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CREDIT REPORTING SYSTEMS, CREDIT RISK AND ACCESS TO CREDIT: EVIDENCE FROM EUROPEAN UNION COUNTRIES

Abstract

The purpose of the article. This paper analyses the impact of credit information exchange systems on banks' credit risk and the availability of credit in European Union countries. The aim of the study was to assess the relationship between selected characteristics of credit information exchange systems – in particular, the scope of data processed and the level of population coverage by private credit bureaus and public registers – and the quality of banks' loan portfolios and access to finance (taking into account the cost of bank credit).

Methodology. The research covered the banking sectors of European Union countries over 2014–2024. Linear regression was used to examine the relationship between CRS characteristics, non-performing loans (NPLs), and credit availability. Dynamic panel data models were estimated using the GMM-SYS method, while static random-effects models were used to analyse credit spreads. The explanatory variables included credit data completeness, information on consumer income and insolvencies, and population coverage by private and public credit registers. Macroeconomic and sectoral indicators identified through a literature review were used as control variables.

Results of the research. Research findings indicate that comprehensive credit information systems, including data on consumer insolvency, are associated with lower credit risk materialization and credit spreads. Broader coverage by private credit bureaus is linked to lower NPL levels and greater access to credit, whereas a greater role for public credit registers is associated with more limited access to finance. The development of CRS systems may also lead to more rigorous borrower selection, reducing the number of borrowers and credit accounts while improving loan portfolio quality. The findings indicate that data completeness is more important for credit market efficiency than the model used to build the information infrastructure. The inclusion of ESG data and BNPL liabilities in credit information is associated with changes in credit availability and pricing, but does not reduce credit risk.

Keywords: credit reporting systems, credit risk, access to credit, credit information agencies, the cost of credit

JEL Class: G21, G28



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Received: 20.01.2026 Accepted: 25.08.2026 Available online: 30.09.2026

Funding information: Some of the research presented in this article was carried out as part of the project: 'Rola systemu wymiany informacji kredytowej w procesie redukcji ryzyka kredytowego, ochrony konsumenta i budowania inkluzywności systemu bankowego – perspektywa prawna i ekonomiczna doświadczeń krajowych i międzynarodowych', funded by the Warszawski Instytut Bankowości. **Conflicts of interests:** None. **Ethical considerations:** The Author assures of no violations of publication ethics and takes full responsibility for the content of the publication.

Introduction

Credit reporting systems (CRS) constitute a key element of the infrastructure supporting access to credit, financial inclusion, prudential supervision and financial stability (World Bank, 2022, pp. 1, 11). Credit reporting systems comprise the institutions, individuals, rules, procedures, standards and technologies that enable the flow of information supporting credit-granting decisions. Credit reporting service providers (CRSPs) – institutions or agencies that collect, process and disseminate data on borrowers and manage credit information sharing systems – provide lenders and businesses with key information on credit ratings, credit histories and cases of fraud. This category includes commercial credit bureaus, public credit registries, business information providers and alternative credit reporting service providers that use innovative methodologies and non-conventional data (World Bank, 2022, p. 15). However, their activities entail significant risks – strategic, operational, cyber, model, reputational, and legal, regulatory and compliance risks – and the use of innovative technologies and alternative data sources further increases the level of risk.

Risk assessment and applicant verification are particularly important for consumer credit, whose portfolios usually comprise a large number of low-value contracts, often with limited collateral effectiveness. Information on how a prospective borrower has met past obligations enables lenders to assess credit risk more accurately, mitigating problems related to adverse selection. Given the high degree of interconnectedness in the financial sector, the absence of a well-developed credit reporting infrastructure may seriously disrupt the functioning of credit markets and, consequently, threaten financial stability at both the national and global levels (World Bank, 2022).

Globally, there are considerable variations in the models of credit reporting systems, both from the institutional perspective and in terms of the scope of data aggregated and processed in the lending transactions. The architecture of the system may be an important factor affecting the ability of banking sector entities to manage credit risk effectively and may influence the direction of banks' lending policies.

The aim of this article is therefore to assess the relationships between selected characteristics of credit information sharing systems (in particular, the scope of the data they process and the population coverage by private and public credit bureaus) and the level of non-performing loans (as a measure of the effectiveness of credit risk management) and access to credit, including its cost. The empirical analysis covers the countries of the European Union in the years 2014–2024. The main hypothesis states that the model of the credit information sharing system (the scope of the data collected in terms of borrowers and products, and the coverage of the population by private and public credit bureaus) is significantly correlated with the effectiveness of bank credit risk management (measured by the level of non-performing loans) and with access to bank credit.

The auxiliary hypotheses specify the direction of this relationship for selected characteristics of the system. Hypothesis 1 (H1) states that a higher level of completeness of the credit information sharing system, understood as reporting covering the full range of entities (individuals, SMEs and large enterprises) and the processing of information on consumer bankruptcy, is associated with a lower level of non-performing loans and lower credit margins. Hypothesis 2 (H2) states that a higher level of completeness of the credit information sharing system is associated with narrower access to credit, measured by the number of borrowers and credit accounts per 1,000 adults and by the ratio of household loans to GDP, which is consistent with a mechanism of tighter borrower selection. According to Hypothesis 3 (H3), higher population coverage by private credit bureaus is associated with a lower level of non-performing loans and broader access to credit, whereas higher coverage by public registries is not associated with the quality of the loan portfolio but is associated with narrower access to credit.

The verification of hypotheses involves an econometric verification of the relationship between the characteristics of credit information exchange systems and measures of risk, access, and the cost of credit.

The importance of an effective credit information sharing market

A fundamental obstacle to the effective functioning of credit markets is information asymmetry between lender and borrower. Two phenomena that are well described in the literature follow from it: adverse selection, consisting in the systematic crowding out of creditworthy applicants from the credit market by high-risk ones, and moral hazard, manifested in changes in the borrower's behavior after the loan agreement has been concluded. Institutional mechanisms for sharing credit information are one of the most effective tools for overcoming this asymmetry (Jappelli & Pagano, 2002). Empirical studies consistently confirm a positive relationship between the existence and quality of credit information systems and the availability and cost of financing.

An effective credit information sharing market has a favorable effect on the cost of debt financing and allows lenders to differentiate risk rationally, which also makes it possible to extend the credit offer to groups of entities previously excluded from the market because of the lack of a credit history or its unverifiability. This is particularly important for so-called credit invisibles – persons without an adequate credit history in databases – and for entities with a limited (thin-file) credit history that does not allow a reliable risk assessment (Fosu et al., 2023). Credit information sharing systems foster growth in the volume of loans granted. The International Finance Corporation (IFC), based on an analysis of 60 countries for 2004–2017, showed a positive relationship between the development of the credit information market and access to credit, bank profitability and broadly understood economic development (Masunda, 2026). Better verification and early-warning analytics reduce the number of non-performing loans

(NPLs), strengthening the resilience of the banking system. Adequate access to credit for small and medium-sized enterprises (SMEs), which are among the groups traditionally hit hardest by credit rationing, is particularly important for financial policy (Masunda, 2026).

An important mechanism through which CRSPs affect access to credit is the creation of reputational incentives. A borrower who is aware that his or her repayment history is recorded and made available to potential future lenders has a stronger incentive to settle obligations on time. In turn, a lender with access to a verifiable history is inclined to offer more favorable financing terms. In sum, credit information sharing mitigates the problems of adverse selection, moral hazard and agency costs, which ultimately leads to lower default rates in credit markets.

Effectiveness of credit information sharing systems

The effectiveness of credit information systems in increasing the efficiency of risk management and access to credit is not automatic and depends on several institutional, legal and technological factors. The literature points to the following key determinants of CRSP effectiveness (World Bank, 2019):

- scope and completeness of data – systems reporting only negative information (delays, debt collection) are much less effective in supporting financial inclusion than full-file reporting systems, which cover both positive and negative information. Negative-only reporting perpetuates a situation in which the reliable repayment of obligations does not translate into an improvement in the borrower's position in the market;
- population coverage – the analytical value of a system is limited when it covers only part of the borrowers. An increase in the number of entities registered raises the informational value of the system for all its participants (network effect) and, at the same time, widens the range of entities to which the system can facilitate access to financing;
- data quality and timeliness – continuously updated data are a condition of the reliability of credit assessments; outdated or erroneous data can lead to both type I errors (refusing credit to a creditworthy entity) and type II errors (granting credit to an entity that is in fact not creditworthy);
- legal framework and personal data protection – the implementation of credit information systems requires coherent regulations guaranteeing the rights of data subjects (access to one's own history, the right to correct erroneous entries, data retention periods) while enabling effective data exchange between system participants.

From the perspective of a banking institution, credit information systems perform an infrastructural function throughout the life cycle of a credit exposure, from the initial assessment of an application, through portfolio monitoring, to the management of distressed receivables. The quality and completeness of the data obtained from CRSPs directly determine the accura-

cy of credit decisions and thereby shape the bank's risk profile at the level of both individual exposures and the entire portfolio (Li et al., 2024). The role of credit information systems is not limited to the application-acceptance phase; their function in the ongoing monitoring of the loan portfolio is equally important. An increase in a client's debt with other institutions, the appearance of new credit inquiries or a deterioration in the limit utilization ratio are signals that allow preventive action: renegotiation of terms, reduction of the available limit, strengthening of collateral or initiation of a restructuring process.

Despite their undeniable benefits, credit information systems also generate specific challenges for risk management in banks. The first is procyclicality risk: scoring models calibrated on historical data may systematically underestimate risk in phases of credit expansion and overestimate it in recessions, thereby amplifying cyclical fluctuations in lending. The second important challenge is the quality and consistency of data in CRSP systems, especially in a cross-border context. The third area of risk is dependence on historical data in the face of structural changes in macroeconomic conditions.

In sum, credit information supports access to financing mainly because it makes it possible to reduce, in part, the weight of collateral requirements and to assess client risk better; this does not, however, mean an automatic increase in lending, but rather the possibility of distinguishing more accurately between entities that are genuinely able to repay and those whose risk profile justifies a refusal of financing or more cautious credit terms (Morscher et al., 2017; Ndoye & Barajas, 2023).

The role of data scope and sources in the proper functioning of the credit information exchange system

Data from credit information systems allow banks to assess not only the situation declared by the client but also his or her actual payment behavior in relations with other lenders. Information on repayment history, the number of active liabilities, the level of debt, limit utilization, arrears and the length of the credit history enables a better estimation of both repayment capacity and creditworthiness. These data reduce the risk of taking decisions solely on the basis of information supplied by the client (Ferretti, 2015; Miller, 2000). The importance of these categories of information is well illustrated by Global Findex data, according to which in low- and middle-income economies a significant share of borrowing continued to take place outside the formal financial sector. This shows that credit inclusion should be analyzed not only through the prism of general access to financial services but also through the possibility of obtaining responsibly granted credit on the basis of sufficient, reliable and verifiable information about the client (Klapper et al., 2025). The quality of the data used in credit reporting systems is particularly important. The report of the World Bank and the International Committee on Credit Reporting (ICCR)

emphasized that integrated reporting mechanisms, such as credit bureaus and credit registries, as a rule ensure higher data quality, greater usefulness of information and greater efficiency than ad hoc, unstructured inquiries addressed directly to individual financial institutions. For the credit process this means that the value of information from credit bureaus derives not only from its scope but also from the way it is organized and updated and from the possibility of comparing it across lenders (World Bank Group & International Committee on Credit Reporting, 2015).

The importance of data in the credit process should be considered not only through the prism of their scope but also of the way they are obtained, processed, integrated and controlled. The effectiveness of scoring and rating models depends not only on the availability of information about the client but also on the quality of the data infrastructure, the rules for integrating sources, documenting data provenance, tracking their transformations and ensuring compliance with privacy and security requirements (Blazquez & Domenech, 2018). The level of granularity of the data used in credit assessment is also important. Data quality consists not only in completeness and timeliness but also in an appropriate observation frequency, which makes it possible to capture changes in the client's financial behavior over time (Goldmann et al., 2025).

Data from credit bureaus are used not only at the stage of the decision to grant credit but also in the broader management of the client relationship and the loan portfolio (Furletti, 2002). The inclusion of alternative data in credit assessment can support credit inclusion primarily because the traditional assessment model based on repayment history creates a barrier to access for clients with a short or non-existent credit history. The World Bank and the ICCR indicate that this problem concerns in particular young people, immigrants, women, minorities, small and medium-sized enterprises and entities operating in the informal sector. The lack of an adequate credit history may limit access to formal financing even though potential borrowers leave other traces of economic activity, e.g., in the form of payments for telephone, utilities and rent, activity on digital platforms, e-commerce, or data related to online settlements. In this perspective, alternative data can reduce the effects of "credit invisibility", but their use should be supplementary and subject to quality control, proportionality and compliance with clients' rights (World Bank Group & International Committee on Credit Reporting, 2025, p. 10).

The importance of information quality is particularly visible in scoring models, in which input data are transformed into a synthetic assessment of client risk. Models used by credit bureaus therefore evolve continuously, as illustrated, among others, by the new scoring model of the Credit Information Bureau (Biuro Informacji Kredytowej, BIK), whose rollout began in 2026. The new model is based on three key groups of data: timeliness of repayments, activity in the financial market and experience in repaying obligations. The first group includes, among others, information on delays in the repayment of loans, amounts of arrears and debt collection or enforcement proceedings. The second concerns amounts of loans, amounts outstanding

and the amount and utilization of credit limits. The third covers the length of the credit history. At the same time, BIK indicates that the new model does not use data from credit applications that did not result in financing, and that credit inquiries are automatically deleted after 14 days if they do not result in financing (BIK, 2025).

The BIK example illustrates that in scoring practice particular weight is attached to information on actual use of credit and its repayment, rather than to the mere fact of applying for financing. Data from credit bureaus have high decision value only when they are complete, up to date, consistent and properly integrated with other information used by the bank (Siddiqi, 2017). Modern credit models increasingly use not only traditional financial data and information on repayment history but also a wider set of data derived from, among others, corporate databases, transaction sources, earlier payment delays, corporate network links or publicly available information. Such a scope of data may increase the models' ability to identify complex risk patterns but at the same time raises requirements for the selection, quality, interpretability and proportionality of the information used.

Digitalization, whose pace was accelerated by the pandemic, has caused an exponential growth in the number and diversity of alternative data sources (World Bank Group & International Committee on Credit Reporting, 2025, p. 10). The use of alternative data in credit risk assessment creates new opportunities but also entails risks and challenges. The main benefits include greater transparency and a more comprehensive picture of potential borrowers, especially consumers with a limited or no credit history, which improves access to services for social groups with limited access to financial services. The use of alternative data may, however, introduce bias, leading to discriminatory outcomes and the perpetuation of inequalities. Therefore, although alternative data can improve financial inclusion, they also carry the risk of deepening inequalities with respect to marginalized groups, including women and minorities (World Bank Group & International Committee on Credit Reporting, 2025).

The more complex the models used in the credit process, the greater the role played by their comprehensibility, transparency and the possibility of explaining the result from a supervisory and organizational perspective (Andriosopoulos et al., 2019). On the other hand, many reports point to the need for a cautious approach to alternative data; their actual use therefore remains limited, and the scale of benefits depends on data quality, their predictive power and control of the risks related to discrimination, privacy and the explainability of credit decisions (Government Accountability Office, 2021). Alternative data can play a supplementary role in assessing clients who are less visible in traditional credit databases, but they do not replace information on the actual history of repayment of obligations (Muñoz-Cancino et al., 2023).

The requirement of data quality control is also confirmed in regulatory guidelines. The EBA guidelines stress the need to ensure the quality, traceability, verifiability, robustness and

resilience of input data and a regular assessment of the quality of model outputs. In practice this means the need to check data correctness, monitor model performance, verify their historical effectiveness and document assumptions, limitations and changes (EBA, 2020). Incomplete data may lead to two basic types of decision errors. The first is false acceptance, i.e., granting a loan to a client who in fact does not have a lasting ability to repay it. The second is false rejection, i.e., refusing financing to a client who would in fact be able to service the obligation on time. In such a case the lack of information may be wrongly equated with high risk, even though the client's actual profile would justify granting financing (Stiglitz & Weiss, 1981; Carroll & Rehmani, 2017). Incomplete data also affect the pricing terms of financing. From the client's perspective, data quality thus affects not only access to financing but also its cost and terms. From the bank's perspective, it determines the accuracy of risk pricing and the efficiency of capital allocation (Müller et al., 2024; Perrotta et al., 2023).

In sum, data quality is one of the basic conditions for an accurate assessment of creditworthiness and credibility. Even extensive procedures, scoring models and analytical tools cannot ensure a correct credit decision if they rely on incomplete, outdated, inconsistent or low-quality information (Basel Committee on Banking Supervision, 2025).

Diversity of credit information sharing systems

There is no single optimal pattern of organizing a CRS. Hybrid models dominate and are constantly transforming, as is the tendency to rely on full data (negative and positive) and to extend their scope to include alternative data. This market is important for key stakeholders (FCA, 2023): credit information agencies (CRAs), data providers and users of credit information, credit information service providers and consumers. Three main models of organizing this market can be distinguished:

- a centralized model, based on the monopoly of a public registry or of a private credit agency/bureau;
- a decentralized model, based on an oligopoly of several agencies with partly different mandates;
- a hybrid model.

Private credit bureaus are commercial entities whose activity focuses on collecting detailed data on borrowers. Public credit registries, which are institutions operating at central banks or financial supervisory authorities, are oriented primarily toward regulatory and supervisory needs. Public registries usually cover loans above a certain threshold amount, which may limit their effectiveness with respect to individuals and small businesses (Ferretti, 2017). In the centralized model, one national (or supranational) institution collects, stores and makes available credit information on all borrowers, e.g., the public credit registry run by the Banque de France.

The advantages of such a model are the comprehensiveness and standardization of data, lower costs owing to the absence of data duplication, and better regulatory oversight of data quality and security. The disadvantages are the potentially severe consequences of a systemic failure, limited competition that may lead to slower introduction of innovations, and the absence of pressure to improve service quality or reduce costs for lenders. A state agency may also be under pressure to place the pursuit of political goals above market efficiency. In the decentralized model, many private credit bureaus compete with one another in collecting and selling credit information. Examples are Experian, Equifax, CRIF and Creditreform, operating in different EU member states. The advantages of the model are innovation driven by competitive pressure, greater resilience to cyberattacks owing to dispersed data, and considerable flexibility and specialization – niche operators can develop expertise in particular sectors. The disadvantages are fragmentation – data on borrowers may be split among many bureaus, which gives each of them an incomplete picture and leaves persistent information asymmetry – as well as gaps in coverage and inconsistent standards that make comparisons between bureaus difficult. This model also entails greater regulatory complexity and inequality in access to data.

Most EU member states use hybrid systems – a public credit registry run by the central bank (usually covering large exposures) and private credit bureaus dealing with retail and SME loans. This solution combines supervisory advantages with concern for market efficiency but creates challenges of coordination and oversight.

The credit information sharing market in the United States is the most mature and most developed system of this kind in the world. Its architecture rests on an oligopoly of three dominant private credit bureaus – Equifax, Experian and TransUnion, known as the Big Three or NCRAs (*nationwide consumer reporting agencies*) – supplemented by specialized entities. According to CFPB data, more than 90% of American adults have active credit reports at one of the three main bureaus. The reporting model is full-information (*full-file reporting*). A key role in operationalizing credit data for lenders' decisions is played by the FICO score (Fair Isaac Corporation), whose successive versions are the industry standard. Since October 2022 the Federal Housing Finance Agency has approved the VantageScore 4.0 model alongside FICO for use in mortgages backed by the federal government, which marks the first significant breaking of FICO's monopoly in this segment in decades (CFPB, n.d.; Board of Governors of the Federal Reserve System et al., 2019). The regulatory framework of the system is set by the Fair Credit Reporting Act (FCRA) of 1970 (amended many times) and the Equal Credit Opportunity Act of 1974, which impose on the bureaus obligations regarding data accuracy, the consumer's right of access to his or her own report and procedures for disputing erroneous entries. Supervision of credit agencies is exercised by the Consumer Financial Protection Bureau (CFPB) (Board of Governors of the Federal Reserve System et al., 2019). The main weakness of the

system, repeatedly documented by the Consumer Financial Protection Bureau and consumer organizations, remains the high share of errors in credit reports.

The British system is the most technically advanced, has the richest data, the most competitive market and the strongest infrastructure for credit assessment. Three global credit information agencies operate in parallel: Experian, Equifax and TransUnion, and competition drives innovation. Beyond them, about 20 smaller entities with the powers of credit reference agencies (CRAs) operate in the market, focusing on niche segments, often using alternative data and open-banking-based models. Banks and lenders use their own internal models based on data from one or all three credit information agencies. The British system is full-information (both positive and negative information is reported) and covers a wide range of data, including bank account history, court judgments, electoral roll data used to verify identity, and obligations toward utility and telecom providers. Regulations do not oblige lenders to submit data to all three agencies – the lender decides which agency's services to use, which may put at a disadvantage consumers who must check all three databases to understand their full credit profile.

A key turning point for sector regulation is the Credit Information Market Study published in December 2023 by the Financial Conduct Authority (FCA), (FCA, 2023). The FCA found that the credit information sector is undergoing its deepest transformation in decades and announced a package of measures centered on four areas: governance, data quality, scope of reporting and consumer engagement. A central element of the reform is the establishment of a new industry oversight body, the Credit Reporting Governance Body (CRGB), replacing the existing self-regulatory committee SCOR (Steering Committee on Reciprocity). As part of the work leading to the full implementation of the CRGB, the three largest credit bureaus began joint work on a standardized data reporting format (Standard Industry Reporting Format, SIRF), intended to improve the consistency and quality of data in the system. A particularly dynamic area of development of the British market is the integration of traditional credit data with open banking data, implemented in the United Kingdom more widely and earlier than in many countries of continental Europe. In 2026 the FCA launched a consultation on further modifications to the reporting system (FCA, 2023, 2026).

The Italian credit information system is distinguished by a clear institutional dualism: a public credit register supervised by the central bank and private credit information systems operate in parallel, and the two have different scopes, reporting thresholds and legal bases (Banca d'Italia, n.d.-a). Banca d'Italia provides registered intermediaries with a monthly aggregate statement of each client's total indebtedness in the banking system, enabling an assessment of concentration risk. It is important that the register is not a scoring system – it supplies raw quantitative data, which are then interpreted by credit institutions in their own risk models (Banca d'Italia, n.d.-b). A limitation of the public system is the high reporting threshold. This gap is filled by private

credit information systems, of which EURISC, a system managed by the CRIF group (Damiani, 2026), holds the dominant position; it integrates positive and negative information on individuals and entrepreneurs, is fed with data from more than 500 market participants and has no amount threshold. CRIF, founded in 1988 in Bologna with the participation of six credit institutions from the Emilia-Romagna region, has grown into a global player. It now operates in more than 50 countries, serves more than 6,500 banks and financial institutions, earns revenue exceeding EUR 500 million a year and in Poland is active especially in the economic information market (CRIF, 2026). A characteristic weakness of the Italian system is the relatively low standardization of data across the individual systems and the absence of a uniform, commonly used scoring model – Italian banks rely on their own models to a greater extent than their Anglo-Saxon counterparts.

The German credit information system is dominated by Schufa (Schutzgemeinschaft für allgemeine Kreditsicherung), a private company owned by banks, retailers and credit card companies. It operates within a broader ecosystem that includes Creditreform (focusing on corporate credit), Bürgel and CRIF. Schufa collects data from more than 10,000 reporting entities, including banks, mobile operators, insurance companies and utility providers, so that its reach extends well beyond the financial sector alone (SCHUFA, 2026). It holds data on the vast majority of adult residents of Germany, which makes it one of the most comprehensive consumer databases in Europe. Schufa was criticized in the past for using opaque methods of calculating the credit score. The 2026 reform introduced a new, simpler credit rating (Huertas, 2026). The reform was partly forced by the case law of the Court of Justice of the European Union, which considered cases in which consumers had been refused credit and Schufa had provided them only with a score and general information without disclosing the exact calculation method.

France represents the most centralized model among the countries analyzed, based on registers run directly by the Banque de France (Banque de France, n.d.). The registers run by the central bank concern:

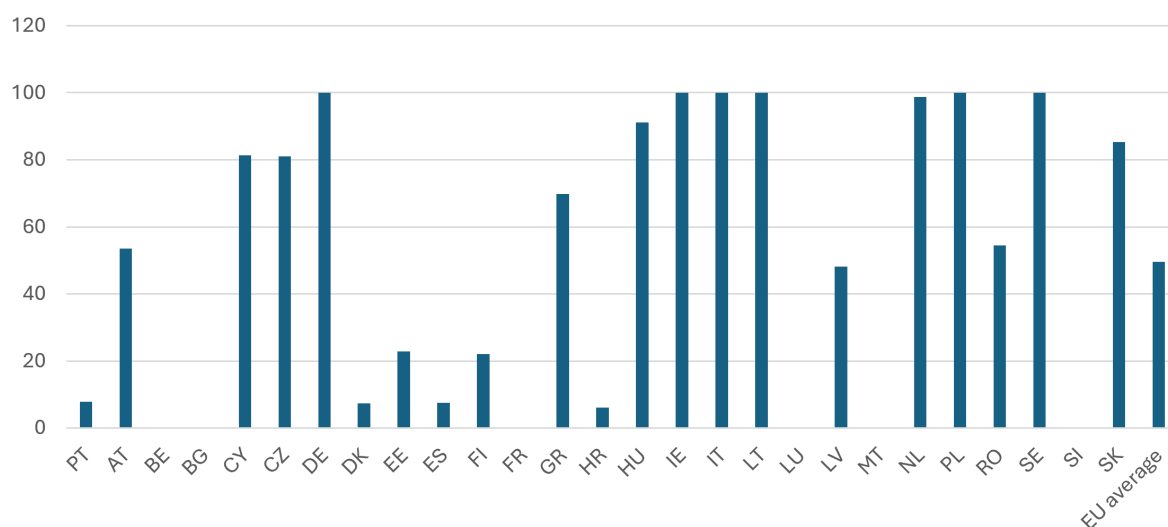
- FICP (Fichier National des Incidents de Remboursement des Crédits aux Particuliers) – insolvency and over-indebtedness in consumer credit;
- FCC (Fichier Central des Chèques) – records cheque fraud and payment incidents;
- FIBEN (Fichier Bancaire des Entreprises) – a database on enterprises, covering firms with turnover above EUR 750,000. FIBEN performs the rarely encountered function of a public creditworthiness assessment system for SMEs.

The French public model offers a high degree of regulatory integrity and coverage of SMEs but is structurally weaker in terms of credit information on retail clients because of its restriction to negative entries only (ACCIS, 2020). Empirical studies show (Brown et al., 2009; Haas Ornelas et al., 2025; Jappelli & Pagano, 2002) that collecting repayment data significantly improves the effectiveness of the database.

Historical information (up to 2020) on the scope of credit bureau activity was also published by the World Bank. Figure 1 presents the credit bureau coverage indicator, while Figure 2 presents the level of coverage by public credit registries.

Figure 1

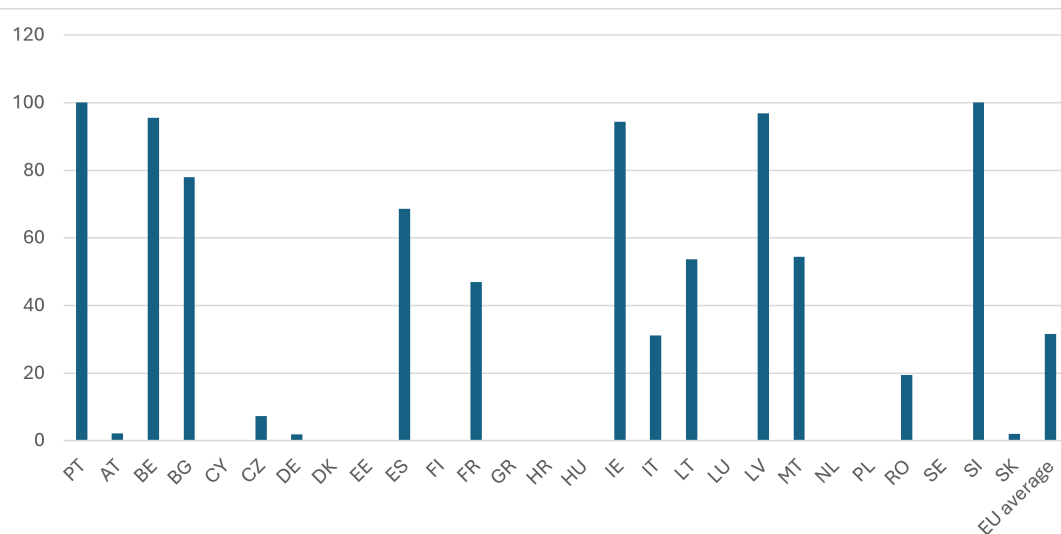
Coverage of private credit bureaus (number of persons for whom credit information is processed, as % of adults) in 2020



Source: own elaboration based on World Bank Group data.

Figure 2

Coverage of public credit registries (number of persons for whom credit information is processed, as % of adults) in 2020



Source: own elaboration based on World Bank Group data.

According to World Bank data, Poland is assessed as a country with full information scope in terms of the data processed. Based on estimates, the depth of credit information index of the credit information sharing system in Poland reached the maximum level of 8 in 2014–2020 (as one of three EU countries). The Polish credit information sharing system took shape in less than three decades and today is among the most mature and comprehensive systems of this kind in Central and Eastern Europe. The leading private credit information agency is BIK (Biuro Informacji Kredytowej, the Credit Information Bureau), founded in 1997 by the Polish Bank Association and commercial banks. It serves as the central point for collecting data on consumer loans and on loans to small and medium-sized enterprises. Separate private agencies focus on negative information, concerning mainly enterprises and non-bank creditors such as telecommunications operators, utility providers and leasing companies (payment arrears, indebtedness) – for example BIG InfoMonitor and KRD (Krajowy Rejestr Długów, the National Debt Register). The National Bank of Poland runs a public credit register, but with a fairly high reporting threshold (exposures $\geq$ PLN 500,000 for non-financial entities and $\geq$ PLN 200,000 for individuals), so it plays a macroprudential rather than a credit-decision-support role in the retail sector. This means that BIK effectively performs the role that in some countries (France, Spain, Italy) is performed by the central bank's public registry.

The credit information exchange system model and credit risk in the light of an econometric study

An important element of the analysis was a statistical assessment of the significance of relationships between selected characteristics of credit information sharing system models in European Union countries and the scale of credit risk materialization in banks, as well as access to credit and its cost. The core period of analysis is 2014–2024. The set of variables used in the econometric study is described in Appendix 1, and descriptive statistics are given in Appendix 2. The analysis was carried out using dynamic panel data models estimated with the GMM-SYS estimator (Blundell-Bond). The lags of the dependent variable were instrumented by their available further lags and other possibly endogenous variables were instrumented also by their available further lags. The Arellano-Bond test in the prepared models indicates the presence of first-order autocorrelation and the absence of second-order autocorrelation, which confirms the correct specification of the dynamic models. The Hansen test does not reject the hypothesis of instrument validity. The number of instruments remains lower than the number of cross-sectional units, which limits the risk of instrument proliferation.

The general form of the models is given by the formula:

$$CM_{i,t} = \text{const} + a_1 CM_{i,t-1} + a_2 CRS_{i,t} + a_3 MACRO_{i,t} + a_4 SECT_{i,t} + v_{it} \quad (1)$$

where: CM – a selected characteristic of the credit market, covering one of two areas – the materialization of credit risk as a measure of the effectiveness of credit risk management, or access to credit, measured by the ratio of loans to GDP, the number of borrowers and credit accounts per 1,000 adults and credit margins; CRS – a selected characteristic of the credit information sharing system model, including features such as the scope of data collected in terms of borrowers and products, the detail and completeness of data, and the level of data coverage in public and private registries; MACRO – a vector of macroeconomic control variables; SECT – a vector of sector-level control variables. In static models (credit margins) the lagged dependent variable was omitted.

The results of the econometric models for credit risk management are presented in Appendix 3. The econometric analysis of the relationship between credit information sharing system models and the level of credit risk materialization (models 1A, 1B, 1C) makes it possible to indicate, based on the estimation results, that:

- the scale of credit risk materialization in the loan portfolio (total, households and enterprises) is strongly determined by its past (the lagged variable is significant at the 1% level in all models), and adjustments occur slowly and with a delay; the highest persistence is observed for household loans;
- the negative and statistically significant coefficient of the variable SEG_COMPL in all NPL models (at the 5% level) indicates that in countries where credit information systems cover the full spectrum of borrowers (households, SMEs and large enterprises), the NPL level is lower, which is consistent with a mechanism of reducing information asymmetry, improving the quality of the creditworthiness assessment process and reducing the risk of adverse selection. The coefficient is largest in absolute value in the segment of loans to enterprises, but differences between segments were not tested, and the scale of the estimates (approximately 1.1 standard deviations of the dependent variable in model 1A) requires cautious interpretation;
- the significant, negative coefficient of the variable BANKR_DATA, which reflects the inclusion of consumer bankruptcy information in credit information systems, indicates that in countries where insolvency data are included the NPL level is lower, which is consistent with better borrower selection, a greater ability of financial institutions to identify risk and faster elimination of impaired receivables from the loan portfolio. In this area too the estimate is largest in absolute value for the portfolio of loans to enterprises;
- a lower NPL level is also associated with the variable PRIV_COV, reflecting the degree of coverage of data on borrowers' credit histories in the population through the activities of private credit bureaus (coefficients significant at the 10% level in models 1A and 1B and at the 5% level in model 1C). A higher share of entities covered by databases is consistent with greater transparency of the credit market, more effective scoring mechanisms and a reduction in the occurrence of "anonymous borrowers". The estimate is largest in absolute value for the port-

folio of loans to enterprises. By contrast, no relationship with NPL is observed for the variable PUB_COV (coverage by public registries);

- the variable ESG, unlike most variables describing the scope and depth of the credit information sharing market, has a positive and statistically significant (at the 1% level) coefficient in NPL models in all the segments analyzed. This result should not, however, be interpreted as indicating a negative role of information. One possible interpretation is the so-called credit expansion effect: the development of information systems, including their extension with ESG components, may co-occur with a larger scale of financing and, consequently, with a higher level of non-performing loans. This interpretation is not, however, confirmed in the other models: the ESG variable is associated with a higher ratio of household loans to GDP but with a smaller number of borrowers and credit accounts per 1,000 adults (Appendix 4). Moreover, the variable is based on a single wave of the ACCIS survey (2025), so its coefficient reflects mainly cross-country differences. The coefficient is largest in absolute value in the enterprise segment, which is characterized by greater volatility and higher risk exposure;
- the variable reflecting access to income data (INCOME_DATA) does not show stable statistical significance. This may suggest that income data alone are not a sufficient source of improvement in credit risk assessment and that their informational value is partly explained by other variables;
- the variable LEGAL_RIGHTS, measuring the strength of legal support for borrowers, has a positive and statistically significant (at the 1% level) coefficient in NPL models. This result can be interpreted as a manifestation of the so-called regulatory trade-off effect, according to which greater protection of borrowers fosters the availability of credit but at the same time may weaken credit discipline and increase the propensity to take risk.

Regarding the control variables, the estimation results indicate significant differences in the role of macroeconomic factors across segments of the loan portfolio – for household receivables macroeconomic variables have limited importance, whereas in the enterprise segment economic growth (GDP_GR) shows a significant, negative relationship with the NPL level. Sector-level variables play a significant role in shaping loan portfolio quality. Bank profitability (ROE) shows a stable and statistically significant negative relationship with the level of non-performing loans, which is consistent with the importance of banking sector efficiency for financial stability. In turn, a higher loan-to-deposit ratio (LTD) is associated with a higher NPL level, which is consistent with the credit expansion channel as a source of deterioration in portfolio quality. Capital adequacy (TCR) has a negative coefficient, significant however only in some specifications, which is consistent with its stabilizing role.

The structure of the banking sector is also important for the NPL level of loan portfolios. A higher level of concentration (HHI) is associated with a lower level of non-performing loans.

At the same time, the size of the banking sector (LN_ASSETS) does not show a stable relationship with loan portfolio quality, from which it can be inferred that the scale of activity does not determine the level of risk in the absence of appropriate management mechanisms. The strongest relationships of sector-level variables with NPL are observed in the group of loans to enterprises.

Credit information sharing systems and access to credit

Regarding the relationship between selected characteristics of credit information sharing system models and access to bank credit, two types of models were built. Dynamic models were used for the dependent variables HHL_GDP, NFCL_GDP, BORR_1000 and CACC_1000, as in the case of the credit risk measures (Appendix 4). For the variables treating the cost of credit as a measure of its availability, it was not possible to use dynamic panel models. Based on the results of the Hausman test, static random-effects models were adopted (Appendix 5).

The key result of the study concerning the relationship between the credit information sharing system model and access to credit, obtained with dynamic models for the variables HHL_GDP, NFCL_GDP, BORR_1000 and CACC_1000, is the identification of two divergent patterns of co-occurrence. On the one hand, a broader scope of data, in particular income information and new forms of financing (such as BNPL), is associated with a higher ratio of household loans to GDP (INCOME_DATA: +28.9; BNPL: +10.9; both coefficients significant at the 1% level), which reflects credit volume. On the other hand, higher completeness of the system and the inclusion of insolvency information are associated with a lower number of borrowers and credit accounts per 1,000 adult inhabitants (SEG_COMPL: -72.1 and -141.9; BANKR_DATA: -105.3 and -166.6), which is consistent with tighter borrower selection.

The estimation results also indicate that both patterns coexist, which is consistent with the changing structure of the credit market. One possible interpretation is the so-called substitution effect, consisting in the concentration of credit among a smaller number of better-rated borrowers. This means that the development of credit information systems may be associated not only with market expansion but also with a qualitative change in the market.

Another important element of the analysis is the coverage of the population by private credit bureaus (PRIV_COV), which, unlike the variables related to system completeness, has a positive coefficient in the models of the number of borrowers (+0.621) and credit accounts (+0.994) per 1,000 adult inhabitants (both significant at the 5% level), with no significant relationship with the ratio of household loans to GDP (for loans to enterprises the coefficient is significant only at the 10% level). This indicates that broader coverage by private bureaus co-occurs with broader access to the market without increasing its total scale, which may constitute an argument for their role in limiting the phenomenon of “over-crediting”. The opposite relationship is observed for coverage by public registries (PUB_COV), which is associated with a lower ratio

of household loans to GDP (-0.061) and with fewer borrowers (-0.721) and credit accounts (-1.092) per 1,000 adults. A detailed presentation is given in Appendix 4.

Based on the estimation results presented in Appendix 5, it can be stated that selected characteristics of credit information sharing systems also affect the level of credit margins and thus the cost of financing. Particularly important is the variable `SEG_COMPL`, reflecting the completeness of data on all categories of borrowers, whose coefficients are negative and statistically significant (at the 5% or 10% level) for all the types of margins analyzed. This means that in countries where credit information systems cover individuals, SMEs and large enterprises alike, margins (both nominal and real) are lower (by about 0.4-0.5 pp). A possible channel of influence here is the reduction of information asymmetry and the improvement in the quality of credit risk assessment, affecting the costs associated with the impairment of receivables.

A similar relationship is observed for the variable `BANKR_DATA` (coefficients from -0.38 to -0.49 , significant at the 5% or 10% level). The inclusion of consumer bankruptcy information in the data aggregated and processed by credit bureaus is consistent with greater market transparency and more effective risk estimation by banks, which may reduce the need to apply high risk premiums in the price of credit.

The positive and partly statistically significant (only at the 10% level) coefficients for the variables `PAYDAY` and `ESG` indicate, by contrast, that extending databases with data on short-term loans and ESG components may be associated with an increase in credit margins, which can be interpreted as an effect of taking additional sources of risk or information costs into account. At the same time, the lack of statistical significance of the variables `LEGAL_RIGHTS`, `CI_DEPTH`, `PUB_COV` and `PRIV_COV` suggests that the formal quality of the regulatory framework, the detail of credit information and the scale of coverage of credit databases are of limited importance for the formation of credit prices compared with the actual scope and content of the data processed.

Summary

The study examined the relationship between selected characteristics of credit information exchange systems and the materialization of credit risk (NPL), access to credit, and the cost of credit. In the NPL models it was shown that extensive and complete credit information sharing systems are associated with a lower level of non-performing loans. Particularly important are the completeness of the database with regard to information on households, SMEs and large enterprises (`SEG_COMPL`) and the inclusion of information on consumer bankruptcy (`BANKR_DATA`), which are associated with a lower NPL in all portfolio segments; the estimates are largest in absolute value for loans to enterprises, where information asymmetry is structurally greatest, although differences between segments were not tested. A difference

can also be observed between models dominated by private databases and those dominated by public credit registries. A higher share of adults covered by private databases is associated with a lower NPL (significance at the 10% level in models 1A and 1B and at the 5% level in model 1C), especially in the enterprise portfolio, whereas no such relationship was found for coverage by public registries.

As regards the cost of credit, it should be emphasized that the completeness of data on borrowers and the inclusion of bankruptcy data are associated with lower credit margins, both nominal and real (by about 0.4–0.5 pp), which is consistent with the interpretation that better information reduces the risk premium built into the price of credit. Extending databases with data on short-term loans and ESG components is, by contrast, associated with higher margins (significance only at the 10% level), which can be interpreted as a reflection of higher information costs or of taking additional types of risk into account. The formal quality of the regulatory framework, the detail of credit information and the scale of coverage of databases do not show a significant relationship with credit prices. This suggests that the actual content and scope of the data processed matter more than the reach of the system alone.

The modeling results thus point to three regularities, corresponding to auxiliary hypotheses H1-H3. The completeness of the credit information system with regard to borrowers and the inclusion of consumer bankruptcy information are associated with both a lower NPL level and lower credit margins. The detail of information (CI_DEPTH) and full reporting (POS_COMPL, NEG_COMPL) do not show such a relationship.

The completeness of the system is associated with narrower access to credit, measured by the number of borrowers and accounts per 1,000 adults, which is consistent with tighter selection; the development of the credit information system is therefore not unambiguously pro-inclusive – it is associated with lower risk and lower costs but at the same time with narrower access, which may concern weaker borrowers in particular. Population coverage by private credit bureaus is associated with a lower NPL and broader access to credit, whereas coverage by public registries is not associated with NPL but is associated with narrower access.

The limitations of the study result from the scope of data availability. The characteristics of the credit information sharing system were entered into the models one at a time because of possible multicollinearity. The variables SEG_COMPL, INCOME_DATA, BANKR_DATA, NEG_COMPL and POS_COMPL are based on two rounds of the ACCIS survey (2020 and 2025), whereas the variables BNPL, PAYDAY and ESG are based on one (2025), which limits their variation over time. The estimates for these variables reflect to a large extent cross-country differences. The research therefore needs to be continued when data from subsequent periods become available.

Appendix 1

Characteristics of the set of variables used in the study of the impact of the credit information sharing system model on credit risk in banks and on the availability of bank credit

Variable	Definition	Area of analysis	Data source
Dependent variables – materialization of credit risk (model group 1)			
NPL_TOT	Value of the NPL ratio of the total loan portfolio in the banking sector of a given country in a given year	Loan portfolio quality and its changes – scale of credit risk materialization in the banking sector	ECB Consolidated Banking Data
NPL_HH	Value of the NPL ratio of the household loan portfolio in the banking sector of a given country in a given year		
NPL_NFC	Value of the NPL ratio of the non-financial corporate loan portfolio in the banking sector of a given country in a given year		
Dependent variables – access to bank credit (model group 2)			
HHL_GDP	Household loans / GDP of the country	Level of financial sector involvement in lending to the economy	EUROSTAT https://ec.europa.eu/eurostat/databrowser/view/tipspd25/default/table
NFCL_GDP	Loans to enterprises / GDP of the country		
BORR_1000	Number of borrowers per 1,000 adults in a given country	Scale of credit involvement	
CACC_1000	Number of credit accounts per 1,000 adults in a given country		

Variable	Definition	Area of analysis	Data source
Dependent variables – price of credit as a component of availability (model group 3)			
MRG_MORT_NOM	Margin (nominal interest rate basis) on housing loans (new business, AAR)	Bank interest margin defined as the difference between the average interest rate on loans in a given exposure category and the yield on risk-free assets (instruments offered by the central bank in a given country as a liquidity-absorbing tool)	Own calculations based on data from the ECB database and the databases of individual central banks
MRG_CONS_NOM	Margin (nominal interest rate basis) on consumer loans (new business, AAR)		
MRG_MORT_REAL	Margin (real interest rate basis) on housing loans (new business, AAR)		
MRG_CONS_REAL	Margin (real interest rate basis) on consumer loans (new business, APRC)		
Explanatory variables – macroeconomic characteristics			
HICP	HICP index – harmonized measure of inflation in the EU	Inflation rate	Eurostat
GDP_GR	Change in the real value of the country’s GDP	Level of economic growth	
PUBDEBT_GDP	General government debt / GDP of the country	Scale of public debt	
Explanatory variables – sector-level characteristics			
HHI	Herfindahl-Hirschman index	Level of market competition in the banking sector of a given country	ECB Structural Financial Indicators https://data.ecb.europa.eu/methodology/structural-financial-indicators

Variable	Definition	Area of analysis	Data source
Explanatory variables – sector-level characteristics			
LN_ASSETS	Natural logarithm of total sector assets	Size of the banking sector	ECB Consolidated Banking Data https://data.ecb.europa.eu/data/data-categories
TCR	Total equity / RWA	Financial stability of banking sectors	
LTD	Total loans to the non-financial sector / total deposits from the non-financial sector	Balance of funding of the non-financial sector	
ROE	Net result / average equity of the banking sector	Profitability/efficiency of the banking sector	
Variables of interest – characteristics of the credit information sharing system model			
SEG_COMPL	Binary variable reflecting the borrower-coverage criterion; 1 – where complete data are processed, covering individuals, small and medium-sized enterprises and large enterprises; 0 – where the data do not cover the enterprise segment	Completeness of data collected and processed by credit bureaus – borrower-coverage criterion	Own analyses based on ACCIS (2025), ACCIS Membership Survey 2025 and ACCIS (2020), ACCIS Membership Survey
INCOME_DATA	Binary variable reflecting the processing by credit bureaus of data on borrowers’ incomes – 1 where the data are collected and processed; 0 – where this component is not included in the information processed	Scope of processing of economic data on borrowers who are natural persons	
BANKR_DATA	Binary variable reflecting the processing of data by credit bureaus on the occurrence of consumer bankruptcy; 1 – where data in this area are analyzed; 0 – otherwise	Inclusion of consumer bankruptcy in the data collected and processed on borrowers	

Variable	Definition	Area of analysis	Data source
Variables of interest – characteristics of the credit information sharing system model			
BNPL	Binary variable reflecting the processing of data by credit bureaus on BNPL loans; 1 – where data in this area are analyzed; 0 – otherwise	Inclusion of information on BNPL receivables in the information processed	ACCIS (2025), ACCIS Membership Survey 2025
PAYDAY	Binary variable reflecting the processing of data by credit bureaus on short-term payday loans; 1 – where data in this area are analyzed; 0 – otherwise	Inclusion of information on receivables from short-term loans in the information processed	
NEG_COMPL	Binary variable reflecting the criterion of the scope of processing of negative information: 1 – where the bureau processes information in at least 4 of 6 areas: a) default status (delay of more than 90 days); b) arrears (30–90 days past due); c) list of rejected cheques; d) number of unpaid/overdue installments; e) impairment write-downs on receivables; f) original amount of the loan agreement (initial exposure amount); 0 – otherwise	Completeness of negative information processed by credit bureaus in a given country	Own analyses based on ACCIS (2025), ACCIS Membership Survey 2025 and ACCIS (2020), ACCIS Membership Survey
POS_COMPL	Binary variable reflecting the criterion of the scope of processing of positive information: 1 – where the bureau processes information in at least 4 of 6 areas: a) amount outstanding; b) payment terms; c) type of interest rate; d) level of interest rate; e) payments made on time; f) credit period; 0 – otherwise	Completeness of positive information processed by credit bureaus in a given country	
ESG	Binary variable concerning the support by credit bureaus for the process of building information databases for estimating ESG risk in the credit process; 1 – bureaus in each country are building a database supporting the process; 0 – no such activities are undertaken	Involvement of credit bureaus in the process of building databases of information on borrowers' ESG standards	ACCIS (2025), ACCIS Membership Survey 2025

Variable	Definition	Area of analysis	Data source
Variables of interest – characteristics of the credit information sharing system model			
LEGAL_RIGHTS	Index of the strength of legal support for borrowers; scale 0–12	Aggregate parameter – measures whether the regulations on collateral and bankruptcy contain elements that facilitate lending	World Bank Group
CI_DEPTH	Depth of credit information index; scale 0–8	Aggregate parameter – measures the scope, range and accessibility of credit information provided by entities offering credit reporting services, such as credit bureaus or credit registries.	
PUB_COV	Number of individuals or business entities included in the databases of public credit registries for which current credit history data are available, including both positive and negative information. The value of the indicator is expressed as a percentage of the adult population.	Scope of coverage of credit information by private and public credit bureaus	
PRIV_COV	Number of individuals or business entities included in the databases of private credit bureaus for which current credit history data are available, including both positive and negative information. The value of the indicator is expressed as a percentage of the adult population.		

Source: Own elaboration

Appendix 2

Descriptive statistics of the variables used in models 1–3

Variable	Mean	Median	Standard deviation	Minimum	Maximum
SEG_COMPL	0.400	0.000	0.491	0.000	1.000
INCOME_DATA	0.250	0.000	0.434	0.000	1.000
BANKR_DATA	0.650	1.000	0.478	0.000	1.000
BNPL	0.550	1.000	0.499	0.000	1.000
PAYDAY	0.600	1.000	0.491	0.000	1.000
NEG_COMPL	0.400	0.000	0.491	0.000	1.000
POS_COMPL	0.250	0.000	0.434	0.000	1.000
ESG	0.424	0.000	0.495	0.000	1.000
LEGAL_RIGHTS	5.497	6.000	2.331	2.000	9.000
CI_DEPTH	6.063	7.000	1.785	0.000	8.000
PUB_COV	20.252	1.900	31.561	0.000	100.000
PRIV_COV	53.067	65.700	39.825	0.000	100.000
NPL_HH	6.279	3.328	9.486	0.633	55.014
NPL_NFC	11.759	6.674	12.740	0.388	67.367
NPL_TOT	5.653	2.962	7.824	0.565	46.776
MRG_MORT_NOM	2.107	2.258	1.227	−2.786	6.541
MRG_CONS_NOM	6.620	6.018	3.717	−3.688	20.064
MRG_MORT_REAL	2.420	2.613	1.264	−2.436	7.288
MRG_CONS_REAL	7.918	7.190	4.934	−3.688	33.218
NFCL_GDP	76.462	63.500	45.592	26.300	248.500
HHL_GDP	51.077	49.100	26.434	12.500	130.700
BORR_1000	412.768	437.175	117.619	204.320	669.260
CACC_1000	652.834	636.515	224.640	309.190	1217.310
HICP	2.690	1.600	3.668	−2.500	20.700
GDP_GR	2.609	2.500	3.753	−10.940	24.620
PUBDEBT_GDP	69.228	61.150	38.863	8.500	209.400
HHI	0.137	0.114	0.075	0.010	0.356
LN_ASSETS	19.687	19.787	1.701	16.911	23.005
TCR	20.033	19.672	3.799	12.045	35.611
LTD	91.386	83.846	34.097	44.117	248.936
ROE	7.381	8.181	5.977	−24.217	21.801

Source: own elaboration based on the dataset.

Appendix 3

Estimation results of model 1A – credit information sharing systems and credit risk of total loan portfolios (NPL_TOT)

VARIABLE	NPL_TOT											
	SEG_ COMPL	INCOME_ DATA	BANKR_ DATA	BNPL	PAYDAY	NEG_ COMPL	POS_ COMPL	ESG	LEGAL_ RIGHTS	CI_ DEPTH	PUB_ COV	PRIV_ COV
NPL_TOT	0.842***	0.856***	0.831***	0.876***	0.869***	0.853***	0.858***	0.847***	0.742***	0.748***	0.751***	0.733***
(-1)	(0.067)	(0.064)	(0.069)	(0.059)	(0.061)	(0.062)	(0.064)	(0.066)	(0.078)	(0.076)	(0.074)	(0.081)
VAR. OF	-8.912**	3.105	-10.443**	2.781*	1.944	4.882	4.603	5.431***	0.401***	-0.082	-0.007	-0.015*
INTEREST	(4.221)	(2.887)	(4.997)	(1.608)	(2.083)	(4.201)	(4.314)	(2.066)	(0.121)	(0.192)	(0.008)	(0.008)
HICP	-0.012	-0.014	-0.011	-0.015	-0.013	-0.012	-0.012	-0.016	0.072	0.068	0.052	0.059
	(0.118)	(0.117)	(0.119)	(0.116)	(0.117)	(0.118)	(0.118)	(0.119)	(0.152)	(0.154)	(0.148)	(0.153)
GDP_GR	-0.082	-0.085	-0.081	-0.089	-0.086	-0.083	-0.084	-0.091	0.071*	0.074*	0.066*	0.069*
	(0.142)	(0.141)	(0.143)	(0.140)	(0.141)	(0.142)	(0.142)	(0.144)	(0.043)	(0.044)	(0.041)	(0.043)
PUBDEBT_ GDP	0.021	0.020	0.022	0.019	0.020	0.021	0.021	0.018	0.061	0.063	0.044	0.060
	(0.061)	(0.061)	(0.062)	(0.060)	(0.060)	(0.061)	(0.061)	(0.062)	(0.050)	(0.051)	(0.052)	(0.051)
HHI	-9.884	-10.228	-9.332	-10.664	-10.441	-10.112	-10.183	-9.451	-32.772***	-34.115***	-33.201***	-35.004***
	(14.003)	(13.821)	(14.221)	(13.572)	(13.601)	(13.667)	(13.719)	(14.055)	(9.412)	(9.633)	(9.512)	(9.083)
LN_ASSETS	0.612	0.629	0.588	0.664	0.645	0.621	0.633	0.682	-0.301	-0.333	-0.072	-0.095
	(1.311)	(1.298)	(1.324)	(1.271)	(1.284)	(1.290)	(1.296)	(1.318)	(1.166)	(1.186)	(1.151)	(1.139)
TCR	-0.031	-0.033	-0.030	-0.034	-0.032	-0.031	-0.032	-0.036	-0.071*	-0.068*	-0.081**	-0.076*
	(0.059)	(0.058)	(0.060)	(0.057)	(0.058)	(0.059)	(0.059)	(0.060)	(0.041)	(0.042)	(0.038)	(0.041)

VARIABLE	NPL_TOT											
	SEG_ COMPL	INCOME_ DATA	BANKR_ DATA	BNPL	PAYDAY	NEG_ COMPL	POS_ COMPL	ESG	LEGAL_ RIGHTS	CI_ DEPTH	PUB_ COV	PRIV_ COV
LTD	0.038* (0.023)	0.037* (0.022)	0.039* (0.023)	0.036* (0.022)	0.037* (0.022)	0.038* (0.022)	0.037* (0.023)	0.035* (0.023)	0.021*** (0.008)	0.021*** (0.008)	0.022*** (0.007)	0.020*** (0.008)
ROE	-0.141*** (0.051)	-0.144*** (0.050)	-0.138*** (0.052)	-0.147*** (0.049)	-0.145*** (0.050)	-0.142*** (0.050)	-0.143*** (0.051)	-0.149*** (0.052)	-0.201*** (0.023)	-0.194*** (0.024)	-0.189*** (0.023)	-0.183*** (0.024)
AR(1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.001***	0.001***	0.001***
AR(2)	0.312	0.287	0.338	0.251	0.266	0.294	0.281	0.303	0.412	0.395	0.377	0.421
Hansen test	0.31	0.28	0.34	0.26	0.27	0.29	0.30	0.33	0.48	0.45	0.41	0.44
Nb. of instruments	24	24	24	24	24	24	24	24	24	24	24	24

Standard errors in parentheses; *** p < 0.01; ** p < 0.05; * p < 0.1.

Estimation results of model 1B – credit information sharing systems and credit risk of household loan portfolios (NPL_HH)

VARIABLE	NPL_HH											
	SEG_ COMPL	INCOME_ DATA	BANKR_ DATA	BNPL	PAYDAY	NEG_ COMPL	POS_ COMPL	ESG	LEGAL_ RIGHTS	CI_DEPTH	PUB_COV	PRIV_COV
NPL_HH	0.861***	0.872***	0.852***	0.889***	0.883***	0.866***	0.871***	0.859***	0.751***	0.758***	0.762***	0.744***
(-1)	(0.063)	(0.060)	(0.067)	(0.057)	(0.059)	(0.060)	(0.061)	(0.064)	(0.075)	(0.073)	(0.072)	(0.078)
VAR. OF	-7.214**	2.884	-9.338**	2.431*	1.602	4.211	4.095	4.872***	0.338***	-0.074	-0.006	-0.013*
INTEREST	(3.512)	(2.563)	(4.114)	(1.442)	(1.876)	(4.982)	(4.071)	(1.854)	(0.098)	(0.151)	(0.007)	(0.007)
HICP	-0.018	-0.019	-0.017	-0.020	-0.019	-0.018	-0.018	-0.021	0.066	0.062	0.048	0.055
	(0.102)	(0.101)	(0.103)	(0.100)	(0.101)	(0.102)	(0.102)	(0.103)	(0.134)	(0.136)	(0.131)	(0.135)
GDP_GR	-0.096	-0.098	-0.095	-0.101	-0.099	-0.097	-0.097	-0.104	0.062*	0.065*	0.058*	0.061*
	(0.124)	(0.123)	(0.125)	(0.122)	(0.123)	(0.124)	(0.124)	(0.126)	(0.038)	(0.039)	(0.036)	(0.038)
PUBDEBT_ GDP	0.018	0.018	0.019	0.017	0.018	0.018	0.018	0.016	0.054	0.056	0.039	0.053
	(0.054)	(0.054)	(0.055)	(0.053)	(0.053)	(0.054)	(0.054)	(0.055)	(0.044)	(0.045)	(0.046)	(0.045)
HHI	-8.442	-8.763	-7.991	-9.215	-9.028	-8.726	-8.791	-8.103	-28.114***	-29.332***	-28.605***	-30.018***
	(12.231)	(12.040)	(12.406)	(11.862)	(11.910)	(11.973)	(12.021)	(12.298)	(8.203)	(8.401)	(8.315)	(7.964)
LN_ ASSETS	0.511	0.526	0.489	0.556	0.539	0.518	0.529	0.575	-0.244	-0.268	-0.061	-0.079
	(1.084)	(1.072)	(1.098)	(1.051)	(1.061)	(1.067)	(1.073)	(1.091)	(0.987)	(1.003)	(0.972)	(0.963)
TCR	-0.028	-0.029	-0.027	-0.030	-0.028	-0.028	-0.028	-0.031	-0.059*	-0.057*	-0.069**	-0.064*
	(0.048)	(0.047)	(0.049)	(0.047)	(0.047)	(0.048)	(0.048)	(0.049)	(0.034)	(0.035)	(0.032)	(0.034)

VARIABLE	NPL_HH											
	SEG_ COMPL	INCOME_ DATA	BANKR_ DATA	BNPL	PAYDAY	NEG_ COMPL	POS_ COMPL	ESG	LEGAL_ RIGHTS	CI_DEPTH	PUB_COV	PRIV_COV
LTD	0.031* (0.018)	0.030* (0.018)	0.032* (0.018)	0.029* (0.018)	0.030* (0.018)	0.031* (0.018)	0.030* (0.018)	0.028* (0.019)	0.018*** (0.006)	0.018*** (0.006)	0.019*** (0.006)	0.017*** (0.006)
ROE	-0.118*** (0.044)	-0.121*** (0.043)	-0.115*** (0.045)	-0.123*** (0.042)	-0.121*** (0.043)	-0.119*** (0.043)	-0.120*** (0.044)	-0.126*** (0.045)	-0.178*** (0.020)	-0.171*** (0.021)	-0.167*** (0.020)	-0.161*** (0.021)
AR(1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.001***	0.001***	0.001***
AR(2)	0.295	0.268	0.321	0.244	0.257	0.281	0.269	0.296	0.401	0.382	0.366	0.408
Hansen test	0.34	0.31	0.36	0.29	0.30	0.32	0.33	0.35	0.49	0.46	0.42	0.45
Nb. of instruments	24	24	24	24	24	24	24	24	24	24	24	24

Standard errors in parentheses; *** p < 0.01; ** p < 0.05; * p < 0.1.

Estimation results of model 1C – credit information sharing systems and credit risk of non-financial corporate loan portfolios (NPL_NFC)

VARIABLE	NPL_NFC											
	SEG_ COMPL	INCOME_ DATA	BANKR_ DATA	BNPL	PAYDAY	NEG_ COMPL	POS_ COMPL	ESG	LEGAL_ RIGHTS	CI_DEPTH	PUB_COV	PRIV_COV
NPL_NFC	0.823***	0.836***	0.812***	0.852***	0.847***	0.831***	0.835***	0.826***	0.702***	0.709***	0.715***	0.694***
(-1)	(0.071)	(0.069)	(0.074)	(0.064)	(0.066)	(0.068)	(0.069)	(0.072)	(0.086)	(0.083)	(0.081)	(0.089)
VAR. OF	-9.874**	4.621	-11.552**	3.984**	2.871	5.911	5.288	6.204***	0.466***	-0.095	-0.011	-0.018**
INTEREST	(4.103)	(3.743)	(4.889)	(1.612)	(2.743)	(5.023)	(5.117)	(1.954)	(0.134)	(0.178)	(0.009)	(0.008)
HICP	-0.009	-0.011	-0.008	-0.012	-0.010	-0.009	-0.009	-0.013	0.081	0.076	0.058	0.066
	(0.129)	(0.128)	(0.130)	(0.127)	(0.128)	(0.129)	(0.129)	(0.130)	(0.167)	(0.170)	(0.163)	(0.168)
GDP_GR	-0.143**	-0.147**	-0.141**	-0.152**	-0.148**	-0.145**	-0.146**	-0.155**	-0.089*	-0.093*	-0.084*	-0.088*
	(0.071)	(0.070)	(0.072)	(0.069)	(0.070)	(0.071)	(0.071)	(0.073)	(0.052)	(0.053)	(0.050)	(0.052)
PUBDEBT_ GDP	0.033	0.032	0.034	0.031	0.032	0.033	0.033	0.029	0.072	0.075	0.052	0.071
	(0.059)	(0.058)	(0.060)	(0.057)	(0.057)	(0.058)	(0.058)	(0.060)	(0.048)	(0.049)	(0.050)	(0.049)
HHI	-18.223	-18.917	-17.441	-19.884	-19.332	-18.765	-18.912	-17.998	-38.774***	-40.112***	-39.228***	-41.667***
	(15.892)	(15.604)	(16.103)	(15.321)	(15.435)	(15.508)	(15.551)	(15.947)	(10.041)	(10.355)	(10.214)	(9.721)
LN_ ASSETS	1.204	1.236	1.156	1.287	1.258	1.221	1.239	1.298	0.112	0.074	0.488	0.462
	(1.331)	(1.309)	(1.351)	(1.276)	(1.292)	(1.301)	(1.308)	(1.344)	(1.178)	(1.196)	(1.152)	(1.136)
TCR	-0.052	-0.054	-0.050	-0.056	-0.053	-0.052	-0.053	-0.057	-0.098**	-0.094**	-0.109***	-0.102**
	(0.051)	(0.050)	(0.052)	(0.049)	(0.050)	(0.051)	(0.051)	(0.052)	(0.041)	(0.042)	(0.038)	(0.041)

VARIABLE	NPL_NFC											
	SEG_ COMPL	INCOME_ DATA	BANKR_ DATA	BNPL	PAYDAY	NEG_ COMPL	POS_ COMPL	ESG	LEGAL_ RIGHTS	CI_DEPTH	PUB_COV	PRIV_COV
LTD	0.049** (0.022)	0.048** (0.021)	0.050** (0.022)	0.047** (0.021)	0.048** (0.021)	0.049** (0.021)	0.048** (0.022)	0.046** (0.022)	0.029*** (0.008)	0.029*** (0.008)	0.030*** (0.008)	0.028*** (0.008)
ROE	-0.163*** (0.048)	-0.167*** (0.047)	-0.159*** (0.049)	-0.170*** (0.046)	-0.167*** (0.047)	-0.164*** (0.047)	-0.166*** (0.048)	-0.172*** (0.049)	-0.221*** (0.024)	-0.214*** (0.025)	-0.209*** (0.024)	-0.203*** (0.025)
AR(1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.001***	0.001***	0.001***
AR(2)	0.271	0.244	0.298	0.229	0.241	0.263	0.252	0.276	0.389	0.371	0.355	0.397
Hansen test	0.29	0.27	0.32	0.25	0.26	0.28	0.30	0.31	0.46	0.43	0.40	0.42
Nb. of instruments	24	24	24	24	24	24	24	24	24	24	24	24

Standard errors in parentheses; *** p < 0.01; ** p < 0.05; * p < 0.1.

Appendix 4

Selected estimation parameters of the model of determinants of credit availability – variables of interest describing the credit information sharing system model (dynamic models)

VARIABLE	SEG_ COMPL	INCOME_ DATA	BANKR_ DATA	BNPL	PAYDAY	NEG_ COMPL	POS_ COMPL	ESG	LEGAL_ RIGHTS	CI_ DEPTH	PUB_ COV	PRIV_ COV
HHL_GDP												
HHL_GDP(−1)	0.781*** (0.082)	0.802*** (0.079)	0.769*** (0.085)	0.816*** (0.072)	0.798*** (0.077)	0.792*** (0.078)	0.801*** (0.076)	0.795*** (0.076)	0.764*** (0.088)	0.771*** (0.086)	0.768*** (0.084)	0.742*** (0.089)
VAR. OF INTEREST	−31.52*** (9.88)	28.94*** (8.72)	−36.11*** (11.43)	10.87*** (3.91)	19.03*** (5.02)	8.72** (4.21)	14.96*** (5.47)	12.64*** (4.18)	0.91** (0.45)	1.08* (0.63)	−0.061** (0.028)	0.031 (0.021)
AR(1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.001***	0.001***	0.001***
AR(2)	0.312	0.301	0.338	0.289	0.294	0.307	0.298	0.303	0.412	0.398	0.377	0.421
Hansen (p)	0.34	0.36	0.33	0.35	0.34	0.32	0.34	0.35	0.48	0.45	0.41	0.44
Nb. of instruments	24	24	24	24	24	24	24	24	24	24	24	24
NFCL_GDP												
NFCL_GDP(−1)	0.753*** (0.091)	0.771*** (0.087)	0.741*** (0.095)	0.788*** (0.080)	0.765*** (0.084)	0.759*** (0.086)	0.767*** (0.083)	0.768*** (0.084)	0.731*** (0.096)	0.739*** (0.093)	0.735*** (0.091)	0.722*** (0.097)
VAR. OF INTEREST	−18.44** (7.89)	24.62*** (8.33)	−15.06 (10.92)	3.91 (4.77)	11.28* (6.31)	−0.94 (5.44)	2.87 (6.81)	6.12 (5.11)	0.83 (0.98)	−0.05 (1.08)	−0.042 (0.039)	0.048* (0.026)

VARIABLE	SEG_ COMPL	INCOME_ DATA	BANKR_ DATA	BNPL	PAYDAY	NEG_ COMPL	POS_ COMPL	ESG	LEGAL_ RIGHTS	CI_ DEPTH	PUB_ COV	PRIV_ COV
NFCL_GDP												
AR(1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.001***	0.001***	0.001***
AR(2)	0.284	0.276	0.312	0.268	0.271	0.289	0.280	0.286	0.401	0.387	0.366	0.408
Hansen (p)	0.31	0.33	0.30	0.32	0.31	0.29	0.31	0.32	0.47	0.44	0.40	0.42
Nb. of instruments	24	24	24	24	24	24	24	24	24	24	24	24
BORR_1000												
BORR_1000(-1)	0.911*** (0.044)	0.924*** (0.041)	0.905*** (0.046)	0.933*** (0.038)	0.919*** (0.041)	0.914*** (0.043)	0.918*** (0.042)	0.918*** (0.042)	0.892*** (0.052)	0.896*** (0.050)	0.893*** (0.049)	0.887*** (0.051)
VAR. OF INTEREST	-72.11** (32.88)	-138.57*** (41.06)	-105.33*** (35.90)	-162.4*** (29.55)	-135.1*** (38.77)	-168.92*** (27.44)	-98.44*** (26.88)	-129.88*** (27.41)	-15.41*** (5.03)	-23.77** (11.62)	-0.721*** (0.281)	0.621** (0.298)
AR(1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.001***	0.001***	0.001***
AR(2)	0.298	0.287	0.321	0.276	0.279	0.292	0.284	0.289	0.409	0.392	0.371	0.413
Hansen (p)	0.35	0.38	0.33	0.36	0.34	0.32	0.34	0.35	0.49	0.46	0.42	0.45
Nb. of instruments	24	24	24	24	24	24	24	24	24	24	24	24

VARIABLE	SEG_ COMPL	INCOME_ DATA	BANKR_ DATA	BNPL	PAYDAY	NEG_ COMPL	POS_ COMPL	ESG	LEGAL_ RIGHTS	CI_ DEPTH	PUB_ COV	PRIV_ COV
CACC_1000												
CACC_1000(-1)	0.903*** (0.052)	0.916*** (0.049)	0.899*** (0.055)	0.924*** (0.045)	0.911*** (0.048)	0.907*** (0.051)	0.909*** (0.050)	0.910*** (0.048)	0.884*** (0.058)	0.889*** (0.057)	0.886*** (0.055)	0.881*** (0.058)
VAR. OF INTEREST	-141.88*** (48.77)	-82.31 (74.22)	-166.55** (67.38)	-178.9*** (43.11)	-150.77** (59.02)	-202.81*** (45.66)	-113.55** (48.01)	-221.77*** (56.02)	-24.11*** (5.19)	-23.88** (10.92)	-1.092*** (0.388)	0.994** (0.472)
AR(1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.001***	0.001***	0.001***
AR(2)	0.271	0.265	0.298	0.254	0.258	0.276	0.267	0.271	0.389	0.374	0.355	0.397
Hansen (p)	0.33	0.36	0.31	0.34	0.32	0.30	0.32	0.33	0.46	0.43	0.40	0.42
Nb. of instruments	24	24	24	24	24	24	24	24	24	24	24	24

Standard errors in parentheses; *** p < 0.01; ** p < 0.05; * p < 0.1.

Appendix 5

Selected estimation parameters of the model of determinants of the nominal and real cost of bank credit – variables of interest describing the credit information sharing system model (static models)

VARIABLE	SEG_ COMPL	INCOME_ DATA	BANKR_ DATA	BNPL	PAYDAY	NEG_ COMPL	POS_ COMPL	ESG	LEGAL_ RIGHTS	CI_ DEPTH	PUB_ COV	PRIV_ COV
MRG_MORT_NOM	−0.42** (0.18)	0.31* (0.17)	−0.38* (0.21)	0.15 (0.11)	0.22* (0.13)	0.05 (0.12)	0.11 (0.14)	0.19* (0.11)	−0.03 (0.04)	−0.02 (0.03)	−0.01 (0.01)	0.01 (0.01)
MRG_CONS_NOM	−0.36* (0.20)	0.28 (0.19)	−0.41* (0.22)	0.18 (0.13)	0.25* (0.14)	0.09 (0.13)	0.16 (0.15)	0.21* (0.12)	−0.04 (0.04)	−0.03 (0.03)	−0.01 (0.01)	0.02 (0.01)
MRG_MORT_REAL	−0.51** (0.21)	0.27 (0.19)	−0.44* (0.23)	0.12 (0.12)	0.20 (0.15)	0.03 (0.14)	0.09 (0.15)	0.18 (0.12)	−0.02 (0.04)	−0.03 (0.03)	−0.01 (0.01)	0.01 (0.01)
MRG_CONS_REAL	−0.47** (0.22)	0.26 (0.20)	−0.49** (0.24)	0.16 (0.13)	0.23 (0.15)	0.08 (0.14)	0.14 (0.16)	0.20 (0.13)	−0.03 (0.04)	−0.02 (0.03)	−0.01 (0.01)	0.02 (0.01)

Standard errors in parentheses; *** p<0.01; ** p<0.05; * p<0.1.

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