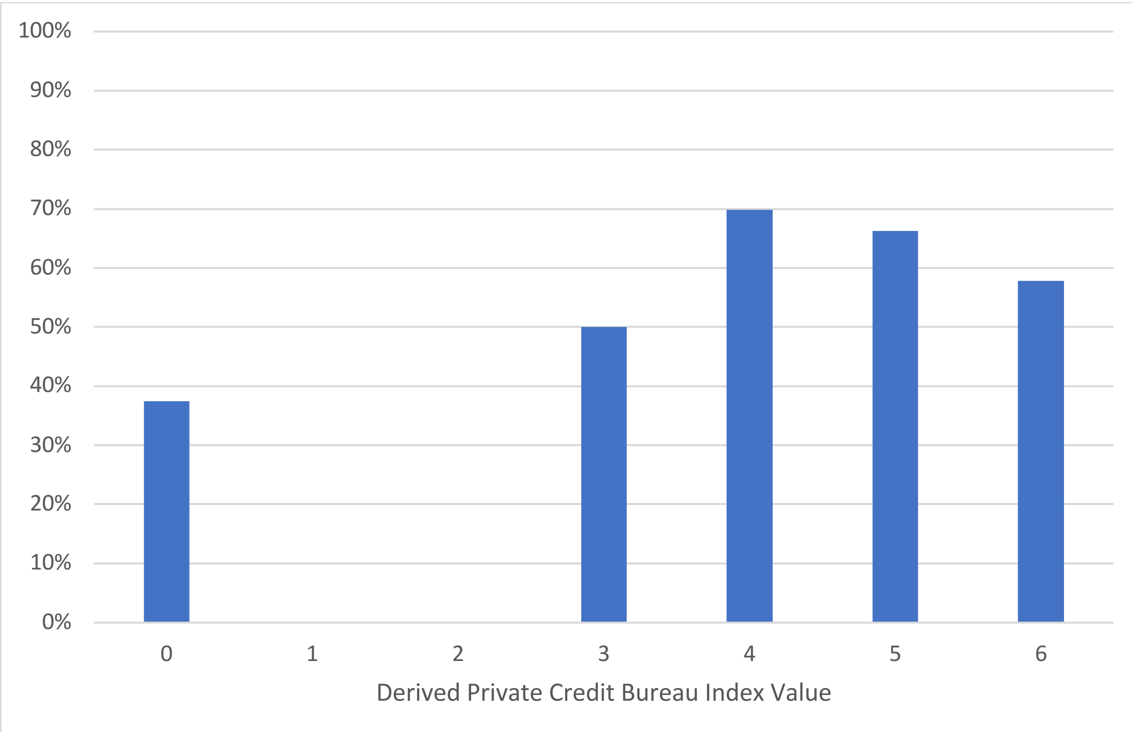
Figure 2.1. Credit Reporting Utility, by Credit Information Index value, 2007 and 2011 combined.



Data sources: Credit Information Index data: World Bank, Doing Business project (http://www.doingbusiness.org). "Credit Reporting Utility" is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html).

The y-axis shows the percentage of institutions reporting "Credit Reporting Utility", which equals 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and 3) the information provided was "frequently" or "very frequently accurate and reliable. Otherwise Credit Reporting Utility equaled 0.

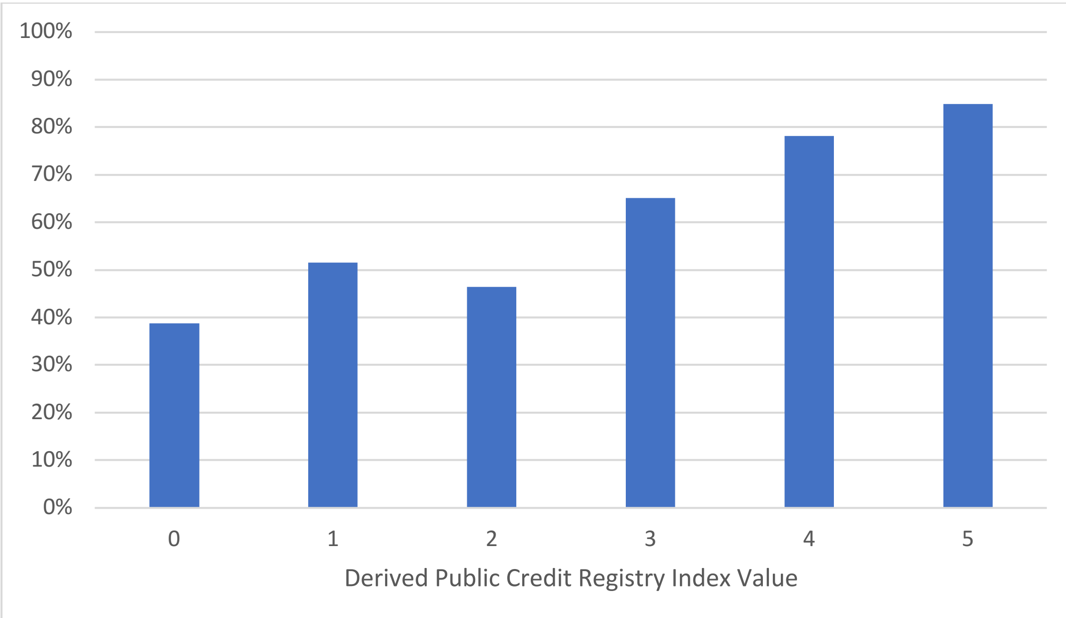
Figure 2.2. Credit Reporting Utility, by Derived Private Credit Bureau Index value, 2007 and 2011 combined.



Data sources: Credit Information Index data: World Bank, Doing Business project (http://www.doingbusiness.org). "Credit Reporting Utility" is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html).

Derived Private Credit Bureau Index represents the country's index specifically for private credit bureau characteristics. The y-axis shows the percentage of institutions reporting "Credit Reporting Utility", which equals 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and 3) the information provided was "frequently" or "very frequently accurate and reliable. Otherwise Credit Reporting Utility equaled 0.

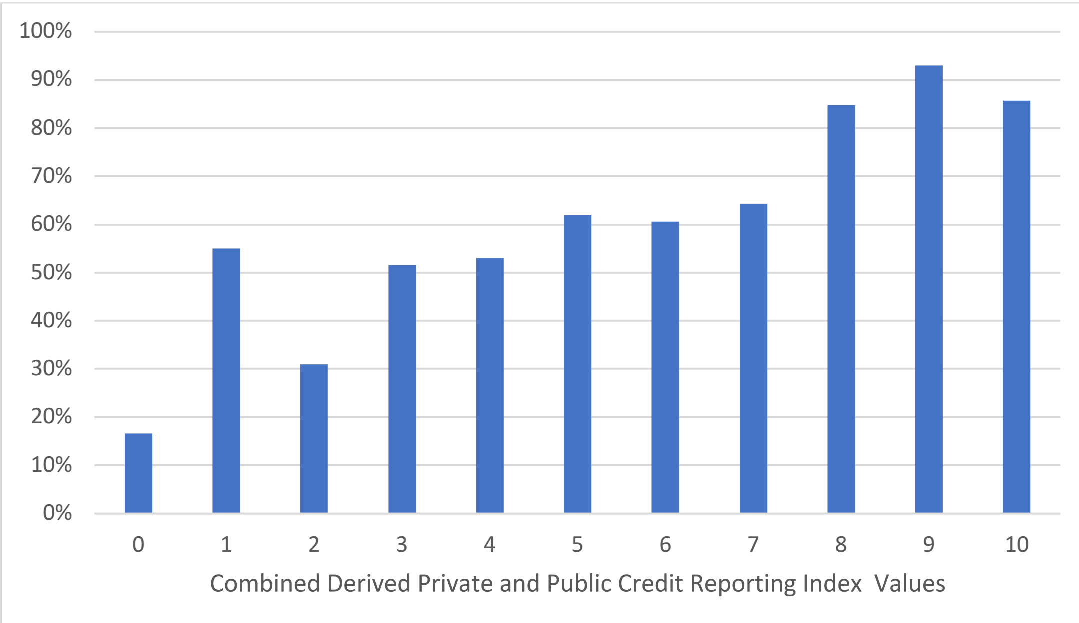
Figure 2.3. Credit Reporting Utility, by Derived Public Credit Registry Index value, 2007 and 2011 combined.



Data sources: Credit Information Index data: World Bank, Doing Business project (http://www.doingbusiness.org). "Credit Reporting Utility" is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html).

Derived Public Credit Registry Index represents the country's index specifically for public credit registry characteristics. The y-axis shows the percentage of institutions reporting "Credit Reporting Utility", which equals 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and 3) the information provided was "frequently" or "very frequently accurate and reliable. Otherwise Credit Reporting Utility equaled 0.

Figure 2.4. Credit Reporting Utility, by combined Derived Private Credit Bureau and Public Credit Registry Index values, 2007 and 2011 combined.



Data sources: Credit Information Index data: World Bank, Doing Business project (http://www.doingbusiness.org). "Credit Reporting Utility" is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html).

Combined Derived Private and Public Credit Reporting Index represents the country's derived index value determined by summing the values of the derived private credit bureau index and derived public credit registry index. "Utility %" represents the percentage of institutions reporting "Credit Reporting Utility", which equals 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and 3) the information provided was "frequently" or "very frequently accurate and reliable. Otherwise Credit Reporting Utility equaled 0.

2.5.2 Individual Credit Reporting System characteristics

Table 2.3 describes the percentage of perceived Credit Reporting Utility by individual characteristics of the credit reporting system. The table describes the percentage of Credit Reporting Utility by whether the factor, 1) was not available in the country; 2) was a characteristic of private credit bureau(s) in the country; 3) was a characteristic of public credit registry(ies) in the country; 4) was a characteristic of both the private credit bureau and public credit registry systems. As seen in the table, across all components, the highest percentages of Credit Reporting Utility were among institutions in countries which contained the characteristic in both PCB and PCR, except for the characteristic related to whether the reporting system distributed data from retailers and/or utility companies, which was not a characteristic of any PCR system. Additionally, by characteristic, after controlling for year, the lowest percentage of Credit Reporting Utility was in countries that did not have the characteristic in either a PCB or a PCR.

Table 2.3. Distribution of Observations and Credit Reporting Utility Percentage, by Reporting System Characteristic, Years 2007 and 2011.

	Year 2007		Year 2011	
Reporting System Characteristic	**N**	**Utility %**	**N**	**Utility %**
Data on firms and individuals				
Neither Private or Public	220	14.1%	101	40.6%
Private Bureau Only	68	54.4%	181	64.1%
Public Registry Only	165	49.1%	139	82.7%
Both Private and Public	61	70.5%	93	86.0%
Positive and negative credit information				
Neither Private or Public	228	22.4%	42	59.5%
Private Bureau Only	89	48.3%	240	57.1%
Public Registry Only	122	32.0%	130	73.8%
Both Private and Public	75	78.7%	102	92.2%
At least two years of historical data				
Neither Private or Public	299	30.8%	77	61.0%
Private Bureau Only	79	44.3%	284	61.6%
Public Registry Only	75	21.3%	88	76.1%
Both Private and Public	61	80.3%	65	96.9%
By law, borrowers have the right to access their data in the largest credit bureau or registry in the economy				
Neither Private or Public	326	26.1%	91	54.9%
Private Bureau Only	68	42.6%	248	57.7%
Public Registry Only	41	43.9%	80	87.5%
Both Private and Public	79	75.9%	95	93.7%
Data on loan amounts below 1% of income per capita				
Neither Private or Public	305	24.6%	76	46.1%
Private Bureau Only	148	59.5%	307	65.5%
Public Registry Only	46	41.3%	78	88.5%
Both Private and Public	15	66.7%	53	88.7%
Data from retailers or utility companies				
Neither Private or Public	438	35.6%	413	68.0%
Private Bureau Only	76	47.4%	101	70.3%
Public Registry Only	0	0.0%	0	0.0%
Both Private and Public	0	0.0%	0	0.0%

Table 2.3 shows the percentage of reported Credit Reporting Utility, stratified by the presence/absence of individual factors comprising the Credit Information Index.

Data sources: Credit Information Index components: World Bank, Doing Business project (http://www.doingbusiness.org). "Credit Reporting Utility" is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). "Utility %" represents the percentage of institutions reporting "Credit Reporting Utility", which equals 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and 3) the information provided was "frequently" or "very frequently accurate and reliable. Otherwise Credit Reporting Utility equaled 0.

2.5.3 Index values, Credit Reporting Utility and Reporting System characteristics, by country

Table 2.4 describes the sample size, CII, PCB index, PCR index, PCB coverage rates, PCR coverage rates, and the percentage of Credit Reporting Utility by country and year. As can be seen, the percentage of Credit Reporting Utility varied significantly across countries, and within countries across years. Table 2.5 provides detail of the presence or absence of the 12 credit reporting system characteristics by PCB vs. PCR and country in 2007 and 2011, respectively.

Table 2.4. Credit Information Index values and Credit Reporting Utility percentage, by country, 2007.

Country	N	CII	PCBI	PCRI	PCB Coverage	PCR Coverage	Utility %
Albania	13	0	0	0	0.0%	0.0%	7.7%
Armenia	16	0	0	3	0.0%	1.5%	75.0%
Azerbaijan	15	0	0	4	0.0%	1.1%	20.0%
Belarus	15	0	0	3	0.0%	1.1%	0.0%
Bosnia and Herzegovina	17	5	5	0	22.9%	0.0%	41.2%
Bulgaria	21	4	4	4	3.0%	20.7%	76.2%
Croatia	27	0	0	0	0.0%	0.0%	29.6%
Czech Republic	8	5	5	4	51.0%	3.5%	75.0%
Egypt, Arab Rep.	13	0	0	2	0.0%	1.5%	23.1%
Estonia	9	5	5	0	18.2%	0.0%	77.8%
Georgia	12	0	0	0	0.0%	0.0%	50.0%
Hungary	11	5	5	0	5.9%	0.0%	36.4%
Jordan	15	0	0	2	0.0%	0.7%	26.7%
Kazakhstan	14	4	4	0	5.5%	0.0%	64.3%
Kyrgz Republiic	9	0	3	0	0.4%	0.0%	44.4%
Latvia	10	0	0	4	0.0%	1.9%	30.0%
Lithuania	11	4	4	4	7.2%	4.2%	45.5%
Moldova	12	0	0	0	0.0%	0.0%	0.0%
Mongolia	9	3	0	3	0.0%	10.2%	55.6%
Montenegro	11	0	0	0	0.0%	0.0%	18.2%
Morocco	6	0	0	1	0.0%	2.3%	0.0%
North Macedonia	13	0	0	2	0.0%	2.1%	53.8%
Poland	18	5	5	0	38.1%	0.0%	5.6%
Romania	24	4	4	4	5.5%	2.6%	87.5%
Russian Federation	65	0	0	0	0.0%	0.0%	12.3%
Serbia	29	4	4	2	43.4%	0.1%	75.9%
Slovak Republic	7	3	3	2	45.3%	1.0%	57.1%
Slovenia	15	0	0	3	0.0%	2.9%	0.0%
Tajikistan	12	0	0	0	0.0%	0.0%	0.0%
Tunisia	14	1	0	1	0.0%	11.6%	78.6%
Turkey	15	5	4	3	27.6%	6.7%	80.0%
Ukraine	28	0	0	0	0.0%	0.0%	3.6%
Total	514						37.4%

Table 2.4., continued. Credit Information Index values and Credit Reporting Utility percentage, by country, 2011

Country	N	CII	PCBI	PCRI	PCB Coverage	PCR Coverage	Utility %
Albania	13	5	0	5	0.0%	12.3%	92.3%
Armenia	16	5	5	4	38.3%	16.9%	100.0%
Azerbaijan	15	5	0	5	0.0%	7.0%	86.7%
Belarus	15	5	0	5	0.0%	33.5%	93.3%
Herzegovina	17	5	5	3	47.2%	30.2%	94.1%
Bulgaria	21	6	6	4	13.1%	37.0%	85.7%
Croatia	27	4	4	0	81.2%	0.0%	55.6%
Czech Republic	8	5	5	4	73.2%	4.9%	100.0%
Egypt, Arab Rep.	13	6	6	1	10.3%	2.9%	46.2%
Estonia	9	5	5	0	22.4%	0.0%	88.9%
Georgia	12	6	6	0	16.4%	0.0%	58.3%
Hungary	11	5	5	0	11.4%	0.0%	54.5%
Jordan	15	0	0	2	0.0%	1.5%	26.7%
Kazakhstan	14	5	5	0	29.9%	0.0%	92.9%
Kyrgz Republic	9	4	4	0	11.9%	0.0%	100.0%
Latvia	10	5	0	5	0.0%	57.2%	60.0%
Lithuania	11	6	5	4	67.8%	20.0%	90.9%
Moldova	12	0	0	0	0.0%	0.0%	66.7%
Mongolia	9	3	0	3	0.0%	19.2%	88.9%
Montenegro	11	3	0	3	0.0%	26.7%	90.9%
Morocco	6	5	5	0	9.9%	0.0%	66.7%
North Macedonia	13	3	0	3	0.0%	39.4%	84.6%
Poland	18	6	6	0	91.7%	0.0%	33.3%
Romania	24	5	4	4	33.3%	13.0%	95.8%
Russian Federation	65	5	5	0	14.4%	0.0%	44.6%
Serbia	29	5	5	0	100.0%	0.0%	89.7%
Slovak Republic	7	4	4	2	44.5%	2.2%	71.4%
Slovenia	15	0	0	2	0.0%	2.7%	26.7%
Tajikistan	12	0	0	0	0.0%	0.0%	0.0%
Tunisia	14	4	0	4	0.0%	22.9%	100.0%
Turkey	15	5	5	3	42.2%	18.3%	93.3%
Ukraine	28	4	4	0	10.1%	0.0%	32.1%
Total	514						68.5%

Table 2.4 shows Credit Information Index values, credit reporting system characteristics and reported Credit Reporting Utility by country for the financial institutions included in the analysis.

Data sources: Credit reporting system characteristics: World Bank, Doing Business project (http://www.doingbusiness.org). “Credit Reporting Utility” is a derived variable sourced from EBRD’s Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). “Utility %” represents the percentage of institutions reporting “Credit Reporting Utility”, which equals 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was “frequently” or “very frequently” able to provide information about the credit histories of potential borrowers, and 3) the information provided was “frequently” or “very frequently accurate and reliable. Otherwise Credit Reporting Utility equaled 0.

Variable name explanations: CII=Credit Information Index. PCBI=Private credit bureau index. PCRI=Public credit registry index. PCB Coverage = Private credit bureau adult coverage rate. PCR Coverage = Public credit registry adult coverage rate.

Table 2.5. Presence of reporting system characteristics among private credit bureaus, by country, 2007.

Country	Firms & Individuals	Positive & Negative	Two-plus years	Right of Access	Amounts < 1%	Retailers/ Utilities
Albania	0	0	0	0	0	0
Armenia	0	0	0	0	0	0
Azerbaijan	0	0	0	0	0	0
Belarus	0	0	0	0	0	0
Bosnia and Herzegovina	1	1	1	0	1	1
Bulgaria	1	1	0	1	0	1
Croatia	0	0	0	0	0	0
Czech Republic	1	1	1	1	1	0
Egypt, Arab Rep.	0	0	0	0	0	0
Estonia	1	0	1	1	1	1
Georgia	0	0	0	0	0	0
Hungary	1	1	1	1	1	0
Jordan	0	0	0	0	0	0
Kazakhstan	1	1	0	1	1	0
Kyrgz Republic	1	0	1	1	0	0
Latvia	0	0	0	0	0	0
Lithuania	1	0	0	1	1	1
Moldova	0	0	0	0	0	0
Mongolia	0	0	0	0	0	0
Montenegro	0	0	0	0	0	0
Morocco	0	0	0	0	0	0
North Macedonia	0	0	0	0	0	0
Poland	0	1	1	1	1	1
Romania	0	1	1	1	1	0
Russian Federation	0	0	0	0	0	0
Serbia	1	1	1	0	1	0
Slovak Republic	0	1	0	1	1	0
Slovenia	0	0	0	0	0	0
Tajikistan	0	0	0	0	0	0
Tunisia	0	0	0	0	0	0
Turkey	0	1	1	1	1	0
Ukraine	0	0	0	0	0	0

Table 2.5., continued. Presence of reporting system characteristics among public credit registries, by country, 2007

Country	Firms & Individuals	Positive & Negative	Two-plus years	Right of Access	Amounts < 1%	Retailers/ Utilities
Albania	0	0	0	0	0	0
Armenia	1	1	0	1	0	0
Azerbaijan	1	1	1	1	0	0
Belarus	1	1	1	0	0	0
Bosnia and Herzegovina	0	0	0	0	0	0
Bulgaria	1	1	0	1	1	0
Croatia	0	0	0	0	0	0
Czech Republic	0	1	1	1	1	0
Egypt, Arab Rep.	1	1	0	0	0	0
Estonia	0	0	0	0	0	0
Georgia	0	0	0	0	0	0
Hungary	0	0	0	0	0	0
Jordan	1	1	0	0	0	0
Kazakhstan	0	0	0	0	0	0
Kyrgz Republ;ic	0	0	0	0	0	0
Latvia	1	0	1	1	1	0
Lithuania	1	1	1	1	0	0
Moldova	0	0	0	0	0	0
Mongolia	1	1	1	0	0	0
Montenegro	0	0	0	0	0	0
Morocco	1	0	0	0	0	0
North Macedonia	1	1	0	0	0	0
Poland	0	0	0	0	0	0
Romania	1	1	1	1	0	0
Russian Federation	0	0	0	0	0	0
Serbia	1	0	1	0	0	0
Slovak Republic	0	1	0	0	1	0
Slovenia	0	1	1	0	1	0
Tajikistan	0	0	0	0	0	0
Tunisia	1	0	0	0	0	0
Turkey	1	1	0	1	0	0
Ukraine	0	0	0	0	0	0

Table 2.5., continued. Presence of reporting system characteristics among private credit bureaus, by country, 2011

Country	Firms & Individuals	Positive & Negative	Two-plus years	Right of Access	Amounts < 1%	Retailers/ Utilities
Albania	0	0	0	0	0	0
Armenia	1	1	1	1	1	0
Azerbaijan	0	0	0	0	0	0
Belarus	0	0	0	0	0	0
Bosnia and Herzegovina	1	1	1	0	1	1
Bulgaria	1	1	1	1	1	1
Croatia	0	1	1	1	1	0
Czech Republic	1	1	1	1	1	0
Egypt, Arab Rep.	1	1	1	1	1	1
Estonia	1	0	1	1	1	1
Georgia	1	1	1	1	1	1
Hungary	1	1	1	1	1	0
Jordan	0	0	0	0	0	0
Kazakhstan	1	1	1	1	1	0
Kyrgz Republic	1	0	1	1	1	0
Latvia	0	0	0	0	0	0
Lithuania	1	1	0	1	1	1
Moldova	0	0	0	0	0	0
Mongolia	0	0	0	0	0	0
Montenegro	0	0	0	0	0	0
Morocco	1	1	1	1	1	0
North Macedonia	0	0	0	0	0	0
Poland	1	1	1	1	1	1
Romania	0	1	1	1	1	0
Russian Federation	1	1	1	1	1	0
Serbia	1	1	1	1	1	0
Slovak Republic	0	1	1	1	1	0
Slovenia	0	0	0	0	0	0
Tajikistan	0	0	0	0	0	0
Tunisia	0	0	0	0	0	0
Turkey	1	1	1	1	1	0
Ukraine	0	1	1	1	1	0

Table 2.5., continued. Presence of reporting system characteristics among public credit registries, by country, 2011

Country	Firms & Individuals	Positive & Negative	Two-plus years	Right of Access	Amounts < 1%	Retailers/ Utilities
Albania	1	1	1	1	1	0
Armenia	1	1	1	1	0	0
Azerbaijan	1	1	1	1	1	0
Belarus	1	1	1	1	1	0
Bosnia and Herzegovina	1	0	1	0	1	0
Bulgaria	1	1	0	1	1	0
Croatia	0	0	0	0	0	0
Czech Republic	0	1	1	1	1	0
Egypt, Arab Rep.	1	0	0	0	0	0
Estonia	0	0	0	0	0	0
Georgia	0	0	0	0	0	0
Hungary	0	0	0	0	0	0
Jordan	1	1	0	0	0	0
Kazakhstan	0	0	0	0	0	0
Kyrgz Republiic	0	0	0	0	0	0
Latvia	1	1	1	1	1	0
Lithuania	1	1	1	1	0	0
Moldova	0	0	0	0	0	0
Mongolia	1	1	1	0	0	0
Montenegro	1	1	0	0	1	0
Morocco	0	0	0	0	0	0
North Macedonia	1	1	0	1	0	0
Poland	0	0	0	0	0	0
Romania	1	1	1	1	0	0
Russian Federation	0	0	0	0	0	0
Serbia	0	0	0	0	0	0
Slovak Republic	0	1	0	0	1	0
Slovenia	0	1	1	0	0	0
Tajikistan	0	0	0	0	0	0
Tunisia	1	1	0	1	1	0
Turkey	1	1	0	1	0	0
Ukraine	0	0	0	0	0	0

Table 2.5 shows the presence/absence of individual components of the Credit Information Index by country for years 2007 and 2011. A value of 1 indicates the component is present.

Data source: Credit reporting system characteristics: World Bank, Doing Business project (http://www.doingbusiness.org).
Variable name explanations:

Firms & Individuals = Data on firms and individuals are distributed.
Positive & Negative = Positive and negative credit information are distributed.
Two-plus years= At least two years of historical data are distributed.
Right of Access= By law, borrowers have the right to access their data in the largest credit bureau or registry in the economy.
Amounts < 1% = Data on loan amounts below 1% of income per capita.
Retailers/Utilities= Data from retailers or utility companies are distributed.

2.5.4 Correlation of individual reporting system characteristics

Table 2.6 shows a correlation matrix of all 12 reporting system characteristics. As can be seen, all six PCB characteristics were statistically significantly (at $p<.001$ level) positively correlated with each other, and all six PCR characteristics were statistically significantly (at $p<.001$ level) positively correlated with each other, but all PCB individual characteristics were negatively correlated with all PCR characteristics, with all correlations being statistically significant (at $p<.001$ level), except the individual correlation between the variable indicating PCB included data from retailers and utilities and the PCR characteristics indicating at least two years of historical data are distributed, and by law, borrowers have the right to access their data in the largest PCR in the country.

Table 2.6. Correlation matrix of public credit registry reporting system characteristics

Credit reporting system characteristic	Firms & Individuals	Positive & Negative	Two-plus years	Right of Access	Amounts < 1%
Firms & Individuals	1	0.76****	0.52****	0.73****	0.51****
Positive & Negative	0.76****	1	0.57****	0.79****	0.49****
Two-plus years	0.52****	0.57****	1	0.54****	0.38****
Right of Access	0.73****	0.79****	0.54****	1	0.48****
Amounts < 1%	0.51****	0.49****	0.38****	0.48****	1

This table shows the correlation (as measured by the correlation coefficient) between components of the Credit Information Index specifically for public credit registry characteristics.

Data source: World Bank, Doing Business Project (www.doingbusiness.org).

Firms & Individuals = Data on firms and individuals are distributed.
Positive & Negative = Positive and negative credit information are distributed.
Two-plus years= At least two years of historical data are distributed.
Right of Access= By law, borrowers have the right to access their data in the largest credit bureau or registry in the economy.
Amounts < 1% = Data on loan amounts below 1% of income per capita.

Key to p-values: *: p<.1; **: p<.05; ***:p<.01:****:p<.001.

Table 2.6, continued. Correlation matrix of private credit bureau reporting system characteristics

Credit reporting system characteristic	Firms & Individuals	Positive & Negative	Two-plus years	Right of Access	Amounts < 1%	Retailers and/or Utilities
Firms & Individuals	1	0.61****	0.64****	0.61****	0.70****	0.46****
Positive & Negative	0.61****	1	0.87****	0.85****	0.92****	0.26****
Two-plus years	0.64****	0.87****	1	0.88****	0.95****	0.22****
Right of Access	0.61****	0.85****	0.88****	1	0.93****	0.17****
Amounts < 1%	0.70****	0.92****	0.95****	0.93****	1	0.32****
Retailers and/or Utilities	0.46****	0.26****	0.22****	0.17****	0.32****	1

This table shows the correlation (as measured by the correlation coefficient) between components of the Credit Information Index specifically for private credit bureau characteristics.

Data source: World Bank, Doing Business Project (www.doingbusiness.org).

Firms & Individuals = Data on firms and individuals are distributed.
Positive & Negative = Positive and negative credit information are distributed.
Two-plus years= At least two years of historical data are distributed.
Right of Access= By law, borrowers have the right to access their data in the largest credit bureau or registry in the economy.
Amounts < 1% = Data on loan amounts below 1% of income per capita.
Retailers/Utilities= Data from retailers or utility companies are distributed.

Key to p-values: *: p<.1; **: p<.05; ***:p<.01:****:p<.001.

Table 2.6, continued. Correlation matrix of private credit bureau and public credit registry reporting system characteristics

Credit reporting system characteristic	PCB: Firms & Individuals	PCB: Positive & Negative	PCB: Two-plus years	PCB: Right of Access	PCB: Amounts < 1%
PCR: Firms & Individuals	-0.24****	-0.31****	-0.43****	-0.45****	-0.39****
PCR: Positive & Negative	-0.41****	-0.43****	-0.56****	-0.44****	-0.52****
PCR: Two-plus years	0.25****	-0.23****	-0.35****	-0.39****	-0.29****
PCR: Right of Access	-0.18****	-0.19****	-0.31****	-0.19****	-0.25****
PCR: Amounts < 1%	-0.21****	-0.32****	-0.34****	-0.49****	-0.38****

This table shows the correlation (as measured by the correlation coefficient) between private credit bureau and public credit registry components of the Credit Information Index.

Data source: World Bank, Doing Business Project (www.doingbusiness.org).

Variable name explanations:

PCB=Private credit bureau. PCR=Public credit registry.
Firms & Individuals = Data on firms and individuals are distributed.
Positive & Negative = Positive and negative credit information are distributed.
Two-plus years= At least two years of historical data are distributed.
Right of Access= By law, borrowers have the right to access their data in the largest credit bureau or registry in the economy.
Amounts < 1% = Data on loan amounts below 1% of income per capita.
Retailers/Utilities= Data from retailers or utility companies are distributed.

Key to p-values: *: p<.1; **: p<.05; ***:p<.01:****:p<.001.

2.5.5 Credit Reporting Utility by adult coverage rates and select characteristics.

Tables 2.7 and 2.8 describe Credit Reporting Utility by adult coverage rates overall and stratified by year. As can be seen in the column labeled Total in Table 2.7, generally, as coverage rates increase in either PCB or PCR systems, Credit Reporting Utility increases, as would be expected. Table 2.8 provides further stratification, now showing the total and yearly percentage of Credit Reporting Utility, stratified by levels of both PCB coverage rates and PCR coverage rates. Table 2.8 shows that generally (as can be seen in the Total columns), the highest levels of Credit Reporting Utility are among institutions in countries with higher levels of both PCB and PCR coverage rates. Additionally, institutions in countries that had zero percent coverage rates in both PCB and PCR systems had the overall lowest rate (16.7%) of Credit Reporting Utility, and institutions in countries with the highest combined categorical levels of PCB and PCR coverage rates had the highest overall level of perceived Credit Reporting Utility (93.8%).

Table 2.7. Credit Reporting Utility, by adult coverage rates, years 2007 and 2011.

	Total		Year 2007		Year 2011	
	N	Utility %	N	Utility %	N	Utility %
Private Credit Bureau Adult Population Coverage %						
Zero	475	37%	321	23.1%	154	67.5%
> Zero and < 5%	30	67%	30	66.7%	0	0.0%
>= 5% and < 25%	260	57%	86	61.6%	174	55.2%
>=25%	263	75%	77	58.4%	186	81.7%
Public Credit Registry Adult Population Coverage (%)						
Zero	510	39%	258	22.5%	252	55.6%
> Zero and < 5%	255	46%	197	45.7%	58	46.6%
>= 5% and < 25%	176	87%	59	74.6%	117	94.0%
>=25%	87	86%	0	0.0%	87	86.2%

Table 2.7 shows the percentage of reported Credit Reporting Utility by different levels of private credit bureau and public credit registry adult population coverage rate, stratified by year.

Data sources: Adult population credit reporting system coverage rate: World Bank, Doing Business project (http://www.doingbusiness.org). “Credit Reporting Utility” is a derived variable sourced from EBRD’s Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). “Utility %” represents the percentage of institutions reporting “Credit Reporting Utility”, which equals 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was “frequently” or “very frequently” able to provide information about the credit histories of potential borrowers, and 3) the information provided was “frequently” or “very frequently accurate and reliable. Otherwise Credit Reporting Utility equaled 0.

Table 2.8. Credit Reporting Utility percentage, stratified by Private Credit Bureau and Public Credit Registry Adult Coverage Rates, years 2007 and 2011.

		Total		Year 2007		Year 2011	
Adult Coverage %		N	Utility %	N	Utility %	N	Utility %
PCB	PCR						
Zero	Zero	204	16.7%	180	14.4%	24	33.3%
Zero	> 0 and < 5%	176	36.9%	118	27.1%	58	56.9%
Zero	>= 5% and < 25%	95	83.2%	23	69.6%	72	87.5%
> 0 and < 5%	Zero	83	50.6%	34	50.0%	49	51.0%
> 0 and < 5%	> 0 and < 5%	43	72.1%	24	87.5%	19	52.6%
> 0 and < 5%	>= 5% and < 25%	42	81.0%	21	76.2%	21	85.7%
>= 5% and < 25%	Zero	125	56.0%	26	53.8%	99	56.6%
>= 5% and < 25%	> 0 and < 5%	87	80.5%	47	66.0%	40	97.5%
>= 5% and < 25%	>= 5% and < 25%	11	90.9%	0	0.0%	11	90.9%
>= 25%	Zero	63	34.9%	18	5.6%	45	46.7%
>= 25%	> 0 and < 5%	67	85.1%	23	78.3%	44	88.6%
>= 25%	>= 5% and < 25%	32	93.8%	0	0.0%	32	93.8%
Total		1028	52.9%	514	37.4%	514	68.5%

Table 2.8 shows the percentage of reported Credit Reporting Utility by different levels of private credit bureau and public credit registry adult population coverage rate, stratified by year.

Data sources: Adult population credit reporting system coverage rate: World Bank, Doing Business project (http://www.doingbusiness.org). “Credit Reporting Utility” is a derived variable sourced from EBRD’s Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). “Utility %” represents the percentage of institutions reporting “Credit Reporting Utility”, which equals 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was “frequently” or “very frequently” able to provide information about the credit histories of potential borrowers, and 3) the information provided was “frequently” or “very frequently accurate and reliable. Otherwise Credit Reporting Utility equaled 0. PCB=Private credit bureau. PCR=Public credit registry.

2.5.6 Credit Reporting Utility by select institution and country characteristics.

Table 2.9 describes the percentage of Credit Reporting Utility by select institution and country characteristics that based on the literature would be expected to be correlated with credit reporting utility. Overall, the results are in line with expectations. First, institutions with foreign ownership, particularly in cases where the foreign parent bank has significant influence on policies related to credit risk assessment of borrowers, have the highest percentage of Credit Reporting Utility for years 2007 and 2011 combined. Beck, et al. (2018) found that foreign-owned banks can overcome distance-related disadvantages (versus domestic banks) by implementing more conservative contract design (collateral, shorter loan maturities) and utilizing credit ratings and credit scoring models, which would likely rely on "hard" data such as credit repayment history (which would come from the bank's internal data and private and public credit reporting systems).

Table 2.9 also shows that institutions in countries with a legal system based on French civil law have overall a higher percentage of Credit Reporting Utility than institutions in countries with other legal systems. These results align with findings and observations of Djankov, et al. (2007), who elaborated the theory that two primary determinants of how much private credit a financial system will extend to businesses and individuals are 1) the power of creditors to enforce repayment guaranties (creditor rights), and 2) the availability of reliable information about a borrower's credit worthiness. Djankov, et al. (2007) found that countries with legal systems with origins in French civil law were weakest in creditor rights, but also were much more likely than other countries to have public credit registries. Therefore, in countries with weaker creditor rights, credit reporting systems providing information about a borrower's repayment history become even more important.

Table 2.9. Credit Reporting Utility, stratified by bank and country characteristics.

		Utility %		
Characteristic	N	Overall	Year 2007	Year 2011
Foreign Bank Ownership and Influence				
< 50% Foreign bank-owned	283	49.0%	31.8%	66.1%
>= 50% Foreign bank-owned and parent bank not an important/very important influence in credit assessment of borrowers	39	47.4%	33.3%	61.5%
>= 50% Foreign bank-owned and parent bank important/very important influence in credit assessment of borrowers	192	59.9%	46.4%	73.4%
Country's Income Group				
Low/Lower middle income	103	39.8%	23.3%	56.3%
Upper middle income	295	60.4%	44.1%	76.6%
High income	116	45.7%	32.8%	58.6%
French Civil Law Country				
Yes	111	64.9%	51.4%	78.4%
No	403	49.7%	33.5%	65.8%

Table 2.9 shows the percentage of financial institutions reporting Credit Reporting Utility, stratified by different levels of foreign ownership and management, the country's income group, and whether the financial institution is in a country with a legal origin in French Civil Law.

Data sources: French Civil Law Country indicates a country whose legal origin was in the civil law of France: (Djankov, McLiesh and Shleifer, 2007). Foreign Bank Ownership and Influence: is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). It equals 1 if the responding financial institution is more than 50% percent owned by a foreign bank and the foreign bank has an "important" or "very important" influence in shaping credit risk assessment of clients. Country's Income Group: World Bank, Doing Business project (http://www.doingbusiness.org).

The outcome variable, "Credit Reporting Utility" is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). "Credit Reporting Utility" equaled 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and 3) the information provided was "frequently" or "very frequently accurate and reliable. Otherwise, Credit Reporting Utility equaled 0.

2.5.7 Logistic regressions

Table 2.10 describes the results of three multiple logistic regression analyses which included as independent variables only factors used in development of the CII, as well as year (2011 vs. 2007). The purpose of these regressions was to see to what extent the variation in Credit

Reporting Utility can be explained by information already collected in development of the CII. As can be seen in Table 2.10, each successive logistic regression incorporates more potentially predictive information. Logistic regression #1 includes only the actual CII value and year. Logistic regression #2 replaces the CII with two derived sub-indices, one a PCB index, and the other a PCR index. Logistic regression #3 adds two more variables: the country's adult PCB coverage rate and the adult PCR coverage rate. The diagnostic value (in predicting the probability of an institution perceiving Credit Reporting Utility) is indicated by the ROC AUC statistic, which increases significantly with each successive addition of predictive information to the model, going from 0.73 in logistic regression #1 to 0.78 in logistic regression #2 to 0.79 in logistic regression #3.

Table 2.11 shows the results of logistic regression models 4, 5 and 6, which use the same variables as in models 1, 2 and 3, respectively, only in this case the index values take into consideration the number of years the country has had the reported index value. As seen in Table 2.11, the ROC AUC statistic for model 4 is slightly higher than the ROC AUC for model 1 (0.76 vs. 0.73), but there is no improvement in ROC AUC for model 5 vs. model 2 (0.76 vs. 0.78), or model 6 vs. model 3 (0.79 vs. 0.79). Therefore, the data from this survey do not support my hypothesis that adding information on the number of years credit reporting systems have had specific characteristics would improve a potential index's diagnostic accuracy.

Table 2.10. Logistic regression results for models 1-3.

	Model 1		Model 2		Model 3	
Variable	*B*	*S.E.*	*B*	*S.E.*	*B*	*S.E.*
Intercept	-1.136****	0.119	-1.702****	0.149	-1.603****	0.150
CII	0.344****	0.036				
Year 2011 (d)	0.462***	0.161	0.889****	0.152	0.604****	0.167
PCBI			0.250****	0.034	0.211****	0.040
PCRI			0.483****	0.045	0.364***	0.057
PCB Coverage (%)					0.837**	0.347
PCR Coverage (%)					3.830***	1.172
Area Under the ROC Curve	0.73		0.78		.79	

Table 2.10 shows factors independently associated with Credit Reporting Utility, after controlling for other factors.

Outcome variable: Credit Reporting Utility.
Independent variables:
CII = Doing Business Credit Information Index.
Year 2011 (d) = Dummy variable that equals 1 for year 2011 and 0 otherwise.
PCBI = Derived private credit bureau index.
PCRI = Derived public credit registry index.
PCB Coverage (%) = Private credit bureau adult coverage rate.
PCR Coverage (%) = Public credit registry adult coverage rate.

B represents the unit change in the natural logarithm of the odds of the outcome variable per unit change in the explanatory variable, after controlling for the other explanatory variables in the model. *SE* represents the standard error of *B*.

Area Under the ROC Curve is a measure of the model's ability to discriminate between institutions that did and did not perceive Credit Reporting Utility and represents the probability that a randomly selected institution perceiving Credit Reporting Utility would have a higher predicted model probability of perceiving this outcome than a randomly selected institution that did not perceive Credit Reporting Utility (Hanley and McNeil, 1982).

Data sources: Credit reporting system characteristics: World Bank, Doing Business project (http://www.doingbusiness.org). The outcome variable, "Credit Reporting Utility" is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). "Credit Reporting Utility" equaled 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and 3) the information provided was "frequently" or "very frequently accurate and reliable. Otherwise, Credit Reporting Utility equaled 0.

Table 2.11. Logistic regression results for models 4-6.

	Model 4		Model 5		Model 6	
Variable	*B*	*S.E.*	*B*	*S.E.*	*B*	*S.E.*
Intercept	-1.041****	0.111	-1.107****	0.113	-1.107****	0.114
Year 2011 (d)	0.141	0.173	0.206	0.177	1.051***	0.365
PCB Coverage (%)					4.664***	1.209
PCR Coverage (%)					0.130	0.180
CII-years adjusted	0.072****	0.008				
PCBI - years adjusted			0.055****	0.009	0.039***	0.011
PCRI - years adjusted			0.103****	0.011	0.067****	0.014
Area Under the ROC Curve	.76		.76		.79	

Table 2.11 shows factors independently associated with Credit Reporting Utility, after controlling for other factors.

Outcome variable: Credit Reporting Utility.
Independent variables:
Year 2011 (d) = Dummy variable that equals 1 for year 2011 and 0 otherwise.
CII-years adjusted= Doing Business Credit Information Index. In models 4,5, and 6, the index values used controlled for the number of years the country had had a particular reporting system characteristic. For example, if in 2011, a country's reporting system had distributed data on both firms and individuals for the past three years, then the value used for computing the index was '3'. If 2011 was the first year the reporting system had distributed these data, the value would be '1'.
PCBI-years adjusted = Derived private credit bureau index.
PCRI-years adjusted = Derived public credit registry index.
PCB Coverage (%) = Private credit bureau adult coverage rate.
PCR Coverage (%) = Public credit registry adult coverage rate.

B represents the unit change in the natural logarithm of the odds of the outcome variable per unit change in the explanatory variable, after controlling for the other explanatory variables in the model. *SE* represents the standard error of *B*.

Area Under the ROC Curve is a measure of the model's ability to discriminate between institutions that did and did not perceive Credit Reporting Utility and represents the probability that a randomly selected institution perceiving Credit Reporting Utility would have a higher predicted model probability of perceiving this outcome than a randomly selected institution that did not perceive Credit Reporting Utility (Hanley and McNeil, 1982).

Data sources: Credit reporting system characteristics: World Bank, Doing Business project (http://www.doingbusiness.org). The outcome variable, "Credit Reporting Utility" is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). "Credit Reporting Utility" equaled 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and 3) the information provided was "frequently" or "very frequently accurate and reliable. Otherwise, Credit Reporting Utility equaled 0.

Table 2.12 shows the results for models 7, 8 and 9, which add explanatory variables to the original models 1, 2, and 3. I don't envision that these added variables would be components of a new index, but that they may provide an indicator that greater diagnostic accuracy at predicting the percentage of Credit Reporting Utility could be obtained by adding additional variables. The variables added for models 7, 8 and 9 are 1) a categorical variable indicating the extent of foreign bank ownership and influence on credit decisions; 2) whether the country's legal system has its origin in French civil law; 3) a dummy variable for countries that have percentages of Credit Reporting Utility lower than what would be expected based on the other predictive criteria, and 4) a dummy variable for countries that have percentages of Credit Reporting Utility higher than what would be expected based on the other predictive criteria. These additional variables significantly improve the models' diagnostic accuracy at predicting the probability of Credit Reporting Utility. The ROC AUC statistic increases to 0.81 in logistic regression #7 (vs. 0.73 for its counterpart, model 1), to 0.84 in logistic regression #8 (vs. 0.78 in model 2), to 0.85 in logistic regression #9 (vs. 0.79 in model 3).

Table 2.12. Logistic regression results for models 7-9.

	Model 7		Model 8		Model 9	
Variable	*B*	*S.E.*	*B*	*S.E.*	*B*	*S.E.*
Intercept	-1.276****	0.173	-1.768****	0.195	-1.697****	0.197
CII	0.327****	0.038				
Year 2011 (d)	0.739****	0.174	1.192****	0.169	1.063****	0.187
PCBI			0.234****	0.037	0.247****	0.044
PCRI			0.588****	0.052	0.488****	0.067
PCB Coverage (%)					-0.176	0.391
PCR Coverage (%)					2.491**	1.141
French civil law country (d)	0.519***	0.187	-0.122	0.207	-0.060	0.213
Foreign bank ownership and influence (d)	0.249	0.157	0.088	0.166	0.084	0.168
Country with lower than expected credit reporting system utility (d)	-0.915****	0.172	-1.178****	0.185	-1.16****	0.193
Country with higher than expected credit reporting system utility (d)	1.193****	0.227	1.385****	0.234	1.371****	0.232
Area Under the ROC Curve	.81		.84		.85	

This table shows factors independently associated with Credit Reporting Utility, after controlling for other factors.

Outcome variable: Credit Reporting Utility.
Independent variables:

CII= Doing Business Credit Information Index.
Year 2011 (d) = Dummy variable that equals 1 for year 2011 and 0 otherwise.
PCBI = Derived private credit bureau index.
PCRI = Derived public credit registry index.
PCB Coverage (%) = Private credit bureau adult coverage rate.
PCR Coverage (%) = Public credit registry adult coverage rate.
French civil law country (d).
Foreign bank ownership and influence (d).
Country with lower than expected credit reporting system utility (d)*.
Country with higher than expected credit reporting system utility (d)*.

* A separate multiple logistic regression (not shown in the tables) was conducted for each country, with a dummy variable created for that country. Other explanatory variables included in the regression are the derived PCB and PCR indices, the PCB and PCR adult coverage rates, a dummy variable for year 2011, whether the country's legal system has an origin in French civil law and a categorical variable indicating the extent of foreign-ownership and influence on credit risk assessment. After controlling for these other variables, countries with associations at a less than .10 level of statistical significance were classified as either "High Credit Reporting Utility" or "Low Credit Reporting Utility" countries, depending on the direction of the beta coefficient. To be classified as a “High” country,

the beta coefficient must be positive, and the p-value must be less than .10. “Low” countries must have a negative beta coefficient, and a p-value less than .10.

B represents the unit change in the natural logarithm of the odds of the outcome variable per unit change in the explanatory variable, after controlling for the other explanatory variables in the model. *SE* represents the standard error of *B*.

Area Under the ROC Curve is a measure of the model's ability to discriminate between institutions that did and did not perceive Credit Reporting Utility and represents the probability that a randomly selected institution perceiving Credit Reporting Utility would have a higher predicted model probability of perceiving this outcome than a randomly selected institution that did not perceive Credit Reporting Utility (Hanley and McNeil, 1982).

Data sources: Credit reporting system characteristics: World Bank, Doing Business project (http://www.doingbusiness.org). French civil law country indicates a country whose legal origin was in the civil law of France: (Djankov, McLiesh and Shleifer, 2007). Foreign Bank Ownership and Influence: is a derived variable sourced from EBRD’s Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). It equals 1 if the responding financial institution is more than 50% percent owned by a foreign bank and the foreign bank has an “important” or “very important” influence in shaping credit risk assessment of clients.

The outcome variable, “Credit Reporting Utility” is a derived variable sourced from EBRD’s Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). “Credit Reporting Utility” equaled 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was “frequently” or “very frequently” able to provide information about the credit histories of potential borrowers, and 3) the information provided was “frequently” or “very frequently accurate and reliable. Otherwise, Credit Reporting Utility equaled 0.

Table 2.13 applies models 1, 2 and 3 to the subset of observations in which the CII value was greater than ‘0’. These models are labeled as models 10, 11, and 12, which correspond to models 1, 2 and 3, respectively. The results show that the CII, and private credit bureau (PCB) index, lose their rank-ordering ability above a CII of ‘0’. The public credit registry (PCR) index retains its statistically significant positive association with Credit Reporting Utility. The ROC AUC of 0.575 for model #10 shows how weakly correlated (and, in a negative direction) the CII is with the percentage of Credit Reporting Utility once the CII goes above ‘0’.

Table 2.13. Logistic regression results for models 10-12.

	Model 10		Model 11		Model 12	
Variable	*B*	*S.E.*	*B*	*S.E.*	*B*	*S.E.*
Intercept	1.559***	0.457	-0.117	0.333	-0.113	0.332
CII	-0.250**	0.104				
Year 2011 (d)	0.657***	0.194	0.650***	0.193	0.607***	0.215
PCBI			-0.037	0.062	-0.086	0.066
PCRI			0.423***	0.060	0.451****	0.083
PCB Coverage (%)					0.759**	0.346
PCR Coverage (%)					-0.477	1.338
Area Under the ROC Curve	.58		.71		.73	

Models 10-12 limit the logistic regression analysis to countries whose Credit Reporting Index (CII) value was greater than 0. This table shows factors independently associated with Credit Reporting Utility, after controlling for other factors.

Outcome variable: Credit Reporting Utility.
Independent variables:
CII = Doing Business Credit Information Index.
Year 2011 (d) = Dummy variable that equals 1 for year 2011 and 0 otherwise.
PCBI = Derived private credit bureau index.
PCRI = Derived public credit registry index.
PCB Coverage (%) = Private credit bureau adult coverage rate.
PCR Coverage (%) = Public credit registry adult coverage rate.

B represents the unit change in the natural logarithm of the odds of the outcome variable per unit change in the explanatory variable, after controlling for the other explanatory variables in the model. *SE* represents the standard error of *B*.

Area Under the ROC Curve is a measure of the model's ability to discriminate between institutions that did and did not perceive Credit Reporting Utility and represents the probability that a randomly selected institution perceiving Credit Reporting Utility would have a higher predicted model probability of perceiving this outcome than a randomly selected institution that did not perceive Credit Reporting Utility (Hanley and McNeil, 1982).

Data sources: Credit reporting system characteristics: World Bank, Doing Business project (http://www.doingbusiness.org). The outcome variable, "Credit Reporting Utility" is a derived variable sourced from EBRD's Banking Environment and Performance Survey II (https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html). "Credit Reporting Utility" equaled 1 if all of the following conditions were met: the financial institution, 1) had obtained information from private credit bureaus or public credit registries for Retail and SME borrowers; 2) reported that the credit reporting system was "frequently" or "very frequently" able to provide information about the credit histories of potential borrowers, and 3) the information provided was "frequently" or "very frequently accurate and reliable. Otherwise, Credit Reporting Utility equaled 0.

2.6 Conclusion

While this study was being conducted, in September 2021 the World Bank discontinued publication of its Doing Business Report and stated that it plans to create a new report within two years. An external panel review of the Doing Business report and methodology published in September 2021 came up with several recommendations, which will not be detailed here. However, one of the panel's recommendations, that the report should seek to measure actual conditions facing a representative cross-section of firms (Alfaro, et al., 2021), links closely to the methodology and recommendations of this study. Although the panel was referring to the Doing Business methodology in general and not to that of the Credit Information Index, their recommendation that it would be helpful to replace or complement the current methodology of using only expert contributors to describe the state of conditions impacting businesses with a survey sample of actual business owners and managers is directly analogous to the methodology I propose here to validate the Credit Information Index (CII). The value of an index of this type would increase by defining outcomes of interest, routinely surveying users of the credit reporting system, and refining the index to optimize its correlation with the desired outcomes. In the context of the Credit Information Index, the firms that should be surveyed are banks and other financial institutions that use credit reporting system information for credit decision-making, as well as borrowers.

This study's methodology seeks to validate the predictive value of the CII by determining the correlation between levels of the CII and the percentage of lenders that used credit reporting information and found the information to be available and reliable for credit decision-making. Using this validation approach, I identified some straightforward potential improvements to the CII. First, by creating two sub-indices, one for private credit bureaus and the other for public credit registries, a significantly more predictive index can be obtained. Therefore, a revised index should take into consideration whether a country has one or the other type of system, or both. An index becomes even more predictive by taking into greater consideration credit registry/bureau coverage rates, the higher the coverage rate, the more useful the reporting system.

After controlling for reporting system characteristics, I found that there are significant country-specific factors influencing the levels of perceived Credit Reporting Utility that could potentially be identified to further refine the indices.

In examining potential confounding variables, through univariate analysis I find that lenders in countries with a legal system with origins in French Civil Law and lenders that were majority foreign owned where the foreign parent bank had significant influence on credit assessment had higher percentages of perceived Credit Reporting Utility than lenders without these characteristics. Based on previous research (Djankov, et al., 2007, Beck, et al., 2018) these outcomes would be expected.

Independent of the Credit Information Index and other covariates, bank usage of credit bureau/registry information for Retail and SME lending and lender perceptions of the availability and reliability of credit reporting information increased significantly between 2007 and 2011. There are probably at least a few explanations for this. First, the credit reporting systems became more seasoned and attained more years of reporting history between 2007 and 2011, particularly the private credit bureaus. All else equal, the more years of credit history contained in the credit reports, the more useful for credit decision-making the reporting would likely be. The Credit Information Index considers whether a public or private credit reporting system contains at least two years of data; however, the source research which informed the development of the Index identified that reporting systems with at least five years of credit history were associated with more private credit (Djankov, McLiesh and Shleifer, 2007). Therefore, the significance of the year 2011 dummy variable could simply be an indicator of a deeper and more seasoned credit reporting system. A potential refinement to the Index would be to weight the values based on a combination of the number of years of credit reporting with the adult population coverage rate.

Another reason for the increased use was likely due to the combination of availability and lender necessity. Over the four-year period of 2007-11 credit portfolio quality declined markedly in many countries, and therefore, use of informative bureaus to screen borrowers became even more important. For example, between 2007 and 2011, non-performing loan (NPL) ratios increased from 3.0% to 11.8% in Bosnia and Herzegovina, from 2.6% to 14.3% in Romania, and from 2.4% to 5.2% in the Czech Republic (https://databank.worldbank.org/reports).

This study has some natural limitations. First, and foremost, the CII was validated using a methodology that I designed, availing of the opportunity to use data from the BEPS II that directly asked lenders about their use and perceptions of credit reporting system information. To my knowledge, the developers of the CII have not indicated that their objective in developing the index is to maximize the percentage of lenders reporting Credit Reporting Utility. I introduced that approach. There is some justification in this choice of validation methodology. It aligns with IFC's approach for measuring the effectiveness of credit reporting providers (IFC, 2020), and it fits the spirit of the World Bank panel's recommendation that a revised Doing Business report should take the actual experience of firms more into consideration (Alfaro, et al., 2021). Nevertheless, there are potentially many other outcomes to use for validation of a credit reporting system index. Ideally, the developers would propose potential validation methods as part of the development process.

Other limitations of this study are that it focused only on banks in EBRD countries that responded to the BEPS II and indicated that they engaged in Retail and SME lending. Additionally, the study does not focus on the current situation of credit reporting systems or of the Credit Information Index methodology, both of which have evolved since 2011. The Credit Information Index was enhanced in 2015.[14] In many EBRD countries credit reporting systems improved substantially between 2007 and 2015. The substantial gains in use and usefulness of credit reporting information in Albania, Belarus, and Moldova between 2007 and 2011 were very likely due to significant improvements in reporting systems during those years. For example, in 2009 Albania established its first credit bureau, Belarus eliminated the minimum threshold for credits reported to the public credit registry's database and guaranteed borrowers' right to inspect their own data in the credit registry, and Moldova enacted a new law to facilitate establishment of a private credit bureau. And since 2011, reporting systems have continued to improve. Tajikistan, for example, established a private credit bureau in 2014, which by 2015 was already providing credit scores.[15]

[14] https://www.doingbusiness.org/en/methodology/changes-to-the-methodology
[15] https://www.doingbusiness.org/en/reforms/overview/topic/getting-credit

Despite the above limitations, it's noteworthy how generally the percentage of Credit Reporting Utility does align with the underlying factors determining the CII and with the research findings of Djankov, et. al (2007) and Beck, et al. (2018). So, the proposed methodology seems to be directionally correct. However, the data raise some questions. How, for example, could 16.7% of lenders perceive Credit Reporting Utility when the adult coverage rate in their country (in both public credit registries and private credit bureaus was 0%? The only possible explanation is that either the coverage rate data were not entirely accurate, or, that the lender's responses were not accurate. Therefore, the results should likely be interpreted directionally and not for absolute accuracy.

This paper contributes to the literature by introducing a simple method for validating an index of credit reporting system quality. Assessment of the association between index values and lender use and perceptions of reporting system usefulness could lead to further refinement of indices and improved reporting systems.

3 Global Survey on Use of and Success with Credit Scoring for Small Business Lending

3.1 Introduction

Use of credit scoring has been associated with an expansion of credit to small businesses (Frame, Srinivasan and Woosley, 2001; Frame, Padhi and Woosley, 2004; Berger, Frame and Miller, 2005), a group with historically restricted access to finance (IFC, 2010). Credit expansion can result from credit scores' more efficient, accurate quantification of borrower risk, which permits more precise risk-based pricing and expansion of lending to riskier marginal borrowers at higher interest rates, as well as expansion of a lender's geographic market beyond its branch network (Akhavein, Frame and White, 2005). This positive impact led to credit scoring's promotion and application throughout the world (IFC, SME Banking Knowledge Guide, 2010, USAID, 2006, Vidal and Barbon, CGAP, 2019).

Given the benefits of credit scoring, are there specific factors associated with successful use for small business lending? Or can any financial institution, regardless of market, size, risk appetite, or model data source used successfully apply the technology? The objective of this research is to make a practical contribution to help inform financial institutions and development organizations of characteristics associated with successful use of credit scoring, to facilitate and make more effective their efforts to promote and implement this technology.

This study's intent is to provide a comparison of institutions in developing countries that have and have not succeeded in using credit scoring for small business lending. The financial institutions solicited for participation either had a client relationship with the International Finance Corporation (IFC) or were members of the IFC's SME Finance Forum. The study results are limited by sample size and potential response bias; the sample included in the final analysis was only 26, the vast majority of which had experienced at least some success with use of credit scoring. More broadly generalizable results would come from a much larger study of this type.

In general, there was a common theme among responding financial institutions reporting being "very successful" with use of credit scoring; they were more likely to use models with data sources related to repayment history and deposit information and more likely to rely on and use credit scores for credit decisions for existing customers. Credit performance with the institution was one of the most used model data sources and was on average deemed by respondents to have the highest predictive value.

The study highlights a key characteristic of small business lending throughout the world, which is that most credit decisions are for existing customers (credit and/or deposit) of the institution. Among respondents, on average, of loan originations, 65% are made to existing borrowers of the institution, 59% are made to existing depositors of the institution, and 14% are made to depositors who do not yet have credit with the institution. Only 20% of originations are to customers that are new to the financial institution.

Given this customer distribution, there is significant value that can be derived from applying credit scoring to a financial institution's existing customers. Financial institutions have potentially much more information on the credit risk of their existing customers (credit and/or deposit) than of applicants that are new to the bank. Whereas credit bureau data are likely essential for an effective credit risk assessment of an institution's non-customers, among an institution's existing customers repayment history and deposit data contain potentially valuable information for ascertaining credit risk (Puri, et al., 2017, FinRegLab, 2019, Vidal and Barbon, 2019). Repayment history with the financial institution, deposit history, and updated credit bureau information (to inform about the borrower's credit with other lenders) are a potentially powerful combination for credit scoring. Additionally, as credit scores are used across the full spectrum of credit origination and portfolio risk management, applying credit scoring to decisioning strategies of existing customers can result in more cost-effective risk measurement, improved customer experience, more refined risk-based pricing, earlier detection of warning signs of credit deterioration, and improved portfolio quality monitoring.

Much research interest focuses on the potential value of credit scoring for expanding access to unbanked borrowers, by using alternative data and/or new credit scoring technologies (e.g., machine learning). This interest is understandable considering the large number of unbanked micro and small businesses and the consensus that existing traditional data sources (i.e., credit bureau data) and credit scoring technologies may have limited additional potential to bring the unbanked into the formal financial system. However, for credit risk assessment of an institution's existing customers (credit and/or deposit), the incremental predictive value of alternative data sources may be limited, as recently suggested by Berg, et al. (2021). Additionally, use of alternative data and/or machine learning-based credit scoring systems brings its own set of risks and model risk management and regulatory compliance challenges. Additional research should explore the question of for which segments (e.g., the unbanked applying for microcredit), alternative data add the most value over existing data sources. Research should also seek to compare the value of credit expansion initiatives to borrowers who are currently new to the institution versus those that are existing depositors who do not yet have a credit relationship.

3.1.1 Background on credit scoring

Credit scoring for consumer lending was first introduced in the United States in the 1950s and began being used on a wide scale for small business lending in the 1990s (Mester, 1997, Miller and Rojas, 2004), used primarily for loan amounts up to $100k (Berger and Udell, 2006). The breakthrough for using credit scoring for small business lending came in the mid-1990s, when it was recognized that the risk of small business loan default was strongly correlated with the personal credit risk of the small business owner (Mester, 1997). This resulted in development of predictive credit scores that incorporated the owner's consumer credit history with additional firmographic variables about the small business. Over the next decade, use of credit scoring for small business lending expanded to banks in developing countries, as well (Wendel and Harvey, 2006, Beck, Demirguc-Kunt, Peria 2008, De la Torre, Peria and Schmukler, 2010).

The early research on credit scoring's use for and impact on small business lending was conducted amid a secular trend in the United States of banking consolidation and greater geographical separation between lenders and their borrowers (Berger, Frame and Miller, 2005, DeYoung, Glennon and Nigro, 2007). Historically, small business lending was more the domain of smaller "community" banks, who made credit approval decisions of "informationally opaque" small businesses based on "soft" qualitative information, acquired through local community knowledge of the borrower (Berger and Udell, 2006). The prevailing view was that large banks made small business loan decisions based on "hard" data (i.e., audited financial statements), and the concern was that because small businesses did not have the type of accounting information needed for approval, banking consolidation to fewer, larger banks could result in less credit availability for small businesses. Credit scoring became recognized as a new form of "hard" data, and several key studies (Frame, Srinivasan and Woosley, 2001; Frame, Padhi and Woosley, 2004; Berger, Frame and Miller, 2005) focused on describing the usage of credit scoring among large institutions and the resulting impact on credit availability for small businesses. Subsequent research conducted in 2005 identified that in the U.S., 46 percent of community banks were using credit scores for decisioning small business loans up to $50,000 (Berger, Cowan, and Frame, 2010). The scores used were the personal credit bureau scores of the small business owners.

There has been limited academic research which distinguishes between the types of financial institutions and markets associated with successful use of credit scoring for small business lending. Studies on the diffusion of innovations across the financial services industry are relatively lacking (Frame and White, 2004). A study on the diffusion of credit scoring found that banking firms with more branches and those located in New York were more likely to adopt credit scoring earlier than other institutions (Akhavein, Frame and White, 2005). A study of financial institutions in Italy found that banks with large branch networks and those with large market shares in concentrated markets were more likely to be successful early adopters of credit scoring (Bofondi and Lotti, 2006). A global study of 91 large banks across 45 countries found that foreign banks were more likely than domestic banks to use transaction-based lending and more centralized business models, although the research did not specifically identify that foreign-owned banks were more likely to use credit scoring (Beck, Demirgüç-Kunt, Pería, 2011).

Although the literature has documented the use of credit scoring and its benefits for small business lending, there remains an information gap, which is a description of the characteristics of financial institutions that are more likely to succeed in its development and use. This topic is of practical importance because credit scoring is not equally effective everywhere, and financial institutions across the world are working to implement the technology. This study's objective is to provide detailed characteristics of financial institutions and their small business lending programs associated with successful use of credit scoring. In this regard, the study provides a unique contribution to the literature, which has either focused on the effect of credit scoring on small business lending (Frame, Srinivasan and Woosley, 2001; Frame, Padhi and Woosley, 2004; Berger, Frame and Miller, 2005), without providing details about key factors contributing to credit scoring's effectiveness, or focused on comparing the effectiveness of alternative versus traditional data and credit scoring methodologies in one specific lender (Arraiz, Ortega and Stucci, 2018, Jagtiani and Lemieux, 2019).

In this study I seek to test several potential factors associated with success with credit scoring for SME lending. A primary factor for consideration is extent of credit reporting infrastructure in the country. For many years industry practitioners have recognized credit reporting's importance for reducing information asymmetries and expanding credit access. The World Bank initiated the Global Credit Reporting Program in 2001 to promote development of credit bureaus around the world (IFC, 2012). There have been significant advances globally in this area over the past few decades. Between 2005 and 2020 of over 150 economies tracked by the World Bank, the percentage of private credit bureaus or public credit registries with at least two years of historical data increased from 34 to 70, and from 2014 to 2020, the percentage of economies with a generic private bureau or public registry credit score increased from 34 to 56 (World Bank, Doing Business)[16]. Empirically, credit information systems are associated with access to credit. A study across 63 countries between 2002 and 2013 identified that after introduction of a credit bureau, the likelihood that a business obtains access to finance increases (Peria, Soledad and Singh, 2014). Use of credit scoring is likely to be more challenging in countries with a less developed credit reporting infrastructure, due to limited availability of timely, accurate, and reliable data in credit bureaus and registries, reluctance of financial institutions to share borrower credit data with credit bureaus, due to concerns about loss of competitive advantage, as well as inadequate record management and MIS systems in financial institutions (Miller and Rojas, 2004, Wendel and Harvey, 2006).

There are several additional factors to consider. For several reasons credit scoring is likely most appropriate for use by lenders with large unit volumes of small, standardized loans, a risk appetite permitting controlled higher loss rates while pricing for risk, using data sources that include borrower repayment history and cash-flow. High quality credit bureau/registry data, or if not available, internal relationship data on credit performance and deposit history may be an essential data source. In the absence of, or in conjunction with, credit bureau/registry data, a financial institution's internal relationship data, deposit and/or credit, can be a significant contributor to a successful credit scoring model and process (Puri, et al., FinRegLab, 2019, Vidal and Barbon, 2019). Lenders that use credit scores that incorporate the deposit history of their borrowers will likely have more effective credit scores, as the level and trend of deposit inflows, outflows and balances can be indicators of borrower cash-flow and liquidity. The 2017 IFC report, *Alternative Data Transforming SME Finance*, indicated that banks have their own valuable data, such as the business owners' daily transaction data that provides visibility into the business's cash flows and credit capacity, but may not be using it (Wilhelm and Owens, 2017).

The institutions that responded to this survey, most of which are experiencing some level of success with credit scoring, are using relationship data; over 75% are using business deposit data in their credit scoring models. However, in general, across the world small business depositors are a relatively under-tapped source of small business loans and therefore, credit scoring data. An analysis of 144 deposit-taking financial institutions reporting to IFC's REACH survey in 2019 reveals that total micro, small and medium-sized enterprise (MSME) loan balances outstanding represent only 5.5% of MSME deposit balances.[17]

The size of the institution may affect success with credit scoring. The limited available research on this topic shows that large financial institutions are early adopters (Frame and White, 2004, Akhavein, Frame and White, 2006) of financial innovation in general and of credit scoring. Large institutions would likely have the resources, data, and economies of scale to develop their

[16] https://www.worldbank.org/en/programs/business-enabling-environment/doing-business-legacy

[17] International Finance Corporation (IFC) REACH database, 2019.

own credit scoring models, but smaller institutions may not. Although research identified two decades ago that community banks were successfully using consumer credit bureau scores for small business lending (Berger, Cowan, and Frame, 2011), these scores were generic and obtained from the credit bureaus; they were not developed within each community bank. Therefore, there is still a question of how large an institution should be to succeed at using credit scoring in markets without a well-established publicly available credit reporting infrastructure and credit scoring services.

Interrelated with the size of the institution and resources available for credit scoring programs is the extent of credit risk management and model risk management. The financial institution needs to have the resources available to have credit risk managers that understand the models and how to use them effectively, and model risk management teams that can ensure that the models are reviewed and validated on a periodic basis and that there is "effective challenge" to the models and their use. In my personal experience conducting an evaluation of an innovative alternative credit score being applied throughout the world, I observed that several financial institutions did not have staff with the expertise to effectively evaluate the models and their associated strategies. Lack of effective model risk management can result in poor outcomes for the financial institution as well as for its customers.

Other factors potentially associated with success (or lack of) with credit scoring include the significant cost of developing and maintaining credit scoring tools, small market sizes not justifying the significant investment, and an inadequate number of defaulted loans available for model development, among others (Miller and Rojas, 2004, Wendel and Harvey, 2006). Having sufficient predictive data is fundamental for building statistical models. To build an effective statistical application scoring model may require up to 2,000 defaulted accounts in the development sample (Siddiqi, 2006). The number of defaulted accounts is a function of several factors, including the size of the MSME credit portfolio, the institution's credit risk appetite, economic conditions, and whether sufficient performance and application data are accessible in a database.

Lenders that have dedicated business lending departments for Micro, Small, Medium, and Large enterprises in which credit scoring is applied to Micro and Small will likely have more success at using credit scoring than lenders that treat all businesses with a similar approach and attempt to use credit scoring for medium and large enterprises. This is due to several factors. As the size of a business increases, it becomes more complex, with unique credit needs, requiring case-by-case evaluation, credit structuring and management. Standardized product programs are appropriate for micro and small businesses but not for larger ones. Furthermore, there is a significant drop off in unit volumes and increase in loan sizes. With low unit volumes of large, non-standardized loans, development of a robust, predictive credit score can be very challenging. Many lenders across the world may not recognize this limitation of credit scoring. In my own experience, I once consulted with a smaller bank in a transitioning economy that was seeking to develop a credit score to use on its portfolio of about 40 medium-sized borrowers, none of which had become delinquent, and each with credit exposures exceeding one million dollars. Small sample sizes for model development can lead to model "over-fitting", which can result in a model being too closely trained to its development data sample only to lose predictive ability on new borrowers.

The use of "alternative" data sources may also be associated with successful use of credit scoring for small business lending. Over the past ten years, financial technology companies throughout the world have worked to take credit scoring and digital lending to the next level, developing models based on both "traditional" (the credit bureau) scoring data, as well as alternative data sources such as mobile phone usage, social media usage, geographic location, psychometric tests, demographic data, and "digital footprints", among others (Owens and Wilhelm, 2017, Arraiz, Ortega and Stucci, 2018, Berg, et al., 2019, Jagtiani and Lemieux, 2019). Across the financial services industry, there is now a significant amount of interest in "alternative" data for credit scoring as well as alternative scoring methods (e.g., machine learning). Research indicates that in certain contexts, use of "alternative" data is more predictive than "traditional" data, and use of machine learning is more predictive than logistic regression models (Gambacorta, et al, 2019, Shi, et al, 2022). It would be beneficial to determine under what conditions (e.g., quality of the credit reporting infrastructure, type of alternative data available), for which segments (e.g., loan amounts, the unbanked versus existing customers), and for which purposes (e.g., fraud screening, credit underwriting, account management, portfolio monitoring) alternative data sources and new scoring approaches add significant incremental value.

A significant challenge for use of machine learning models is that they can be "black boxes", with a lack of transparency about how the determination of credit risk was made (Shi, et al, 2022). This could in many cases preclude their use for decisioning of credit applications, as regulations such as the U.S. Equal Credit Opportunity Act (ECOA) require lenders to provide reasons for credit denial (U.S. Consumer Finance Protection Bureau).[18] The need for an "explainable" model is a major constraint on use of machine learning for credit decisioning. To work towards addressing this challenge, in 2018 leaders in industry and academia initiated the Explainable Machine Learning Challenge, where contestants were given a home equity line of credit performance dataset and challenged to develop a "black box" machine learning model for loan default and make it explainable.[19] In this competition, a special award was given to one team that developed a fully-explainable model, based on traditional linear modeling, that was almost as predictive as opaque black-box models (Rudin and Radan, 2019). A key question, then, is "does this black box really provide that much "lift" in predictive power?" There may be contexts when they do not.

Amid inherent historical challenges and new developments, several questions arise concerning practices and level of success with use of credit scoring for small business lending among financial institutions throughout the developing world. Questions include, is credit scoring being used for small business lending? For which purposes? What is the institution's level of success with using credit scoring? Do the institutions have model risk management programs? What are the key benefits derived from using credit scoring, and what are the key challenges with using it? How useful are credit bureau/registry data and credit bureau scores for informing the credit decision? What are the data sources being used for the credit scoring models, and what is the observed predictive value of those sources? Are institutions using and finding value from alternative data and new scoring techniques for their models?
In effort to answer the above and other questions, in collaboration with SME Finance Forum I created an online survey and solicited by email approximately 80 financial institutions from

[18] https://files.consumerfinance.gov/f/201306_cfpb_laws-and-regulations_ecoa-combined-june-2013.pdf
[19] https://www.fico.com/en/newsroom/fico-announces-winners-inaugural-xml-challenge.

across the world that either had a client relationship with the International Finance Corporation (IFC) or were members of the IFC SME Finance Forum. Per IFC's website, IFC "… helps to build the capacity of financial intermediaries and to raise awareness of best SME-banking practices". The SME Finance Forum "works to expand access to finance for small and medium businesses. The Forum operates a global membership network of +240 members that brings together financial institutions, technology companies, and development finance institutions to share knowledge, spur innovation, and promote the growth of SMEs."

Of the institutions solicited, 46 started the survey, and 33 responded to at least most of the questions. With as many respondents as possible, I followed up the online survey with a video call to clarify responses. Responding institutions came from 28 different countries, located across the world. The final analysis was restricted to 26 institutions across 19 countries that provided lines or loans to small businesses, were in one specific country and used credit scoring for small business lending.

The focus of the study was on use of credit scoring for small business loans at origination that had approved amounts from $1,000-$100,000. I selected this range to focus on loan amounts larger than the very smallest micro-loans, yet small enough where the upper bound of the range is still conducive to use of credit scoring. Among the 26 respondents included in the analysis the median institution loan balances outstanding were $1.8 billion, with a median 8,178 small business loans and $131MM in small business loan balances between $1,000-$100,000. The median average small business loan balance was $10,518.

The rest of this paper is organized as follows. Section 3.2 describes the study methodology. Section 3.3 presents results. Section 3.4 concludes.

3.2 Methodology

I created an online survey and solicited participation by email from approximately 80 financial institutions from across the world that either had a client relationship with IFC or were members of the IFC SME Finance Forum. To include information on the credit reporting infrastructure in the study participant's country, I merged survey data by country with the World Bank's Doing Business Credit Information Index data. When possible, with many of the respondents I conducted preliminary and follow-up video calls to introduce the study and gain clarification on responses. The study, including survey and follow-up, was conducted over a two-year period between 2020-2022.

The intent of the survey was to compare along several dimensions institutions that were and were not having success with using credit scoring for MSME lending. Due to the relatively limited number of responses, and that most responders were having at least some level of success with using credit scoring, the use of statistical significance testing for comparative analysis was limited. Therefore, the results are mostly descriptive. Nevertheless, I did conduct statistical significance testing in assessing factors associated with institutions having been "very successful" at using credit scoring.

The primary **outcomes** of interest were whether the institution was using credit scores in some way for MSME lending, management's subjective assessment of their use of credit scoring to date level of success, which ranged from "tried using the score, but it has not been successful" to "a work in progress", to "somewhat successful" and at the top of the range, "very successful". Other outcome questions pertained to how credit scores are being used for credit decisioning, including for underwriting and account management and the degree to which they are relied on to inform/make the credit decision, and the benefits (e.g., faster turn-around times, reduced loan origination costs, increased underwriting effectiveness) derived from use of credit scoring. The remainder of the survey was aimed at identifying potential factors that could explain the level of success (or lack of) with use of credit scoring.

Explanatory variables I hypothesized to be associated with credit scoring success covered several dimensions, including the quality of the country's **credit reporting infrastructure**; **financial institution factors** such as the size of the financial institution and its MSME credit portfolio, the average size of the MSME credit facility, whether the financial institution has standardized credit products for MSME lending, the bank's risk appetite, as assessed by the average loss rate in their MSME credit portfolio and whether the institution employs risk-based pricing, where (Retail, Commercial, a dedicated SME unit) in the organization the department that lends to MSMEs is located, whether the financial institution had dedicated units for credit risk management for small business lending, model validation and model risk management, the level of education of the FI's credit scoring modelers, whether the FI had a loan origination system (LOS) and databases on customer applications and performance, whether the FI had a process for validating the accuracy of data in databases, and whether the institution had experienced any common challenges (e.g., data not predictive of default, data not in a database, insufficient number of defaults, difficulty in hiring/retaining experienced modelers) with developing effective credit scoring models; **underwriting due diligence and predictive data source** factors including the extent of MSME customer relationship with the financial institution at the time of loan origination/credit scoring, elements reviewed during the underwriting process, including whether a visit was made to the small business premises, data sources used in the credit scoring models and management's assessment of the predictive value of each data source, whether the credit products are unsecured or secured by collateral and the type of collateral, and whether the FI had used machine learning for their credit scoring modeling and their assessment of the relative value of machine learning versus traditional statistical scoring methods.

As credit reporting infrastructure is potentially fundamental to successful use of credit scoring, the study aimed to determine the availability and usefulness of credit reporting data through two means. External data was obtained from the World Bank's Doing Business Credit Information Index to provide an objective assessment of the quality of credit reporting systems in the country. Also, the survey contained several questions aimed at determining the financial institution's subjective assessment of the credit reporting system's data for informing the credit decision, including the data's depth (quantity and length of credit history), breadth (type of information collected), and predictive value, as well as their opinion of how effective credit bureau/registry scores are for assessing credit risk of small business borrowers.

Another potential explanatory variable is the unit and dollar volume of the financial institution's MSME credit portfolio for loans at origination from $1,000-$100,000. This is a potentially significant factor for a variety of reasons. Credit scoring models are most effective when used for loan portfolios with large unit volumes of relatively small, standardized credits. Ceterus paribus, the larger the MSME loan portfolio, the more effective the development and application of credit scoring models. For most responding institutions, data on the size of the MSME credit portfolio from $1,000-$100,000 was obtained from the IFC's REACH database.

The survey asked about the type of data sources used for credit scores, and the lender's assessment of the predictive value of the data source. I also sought to determine whether the financial institution was more likely to apply credit scores to decisions for existing credit customers of the bank versus completely new customers.

The types of credit scores asked about included a credit bureau/registry score, an in-house developed statistical score, an in-house developed "expert" score, a vendor-developed statistical score, and a vendor-developed "expert" score.

3.3 Results

Of the 26 respondents included in the analysis, 11 are in countries with a Doing Business Credit Information Index score of '8' (the highest score possible); six are based in countries with an Index level of '7'; six are based in countries with an Index of '6', and three are in countries with an Index level of '4'. The mean Credit Information Index was 6.9 (Table 3.3).

The mean private credit bureau coverage as a percentage of the adult population was 27.8%, and the mean public registry coverage was 14.8%. Thirty-five percent (35%) of responding institutions are in countries with no private credit bureau coverage, and 39% are in countries with no public registry coverage. Fifty-eight percent (58%) of respondents are in countries which have a generic private credit bureau score and 15% have a public credit registry score (Table 3.3).

Of respondents, for 20 (69%) the most common product offered was a loan, either for working capital, equipment, or an unspecified reason. Other primary products were overdraft (11% of respondents), real estate loan (8%) and working capital line (4%).

The most common location from which an application is submitted was a branch or other office (92%), online (50%), from headquarters (46%), and in the field (via a tablet, for example) (35%). The most common location for making the credit decision was headquarters (54%), followed by a centralized unit (46%), branch (42%), and automated (35%).

There were 22 responses to the question of whether a visit to the business premises is made as part of the underwriting due diligence; of respondents, 20 (91%) conduct a premises visit.

There were 25 responses to the question of whether the borrower is required to provide collateral for the loan. Of respondents, 24 (96%) require collateral for at least some percentage of loans. On average, 64% of loans require collateral. For lenders, the most important collateral for making a credit approval were cash/liquid securities (54%) and real estate (40%).

For their SME lending business, 62% of respondents currently use a credit bureau/registry score, 50% use a custom statistical score developed within the institution; 58% use an “expert” (non-statistical) score developed within the institution; 23% use a statistical score developed by a vendor, and 8% use an expert score developed by a vendor (Table 3.5). The responding institutions had been using some type of credit score for a median of 10 years.

Of the 26 respondents, 19 (73.1%) reported being “somewhat” or “very” “successful” at using credit bureau/registry scores for MSME lending. In contrast, only one respondent (3.9%) reported this level of success with using vendor non-statistical scores (Table 3.6).

Twenty-five respondents (92%) have scores which use repayment history (either performance with the bank, credit bureau/registry information, or performance on micro-credit), and 81% have scores that use both repayment history and the borrower’s deposit data with their institution (Table 3.7). Of potential data sources, on average, the participants in this study consider performance with the bank as the most predictive scoring variable; alternative data sources such as social media and mobile phone data had the lowest usage and perceived predictive value (Table 3.8).

Four financial institutions reported using machine learning for their credit scoring models. Two institutions reported that machine learning models were similar in predictive power to traditional statistical models, and two reported that machine learning models are not uniformly superior to traditional models but add value for certain purposes (e.g., fraud scoring) or certain segments (e.g., sparse data).

To approve credit applications, 12% use credit scores independently, 62% use scores in conjunction with policy rules, 69% use scores as one input to a judgmental credit decision, and 31% use scores to automatically decline applications. Although 88% of lenders differentiate price at loan origination by risk, 23% percent use scores to inform loan origination risk-based pricing. For existing credit customers, 58% use credit scores for early warning indicators, 54% for auto or streamlined credit renewal, 42% for line increase decisions, 39% for auto-approval of new credit, 31% for risk-based pricing, and 15% use scores for loss forecasting (Table 3.9).

Most credit decisions for MSME loans at origination from $1,000-$100,000 are made to existing (credit and/or deposit) customers of the financial institution. On average, new to the financial institution customers comprised only 20.3% of credit approvals (Table 3.4). Fifty-eight (58%) percent of respondents rely more on credit scores for decisioning of existing borrowers than new applicants (Table 3.9).

Concerning credit and model risk management, 23% have a dedicated risk management department for lending for small businesses, 81% have a model risk management unit, 73% have a model validation team, 54% validate models at least annually, and 23% conduct out-of-time back-testing analysis for model development/validation (Table 3.10).

Concerning data, 69% have data on all applicants, 96% have data on approved applications, 65% have data on declines, 73% have a loan origination system for small business lending. Eighteen respondents (69%) indicated they can link application with performance data (Table 3.11).

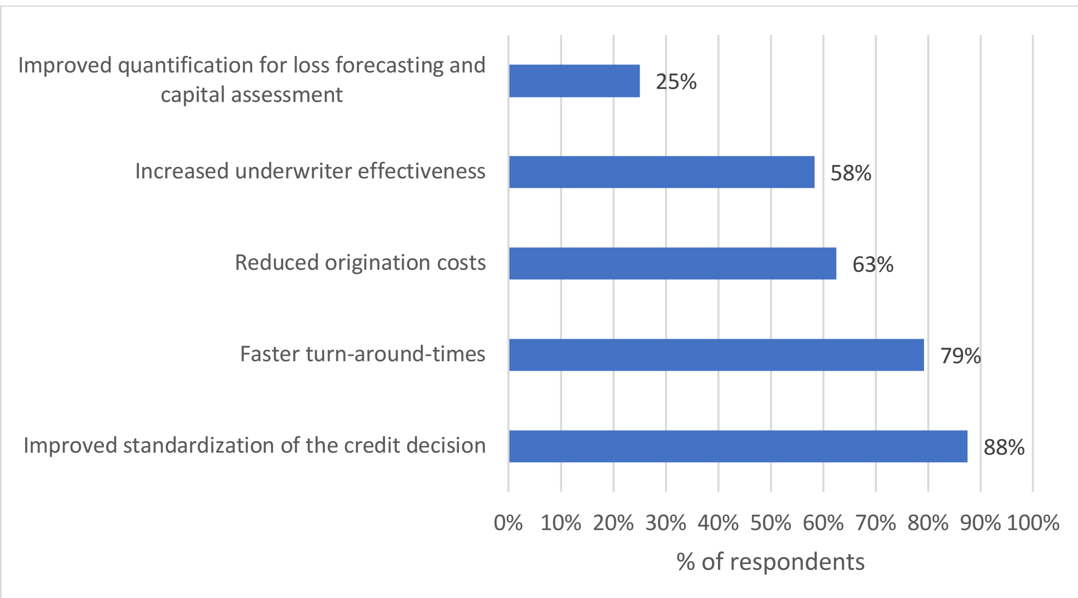
Organizationally, for the group that extends small business loans up to $100,000, 62% are a dedicated SME department, 19% are in Retail, 15% are in Retail for small loans and Commercial for medium, and 4% are in Commercial (Table 3.12).

3.3.1 Success and Challenges with Using Credit Scoring

Overall, 23 (88%) report having been either "somewhat successful" or "very successful" with use of some type of credit scoring for MSME lending, with 13 (50%) reporting having been "very successful". By type of credit score, the highest "very successful" percentage (23%) was with use of a credit bureau/registry score (Table 3.6).

Concerning benefits derived from using credit scoring, of 24 respondents, 88% indicated that use of scores improved standardization of credit decisioning, 79% reported faster credit decision turn-around times, 63% indicated reduced origination costs, 58% reported improved underwriter effectiveness, and 25% reported improved quantification of risk (Figure 3.1).

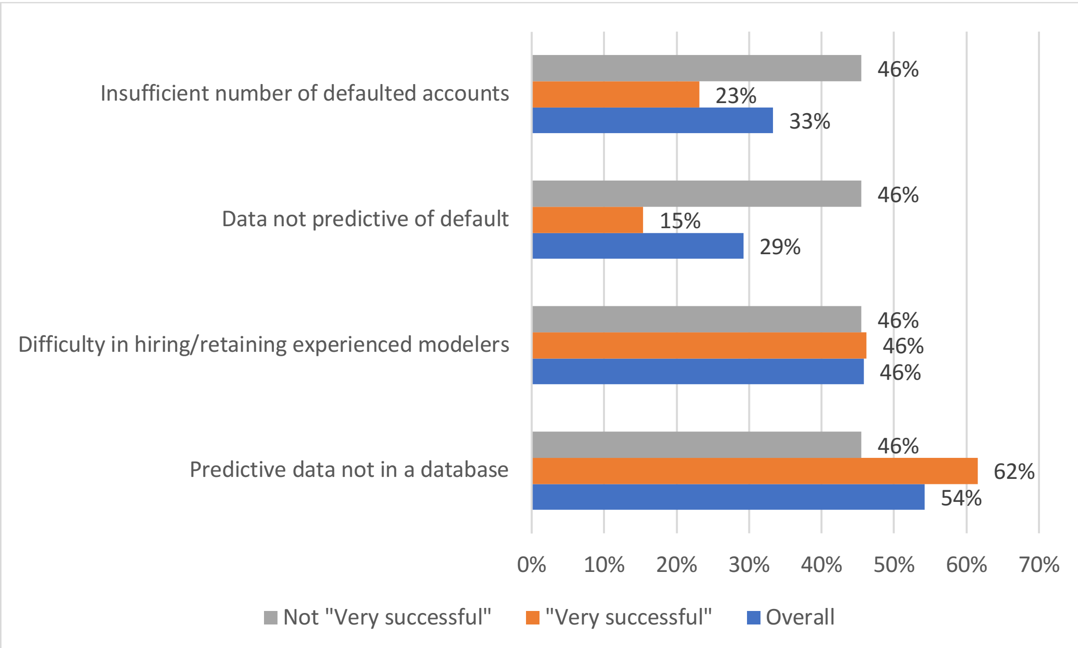
Figure 3.1. Responding financial institution benefits derived from using credit scoring.



Source: Survey responses from 24 financial institutions.

Concerning challenges for developing an effective credit scoring model, 54% indicated that predictive data were not in a database, 46% reported having difficulty in hiring/retaining experienced modelers, 29% reported that data were not predictive of default, and 33% reported that there were an insufficient number of defaults to build a model (Figure 3.2).

Figure 3.2. Responding financial institution challenges with developing an effective credit score, by level of success.



Source: Survey responses from 24 financial institutions.

3.3.2 Factors associated with "very successful" usage of credit scoring.

Because of the small sample size, the results must be interpreted with caution; however, as shown in Table 3.13, factors that were positively associated (at a minimum of $p < .10$ level) with "very successful" use of credit scoring include having a database which includes data on all applicants, use of model data sources that included both repayment history and current/savings account data or business current/savings account data, and model usage applied to account management of existing customers, including line increase strategies and risk-based pricing of existing customers.

Table 3.1. Country of responding financial institutions.

Country	N	%
Bangladesh	3	11.5
Cambodia	2	7.7
Cameroun	1	3.9
Ghana	2	7.7
Honduras	2	7.7
India	1	3.9
Indonesia	1	3.9
Kenya	2	7.7
Kosovo	1	3.9
Mongolia	1	3.9
Nigeria	2	7.7
Palestine	1	3.9
Qatar	1	3.9
Romania	1	3.9
Singapore	1	3.9
South Africa	1	3.9
Turkey	1	3.9
Ukraine	1	3.9
Zambia	1	3.9

Source: Survey responses from 26 financial institutions.

Table 3.2. Total loan balances of responding financial institutions.

	Total		"Very Successful"			
Total Loan Balances	N	%	Yes	%	No	%
< $1 Billion	10	38.5%	4	30.8%	6	46.2%
$1 Billion - < $2 Billion	4	15.4%	1	7.7%	3	23.1%
>= $2 Billion	12	46.2%	8	61.5%	4	30.8%

Source: Survey responses from 26 financial institutions.

Table 3.3. Credit reporting system characteristics and financial institution assessment.

Variable	Data Source	N	%
Private Credit Bureau Coverage	1	26	27.8%
Public Credit Registry Coverage	1	26	14.8%
Private Bureau Coverage is 0%	1	26	35.0%
Public Credit Registry Coverage is 0%	1	26	39.0%
Country has a Private Credit Bureau Score	1	26	58.0%
Country has a Public Credit Registry Score	1	26	15.0%
Country has COVID Forbearance programs	2	26	96.0%
Financial Institution Uses a Credit Bureau/Registry Score	2	26	61.5%
		N	Mean
Doing Business Credit Information Index	1	26	6.9
Breadth of Business Credit Bureau/Registry Data	2	23	2.7
Breadth of Individual Credit Bureau/Registry Data	2	23	3.5
Depth of Business Credit Bureau/Registry Data	2	23	3.0
Depth of Individual Credit Bureau/Registry Data	2	23	3.7
Predictive Value of Business Credit Bureau/Registry Data	2	23	2.4
Predictive Value of Individual Credit Bureau/Registry Data	2	23	3.1

This table shows select credit reporting system characteristics for the countries in which the responding financial institutions are located, as well as the responding financial institution's perception of the breadth, depth, and predictive value of the credit reporting system information.

Note: For Breadth, Depth and Predictive Value questions, respondents answered to a scale of 1-5, with 1 being "poor", "limited", and 5 being "excellent", "extensive".

Data sources Key: 1= World Bank: Doing Business 2020: Comparing Business Regulation in 190 Economies (Washington, DC: World Bank, 2020). 2=Survey responses from 23-26 financial institutions.

Table 3.3., continued. Credit reporting system characteristics and financial institution assessment, stratified by reported level of success with credit scoring.

				"Very Successful"			
Variable	Data Source	N	%	Yes	%	No	%
Private Credit Bureau Coverage (%)	1	26	27.8%	13	25.0%	13	30.7%
Public Credit Registry Coverage (%)	1	26	14.8%	13	12.3%	13	17.4%
Private Bureau Coverage is 0%	1	26	35.0%	13	30.8%	13	38.5%
Public Credit Registry Coverage is 0%	1	26	39.0%	13	46.2%	13	30.8%
Country has a Private Credit Bureau Score	1	26	58.0%	13	53.8%	13	61.5%
Country has a Public Credit Registry Score	1	26	15.0%	13	15.4%	13	15.4%
Country has COVID Forbearance programs	2	26	96.0%	13	92.3%	12	100.0%
Financial Institution Uses a Credit Bureau/Registry Score	2	26	61.5%	13	61.5%	13	61.5%
		N	Mean	Yes	Mean	No	Mean
Doing Business Credit Information Index	1	26	6.9	13	6.7	13	7.0
Breadth of Business Credit Bureau/Registry Data	2	23	2.7	10	2.5	13	2.9
Breadth of Individual Credit Bureau/Registry Data	2	23	3.5	10	3.4	13	3.5
Depth of Business Credit Bureau/Registry Data	2	23	3.0	10	2.6	13	3.2
Depth of Individual Credit Bureau/Registry Data	2	23	3.7	10	3.6	13	3.8
Predictive Value of Business Credit Bureau/Registry Data	2	23	2.4	10	2.6	13	2.2
Predictive Value of Individual Credit Bureau/Registry Data	2	23	3.1	10	3.3	13	2.9

This table shows select credit reporting system characteristics for the countries in which the responding financial institutions are located, as well as the responding financial institution's perception of the breadth, depth, and predictive value of the credit reporting system information, stratified by the responding financial institution's reported level of success with using credit scoring.

Note: For Breadth, Depth and Predictive Value questions, respondents answered to a scale of 1-5, with 1 being "poor", "limited", and 5 being "excellent", "extensive".

Data sources Key: 1= World Bank: Doing Business 2020: Comparing Business Regulation in 190 Economies (Washington, DC: World Bank, 2020). 2=Survey responses from 23-26 financial institutions.

Table 3.4. Distribution of small business loan originations, by customer relationship and level of success with using credit scoring.

			"Very Successful"			
Customer Type	Total	%	Yes	%	No	%
Existing Credit Customers	26	65.2	13	66.4%	13	64.0%
Existing Depositors	26	59.4	13	66.2%	13	52.7%
Existing Credit and Deposit Customers	26	44.9	13	49.8%	13	39.9%
New Customers	26	20.3	13	17.3%	13	23.2%
Existing Depositors but not Credit	26	14.5	13	16.3%	13	12.8%

Data source: Survey responses from 26 financial institutions.

This table describes the distribution of small business loan originations, stratified by customer relationship and the financial institution's reported level of success with using credit scoring.

Table 3.5. Type of credit score used by responding financial institution, stratified by the institution's reported level of success with using credit scoring.

			"Very Successful"			
Type of credit score	Total	%	Yes	%	No	%
Credit bureau score	26	61.5%	13	61.5%	13	61.5%
In-house built expert (non-statistical score)	26	57.7%	13	61.5%	13	53.8%
In-house built statistical score	26	50.0%	13	53.8%	13	46.2%
Outside vendor expert (non-statistical) score	26	7.7%	13	0.0%	13	15.4%
Outside vendor statistical score	26	23.1%	13	23.1%	13	23.1%

Data source: Survey responses from 26 financial institutions.

This table describes the type of credit score used, stratified by the financial institution's reported level of success with using credit scoring. For example, 61.5% of financial institutions that reported "very successful" use of credit scoring used a credit bureau score, versus 61.5% of financial institutions that did not.

Table 3.6. Financial institution reported level of success with using credit scores, by type of score.

Type of credit score	Total	Very successful	Somewhat successful	Still a work in progress	Tried using, not successful	Have not used
Credit bureau score	26	23.1%	50.0%	11.5%	3.9%	11.5%
Vendor statistical score	26	3.8%	11.5%	11.5%	3.8%	61.5%
In-house statistical score	26	19.2%	30.8%	11.5%	0.0%	38.5%
Vendor (non-statistical)	26	0.0%	3.9%	3.9%	7.7%	80.8%
In-house (non-statistical)	26	19.2%	23.1%	15.4%	0.0%	38.5%

Data source: Survey responses from 26 financial institutions.

Table 3.6 describes the financial institution's reported level of success with using credit scoring, stratified by the type of credit score used. For example, 23.1% of financial institutions reported use of credit bureau scores to be "very successful". Note: of the 26 respondents, 13 (50%) reported having been "very successful" with using at least one kind of credit score.

Table 3.7. Data sources used in credit scores, by level of success with using credit scores.

Credit Score Data Source	Total	%
Repayment History	26	92.3%
Credit Performance with the Financial Institution	26	88.5%
Repayment History and Current/Savings Account Data	26	80.8%
Individual Credit Bureau/Registry Report	26	76.9%
Business Current/Savings Account Data	26	76.9%
Firmographic Data	26	73.1%
Collateral	26	73.1%
Individual Current/Savings Account Data	26	69.2%
Financial Statement Information	26	69.2%
Business Credit Bureau/Registry Report	26	65.4%
Demographic Data	26	61.5%
Performance on Micro-credit	26	53.8%
Mobile Phone Data	26	23.1%
Utility Bill Data	26	23.1%
GPS data	26	19.2%
Social Media Data	26	19.2%
Psychometric Data	26	0.0%

Data source: Survey responses from 26 financial institutions.

This table describes the financial institutions reported data sources used in credit scores. For example, 92.3% of institutions use credit scores that include repayment history as a data source.

Table 3.7, continued. Data sources used in credit scores, by level of success with using credit scores.

	Very Successful				
Credit Score Data Source	Yes	%	No	%	Statistical significance
Repayment History	13	100.0%	13	84.6%	
Credit Performance with the Financial Institution	13	92.3%	13	84.6%	
Repayment History and Current/Savings Account Data	13	100.0%	13	61.5%	**
Individual Credit Bureau/Registry Report	13	84.6%	13	69.2%	
Business Current/Savings Account Data	13	100.0%	13	53.8%	**
Firmographic Data	13	84.6%	13	61.5%	
Collateral	13	84.6%	13	61.5%	
Individual Current/Savings Account Data	13	69.2%	13	69.2%	
Financial Statement Information	13	76.9%	13	61.5%	
Business Credit Bureau/Registry Report	13	76.9%	13	53.8%	
Demographic Data	13	53.8%	13	69.2%	
Performance on Micro-credit	13	46.2%	13	61.5%	
Mobile Phone Data	13	23.1%	13	23.1%	
Utility Bill Data	13	30.8%	13	15.4%	
GPS data	13	30.8%	13	7.7%	
Social Media Data	13	23.1%	13	15.4%	
Psychometric Data	13	0.0%	13	0.0%	

Data source: Survey responses from 26 financial institutions.

This table describes the financial institution's reported data sources used in credit scores., stratified by the financial institution's reported level of success with using credit scoring. For example, of institutions that report being "very successful" with using credit scoring, 100% use credit scores that include borrower's repayment history and current/savings account data, versus 61.5% of those that do not report being "very successful".

Key to p-values: * p<.1; ** p<.05.

Table 3.8. Average perceived predictive value of credit score data sources.

Data Source	N	Mean
Credit Performance with the Financial Institution	25	4.24
Performance on Micro-credit	17	4.06
Business Credit Bureau/Registry Report	19	4.00
Individual Credit Bureau/Registry Report	21	4.00
Business Current/Savings Account Data	20	3.95
Individual Current/Savings Account Data	18	3.55
Collateral	19	4.00
Financial Statement Information	18	3.72
GPS data	4	3.50
Demographic Data	18	2.94
Firmographic Data	20	3.65
Social Media Data	5	3.00
Mobile Phone Data	6	3.38
Utility Bill Data	9	3.56

Data source: Survey responses from 26 financial institutions.

This table shows responding financial institutions' average perceived predictive value of various data sources. Value range: 2=Not at all predictive; 3=Not very predictive; 4=Somewhat predictive; 5=Very predictive. The data source with the highest predictive value was Credit Performance with the Financial Institution, with an average value of 4.24.

Table 3.9. Uses of credit scoring for credit monitoring and decisioning.

Use	Total	%
Loan origination	26	76.9%
Auto-approval using score only	26	11.5%
Auto-approval using score + policy rules	26	61.5%
Auto-decline	26	30.8%
Risk-based pricing	26	23.1%
As an input to a judgmental credit decision	26	69.2%
Account management	26	73.1%
Early warning review	26	57.7%
Auto-approval of existing borrowers for new credit	26	38.5%
Auto-renewal	26	53.8%
Line increase strategies	26	42.3%
Loss forecasting	26	15.4%
Risk-based pricing of existing customers	26	30.9%
Rely more for credit decisions of existing borrowers	26	57.7%

Data source: Survey responses from 26 financial institutions.

Table 3.9 shows responding financial institution use of credit scoring for small business lending. For example, 30.8% of financial institutions report using credit scores for auto-decline decisions.

Table 3.9., continued. Uses of credit scoring for credit monitoring and decisioning, by level of success with credit scoring.

	"Very Successful"				
Use	Yes	%	No	%	Statistical significance
Use for loan origination	13	84.6%	13	69.2%	
Auto-approval using score only	13	15.4%	13	7.7%	
Auto-approval using score + policy rules	13	61.5%	13	61.5%	
Auto-decline	13	30.8%	13	30.8%	
Risk-based pricing	13	23.1%	13	23.1%	
As an input to a judgmental credit decision	13	53.8%	13	84.6%	*
Use for account management	13	92.3%	13	53.9%	**
Early warning review	13	61.5%	13	53.8%	
Auto-approval of existing borrowers for new credit	13	53.8%	13	23.1%	
Auto-renewal	13	69.2%	13	38.5%	
Line increase strategies	13	61.5%	13	23.1%	**
Loss forecasting	13	23.1%	13	7.7%	
Risk-based pricing of existing customers	13	54.0%	13	7.7%	**
Rely more for credit decisions of existing borrowers	13	69.2%	13	46.2%	

Data source: Survey responses from 26 financial institutions.

The continuation of Table 3.9 shows responding financial institution use of credit scoring for small business lending, stratified by level of success with using credit scoring. For example, 92.3% of institutions reporting being "very successful" use credit scores for account management purposes, versus 53.9% of those that did not report this level of success.

Key to p-values: * p<.1; ** p<.05.

Table 3.10. Credit and model risk management characteristics.

Credit/Model Risk Management Characteristic	Total	%
Have a dedicated credit risk management	26	23.1%
Have a model risk management unit	26	80.8%
Have a model validation team	26	73.1%
Validate models at least annually	26	53.7%
Conduct out-of-time backtesting analysis	26	23.1%

Data source: Survey responses from 26 financial institutions.

Table 3.10 shows responding financial institution credit and model risk management characteristics. For example, 80.8% of respondents have a model risk management team within the institution.

Table 3.10., continued. Credit and model risk management, by level of success with using credit scoring.

	"Very Successful"			
Model Risk Management Characteristic	Yes	%	No	%
Have a dedicated credit risk management	13	23.1%	13	23.1%
Have a model risk management unit	13	76.9%	13	84.6%
Have a model validation team	13	69.2%	13	76.9%
Validate models at least annually	13	61.2%	13	46.2%
Conduct out-of-time backtesting analysis	13	15.4%	13	30.8%

Data source: Survey responses from 26 financial institutions.

The continuation of Table 3.10 shows responding financial institution credit and model risk management characteristics, stratified by institution level of success with using credit scoring. For example, 61.2% of institutions reporting being "very successful" with using credit scoring validate models at least once annually, versus 46.2% of institutions not reporting this level of success.

Table 3.11. Data characteristics, by level of success.

			"Very Successful"				
Data Characteristic	Total	%	Yes	%	No	%	Statistical significance
Have data on all applicants	26	69.2%	13	84.6%	13	53.8%	*
Have data on approved applications	26	96.2%	13	100.0%	13	92.3%	
Have data on declined applications	26	65.4%	13	76.9%	13	53.8%	
Have a loan origination system for small business lending	26	73.1%	13	76.9%	13	69.2%	
Can link application and performance data	18	100.0%	10	100.0%	8	100.0%	
Have a process for validating accuracy of model data	9	88.9%	6	83.3%	3	100.0%	

Data source: Survey responses from 26 financial institutions.

This table shows data and data management characteristics of responding financial institution, stratified by level of success with using credit scoring. For example, 69.2% of institutions reporting being "very successful" with use of credit scoring have data on all applicants, versus 53.9% of those that did not report this level of success.

Key to p-values: * p<.1; ** p<.05.

Table 3.12. Organizational location of SME department, by level of success.

			"Very Successful"			
Location of SME Lending Department	Total	%	Yes	%	No	%
Commercial	26	3.9%	13	7.7%	13	0.0%
Dedicated SME department	26	61.5%	13	61.5%	13	61.5%
Retail	26	19.3%	13	7.7%	13	30.8%
Retail for Small, Commercial for Medium	26	15.4%	13	23.1%	13	7.7%

Data source: Survey responses from 26 financial institutions.

This table shows the organizational location of the responding financial institution, stratified by level of success with using credit scoring. For example, regardless of the institution's level of success with using credit scoring, 61.5% of institutions have a dedicated department for SME lending.

Table 3.13. Factors associated with "very successful" use of credit scoring.

Variable	Category	Association	Statistical significance
Repayment history and current/savings account	Data source	Positive	**
Business current/savings account	Data source	Positive	**
As an input to a judgmental credit decision	Usage	Negative	*
Account management	Usage	Positive	**
Line increase strategies	Usage	Positive	**
Risk-based pricing of existing customers	Usage	Positive	**

Data source: Survey responses from 26 financial institutions.

This table summarizes factors significantly associated with "very successful" use of credit scoring. As shown, significant positive associations relate to usage for account management strategies, such as line increase programs and risk-based pricing of existing customers. Lenders that use credit scores as an input to a judgmental credit decision are less likely to report "very successful" use of credit scoring.

Key to p-values: * p<.1; ** p<.05.

3.4 Discussion

Over the past twenty years there have been several studies concerning credit scoring for small business lending. Early studies focused on whether credit scoring, primarily a credit bureau score of the small business owner, as a new form of "hard data", resulted in expanded small business access to credit. In recent years several studies have focused on whether alternative data sources and new credit scoring techniques (e.g., machine learning) can sustainably expand access beyond the already banked population. However, to date there are no global studies on use of credit scoring for small business lending in developing countries and key factors associated with success. More data on this subject would help financial institutions and development agencies focus their credit scoring efforts on initiatives that would be more likely to succeed. This study is an attempt to fill this gap and describe usage and compare institutions with and without success.

Methods for evaluating the credit risk of small business borrowers are evolving rapidly. Machine learning models and alternative data sources are increasingly being applied across the world. This rapid change introduces significant model and credit risk. It is essential for development organizations promoting credit scoring and its innovations to take stock of financial institution success levels and their ability to effectively develop, validate, implement, monitor, and manage these models.

This genesis of this study came from observations from my own professional experience. I spent many years as a credit risk manager for small business lending at one of the United States' largest banks that was one of the pioneering institutions in using credit scoring for MSME lending. Through this experience I learned about key prerequisites for successful use of credit scoring. In parallel, with a variety of development organizations I consulted with financial institutions in developing markets on credit risk management and credit scoring for MSME lending. Through these field visits, I saw many cases where it appeared that the institution's efforts at developing and using credit scoring would not succeed, due to the absence of key prerequisites for success. These observations led me to believe that resources were possibly being expended globally on initiatives with limited prospects of success. Beyond just wasted resources, I observed several cases where models were not being effectively managed, leading to increasing risk for the lenders and potentially unnecessarily adverse outcomes for the borrowers. For this reason, I sought to identify the factors associated with successful outcomes, and to document them.

Although the study sample size is small, there are some noteworthy results. First, although the study included institutions from countries across emerging markets, most of the respondents are having at least some level of success with using credit scoring for MSME lending, and half report having been "very successful". This indicates that successful use of credit scoring for small business lending is attainable for financial institutions in emerging markets across the world. This result seemed somewhat surprising to me, as it contrasted with my field observations. However, it could be that the results are due to response bias, and that only the institutions that were having some level of success chose to complete the survey. The study in any case can serve as a descriptor of characteristics of financial institutions having success with credit scoring, although it cannot provide analysis and insights about those that have not succeeded.

The respondents have several characteristics which seem conducive to successful use of credit scoring. First, in general the credit reporting infrastructure (as measured by the Doing Business Credit Information Index and its underlying components) was well-established, with only a few exceptions. This is instrumental, as the foundation of "traditional" credit scoring are data on a borrower's repayment history. Most lenders conduct a premises visit to the borrower's place of residence/business; given that credit scoring results in potentially a mostly automated decision, confirmation that the business premises exist and are in good condition is a prudent component of the process. Most respondents are using risk-based pricing, indicating that their risk appetite is directed at balancing risk versus return, rather than aimed at loss minimization, which would possibly be less likely to result in successful use of credit scoring. Most lenders have dedicated teams for model risk management and model validation and validate models at least once annually. This is very important, as the ability to independently validate models and provide "effective challenge" is an essential determinant of long-run success with credit scoring.

"Very successful" lenders are more likely to incorporate business deposit data, use deposit data combined with repayment history, rely more on credit scores for decisioning existing customers, and use credit scores for account management strategies, such as line increase programs, risk-based pricing, auto-renewal, or approval of additional credit. Given that a financial institution's knowledge of their own customer, through analysis of repayment and/or deposit history, is potentially one of the most powerful sources for assessing the borrower's credit risk, it is not surprising that what differentiates being "very" versus "somewhat" successful is the extent to which the lender uses this information and applies it in credit risk models and decisioning strategies. Additionally, the fact that an institution is using credit scores for account management strategies is a potential indicator of a deeper level of lender credit scoring knowledge and sophistication.

Having databases that contain data on all (approvals and declines) applicants is also significantly associated with "very successful" use of credit scoring. This result is also not surprising. Analysis of both approvals and declines is essential for optimization of credit policy, and data on declines is potentially important for credit model development, as well, for application of a modeling approach called reject inference analysis. Without using reject inference during model development, credit scores will tend to underestimate borrower risk.

Use of alternative (e.g., GPS data, utility payments, social media, psychometric) data was not common, and on average was not highly valued as a predictive data source. Additionally, use of machine learning for modeling was uncommon, although for the few lenders who were using machine learning, at least some benefit was reportedly derived. However, the results suggest that in financial institutions where most credit originations are to existing customers, use of alternative predictive data sources and modeling approaches may be less important than in contexts where institutions are primarily lending to non-customers and the unbanked. However, this conclusion may change over time as machine learning technology becomes more advanced, available, and explainable. A European Bank for Reconstruction and Development (EBRD) Banking Environment and Performance Survey (BEPS III) conducted in 2020 across 33 countries and 328 financial institutions revealed that 23% of those surveyed were already using some form of alternative data (e.g., e-commerce data for SME lending) and 38% were using "algorithms and/or machine learning" to improve credit decision making (author's analysis of BEPS III survey data, unpublished).

Because of the small sample size many expected associations were identified, but the results were not statistically significant. For example, "very successful" institutions were more likely to be larger (e.g., >= 2$ billion in assets) and less likely to report an insufficient number of defaults for model development, however, neither of these associations were statistically significant (at the $p < 0.1$ level). For a variety of reasons (e.g., data, financial resources, economies of scale, use cases) it is intuitive that larger institutions would be more likely to be using and succeed with use of credit scoring. And the same would apply to the use of emerging financial technologies, as well. A recent EBRD report of BEPS III survey results indicated that larger banks are more likely to have greater involvement in fintech, whether in use of new technologies or as through investment in financial technology companies (EBRD, 2021).

Based on IFC's REACH data, at financial institutions throughout the world, there are many more MSME depositors than borrowers. Across emerging markets, among MSME lenders, MSME deposit balances are on average over 15 times greater than MSME loan balances; indicating that financial institutions are much more likely to consider MSMEs as sources of funds rather than a segment for credit expansion. For targeting sustainable expansion of MSME access to credit, there appears to be a large, relatively untapped, and potentially promising segment: an institution's own customers. As Puri, et al. stated: "Our research suggests a practical solution to reducing loan defaults for new customers: Have the customer open a simple transactions account –savings or checking account, observe for some time and then decide whether to make a loan" (Puri, et al., 2017). Analysis of internal relationship data (credit and deposit) could be one key to successful use of credit scoring and sustainable expansion of access to credit to MSME borrowers. Hopefully, the results of this study will spark additional interest in this area.

4 Factors Associated with Use of Alternative Data and/or New Credit Scoring Methods for Retail and SME Lending

4.1 Introduction

Credit scoring for Retail and small and medium enterprise (SME) lending has been successfully used for several decades (Feldman, 1997) and has been associated with a greater reliance on use of "hard" predictive data and less on "soft" personal knowledge of the customer and face-to-face contact (Berger and Udell, 2006; Akhavein, Frame and White, 2005), a more accurate and quantitative evaluation of risk, resulting in pricing that more closely matches risk levels (Akhavein, Frame and White, 2005), increased lender profitability (Einav, at al., 2013), and increased access to credit (Frame, Srinivasan and Woosley, 2001; Frame, Padhi and Woosley, 2004; Berger, Frame and Miller, 2005).

A limitation of traditional credit scoring is that it has historically relied on the borrower's formal financial credit history as its key data source. Borrowers without a formal credit history face the "Catch-22" of not having a credit score, and therefore, are not able to obtain formal credit.[20] Addition of "alternative" data to credit scoring models brings the potential to score and approve a large new population of individuals and small businesses previously deemed "credit invisibles". Additionally, new credit scoring methods using machine learning can potentially improve upon traditional linear models such as logistic regression by factoring in non-linear information from variables (Gambacorta, et al., 2019), thus improving predictive power.

Credit scoring for Retail and SME lending continues to evolve, with new data sources and scoring methods increasingly being applied, with predictive power improved in certain contexts (Agarwal, et al.,2017, Arraiz, Ortega and Stucci, 2018, Berg, et al., 2019, Jagtiani and Lemieux, 2019, Gambacorta, et al, 2019, Shi, et al, 2022, Owens and Wilhelm, 2017). Lenders who can effectively integrate alternative data sources and advanced scoring methods into their lending procedures are likely to gain a competitive advantage in credit risk measurement. Conversely, those unable to do so may be at risk of adverse selection, a decline in market share, and reduced profitability.

The growth of new data sources and credit scoring methods comes with additional risks. First, not all financial institutions (FIs) may be able to successfully adapt these methods, which come with their own costly complexities. To do so, FIs may need to partner with new financial technology companies ("Fintechs"), which have emerged since the Great Recession as a growing source of financial technology innovation (Arner, et al., 2015). Second, there are unique risks associated with use of alternative data and new credit scoring methods. For example, an increasing concern has arisen about privacy and how data are collected and used, as well as data accuracy, protection, and retention (IFC, 2017). The data sources and models can be opaque "black boxes" (IFC, 2017, Shi, 2022, Snyder, 2017), making it difficult for lenders to determine the key drivers of the credit risk assessment. The increasing complexity makes model risk management more challenging and costly to effectively apply.

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[20] This well-known "Catch-22" is articulated at https://www.perc.net/problem/#catch.

With the preceding as context, this study aims to identify the prevalence and characteristics of the financial institutions that are currently using alternative data sources and/or new methods for credit scoring for Retail and SME lending.

There has been limited academic research that identifies factors associated with successful FI use of credit scoring. The lack of research includes whether the credit score is "traditional" (i.e., scores that rely primarily on credit bureau/registry data and are built with logistic regression analysis) or "alternative" (e.g., the score is built with data not based on bank tradeline credit history data reported to the credit bureau/registry and may use new credit scoring methods, such as machine learning). Berger and Udell elaborated that large FIs may have a comparative advantage in transactions (e.g., using credit scoring) lending, and small FIs may have an advantage in relationship lending, because large FIs may have greater economies of scale in the processing of hard information, but not have the organizational size and structure conducive to using "soft" (i.e., personal knowledge of the borrower) information (Berger and Udell, 2006). An early study in the U.S. found that banking firms with more branches and those located in New York were more likely to adopt credit scoring earlier than other institutions (Akhavein, Frame and White, 2005), and a similar study of financial institutions in Italy found that banks with large branch networks and those with large market shares in concentrated markets were more likely to be successful early adopters (Bofondi and Lotti, 2006). A global study of 91 large banks across 45 countries found that foreign banks were more likely than domestic banks to use transaction-based lending and more centralized business models (Beck, Demirgüç-Kunt, Pería, 2011), which would imply more reliance on "hard" data and credit scoring and less on personal knowledge of the borrower.

Factors potentially associated (positively or negatively) with usage and/or development of new credit scoring data sources and methods include the cost of development, the size of the potential market, and the number of defaulted loans available for model development (Miller and Rojas, 2004, Wendel and Harvey, 2006). Larger institutions, which would be more likely to have the resources, data, and economies of scale, may be more likely to be early adopters of credit scoring and new credit risk assessment methods (Frame and White, 2004, Akhavein, Frame and White, 2006, EBRD, 2021).

In this analysis, I seek to evaluate these and other factors by combining data from the European Bank for Reconstruction and Development's (EBRD) Banking Environment and Performance (BEPS III)[21] survey (2020) with other information potentially associated with usage, including select financial institution balance sheet and income statement metrics, information about countries' credit information infrastructure, lender protections, extent of alternative finance usage, the number of micro, small and medium enterprises (MSMEs), and the extent of MSME financing gap. To match with the timing of the BEPS III survey, unless otherwise specified, all values in the analysis are as of year 2020.

It is pertinent to clarify the definitions of SME and Retail lending, "alternative data" and "new credit scoring methods". In the BEPS III study and in this analysis, "SME" is defined as an enterprise with between 10 and 250 employees; "Retail" is defined as individuals and small businesses with less than 10 employees. Based on this definition, at least 75% of businesses fall

[21] https://www.ebrd.com/what-we-do/economics/data/banking-environment-and-performance-survey.html

in the Retail segment (IFC, 2010). Therefore, for this context “Retail” lending encompasses not only loans to individuals for personal consumption purposes (e.g., mortgages, auto loans, credit cards) but also extends to micro businesses for business related needs (e.g., working capital).

The term “alternative data” is broad and can include a diverse range of information sources. This includes, but is not limited to, utility and rent payments, bank account data, “digital footprints” – (information that people leave online, such as device type -desktop, tablet, mobile - operating system -Windows, IOS, Android, Mac- and email host - Yahoo, Gmail, etc.), psychometric data, mobile call pattern data, mobile business and expense data, mobile recharge history, mobile E-money transactions, mobile geo-locational data, social media data, search history, website history, online rankings and reviews, online accounting data, among others (Jagtiani and Lemieux, 2019, Berg, et al., 2018, Arraiz, et al., 2018, Agarwal, et al., 2019, Owens and Wilhelm, 2017). The BEPS III survey leaves the definition of alternative data mostly open to the respondent’s interpretation and provides specific guidance only in the form of, “Use of alternative credit scoring data sources such as SME data procured from their e-commerce activities (sales and cash flow)”. However, in practice, alternative data can be defined as information not routinely captured by the loan application, internal relationship, or credit bureau (Mays, 2011). Therefore, for the BEPS III survey, the FI’s response may vary based on how the respondent interpreted the term “alternative data”.

I am defining use of “new credit scoring methods” as an FI’s affirmative response to the BEPS III survey question of whether the FI is currently commercially using “algorithms and/or machine learning to improve credit decision-making, including through credit scoring”. Again, the BEPS III survey question leaves room for interpretation. For this analysis, I interpret the question as implying use of credit scores beyond those that use traditional credit scoring approaches.

For the reader it may be useful to provide at a brief taxonomy of new potential credit scoring methods. The most common statistical method for building a traditional credit score is logistic regression (Mays, 2011), which is a generalized linear model appropriate for binary outcomes. While robust and predictive, logistic regression’s limitation is that it requires assumption of a linear relationship between the predictor variables and the logarithm of the odds of the outcome variable (e.g., loan default). Machine learning models can in some cases improve on the performance of generalized linear models by factoring in non-linear relationships.

Machine Learning is a subcategory of Artificial Intelligence. Machine Learning has been defined as “a method of designing a sequence of actions to solve a problem, known as algorithms, which optimise automatically through experience and with limited or no human intervention. These techniques can be used to find patterns in large amounts of data (big data analytics) from increasingly diverse and innovative sources” (Financial Stability Board, 2017). Kandani, et al. (2010) defined machine learning as “algorithms specifically designed to tackle computationally intensive pattern recognition problems in extremely large datasets” (Kandani, et al. 2010),

There are several different machine learning algorithms being applied, including Support Vector Machines, k-Nearest Neighbor, Random Forests, Decision Trees, AdaBoost, Extreme Gradient Boosting (XGBoost), Stochastic Gradient Boosting, Bagging, Extreme Learning Machine, Genetic Algorithm, and Deep Learning methods (Shi, 2022). Bazarbash (2019) described three classes of machine learning models that have been of particular interest in credit risk modelling: Tree-based models (Decision Trees, Random Forest, and Gradient Boosting Trees), Support Vector Machines, and Neural Networks. The detailed characteristics and relative value of these methods are beyond the scope of this paper but are described in Bazarbash (2019). Shi, et al. (2022) also provide a detailed description of the various machine learning techniques.

Relevant examples where machine learning models outperform traditional regression models can be found in Gambacorta, et al. (2019), Butaru, et al. (2016), and Marceau, et al. 2019. Butaru, et al. (2016) analyzed over 500 million consumer credit card accounts from six large U.S. banks to develop and compare predictive models using three techniques: logistic regression, Decision Trees and Random Forest. The researchers identified that decision trees outperformed the other two methods. For predicting consumer credit risk, Marceau, et al. (2019) found that XGBoost (a form of decision tree model) outperforms logistic regression, Support Vector Machines and Random Forest. Thus, XGBoost may become an important alternative to logistic regression models for micro and small business lending.

EBRD has already conducted significant analysis of the BEPS III survey data (EBRD, 2021) and identified several factors associated with increased likelihood of Fintech[22] usage in general, including certain countries (e.g., the Baltic states), larger financial institutions, and institutions and CEOs focused on innovation.

This study, which focuses on Fintech specific to alternative data and new credit scoring methods, identifies some of these factors as well as some new ones. Utilization of these credit scoring advancements is prevalent and tends to occur in tandem. Of 234 responding financial institutions included in the analysis, 23% already are using alternative data; 36% are using new credit scoring methods, and 69% of FIs currently using alternative data are also using new credit scoring methods. Larger, more profitable FIs are more likely to be using alternative data and/or new credit scoring methods, as are FIs that have an ongoing relationship with a Fintech company. Country-specific factors such as financial and credit infrastructure, population size, and the prevalence of alternative finance in the market are also instrumental and correlated with usage. An unexpected finding based on implications from the previous literature is that majority foreign-bank owned FIs are less likely to currently use alternative data and/or new credit scoring methods.
The likelihood of larger, profitable financial institutions adopting these credit scoring advancements more readily implies that, to remain competitive, smaller, and less profitable institutions may need to focus on successful collaboration with Fintech companies.

The rise of new credit scoring data sources and methods creates additional model risks. Regulators should require and enforce borrower protections and model risk management capabilities commensurate with these new sources of risk.

[22] Fintech is defined as "advances in technology that have the potential to transform the provision of financial services, spurring the development of new business models, applications, processes, and products. Examples include e-money, peer-to-peer lending, credit scoring and decisioning, robo-advisory services, and distributed ledger technology." A fintech firm, referred to as "fintechs" or "a fintech", is a company that specializes in offering digital financial services. (IMF and World Bank, 2019).

The rest of this paper is organized as follows. Section 4.2 describes the data sources for the analysis. Section 4.3 describes the analytical methodology and factors evaluated. Section 4.4 presents results for the univariate and multivariate analyses. Section 4.5 concludes.

4.2 Data Sources

Various data sources are combined into a single analytical dataset. The initial dataset encompasses responses to the EBRD BEPS III survey from 328 financial institutions. The data is refined to encompass only the 289 financial institutions actively involved in both Retail and SME lending. At the financial institution level, the dataset is integrated with balance sheet and income statement data for the fiscal year 2020, as reported in the S&P Capital IQ Pro database, specifically including the 234 financial institutions with total assets reported in the database for FY 2020. Next, country-level data from diverse sources are incorporated into the dataset, DataBank-World Bank;[23] World Bank Doing Business Getting Credit;[24] the 2nd University of Cambridge Center for Alternative Finance Global Alternative Finance Benchmarking Report,[25] and the World Bank MSME Finance Gap Report for 2017.[26]

4.3 Methodology

This study focuses on a subset of the BEPS III survey respondents, 234 financial institutions (FIs) that had balance sheet and income statement data reported to the S&P Capital IQ Pro database,[27] engage in both Retail and SME lending, and on a specific area: use of alternative data and/or new credit scoring methods. I limit the analysis to lenders engaged in both Retail and SME lending because alternative data and new credit scoring methods are mostly being applied to lending at the lower end of the loan amount spectrum, ranging in average loan sizes from about $300 (Berg, et al., 2019, Agarwal, et al., 2020) to between $2,000-$6,000 (Gambacorta, 2019, Arraiz, et al., 2016, Frost, et al., 2019) and at the higher end, $13,000 (Frost, et al., 2019) and less than $18,000 (Jagtiani and Lemieux, 2019). Therefore, I would expect financial institutions extending small Retail loans to be more likely to be using alternative credit scoring data and methods. For this study I do not have data on the size of the institutions' Retail and SME loans but expect that this would be an important determinant of usage of alternative data and new credit scoring methods. This is suggested by the survey data, as well. Of the 234 respondents, whereas 195 (83.3%) consider credit scoring to be "important" or "very important" for Retail lending, 125 (53.4%) consider this to be the case for SME lending.

Because of the strong correlation between usage of alternative data and new credit scoring methods, and because both are used for the purpose of improving the effectiveness of credit risk assessment, I created one **binary outcome** variable, with a value of '1' if the financial institution

[23] https://databank.worldbank.org/
[24] https://archive.doingbusiness.org/en/data/exploretopics/getting-credit
[25] https://www.jbs.cam.ac.uk/faculty-research/centres/alternative-finance/publications/the-2nd-global-alternative-finance-market-benchmarking-report/
[26] (https://documents1.worldbank.org/curated/en/653831510568517947/pdf/121264-WP-PUBLIC-MSMEReportFINAL.pdf
[27] https://www.spglobal.com/marketintelligence/en/solutions/sp-capital-iq-pro

is already commercially using either alternative data or new credit scoring methods (algorithms or machine learning), and a value of '0' otherwise. Of the 234 institutions included in the analysis, 102 (44%) are currently using alternative data and/or new credit scoring methods.

4.3.1 Analytical Method

I initially conducted univariate analysis by using simple logistic regression, determining the univariate association between each variable and the outcome.

For the multivariate analysis I included all variables that had a p-value of less than 0.2 based on univariate analysis and used a stepwise logistic regression procedure, retaining only variables in the final model that had a p-value less than 0.1.

Logistic regression models the probability that a binary outcome variable equals 1 (yes, present) given a set of predictor variables. The general formula for logistic regression is:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}}$$

Where:

- $P(Y = 1)$ is the probability of the binary outcome variable being 1.
- e is the base of the natural logarithm.
- β_0 is the intercept
- $\beta_1, \beta_2, \ldots \beta_n$ are the coefficients of the predictor variables.
- $X_1, X_2, \ldots X_n$ are the predictor variables.

The logistic regression model estimates the coefficients that maximize the likelihood of the observed data given the model. The logistic function constrains the predicted probabilities to range between 0 and 1, making it a standard approach for binary classification problems.

I assessed the overall ability of the resulting model to predict outcomes using the Area Under the Receiver Operating Characteristic Curve (AUC). The AUC measures the ability of a diagnostic screening tool to discriminate between whether a specific condition (outcome) is present or not present. The AUC is a standard metric for measuring the discriminatory ability of a binary classification tool, including, incidentally, credit scores (Hanley and McNeil, 1982, Stein, et al. 2007, Hoo, et al., 2017, Berg, et al. 2020). An AUC of 0.5 indicates the screening tool has no ability to discriminate, whereas AUC of 1.0 represents a tool with perfect discrimination.

In investigating associations, I explore the following factors among the following broad categories: **Institutiona**l (factors particular to the responding FI); characteristics of the FI's **CEO**; **Alternative Competition** (factors indicating the potential level of competition from non-bank credit providers); **Country-level** factors for the country in which the responding FI is located, such as demographic, income, general financial infrastructure, credit reporting infrastructure, and potential credit demand for MSMEs.

Institution-specific factors: In general, I expect current commercial usage of alternative data and/or new credit scoring methods to be associated with the following factors:

Balance Sheet metrics

Size as measured by **total assets, total net loans**, and **total deposits**; the expected relationship between FI size and comparative advantage in transactions lending technologies (e.g., credit scoring) was elaborated by Berger and Udell in 2006 (Berger and Udell, 2006). Additionally, EBRD has reported that on a univariate basis Fintech usage is correlated with size as measured by total assets (EBRD, 2021); therefore, I expect this correlation to extend to use of alternative data and/or new credit scoring methods. The **ratio of problem loans to total loans**. I expect that use of credit scoring for Retail and SME lending would be positively associated with a higher ratio, assuming that FIs more likely to be using alternative data and/or new credit scoring methods would be more likely to have a risk appetite that permits higher loss rates compensated by pricing for risk. Liquidity preference, as measured by the FI's **loan to deposit ratio**. I expect FIs with lower loan to deposit ratios to be more conservative with credit granting and therefore, less likely to use alternative data and/or new credit scoring methods. Therefore, I expect the higher the loan to deposit ratio, the greater the percentage usage of alternative data and/or new credit scoring methods. The ratio of **equity to assets**, and the FI's **leverage ratio** (defined as debt/equity). I expect FIs with higher ratios of equity to assets and lower leverage ratios, to be more conservative and therefore less likely to use alternative data and/or new credit scoring methods.

Income Statement metrics

Profitability, as measured by **net income before taxes (NIBT)**, **return on average equity (ROAE)**, and **return on average assets (ROAA)**. I expect the more profitable the FI, the more likely it would have the resources available to use alternative data and/or new credit scoring methods. Therefore, I expect a positive association with the outcome. **Net interest margin (NIM)**. I expect the larger the NIM, the more likely the FI's risk appetite permits higher loss rates compensated by pricing for risk, which is associated with use of credit scoring and therefore, use of alternative data and/or new credit scoring methods.

Foreign Ownership

The published literature has suggested that foreign-owned FIs can overcome local informational disadvantages by relying less on "relationship" and more on transactions technologies such as credit scoring (Berger and Udell, 2006, Beck, et. al, 2017). Therefore, I expect a positive association with the outcome.

Involvement with Fintech

Based on *Alternative Data Transforming SME Finance* (Owens and Wilhelm, 2017) and the EBRD's analysis of the BEPS III data (EBRD, 2021) I expect any type of **involvement with a Fintech** company, either through partnership, acquisition, investment, non-commercial relationship, or establishment or sponsorship of a Fintech incubator/accelerator to be positively correlated with use of alternative data and/or new credit scoring methods. I expect **challenges with engaging with Fintech**, such as FIs that have difficulty in engaging with Fintechs, or have financial constraints to impede investing in Fintech, or are concerned about IT security and regulatory uncertainty related to Fintech to be negatively associated with use of alternative data and/or new credit scoring methods.

Use of new technology and automation

I expect usage of other new technological advancements in credit underwriting or financial services, such as current use of biometric authentication for customer identification and/or distributed ledger technology such as blockchain in smart contracts, to be positively correlated with the outcome. I expect a positive association with current use of alternative data and/or new credit scoring methods if the CEO responded: “agree” or “strongly agree” to the statement, “In my bank, we create value through our innovative outputs, transformation, and agility”; “agree” or “strongly agree” to the statement, “In my bank, we create value through our efficiency, timeliness, and consistency, and uniformity”; that Fintech is an opportunity and/or a threat to the FI’s current Retail and/or SME lending business model; that automation and robotization will be the most important issue facing the FI over the next 25 years; that the FI’s branch network will decline by more than 10% over the next five years.

Government Ownership

In the published literature it has been suggested that state-owned FIs may be more inefficient due to a lack of market discipline, and their funding to small businesses may be more likely to be based on government mandates rather than expectations of profitability (Berger and Udell, 2006); thus, they may have less incentive to use the most recent advances in credit risk assessment.

Lending Approach

I expect a positive association between an FI management’s belief that use of credit scoring is “important” or “very important” for Retail and/or SME lending decisions and current use of alternative data and/or new credit scoring methods. Conversely, FIs which consider **relationship** (personal knowledge of the customer) and/or **collateral** to be “important” or “very important” for Retail and/or SME lending may be less likely to be using these innovations, because these FIs may place less emphasis on use of hard data risk assessment methods such as credit scoring.

The FI’s CEO-specific factors

I evaluate the age of the CEO, the years the CEO has worked at the FI, and the number of years the CEO has been in his/her current position, and whether the CEO has a graduate (master’s or higher) degree, an MBA degree, or a PhD.

Country-level factors

Credit Reporting Infrastructure

Credit reporting's importance for reducing information asymmetries and expanding credit access has been recognized for many years, and for this reason the International Finance Corporation (IFC) initiated the Global Credit Reporting Program in 2001 to promote development of credit bureaus around the world (IFC, 2006). The empirical association between credit bureaus and small business access to credit was established in a 2014 study covering 63 countries (Peria, Soledad and Singh, 2014). Therefore, the extent of credit reporting infrastructure is a likely factor associated with use of alternative data and/or new credit scoring methods. Although a lack of credit reporting infrastructure would likely be a driver for influencing usage of alternative credit risk assessment data and methods; conversely, FIs in countries with well-developed infrastructure may be more likely to already be using credit scoring for Retail and SME lending, and hence would be in a better position to also use alternative data and/or new scoring methods. Additionally, credit reporting agencies may also be working to incorporate alternative data into their product offerings. I expect the more developed the credit reporting infrastructure, the more likely the FI would be currently using alternative data and/or new credit scoring methods.

For this analysis I include several credit reporting infrastructure indicators, as measured by the year 2020 World Bank Doing Business Report,[28]including the country's Depth of Credit Information Index in 2015 and 2020; the adult credit bureau coverage rate; the adult credit registry coverage rate; whether the bureau and/or registry provide credit scores as a value-added service; positive and negative credit information; at least two years of credit history in file; retail and/or utility data in the credit file; whether by law, borrowers have the right to access their data in the largest credit bureau or registry in the economy, and whether data on firms and individuals are distributed.

I also include the country's overall Doing Business Getting Credit score in 2015 and 2020, and the country's Legal Rights index. The Getting Credit score is a combined indicator of the strength of credit reporting systems and the effectiveness of collateral and bankruptcy laws in facilitating lending.[29] The Legal Rights index is a sub-component of the Getting Credit score and measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders.

The ability of a lender to secure repayment and enforce collateral agreements may be associated with efforts to improve credit risk assessment. As elaborated by Djankov, et al. (2007), theory suggests two key determinants of the amount of private credit in each market: the power of creditors to secure repayment (legal rights) and the extent of information about the borrower's likelihood of repaying the loan. Therefore, in countries where legal rights are lower, there may be an increased incentive to seek improvements in credit risk assessment.

Population and Income

[28] Note: The World Bank Doing Business project was discontinued in 2021. https://www.worldbank.org/en/businessready/doing-business-legacy.
[29] https://archive.doingbusiness.org/en/data/exploretopics/getting-credit

Based on recent research by Frost, et al. (2020) and Claessens, et al. (2018), I expect countries with higher income (Claessens, et al., 2018), younger populations (Claessens, et al., 2018) and greater unmet demand for credit (Frost, et al., 2020) to have more Fintech, and therefore, more potential FI collaboration with Fintech and usage of alternative data and/or new credit scoring methods. For year 2020, I included Gross Domestic Product (GDP) and GDP per capita; the country's income level classification (High, upper-middle, lower-middle, low); the total population; the overall urban population; the urban population percentage; the rural population percentage, and the percentage of the population aged 65 years and older.

Fintech and Alternative Competition

A starting assumption for this analysis is that financial institutions that adopt usage of alternative data and/or new credit scoring methods may be more likely to be collaborating in some way with a Fintech. The World Bank publication, *Alternative Data Transforming SME Finance*, highlighted the reasons why for many institutions the future will likely be one of some form of partnership between Fintechs and banks. Both Fintech companies and banks have unique characteristics that complement each other. Among several advantages, banks have a large customer base, brand recognition, valuable internal data, and a low-cost, stable source of funds. Fintech are not burdened by inflexible legacy systems, and can quickly develop simple applications, incorporate more data sources, use advanced risk models, and for now face lighter regulation (Owens and Wilhelm, 2017). Therefore, both sectors have an inherent incentive to partner with each other. An example of this type of FI-Fintech partnership is the case of the U.S. Fintech, Upstart,[30] which uses advanced credit scoring based on artificial intelligence (AI) and incorporates alternative data sources for credit decisioning. Upstart provides a complete loan origination decisioning platform, product and process for smaller banks that lack the economies of scale to create their own bespoke solutions.

Because collaboration with a Fintech may be a key factor, I expect that financial institutions located in countries with greater Fintech availability, supply and demand would be more likely to be currently using alternative data and/or new credit scoring methods. The more Fintech, the more potential for collaboration.

I also expect that the level of competition from non-bank lenders would be positively correlated with the outcome. I evaluate alternative finance volume per capita in 2019, whether the CEO believes non-bank online lenders, non-bank finance companies, credit card issuers, and/or internet banks are strong competitors for Retail and/or SME lending, and whether Fintech is perceived as a threat to and/or opportunity for the FI's current Retail and/or SME lending business model.

Potential MSME Credit Demand

As indicated by the number of MSMEs in the country and the percentage MSME financing gap in 2017. These factors directly relate to potential overall and unmet demand for MSME finance. I expect these to be positively associated with the outcome variable.

[30] https://www.upstart.com/i/about

Financial Infrastructure

Although the increasing use of alternative data for credit scoring reflects in many respects a failure of traditional data sources to adequately cover "unscorable" potential borrowers, and this would potentially reflect a lack of market development, the evidence suggests that Fintech adoption in general is positively correlated with the wealth and development of the market (Frost, 2020). Additionally, even in the United States, which has one of the most developed credit reporting systems in the world, about 11% of the adult population lacks sufficient formal credit history and a credit score, and in 2020 the U.S. was the global leader in online alternative finance market volume (Cambridge Center for Alternative Finance, 2021) and was ranked number one in the Global Fintech Index 2020 (Findexable, 2020). Therefore, I expect a positive association with financial infrastructure factors, such as the number of commercial bank branches per 100,000; the number of ATMs per 100,000 population; the percentage of the population using the internet; the number of secure internet servers; the number of internet servers per one million population, and the number of mobile phones per 100 people.

4.4 Results

4.4.1 Univariate analysis

Overall, included in the analysis are 234 responding financial institutions, of which 102 (43.6%) are currently using alternative data and/or new credit scoring methods. The respondents come from 31 EBRD countries. The number of observations by country varies from a low of one in Greece to a high of 16 in Azerbaijan. The median number of responses by country is seven. Current commercial usage of alternative data and/or new credit scoring methods ranges from a low of zero percent in Tajikistan and Lithuania to 100% in Greece. Among countries that have at least ten observations, current usage ranges from a low of 7.1% in Bosnia-Herzegovina to a high of 71.4% in Armenia.

Tables 4.1 through 4.5 quantitatively compare characteristics of FIs that are currently using alternative data and/or new credit scoring methods with those that are not. For dichotomous independent variables, the tables provide the percentage of FIs with the characteristic, stratified by whether the FI is currently using alternative data and/or new credit scoring methods. For example, Table 4.1 shows that 62.1% of FIs that do not currently use alternative data and/or new credit scoring methods have "any ongoing relationship with a Fintech company", versus 84.3% of FIs that are currently using alternative data and/or new credit scoring methods. For continuous variables, the tables show the mean value of the independent variable, stratified by whether the FI is currently using alternative data and/or new credit scoring methods. For example, Table 4.1 shows that the average total assets in 2020 of FIs that do not currently use alternative data and/or new credit scoring methods is \$5.36 billion, versus \$10.92 billion for FIs that are currently using alternative data and/or new credit scoring methods.

Table 4.1 compares characteristics of the responding financial institution by levels of the outcome variable. Sixteen institution-specific variables are associated (at a p-value < 0.1) with the current use of alternative data and/or new credit scoring methods. All the sixteen variables are positively associated with current use of alternative data and/or new credit scoring methods except majority foreign ownership, which has a negative association. All variables are included in the multivariate analysis except current commercial use of biometrics, which I consider to be more of an outcome variable similar to use of alternative data and/or new credit scoring methods than an explanatory variable, and return on average equity, which is highly (r=.96) correlated with return on average assets (ROAA), and on testing each of these two variables separately in multivariate analysis, has a slightly weaker correlation with the outcome than ROAA.

Table 4.2 compares characteristics of the FI's CEO by levels of the outcome variable. The CEO-related variables analyzed are in general not significantly correlated with current use of alternative data and/or new credit scoring methods. One binary variable, whether the CEO has a master's or PhD degree, is positively associated (p=.09) with the outcome and included in the multivariate analysis.

Table 4.1. Characteristics of the financial institution, stratified by whether the institution is currently using alternative data and/or new credit scoring methods.

Variable description	Data source	No	Yes	P-value	Statistical significance
Fintech_relationship	1	62.1%	84.3%	0.00	***
Use_biometrics	1	33.3%	54.9%	0.00	**
Fintech_partnership	1	37.1%	56.9%	0.01	**
Scoring_retail	1	78.0%	90.2%	0.01	**
Loans	2	3,034,106	6,195,143	0.02	**
Assets	2	5,359,906	10,923,349	0.02	**
NIBT	2	37,490	100,382	0.02	**
Deposits	2	3,930,822	7,657,267	0.02	**
ROAA	2	0.69	1.22	0.02	**
ROAE	2	5.48	9.13	0.02	**
Foreign_owned	1	54.5%	41.2%	0.02	**
Invested_fintech	1	12.1%	23.5%	0.03	**
Acquired_fintech	1	9.1%	17.6%	0.05	**
Assets >= $25b	2	4.5%	11.8%	0.05	*
NIM	2	3.54	4.10	0.07	*
Innovation	1	79.5%	87.3%	0.09	*
Observations		132	104		

Data source key: 1: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. 2: S&P Capital IQ Pro database; retrieved June 2023. Variable descriptions are shown in Table 4.8.

Table 4.1 quantitatively compares characteristics of financial institutions (FIs) that are currently using alternative data and/or new credit scoring methods with those that are not. For dichotomous independent variables, the tables provide the percentage of FIs with the characteristic, stratified by whether the FI is currently using alternative data and/or new credit scoring methods. For continuous variables, the tables show the mean value of the independent variable, stratified by whether the FI is currently using alternative data and/or new credit scoring methods.

Key to p-values: *: p<.1; **: p<.05; ***: p<.01; ****: p<.001.

Table 4.1, continued. Characteristics of the financial institution, stratified by whether the institution is currently using alternative data and/or new credit scoring methods.

Variable description	Data source	No	Yes	P-value
Non_commercial	1	43.2%	53.9%	0.11
Scoring_sme	1	48.5%	59.8%	0.11
Financial_constraints	1	41.7%	31.4%	0.14
Relationship_sme	1	95.0%	90.0%	0.14
Collateral	1	89.4%	94.1%	0.19
Credit_to_large	1	92.4%	96.1%	0.23
In-house_tech	1	81.8%	88.2%	0.25
Relationship_retail	1	64.0%	57.0%	0.29
Loan/deposits	2	0.8	0.9	0.41
Efficiency	1	74.2%	76.5%	0.44
Use_blockchain	1	3.8%	5.9%	0.49
Fintech_future	1	86.4%	89.2%	0.50
IT/regulatory_concerns	1	84.8%	82.4%	0.53
Fintech_difficulty	1	26.5%	23.5%	0.55
Problem_loans_pct	1	7.6	8.3	0.62
Fintech_incubators	1	31.8%	34.3%	0.78
Branch_decline	1	30.3%	29.4%	0.83
Automation_25	1	42.4%	40.2%	0.90
Equity/assets	2	13.0	13.0	0.94
State_owned	1	7.6%	7.8%	0.99
Observations		132	104	

Data source key: 1: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. 2: S&P Capital IQ Pro database; retrieved June 2023. Variable descriptions are shown in Table 4.8.

This table quantitatively compares characteristics of financial institutions (FIs) that are currently using alternative data and/or new credit scoring methods with those that are not. For dichotomous independent variables, the tables provide the percentage of FIs with the characteristic, stratified by whether the FI is currently using alternative data and/or new credit scoring methods. For continuous variables, the tables show the mean value of the independent variable, stratified by whether the FI is currently using alternative data and/or new credit scoring methods.

Table 4.2. Select characteristics of the financial institution's CEO, stratified by whether the institution is currently using alternative data and/or new credit scoring methods.

Variable name	No	Yes	Prevalence ratio	P-value	Statistical significance
CEO_Master's	78.0%	88.2%	1.13	0.09	*
CEO_age	47.2	48.0	NA	0.24	
Years_CEO	3.7	4.5	NA	0.24	
CEO_MBA	33.3%	36.3%	1.09	0.72	
CEO_PHD	13.6%	10.8%	0.79	0.37	
CEO_Years_FI	10.1	10.1	NA	0.93	
Observations	132	102			

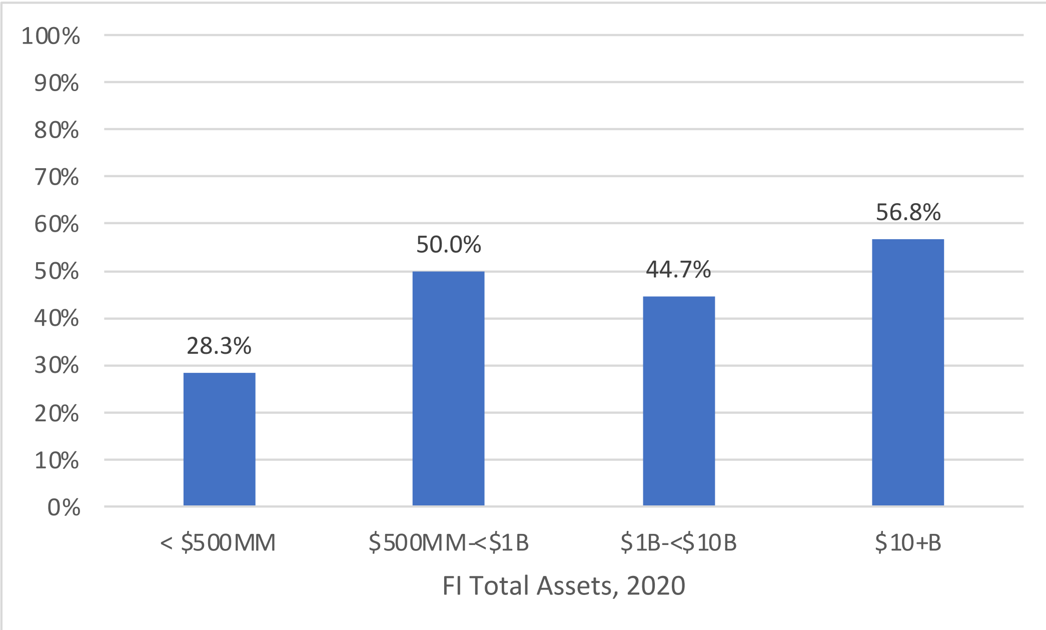
Data source: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021.

This table quantitatively compares CEO characteristics of financial institution's (FI's) that are currently using alternative data and/or new credit scoring methods with those that are not. For example, of FIs that are currently using alternative data and/or new credit scoring methods, 88.2% of CEOs have a master's degree or higher, versus 78.0% of CEOs of institutions that are not. Variable descriptions are shown in Table 4.8.

Key to p-values: *: p<.1; **: p<.05; ***: p<.01; ****: p<.001.

Figures 4.1-4.7 provide a graphical description of the relationship between key variables and current use of alternative data and/or new credit scoring methods and the extent of the FI's relationship with Fintechs.

Figure 4.1. Current use of alternative data and/or new credit scoring methods, by responding financial institution's total assets in 2020.

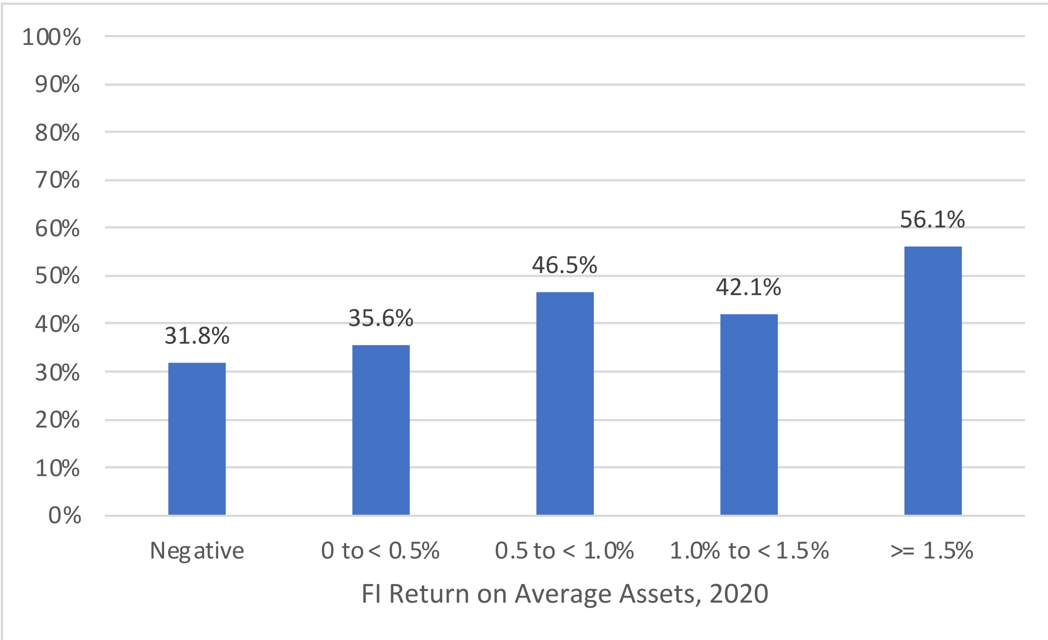


Data sources: Usage of alternative data and/or new credit scoring methods: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Total Assets: S&P Capital IQ Pro database; retrieved June 2023.

Figure 4.1 shows current use of alternative data and/or new credit scoring methods, stratified by the responding financial institution's (FI's) total assets in 2020. As can be seen, generally, the greater the total assets, the more likely the FI is currently using alternative data and/or new credit scoring methods.

Figure 4.2 shows a similar pattern by profitability, the greater the percentage return on average assets (ROAA), the more likely the FI is currently using alternative data and/or new credit scoring methods. For example, FIs with an ROAA of 1.5% or higher in 2020 are 1.8 times (56.1% vs. 31.8%) more likely to be currently using alternative data and/or new credit scoring methods than FIs with a negative ROAA that year.

Figure 4.2. Current use of alternative data and/or new credit scoring methods, by responding financial institution's return on average assets in 2020.

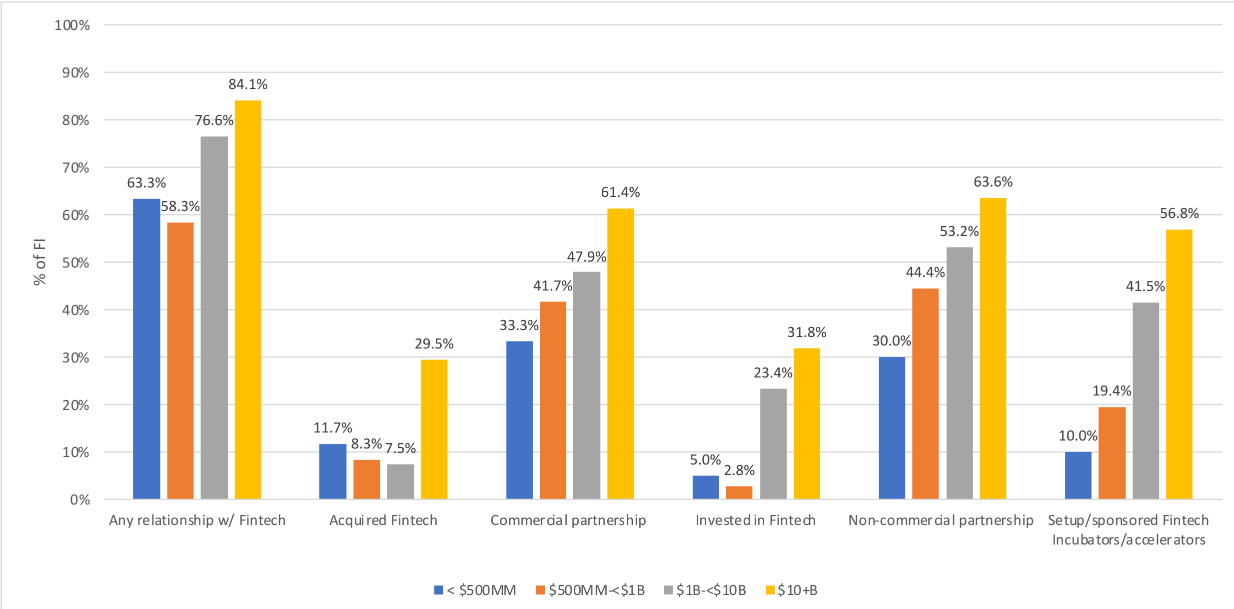


Data sources: Usage of alternative data and/or new credit scoring methods: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Total Assets: S&P Capital IQ Pro database; retrieved June 2023.

Figure 4.2 shows current use of alternative data and/or new credit scoring methods by the responding financial institution's (FI's) return on average assets (ROAA) in 2020. The greater the percentage ROAA, the more likely the FI is currently using alternative data and/or new credit scoring methods.

Figure 4.3 shows the percentage of FIs that have a relationship with a Fintech, stratified by the type of relationship and the responding FI's total assets in 2020. As can be seen, whereas larger FIs are much more likely than smaller FIs to have acquired, formed a commercial or non-commercial partnership with, invested in a Fintech or set up/sponsored a Fintech incubator/accelerator, they are only moderately more likely to have any type of relationship with a Fintech. For example, whereas FIs with total assets of $10 billion or greater are 6.4 times (31.8% vs. 5.0%) more likely than FIs with total assets less than $500MM to have invested in a Fintech, they are 1.3 times (84.1% vs. 63.3%) more likely to have any relationship with a Fintech. This indicates that FI size is not necessarily a strict prerequisite for engagement with Fintech companies.

Figure 4.3. Percentage of responding financial institutions (FIs) by type of Fintech relationship and responding FI's total assets in 2020.

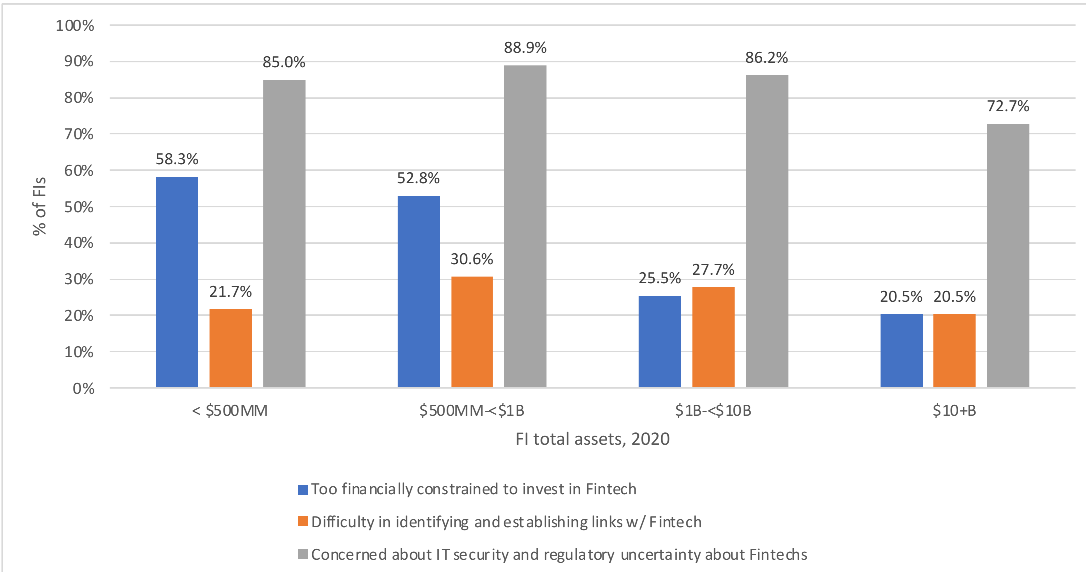


Data sources: Type of fintech relationship: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Total Assets: S&P Capital IQ Pro database; retrieved June 2023.

Figure 4.3 shows the percentage of responding financial institutions (FIs), stratified by the FI's type of relationship with a fintech company and the responding FI's total assets in 2020.

Figure 4.4 highlights FI challenges with engagement with Fintech, stratified by the responding FI's total assets in 2020. As can be seen, FIs with total assets less than $500MM are 2.8 times more likely (58.3% vs. 20.5%) than FIs with total assets of $10 billion or greater to report being too financially constrained to invest more in Fintech and/or new technologies. However, FIs with total assets less than $500MM are only 1.1 times more likely (21.7% vs. 20.5%) than FIs with total assets of $10 billion or greater to report facing difficulties in identifying and establishing links with relevant Fintech companies. This indicates that FI size is not necessarily a strict prerequisite for establishing links with Fintech companies.

Figure 4.4. Percentage of responding financial institutions (FIs) by type of challenges with investing/partnering with Fintech and the responding FI's total assets in 2020.



Data sources: challenges with investing/partnering with fintech: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Total Assets: S&P Capital IQ Pro database; retrieved June 2023.

Figure 4.4 shows the percentage of responding financial institutions (FIs), stratified by the type of challenge faced by the FI with investing/partnering with fintech and the responding FI's total assets in 2020.

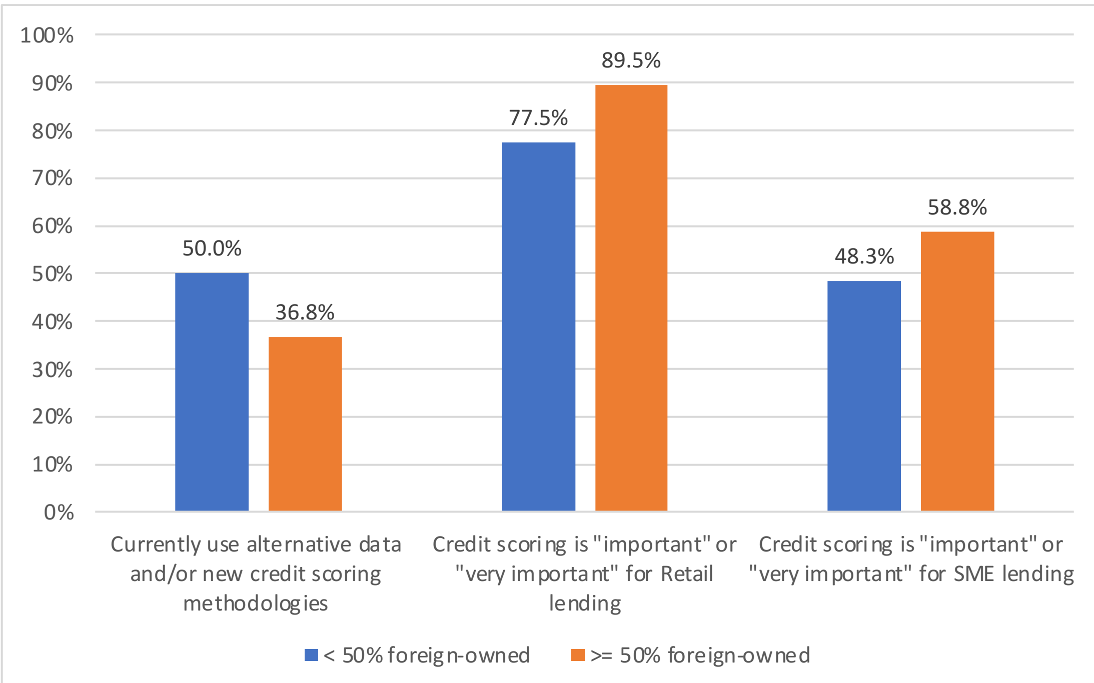
Majority foreign bank owned.

Of the 234 FIs included in the analysis, 114 (48.7%) are majority foreign bank owned. Of these institutions, 36.8% are currently using alternative data and/or new credit scoring methods, versus 50% of majority domestic owned FIs (p=.04). These results appear to be contradictory to the published literature suggesting that foreign-owned FIs can overcome local informational disadvantages by relying less on "relationship" and more on transactions technologies such as credit scoring (Berger and Udell, 2006, Beck, et. al, 2017). However, as shown in Figure 4.5, whereas majority foreign-bank owned FIs are less likely to be using alternative data and/or new credit scoring methods, they are more likely to consider credit scoring to be important for Retail lending (p=.01) and SME lending (p=.10) than majority domestic owned FIs (Figure 4.5). Therefore, the difference relates specifically to use of alternative data and/or new credit scoring methods.

Figures 4.6 and 4.7 present additional results, categorized by whether the FI is majority-owned by a foreign bank. As can be seen in Figure 4.6, the biggest difference in current use of alternative data and/or new credit scoring methods is in the FI total asset range of $1 billion to less than $10 billion. In this total asset range, FIs less than 50% foreign bank owned are 2.4 times (64.4% vs. 26.5%) more likely to be currently using alternative data and/or new credit scoring methods than majority foreign bank owned FIs. Figure 4.7 shows that majority foreign-

bank owned FIs are significantly more likely to have difficulty identifying and establishing links with Fintechs than majority domestic owned banks (29.8% vs. 20.8%, p=.11).
Figure 4.8 shows that among the responding FIs, the larger the FI in terms of total assets, the more likely the FI is majority foreign bank owned. Given that current use of alternative data and/or new credit scoring methods is positively correlated with the size of the FI, it is surprising that overall, majority foreign-owned FI's (which tend to be larger) are less likely to be using alternative data and/or new credit scoring methods. The multivariate analysis (presented later) controls for these factors.

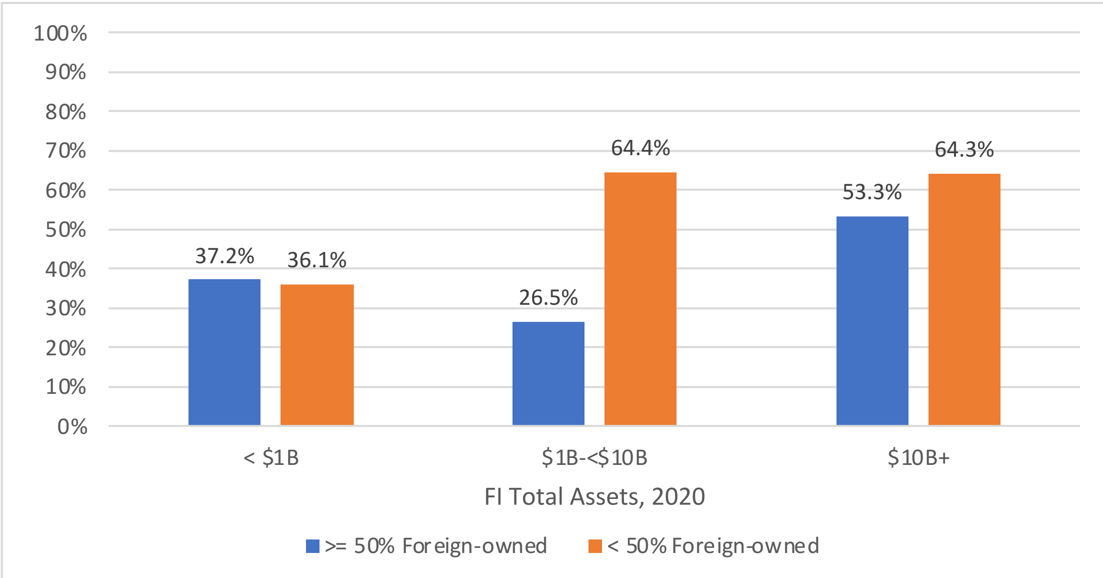
Figure 4.5. Financial Institution current use of alternative data and/or new credit scoring methods, and the importance of credit scoring for Retail and SME lending, stratified by percentage foreign bank ownership.



Data sources: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021.

Figure 4.5 shows the percentage of financial institutions (FIs) currently using alternative data and/or new credit scoring methods and the percentage of FIs that consider credit scoring to be "important" or "very important" for Retail and SME lending, stratified by percentage foreign bank ownership.

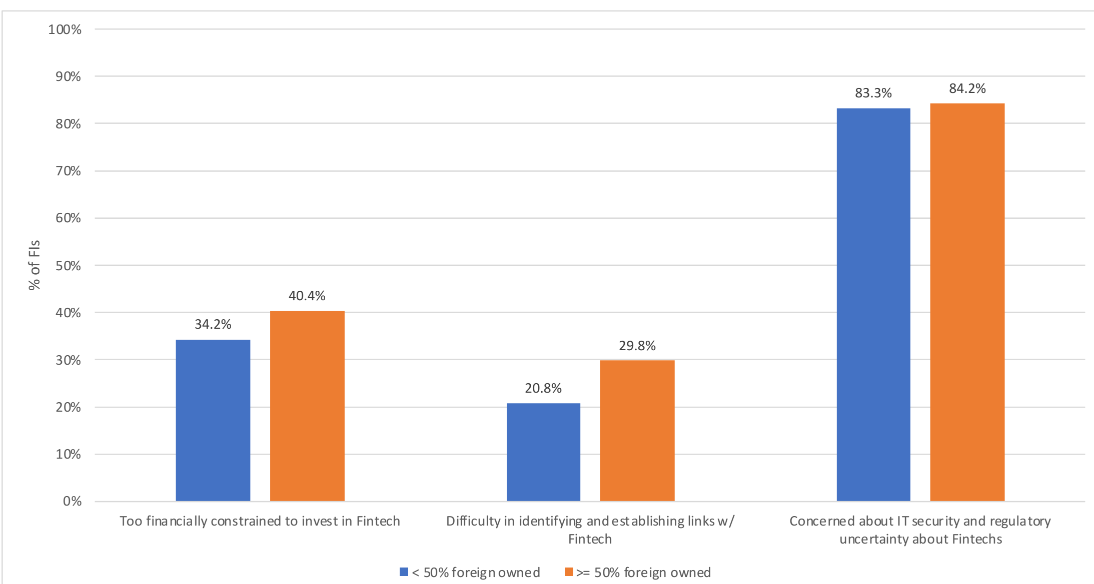
Figure 4.6. Current use of alternative data and/or new credit scoring methods, by percentage foreign bank ownership and responding financial institution's total assets, 2020.



Data sources: Usage of alternative data and/or new credit scoring methods and percentage foreign bank ownership: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Total assets: S&P Capital IQ Pro database; retrieved June 2023.

Figure 4.6 shows current financial institution (FI) usage of alternative data and/or new credit scoring methods, stratified by the FI's percentage foreign bank ownership and total assets in 2020.

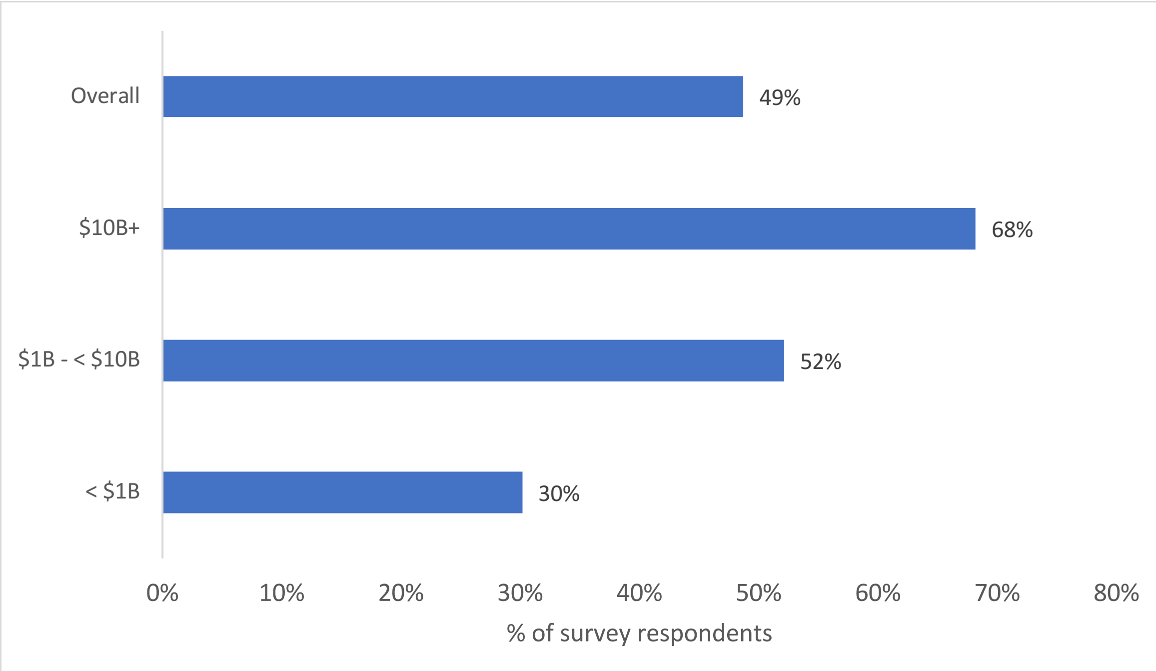
Figure 4.7. Percentage of responding financial institutions by type of challenges with investing/partnering with Fintech and percentage foreign bank ownership.



Data sources: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021.

Figure 4.7 shows the percentage of responding financial institutions (FIs) by type of challenges with investing or partnering with fintech and percentage foreign bank ownership.

Figure 4.8. Percentage of survey respondents that are majority foreign bank owned, by responding financial institution's total assets in 2020.



Data sources: Percentage foreign bank ownership: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Total assets: S&P Capital IQ Pro database; retrieved June 2023.

Figure 4.8 shows percentage foreign bank ownership, stratified by the responding financial institution's total assets in 2020.

Table 4.3 compares characteristics of the FI's alternative competition by levels of the outcome variable. Four variables are positively associated with the outcome (at a p-value of less than 0.1 level) and included in the multivariate analysis:

Table 4.3. Characteristics of the financial institution's competition, stratified by whether the institution is currently using alternative data and/or new credit scoring methods

Variable name	No	Yes	P-value	Statistical significance
Internet_retail	19.7%	30.4%	0.04	**
Non-bank_sme	6.8%	5.9%	0.06	*
Online_retail	15.2%	25.5%	0.06	*
Card_sme	7.6%	13.7%	0.07	*
Non-bank_retail	40.2%	50.0%	0.11	
Fintech_opp_retail	34.1%	44.1%	0.12	
Fintech_threat_sme	8.3%	3.9%	0.17	
Card_retail	22.7%	26.5%	0.38	
Internet_sme	9.1%	10.8%	0.56	
Online_sme	29.5%	32.4%	0.62	
Fintech_opp_sme	53.8%	52.9%	0.90	
Fintech_threat_retail	8.3%	8.8%	0.95	
Observations	132	102		

Data sources: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Variable descriptions are shown in Table 4.8.

This table shows the characteristics of the financial institution's (FI's) competition, stratified by whether the FI is currently using alternative data and/or new credit scoring methods.
Key to p-values: *: p<.1; **: p<.05; ***: p<.01; ****: p<.001.

Table 4.4 compares characteristics of the credit reporting infrastructure of the country in which the financial institution is located by levels of the outcome variable. Three credit reporting variables are significantly associated (at a p-value less than 0.1 level) with current use of alternative data and/or new credit scoring methods and included in the multivariate analysis.

Table 4.4. Characteristics of the credit reporting infrastructure of the country in which the financial institution is located, stratified by whether the institution is currently using alternative data and/or new credit scoring methods.

Variable name	No	Yes	P-value	Statistical significance
Scores_offered	61.4%	78.4%	0.01	**
Right_to_access	91.7%	99.0%	0.03	**
CII_2015	6.9	7.2	0.06	*
Two_years_data	90.2%	88.2%	0.40	
CII_2020	6.0	6.1	0.70	
Pos_neg_data	98.5%	99.0%	0.70	
Utility_data	53.8%	56.9%	0.74	
Registry_coverage_2015	19.0	20.1	0.76	
Getting_credit_2020	14.8	14.8	0.77	
Registry_coverage_2020	23.5	22.6	0.82	
Getting_credit_2015	11.8	11.8	0.84	
Bureau_coverage_2015	37.3	37.5	0.85	
Data_on_firms/ind	94.7%	95.1%	0.85	
Bureau_coverage_2020	43.1	44.1	0.94	
Observations	132	102		

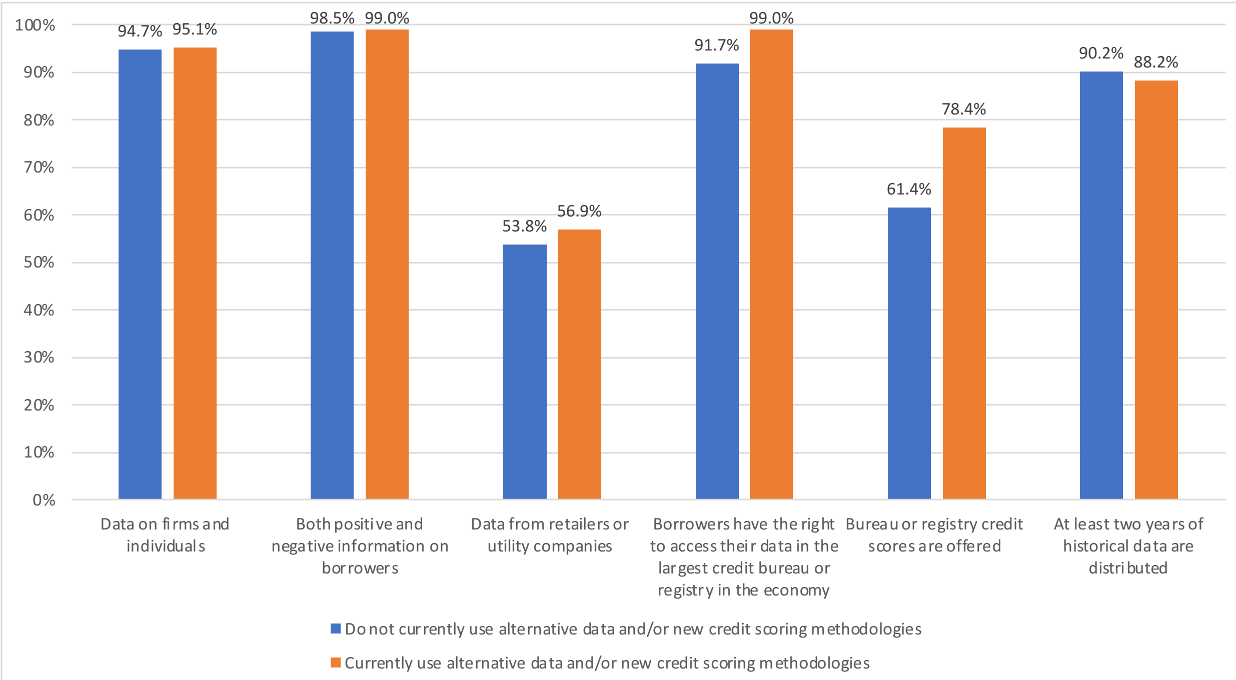
Data sources. Usage of alternative data and/or new credit scoring methods: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Country level credit reporting infrastructure information: World Bank: 2020. Doing Business 2020: Comparing Business Regulation in 190 Economies. Washington, DC: World Bank. DOI:10.1596/978-1-4648-1440-2. Variable descriptions are shown in Table 4.8.

This table compares country-level credit reporting infrastructure indicators in 2020 between financial institutions (FIs) that are currently using alternative data and/or new credit scoring methods with those that are not. For example, in 2020, 78.4% of FIs that were currently using alternative data and/or new credit scoring methods were in a country whose credit reporting system offered generic credit scores as a value-added service versus 61.4% of financial institutions that were not using alternative data and/or new credit scoring methods.

Key to p-values: *: p<.1; **: p<.05; ***: p<.01; ****: p<.001.

As shown in Figure 4.9, the most noteworthy difference in credit reporting infrastructure between financial institutions that are and are not currently using alternative data and/or new credit scoring methods lies in the provision of bureau/registry credit scores as a value-added service. This difference makes logical sense. The fact that bureau or registry scores are offered is an indicator of credit reporting infrastructure maturation. It indicates that there are sufficient high-quality credit reporting data to build a predictive credit score.

Figure 4.9. Credit reporting infrastructure characteristics in the country in which the responding financial institution (FI) is located, stratified by whether the FI is currently using alternative data and/or new credit scoring methods.



Data sources. Usage of alternative data and/or new credit scoring methods: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Country level credit reporting infrastructure information: World Bank: 2020. Doing Business 2020: Comparing Business Regulation in 190 Economies. Washington, DC: World Bank. DOI:10.1596/978-1-4648-1440-2.

Figure 4.9 compares country-level credit reporting infrastructure indicators in 2020 between financial institutions (FIs) that are currently using alternative data and/or new credit scoring methods with those that are not.

Table 4.5 compares characteristics of the country in which the financial institution is located by levels of the outcome variable. Nine country-related variables (all for year 2020) were associated (at a p-value of less than 0.1) with current use of alternative data and/or new credit scoring methods and included in the multivariate analysis.

Table 4.5. Select average characteristics of the country in which the financial institution (FI) is located, stratified by whether the FI is currently using alternative data and/or new credit scoring methods.

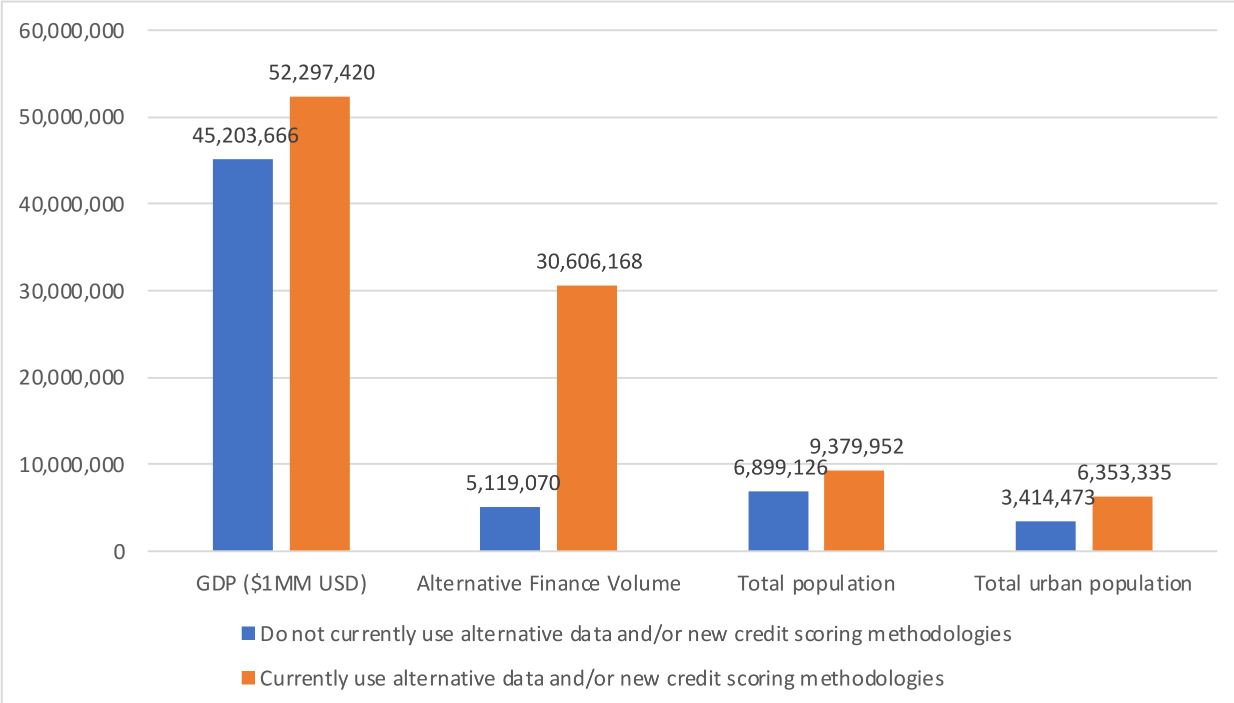
Variable name	No	Yes	P-value	Statistical significance
Number_MSMEs	326,450	543,291	0.01	**
ATM/100k	59.9	67.8	0.01	**
Urban_population	7,551,370	12,183,409	0.02	**
Rural_population_pct	39.4	35.1	0.02	**
Urban_population_pct	60.6	64.9	0.02	**
Total_population	11,452,530	17,386,077	0.02	**
GDP ($mms)	84,281	157,905	0.02	**
Internet_servers	132,215	208,839	0.02	**
Alt_fin_vol ($000s)	65,111	98,287	0.04	**
Mobile/100	115.6	119.2	0.09	*
MSME_fin_gap	18.6%	20.4%	0.16	
Internet_servers/1mm	10,837	13,243	0.28	
GDP_per_capita	7,395	8,292	0.31	
Population_65+_pct	14.3	13.9	0.46	
Lower_mid_income	20.5%	21.6%	0.54	
Upper_mid_income	56.8%	54.9%	0.60	
High_income	20.5%	23.5%	0.66	
Legal_rights_2020	7.9	7.6	0.67	
Branches/100k	22.1	21.4	0.67	
Lower_income	2.3%	0.0%	0.98	
Observations	132	102		

Table 4.5 compares select characteristics in 2020 of the country in which the financial institution is located between financial institutions (FIs) that are currently using alternative data and/or new credit scoring methods with those that are not. For example, in 2020, on average, the total country population was larger among FIs that were currently using alternative data and/or new credit scoring methods than among FIs that were not.

Data sources. Number_MSMEs; MSME_fin_gap; Lower_mid_income; Upper_mid_income; Hign_income: International Finance Corporation. 2017. MSME Finance Gap: Assessment of the Shortfalls and Opportunities in Financing Micro, Small, and Medium Enterprises in Emerging Markets. Alt_fin_vol: The 2nd Global Alternative Finance Market Benchmarking Report (June 30, 2021). Cambridge, UK: Cambridge Centre for Alternative Finance. Data obtained from World Bank (DataBank. https://data.worldbank.org): ATM/100k (FB.ATM.TOTL.P5); Branches/100K (FB.CBK.BRCH.P5); Urban_population (SP.URB.TOTL); Rural_population_pct (SP.RUR.TOTL.ZS); Urban_population_pct (SP.URB.TOTL.IN.ZS); Total_population (SP.POP.TOTL); GDP_per_capita (NY.GDP.PCAP.CD); GDP (NY.GDP.MKTP.CD); Mobile_100 (IT.CEL.SETS.P2); Internet_servers (IT.NET.SECR.P6); Internet_servers/1MM (IT.NET.SECR.P6). Variable descriptions are shown in Table 4.8.

Key to p-values: *: p<.1; **: p<.05; ***: p<.01; ****: p<.001

Figure 4.10. Median country-level values for select indicators, stratified by financial institution current use of alternative data and/or new credit scoring methods, 2020.



Data sources. Usage of alternative data and/or new credit scoring methods: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Alt_fin_vol: The 2nd Global Alternative Finance Market Benchmarking Report (June 30, 2021). Cambridge, UK: Cambridge Centre for Alternative Finance. Data obtained from World Bank (DataBank. https://data.worldbank.org): GDP (NY.GDP.MKTP.CD); Total Population (SP.POP.TOTL); Total Urban Population (SP.URB.TOTL). Variable descriptions are shown in Table 4.8.

This figure shows median country-level values for select indicators, stratified by current use of alternative data and/or new credit scoring methods, 2020.

4.4.2 Multivariate analysis

4.4.2.1 Multiple logistic regression #1: Factors associated with current commercial use of alternative data and/or new credit scoring methods.

Table 4.6 describes the results of the initial multivariate analysis. As indicated previously, I conduct a stepwise multiple logistic regression, including in the initial model only variables that have a univariate p-value less than 0.2 and retaining in the final model only variables that have a p-value of less than 0.1, after controlling for the other variables. The variables included in the final model, all of which are positively associated with the outcome, are shown in Table 4.7.

The model's Area Under the Curve (AUC) statistic is 73.9 (Figure 4.11), indicating there is a 73.9% chance that a randomly selected institution that is currently using alternative data and/or new credit scoring methods will be assigned a higher model probability of this outcome than a randomly selected institution that is not.

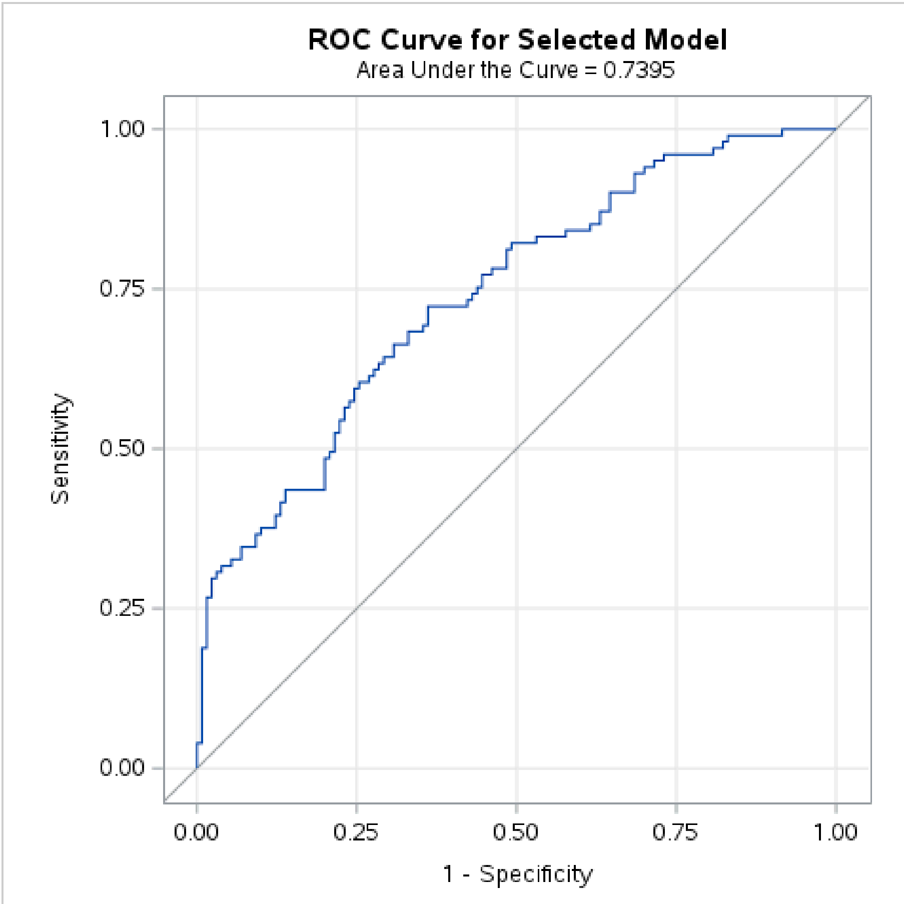
Table 4.6. Factors independently associated with current commercial use of alternative data and/or new credit scoring methods.

Variable name	Beta Coefficient	Standard Error	P-value
Intercept	-3.07	0.58	< .0001
Fintech_relationship	1.22	0.39	0.00
Online_retail	0.64	0.37	0.08
Scoring_retail	0.86	0.44	0.05
Loans	0.00	0.00	0.02
Debt/equity	0.40	0.15	0.01
ROAA	0.30	0.13	0.02
Fintech_opp_retail	0.70	0.32	0.03

Table 4.6 shows results of the multiple logistic regression analysis. The variables shown all were independently associated with current usage of alternative data and/or new credit scoring methods at a p-value of < 0.10. The beta coefficient indicates the unit change in the logarithm of the odds of the outcome variable for every unit change in the independent variable, after controlling for other variables in the model.

Data sources. Usage of alternative data and/or new credit scoring methods; Fintech_relationship; Online_retail; Scoring_retail; Fintech_opp_retail: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Loans; Debt/Equity; ROAA: S&P Capital IQ Pro database; retrieved June 2023. Variable descriptions are shown in Table 4.8.

Figure 4.11. Receiver Operating Characteristic (ROC) Curve for Multiple Logistic Regression #1.



The Receiver Operating Characteristic (ROC) curve plots the true-positive versus false positive rate for a binary classification tool at a variety of decision cut-offs.

4.4.2.2 Multiple logistic regression #2: Factors associated with current commercial use of alternative data and/or new credit scoring methods for FIs with total assets less than $1 billion.

As shown previously in Figure 4.1, in general as the FI's total assets increase, the percentage of FIs currently using alternative data and/or new credit scoring methods increases. For example, FIs with total assets less than $500MM are much less likely than FIs with total assets more than $10 billion to currently use alternative data and/or new credit scoring methods. To gain further insights into factors associated with use of alternative data and/or new credit scoring methods among smaller FIs, I conduct a second multiple logistic regression analysis on the subset of 96 FIs with total assets less than $1 billion. The dependent variable is the same as in multiple logistic regression #1, indicating whether the FI is currently using alternative data and/or new credit scoring methods.

All three final variables have a positive association with current use of alternative data and/or new credit scoring methods.

The final model has an AUC statistic of 78.8 and contains three variables, all with p-value of .05 or lower.

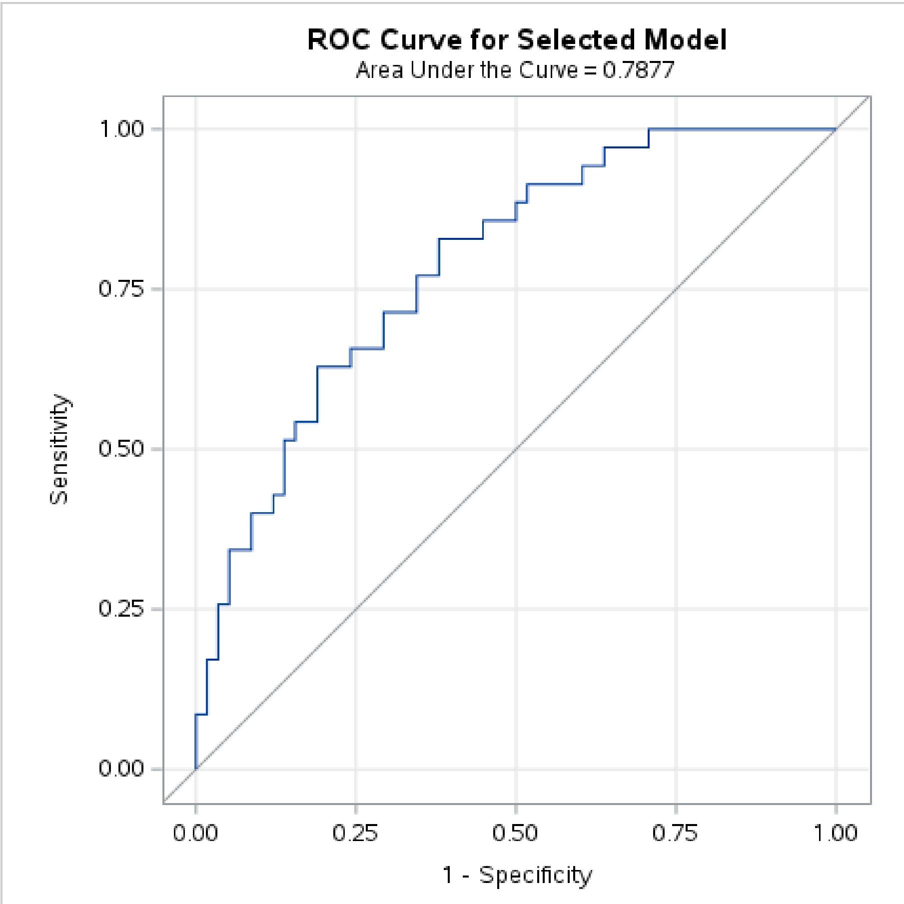
Table 4.7. Factors independently associated with current commercial use of alternative data and/or new credit scoring methods among financial institutions with less than $1 billion in assets.

Variable Name	Beta Coefficient	Standard Error	P-value
Intercept	-2.38	0.58	<.0001
Fintech_relationship	1.29	0.54	0.02
Alt_fin_vol	0.00	0.00	0.01
ROAA	0.69	0.23	0.00

This table shows results of the multiple logistic regression analysis among financial institutions with less than $1 billion in total assets in 2020. The variables shown all were independently associated with current usage of alternative data and/or new credit scoring methods at a p-value of < 0.05. The beta coefficient indicates the unit change in the logarithm of the odds of the outcome variable for every unit change in the independent variable, after controlling for other variables in the model.

Data sources. Usage of alternative data and/or new credit scoring methods; Fintech_relationship: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021. Alt_fin_vol: The 2nd Global Alternative Finance Market Benchmarking Report (June 30, 2021). Cambridge, UK: Cambridge Centre for Alternative Finance. ROAA: S&P Capital IQ Pro database; retrieved June 2023. Variable descriptions are shown in Table 4.8.

Figure 4.12. Receiver Operating Characteristic (ROC) Curve for Multiple Logistic Regression #2



The Receiver Operating Characteristic (ROC) curve plots the true-positive versus false positive rate for a binary classification tool at a variety of decision cut-offs.

Table 4.8. Variables evaluated in the univariate analysis.

Variable description	Variable name	BEPS III Question
Age of CEO	CEO_age	C77
Automation and robotisation is the most important issue FI will face over the next 25 years	Automation_25	C12_A
CEO has a Master's degree or higher	CEO_Master's	C78
CEO has a PhD	CEO_PHD	C78
CEO has an MBA	CEO_MBA	C80
CEO response to statement: "In my bank, we create value through our efficiency, timeliness, and consistency and uniformity"	Efficiency	C59_C
CEO response to statement: "In my bank, we create value through our innovative outputs, transformation, and agility"	Innovation	C59_B
Collateral is important for SME lending	Collateral	H8_D; H8_E; H8F; H8_G
Credit card Issuers are strong competitors for Retail lending	Card_retail	C6_H
Credit card Issuers are strong sompetitors for SME lending	Card_SME	C4_H
Credit scoring is important for Retail lending	Scoring_retail	H28_C
Credit scoring is important for Retail lending, relationship is not	No_relationship	H28_A; H28_C
Credit scoring is important for SME lending	Scoring_SME	H8_C
Developed own products/services in-house using new technologies without cooperating with Fintech companies	In-house_tech	C67_D
FI faces difficulties in identifying and establishing links with Fintech companies relevant to its business	Fin_difficulty	C68_C
FI formed a commercial partnership with a Fintech company	Fin_partner	C67_A
FI has acquired a Fintech company	Acquired_fin	C67_B
FI has an ongoing relationship with a Fintech company	Fin_relation	C68_A
FI has invested in Fintech companies	Invested_fin	C67_C
FI has participated in non-commercial partnerships with Fintech companies	Fin_non-commercial	C67_E
FI has set-up/sponsored Fintech incubators/ accelerators	Fin_incubator	C67_F
FI is already commercially using biometric authentication	Use_biometrics	C66_A
FI is concerned about IT security and regulatory uncertainty about Fintechs	IT/regulatory	C68_D

Data source: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021.

Table 4.8, continued. Variables evaluated in the univariate analysis.

Variable description	Variable name	BEPS III Question
FI plans to have a relation with Fintech companies in the future	Fin_future	C68_B
FI provides credit to large (> 250 employees) companies	Credit_to_large	C3_B
FI would like to invest more in Fintech companies but is financially constrained and cannot do so	Constraints	C68_F
Fintech is perceived as a threat to FI's Retail lending	Fin_threat_retail	C65_A
Fintech is perceived as a threat to FI's SME lending	Fin_threat_SME	C65_B
Fintech is perceived as an opportunity for FI's Retail lending	Fin_opp_retail	C65_A
Fintech is perceived as an opportunity for FI's SME lending	Fin_opp_SME	C65_B
Internet Banks are strong competitors for Retail lending	Internet_retail	C6_F
Internet Banks are strong competitors for SME lending	Internet_SME	C4_F
Non-bank Finance are strong competitors for SME lending	Non-bank_SME	C4_I
Nonbank Finance are strong competitors for Retail lending	Non-bank_retail	C6_I
Nonbank Online Lenders are strong competitors for Retail lending	Online_retail	C6_G
Nonbank Online Lenders are strong competitors for SME lending	Online_SME	C4_G
Number of years CEO has been at FI	CEO_years_fi	C83B
Over the next five years, CEO expects number of branches to decline by more than 10%	Branch_decline	C53
Relationship is important for Retail lending	Rel_retail	H28_A
Relationship is important for SME lending	Rel_SME	H8_A
Use of distributed leger technology (DLTs) such as block chain in smart contracts	Use_blockchain	C66_C
Years in current CEO position	Years_CEO	C84B

Data source: EBRD Banking Environment and Performance Survey III, European Bank for Reconstruction and Development, 2021.

Table 4.8., continued. Variables evaluated in the univariate analysis.

Variable description	Variable name
ATMs per 100,000 adults, 2020	ATM/100k
Commercial bank branches per 100,000, 2020	Branches/100k
GDP per capita, 2020 (in constant 2015 USD)	GDP_per_capita
GDP ($MMs), 2020 (in constant 2015 USD)	GDP ($mms)
Mobile cellular subscriptions per 100 people	Mobile/100
Number of secure internet servers, 2020	Internet_servers
% of population aged 65 years and above, 2020	Population_65+_pct
Rural population % of total population, 2020	Rural_population_pct
Secure internet servers per 1 million, 2020	Internet_servers/1mm
Total population, 2020	Total_population
Total urban population, 2020	Urban_population
Urban population % of total population, 2020	Urban_population_pct

Data source. World Bank. Databank. https:databank.worldbank.org

Table 4.8., continued. Variables evaluated in the univariate analysis.

Variable description	Variable name
Total deposits	Deposits
Total net assets	Assets
Total equity/total net assets ratio	Equity/assets
Total debt/total equity	Debt/equity
Loan to deposit ratio	Loan/deposits
Net income before taxes	NIBT
Net interest income	NII
Net interest margin	NIM
Net loans	Loans
Problem loans to loans ratio	Problem_loans_pct
Return on average assets	ROAA
Return on average equity	ROAE

Data source: S&P Capital IQ Pro Database, retrieved June 2023.

Table 4.8., continued. Variables evaluated in the univariate analysis.

Variable description	Variable name	Data Source
Country is in the top ten of alternative finance volume per capita, 2019	Alt_fin_top_10	1
Country's total alternative finance volume (in $000s, USD), 2020	Alt_fin_vol ($000s)	1
At least two years of historical data are distributed	Two_years_data	2
Both positive and negative information are distributed	Pos_neg_data	2
Bureau or registry credit scores are offered	Scores_offered	2
By law, borrowers have the right to access their data in the largest credit bureau or registry in the economy	Right_to_access	2
Data from retailers or utility companies are distributed in addition to data from financial institutions	Utility_data	2
Data on firms and individuals	Data_on_firms/ind	2
Credit Information Index, 2015	CII_2015	2
Credit Information Index, 2020	CII_2020	2
Getting Credit total score, 2015	Getting_credit_2015	2
Getting Credit total score, 2020	Getting_credit_2020	2
Private credit bureau coverage, % of adults, 2015	PCB_coverage_2015	2
Private credit bureau coverage, % of adults, 2020	PCB_coverage_2020	2
Public credit registry coverage, % of adults, 2015	REG_coverage_2015	2
Public credit registry coverage, % of adults, 2020	REG_coverage_2020	2
Strength of legal rights index, 2020	Legal_rights_2020	2
Lower-income country	Lower_income	3
Middle-income country	Lower_mid_income	3
Upper-middle-income country	Upper_mid_income	3
Higher-income country	High_income	3
MSME Finance Gap, % of GDP, 2017	MSME_fin_gap	3
Number of MSMEs, 2017	Number_MSMEs	3

Data sources key:
1: The 2nd Global Alternative Finance Market Benchmarking Report (June 30, 2021). Cambridge, UK: Cambridge Centre for Alternative Finance.
2: World Bank: 2020. Doing Business 2020: Comparing Business Regulation in 190 Economies. Washington, DC: World Bank. DOI:10.1596/978-1-4648-1440-2.
3: Cambridge Center for Alternative Finance. 2021. The 2nd Alternative Finance Benchmarking Report. Edited by Ziegler T, Shneor R, Wenzlaff K, et al.

4.5 Conclusion

Financial institutions that currently use alternative data and/or new credit scoring methods are significantly more likely to be large (in terms of net loans), profitable, and have some form of relationship with a Fintech. They are also more likely to perceive Fintech as an opportunity for their Retail lending business and consider non-bank online lenders to be a strong competitor in Retail lending.

Financial institution credit scoring innovation tends to be intertwined with collaboration with Fintech companies. The trend towards increasing collaboration between banks and Fintechs was described in *Alternative Data Transforming Finance* (IFC, 2017), with the authors providing several explanatory factors supporting the synergy. This study shows that FI size and profitability are key factors. However, the results also indicate that smaller and less profitable institutions are collaborating with Fintechs and are currently using alternative data and/or new credit scoring methods. However, the nature of the collaboration varies by size. For example, in comparison with FIs with less than $1 billion in total assets, institutions with over $10 billion in assets had 6.4 times higher rates of investing in Fintech (31.8% Vs. 5.0%), 2.5 times higher rates of acquiring Fintech (29.5% vs. 11.7%), but only a 1.3 times higher rate of having an ongoing relationship with a Fintech (84.1% vs. 63.3%). Thus, although the nature of the relationship with a Fintech may vary significantly by asset size, across the institution size spectrum there may be effective options for collaboration with Fintech. The largest institutions may be much more likely to invest in or acquire Fintechs and take ownership and control of alternative data and/or new credit scoring solutions, whereas smaller FIs may be more likely to establish relationships with Fintechs which focus on partnering with financial institutions which lack the volume, resources, and economies of scale to develop their own bespoke solutions. Nevertheless, the data indicate that larger, more profitable institutions are more likely to be using these new credit scoring enhancements. If these result in significantly improved credit risk assessment, then the larger, more profitable institutions will gain an even greater advantage over their smaller, less profitable counterparts.

Current use of alternative data and/or new credit scoring methods is also positively associated (either on a univariate or multivariate basis) with several country-level factors: population; urban population; GDP; extent of development of the credit reporting infrastructure; alternative finance volume, among others. Use of alternative data and new credit scoring methods for Retail and SME lending is likely a result of, not a replacement for, well-developed financial and credit reporting infrastructures. Therefore, the vanguard financial institutions are probably more likely to be operating in countries where the existing infrastructure is already well developed and has resulted in a fair level of lender success at efficiently and profitably lending to Retail and SME borrowers. Alternative data and new credit scoring methods, then, are not necessarily the starting point for extending credit in each market, but are solutions aimed at filling gaps that a well-developed credit reporting infrastructure and traditional credit scoring methods have to date not been able to address. Although there are potentially exceptions (e.g., extension of tiny, short-term loans through mobile phones to the unbanked), a well-established credit reporting infrastructure likely remains a fundamental prerequisite to effective use of alternative data, which is an enhancement of that same infrastructure. For example, long-time global leaders in credit reporting and credit scoring such as Experian and FICO have embraced alternative data and are incorporating it into their existing platforms.[31,32]

[31] https://www.experian.com/blogs/insights/2022/09/using-alternative-credit-data-credit-underwriting/
[32] https://www.fico.com/independent/alternative-data

A somewhat surprising result from this study is the negative association between majority foreign bank ownership and current use of alternative data and/or new credit scoring methods. However, as shown in Figure 4.5, majority foreign-bank owned FIs are significantly more likely to consider credit scoring to be "important" or "very important" for Retail lending, which is in line with expectations based on the published literature. There are at least a few potential explanations for this dichotomy. One is that alternative data may be more likely than credit reporting data to be unique to certain markets and contexts and not standardized; thus, foreign-owned institutions, whose parent may seek standardization in underwriting practices across multiple regions, may be on the one hand more likely to use credit scoring for their Retail loans but less likely to incorporate an alternative local data source or new credit scoring technology, which inherently may be less standardized and more of an opaque "black box" (IFC, 2017, Shi, 2022, Snyder, 2017). Another potential reason is that majority foreign-owned FIs may have more difficulty in engaging with local Fintech companies for partnership as well as securing the resources to invest in Fintech solutions (Figure 4.7). In this regard, majority domestic-owned institutions, with more local market knowledge, may have an advantage in implementing non-standardized credit scoring solutions.

For many financial institutions, collaboration with Fintech companies is likely a prerequisite to rapid and effective implementation of alternative data and/or new credit scoring methods. Therefore, successful adoption of these credit scoring enhancements is likely a function of financial institution-specific factors: size, profitability, product-set, desire for innovation, ability to identify and engage with Fintechs, and country-specific factors: financial and credit infrastructure, population, and the amount of alternative finance in the market.

This study found that the use of alternative data and/or new credit scoring methods is prevalent in financial institutions served by EBRD. These new approaches to credit risk assessment will likely continue to expand in usage. With this expansion comes policy and risk management issues to be considered. The 2017 IFC publication, *Alternative Data Transforming SME Finance*, described several potential policy issues, a few of which are mentioned here. For example, regulatory agencies should ensure development of appropriate rules for use, security and control of individual and SME data, and data information should be shared with other parties only with the borrower's approval. An international framework should be developed for all financial services providers, led by the International Committee on Credit Reporting (ICCR), which would require borrower recourse mechanisms for identifying, correcting, and/or deleting inaccurate data, and establishing standard data retention periods. There should be "opt-in/opt-out" mechanisms established so that borrowers can decide whether they want to have alternative data used for their application. Other recommendations come from my own experience conducting a global evaluation (Snyder, 2017) of a fintech-developed alternative credit score that was being implemented across developing countries in Africa, Asia, and Latin America. First, model risk management becomes all the more challenging when using "black-box" models that may not be adequately understood by the model developers and/or lenders applying the models. It is essential that FIs adhere to model risk management guidance that meets the spirit of the U.S. Office of the Comptroller of the Currency's *Supervisory Guidance on Model Risk Management*.[33] To address the "black-box" nature of machine learning models, FIs should apply quantitative techniques such as analysis of Shapley values (Lundberg and Lee, 2017) to facilitate

[33] https://occ.gov/news-issuances/bulletins/2011/bulletin-2011-12a.pdf

model interpretation and monitoring. Finally, lenders should determine when use of alternative data and/or new credit scoring methods is superior to use of their own internal relationship data and traditional statistical models. As Gambacorta, et al. (2019) found, the comparative advantage of alternative data and machine learning models tends to decline as the length of the borrower relationship increases. Lenders that do not have the resources available to hire model risk management teams with sufficient expertise to provide effective challenge to vender-developed models should consider simpler, more traditional credit scoring approaches.

REFERENCES

Agarwal, S., Alok, S., Ghosh, P., et al. 2019. Financial Inclusion and Alternate Credit Scoring: Role of Big Data and Machine Learning in Fintech. Indian School of Business. SSRN: https://ssrn.com/abstract=3507827 or http://dx.doi.org/10.2139/ssrn.3507827

Akhavein, J., Frame, W. S., White, L. J. 2005. The Diffusion of Financial Innovations: An Examination of the Adoption of Small Business Credit Scoring by Large Banking Organizations. The Journal of Business, 78(2), pp. 577-596.

Alfaro, L., Auerbach, A., Cárdenas, M., Ito, T., Kalemli-Özcan, S., Sandefur, J. 2021. Doing Business: External Panel Review. World Bank Group. [online] Available at: https://www.worldbank.org/content/dam/doingBusiness/pdf/db-2021/Final-Report-EPR-Doing-Business.pdf

Allee, K., Yohn, T. 2009. The Demand for Financial Statements in an Unregulated Environment: An Examination of the Production and Use of Financial Statements by Privately Held Small Businesses. The Accounting Review, 84(1), pp. 1-25.

Anderson, R. 2007. The Credit Scoring Toolkit: Theory and Practice for Retail Credit Risk Management and Decision Automation. Oxford: Oxford University Press.

Arner, D. W., Barberis, J. N., Buckley, R. P. 2015. The evolution of fintech: a new post-crisis paradigm? SSRN Electronic Journal, 47, pp. 1271–1320.

Arraiz, I., Bruhn, M., Stucchi, R. 2015. Psychometrics as a Tool to Improve Screening and Access to Credit. IDB Working Paper Series Nº IDB-WP-625. Washington, DC: Inter-American Development Bank.

Asch, L. 1995. How the RMA/Fair, Isaac credit-scoring model was built. Journal of Commercial Lending, 77(June), pp. 10–16.

Ayagari, M., Beck, T., Demirguc-Kunt, A. 2007. Small and Medium Enterprises across the Globe. Small Business Economics, 29(4).

Bazarbash, M. 2019. FinTech in Financial Inclusion: Machine Learning Applications in Assessing Credit Risk. IMF Working Paper No. 19-109. Washington, D.C.: International Monetary Fund.

Beck, T., Demirguc-Kunt, A., Pería, M. 2011. Bank Financing for SMEs: Evidence Across Countries and Bank Ownership Types. Journal of Financial Services Research, 39, pp. 35-54.

Beck, T., Ioannidou, V., Shaffer, L. 2017. Foreigners vs. Natives: Bank Lending Technologies and Loan Pricing. Management Science, 64(8), pp. 3792-3820.

Berg, T., Burg, V., Gombović, A., Puri, M. 2020. On the Rise of Fintechs: Credit Scoring Using Digital Footprints. The Review of Financial Studies, 33(7), pp. 2845–2897.

Berg, T., Fuster, A., Puri, M. 2021. Fintech Lending. Working Paper 29421. National Bureau of Economic Research (NBER), October.

Berger, A. N., Black, L. K. 2011. Bank Size, Lending Technologies, and Small Business Finance. Journal of Banking and Finance, 35, pp. 724–735.

Berger, A. N., Cowan, A. M., Frame, W. S. 2011. The Surprising Use of Credit Scoring in Small Business Lending by Community Banks and the Attendant Effects on Credit Availability, Risk, and Profitability. Journal of Financial Services Research, 39, pp. 1–17.

Berger, A. N., Frame, W. S. 2007. Small Business Credit Scoring and Credit Availability. Journal of Small Business Management, 47, pp. 5–22.

Berger, A. N., Klapper, L., Udell, G. 2001. The Ability of Banks to Lend to Informationally Opaque Small Businesses. Journal of Banking and Finance, 25, pp. 2127–2167.

Berger, A. N., Udell, G. 2006. A More Complete Conceptual Framework for SME Finance. Journal of Banking and Finance, 30, pp. 2945–2966.

Bofondi, M., Lotti, F. 2006. Innovation in the Retail Banking Industry: The Diffusion of Credit Scoring. Review of Industrial Organization, 28(4), pp. 343-358.

Brown, M., Japelli, T., Pagano, M. 2009. Information Sharing and Credit: Firm-Level Evidence from Transition Countries. Journal of Financial Intermediation, 18, pp. 151–172.

Butaru, F., Chen, Q., Clark, B., Das, S., Lo, A. W., Siddique, A. 2016. Risk and Risk Management in the Credit Card Industry. Journal of Banking & Finance, 72, pp. 218-239.

Claessens, S., Frost, J., Turner, G., Zhu, F. 2018. Fintech Credit Markets Around the World: Size, Drivers and Policy Issues. BIS Quarterly Review, September.

Cornelli, G., et al. 2020. Fintech and Big Tech Credit: A New Database. BIS Working Paper No. 887. BIS Quarterly Review, September.

Cowan, C. D., Cowan, A. M. 2006. A Survey-Based Assessment of Financial Institution Use of Credit Scoring for Small Business Lending. Small Business Administration, Office of Advocacy Report No. 283.

Dastile, X., Celik, T., Potsane, M. 2020. Statistical and Machine Learning Models in Credit Scoring: A Systematic Literature Survey. Applied Soft Computing Journal, 91, 106263.

De la Torre, A., Pería, M., Schmukler, S. 2010. Bank Involvement with SMEs: Beyond Relationship Lending. Journal of Banking and Finance, 34, pp. 2280–2293.

DeYoung, R., Frame, W. S., Glennon, D., Nigro, P. 2011. The Information Revolution and Small Business Lending: The Missing Evidence. Journal of Financial Services Research, 39, pp. 19-33.

Djankov, S., McLiesh, C., Shleifer, A. 2007. Private Credit in 129 Countries. Journal of Financial Economics, 12(2), pp. 77-99.

Doblas-Madrid, A., Minetti, R. 2013. Sharing Information in the Credit Market: Contract-Level Evidence from U.S. Firms. Journal of Financial Economics, 109, pp. 198–223.

European Bank for Reconstruction and Development (EBRD). 2021. Transition Report 2021-2022: System Upgrade: Delivering the Digital Dividend. Chapter 4. Fintech and Banks in Transition. ISBN: 978-1-898802-53-2.

Feldman, R. 1997. Banks and a Big Change in Technology Called Credit Scoring. Federal Reserve Bank of Minneapolis. The Region, September, pp. 19-25.

Financial Stability Board. 2017. Artificial Intelligence and Machine Learning in Financial Services: Market Developments and Financial Stability Implications.

Findexable. 2020. The Global Fintech Index 2020. Available at: https://findexable.com.

FinRegLab. 2019. The Use of Cash-flow Data in Underwriting Credit: Small Business Spotlight.

Frame, W. S., Srinivasan, A., Woosley, L. 2001. The Effect of Credit Scoring on Small Business Lending. Journal of Money, Credit, and Banking, 33, August, pp. 813–825.

Frame, W. S., White, L. J. 2004. Empirical Studies of Financial Innovation: Lots of Talk, Little Action? Journal of Economic Literature, 42, March, pp. 116–114.

Frame, W. S., Padhi, M., Woolsey, L. 2004. The Effect of Credit Scoring on Small Business Lending in Low- and Moderate-Income Areas. Financial Review, 39, pp. 35–54.

Frost, J. 2020. The Economic Forces Driving Fintech Adoption Across Countries. BIS Working Paper No. 838, February.

Gambacorta, L., Huang, Y., Qiu, H., et al. 2019. How Do Machine Learning and Non-Traditional Data Affect Credit Scoring? New Evidence from a Chinese Fintech Firm. BIS Working Papers No. 834.

Hanley, J., McNeil, B. 1982. The Meaning and Use of the Area Under a Receiver Operating Characteristic (ROC) Curve. Radiology, 143, pp. 29–36.

Hoo, Z. H., Candlish, J., Teare, D. 2017. What Is an ROC Curve? Emergency Medicine Journal, 34, pp. 357-359. http://dx.doi.org/10.1126/science.3287615

International Monetary Fund (IMF) and World Bank. 2019. Fintech: The Experience So Far. Policy Paper No. 2019/024, IMF and World Bank, Washington, DC.

International Finance Corporation. 2006. Credit Bureau Knowledge Guide. Washington, D.C.

International Finance Corporation. 2009. The SME Banking Knowledge Guide. Washington, DC.

International Finance Corporation. 2012. Credit Reporting Knowledge Guide. Washington, DC. © World Bank. https://openknowledge.worldbank.org/handle/10986/21545 License: CC BY-NC-ND 3.0 IGO.

Jagtiani, J., Lemieux, C. 2018. Do Fintech Lenders Penetrate Areas That Are Underserved by Traditional Banks? Journal of Economics and Business, 100, pp. 43–54.

Jagtiani, J., Lemieux, C. 2019. The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the Lending Club Consumer Platform. Financial Management, 48, pp. 1009–1029.

Jappelli, T., Pagano, M. 2002. Information Sharing, Lending and Defaults: Cross-country Evidence. Journal of Banking & Finance, 26, pp. 2017–2045.

Khandani, A., Kim, A., Lo, A. 2010. Consumer Credit-Risk Models via Machine-Learning Algorithms. Journal of Banking & Finance, 34(11), pp. 2767–2787.

Love, I., Mylenko, N. 2003. Credit Reporting and Financing Constraints. World Bank, Working Paper.

Lundberg, S., Lee, S.-I. 2017. A Unified Approach to Interpreting Model Predictions. Preprint at arXiv. https://doi.org/10.48550/arXiv.1705.07874.

Marceau, L., Qiu, L., Vandewiele, N., Charton, E. 2019. A Comparison of Deep Learning Performances with Other Machine Learning Algorithms on Credit Scoring Unbalanced Data. arXiv. https://arxiv.org/abs/1907.12363.

Mays, E., Lynas N. 2011. Credit Scoring for Risk Managers: The Handbook for Lenders., 2nd edition. CreateSpace Independent Publishing Platform. ISBN 1450578969. 264 pages.

Mester, L. J. 1997. What's the Point of Credit Scoring? Federal Reserve Bank of Philadelphia Business Review, September/October, pp. 3–16.

Miller, M., Rojas, D. 2004. Improving Access to Credit for SMEs: An Empirical Analysis of the Viability of Pooled Data SME Credit Scoring Models in Brazil, Colombia, and Mexico. World Bank, Working Paper.

Owens, J., Wilhelm, L. 2017. Alternative Data Transforming SME Finance. International Finance Corporation.

Padilla, A., Pagano, M. 2000. Sharing Default Information as a Borrower Discipline Device. European Economic Review, 44(10), pp. 1951–1980.

Pagano, M., Japelli, T. 1993. Information Sharing in Credit Markets. Journal of Finance, 48, pp. 1693–1718.

Peria, M. S. M., Singh, S. 2014. The Impact of Credit Information Sharing Reforms on Firm Financing. World Bank, Policy Research Working Paper No. 7013.

Puri, M., Rocholl, J., Steffen, S. 2017. What Do a Million Observations Have to Say About Loan Defaults? Opening the Black-Box of Relationships. Journal of Financial Intermediation, 31, pp. 1-15.

Rudin, C., Radan, J. 2019. Why Are We Using Black-Box Models in AI When We Don't Need To? A Lesson from an Explainable AI Competition. Harvard Data Science Review, Issue 1.2, Fall.

Sedunov, J. 2017. Does Bank Technology Affect Small Business Lending Decisions? The Journal of Financial Research, XL(1), pp. 5–32. Spring.

Shi, S., Tse, R., Luo, W., et al. 2022. Machine Learning-Driven Credit Risk: A Systemic Review. Neural Computing and Applications, 34, pp. 14327–14339.

Siddiqui, N. 2006. Credit Risk Scorecards: Developing and Implementing Intelligent Credit Scoring. Hoboken, N.J.: Wiley.

Snyder, D. 2017. EFL Evaluation Study. International Finance Corporation.

Stein, R. 2007. Benchmarking Default Prediction Models. Pitfalls and Remedies in Model Validation. Journal of Risk Model Validation, 1, pp. 77-113.

Stiglitz, J., Weiss, A. 1981. Credit Rationing in Markets with Imperfect Information. The American Economic Review, 71(3), pp. 393-410.

Swets, J. A. 1988. Measuring the Accuracy of Diagnostic Systems. Science, 240, pp. 1285-1293.

United States Agency for International Development (USAID). 2006. A Handbook for Developing Credit Scoring Systems in a Microfinance Context.

Vidal, M. F., Barbon, F. 2019. Credit Scoring in Financial Inclusion. Technical Guide. Washington, D.C.: CGAP.

Wendel, C. B., Harvey, M. 2006. SME Credit Scoring: Key Initiatives, Opportunities, and Issues. World Bank, Access Finance, 10 (March).

World Bank Group. 2019. Credit Reporting Knowledge Guide. Washington, D.C.