Bundling Credit Card and Electricity Bills

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Abstract

This paper studies how partnerships between financial and non-financial firms mitigate information and enforcement frictions in consumer lending. I examine *Crédito Fácil Codensa* (CFC), a financial inclusion program jointly operated by DaviBank and Enel in Colombia. The partnership combines the bank's lending technology with the utility company's customer information and billing infrastructure, which bundles credit card repayments with electricity bills. Using administrative data on credit applications, electricity payments, and repayment outcomes, I evaluate both mechanisms. Utility payment and consumption information improves credit risk prediction, particularly for applicants without prior credit histories. Moreover, permanently separating credit card repayments from electricity bills increases delinquency and default, indicating that bundling strengthens repayment performance. These findings show that partnerships with non-financial firms can expand consumer credit while maintaining portfolio quality through improved screening and repayment.

Keywords: Consumer Credit, Financial Inclusion, Non-bank Financial Institutions

JEL Codes: G21, G23, G51, G53

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1 Introduction

Expanding access to consumer credit among financially underserved households remains a major challenge for lenders. Although financial inclusion is widely recognized as an important driver of economic development (Bruhn and Love, 2014), extending credit to borrowers with limited credit histories remains difficult. Two frictions are particularly important. First, information asymmetries make it difficult to distinguish creditworthy borrowers from high-risk applicants (DeFusco et al., 2022). Second, the high origination, monitoring, and enforcement costs associated with small unsecured loans reduce the profitability of serving these borrowers (Bachas et al., 2018; Dupas et al., 2018). Together, these frictions limit credit supply, particularly for households outside the traditional financial system.

In recent years, financial institutions have increasingly formed partnerships with non-financial firms to overcome these frictions. Utility companies, retailers, digital platforms, and technology firms possess complementary assets that traditional banks often lack, including detailed information on customer behavior and proprietary payment and billing infrastructures. A growing literature shows that alternative data generated by these firms can improve the prediction of repayment outcomes and expand access to credit for borrowers with limited financial records (Berg et al., 2020; Frost et al., 2019). At the same time, their existing payment and billing infrastructures may also influence how borrowers repay their financial obligations.[1] Despite the rapid growth of these partnerships, relatively little is known about how banks can jointly leverage these complementary informational and infrastructural assets to improve lending outcomes.

This paper addresses this question by studying a partnership between a commercial bank and a utility company that simultaneously affects both the screening and repayment stages of consumer lending. Specifically, I examine *Crédito Fácil Codensa* (CFC), a financial inclusion program

[1]There are several examples of non-financial entities that offer consumer credit to their customers. For instance, car companies played an important role in offering credit to their clients in the United States in the 1980s (Aguilar, 1990). Sears was among the pioneers in retail lending and later introduced the Discover credit card (Aguilar, 1990). More recently, technology companies such as Alphabet (Google), Amazon, Meta (Facebook), and digital platforms such as Alipay have become important providers of consumer credit (Ouyang, 2021).

implemented in Bogotá, Colombia, since 2009. The program is jointly operated by Enel-Codensa (Enel), the electricity distribution company serving Bogotá and surrounding municipalities, and DaviBank (DaviBank), one of Colombia's largest commercial banks. Through this partnership, DaviBank combines its lending technology with two complementary assets provided by Enel: proprietary information on customers' electricity payment behavior and an existing billing infrastructure through which credit card repayments are bundled with electricity bills. This institutional design provides a unique setting to examine how partnerships with non-financial firms can simultaneously improve borrower screening and repayment performance.

The institutional design of the program provides a unique setting to study two complementary innovations in consumer lending. At origination, DaviBank combines traditional information from the credit application and credit bureau records with detailed information on electricity consumption and bill payment behavior provided by Enel, allowing the bank to assess the creditworthiness of more than 5.4 million residential customers, including many individuals with limited or no formal credit history.[2]

After loan approval, repayment takes place through a bundled billing system in which monthly credit card installments are incorporated into the electricity bill. Although Colombian regulation prohibits electricity providers from disconnecting service due to the non-payment of unrelated financial obligations,[3] this repayment technology may still influence borrower behavior by increasing payment salience, reducing transaction costs, and integrating loan repayment into one of the household's most routine financial obligations.

The central hypothesis of the paper is that these two institutional features jointly explain how DaviBank expanded consumer lending while maintaining portfolio quality in municipalities where the CFC program operates. I evaluate two complementary mechanisms. First, I examine whether electricity consumption and bill payment records improve the bank's ability to identify creditworthy borrowers before loan origination. Second, I investigate whether bundling credit

[2]Information provided by Enel during an in-person interview conducted on August 21, 2023.

[3]This restriction is based on consumer protection regulations, which prohibit utility companies from disconnecting essential services such as electricity due to the non-payment of unrelated financial obligations.

card repayments with the electricity bill improves repayment performance after credit is granted. Together, these mechanisms capture how partnerships with non-financial firms can affect both the screening and enforcement stages of the lending process.

To motivate the analysis, I first document several stylized facts using municipality-level administrative data from the Colombian financial regulator. Municipalities where the CFC program operates experienced a substantial increase in consumer lending by DaviBank following the introduction of the program. Importantly, this expansion was not accompanied by a corresponding increase in portfolio risk. Moreover, the evidence suggests that the observed growth was not driven by a reallocation of borrowers from competing banks. These patterns raise a natural question: how was DaviBank able to expand lending without a deterioration in repayment performance?

To answer this question, I combine regulatory data with a unique administrative dataset provided by DaviBank and Enel covering the universe of approved CFC credit card applicants between 2010 and 2019. The dataset contains information on credit applications, credit bureau records, electricity consumption, utility payment histories, and subsequent credit card repayment outcomes.

The first set of results shows that utility payment and consumption information substantially improves credit risk prediction. For applicants without prior credit histories, incorporating utility information increases the area under the ROC curve (AUC) from 0.682 to 0.732. Among applicants with existing credit histories, utility information performs similarly to traditional credit bureau scores and provides additional predictive power when combined with bureau information. These findings suggest that utility data contain economically meaningful information about repayment capacity and financial discipline that is not fully captured by traditional financial records.

The second set of results examines the enforcement role of the bundled repayment arrangement. To identify this mechanism, I exploit variation generated by borrowers who request the separation of electricity and credit card payments unbundling. Because unbundling typically occurs when borrowers move outside Enel's service territory, it provides a natural setting to evaluate the consequences of losing the bundled repayment infrastructure. The results indicate that unbundling

significantly increases both delinquency and default rates, suggesting that bundling strengthens repayment performance even in the absence of a direct disconnection threat.

Beyond documenting the predictive value of utility information, I quantify its economic value for lenders through a simulation exercise that combines estimated repayment probabilities with a simple lending decision framework. Preliminary results indicate that utility information improves borrower ranking and generates economically meaningful gains in credit allocation, particularly among applicants without prior credit histories. The framework also provides the basis for a second simulation, currently under development, that quantifies the economic value of the bundled repayment technology using the estimated repayment effects presented later in the paper.

Related Literature

This study relates to four strands of literature. First, this study contributes to the literature on the role of financial inclusion in reducing financial intermediation costs. By leveraging alternative data and existing infrastructure from a non-financial entity, the CFC program lowers screening and enforcement costs associated with serving low-income and unbanked borrowers- groups traditionally considered too costly or risky by formal financial institutions. This aligns with recent theoretical and empirical work highlighting how access to alternative data and platform-based financial services can relax financial frictions (e.g., Bachas et al., 2018; Ouyang, 2021). Unlike previous studies that often examine the impact of bank branch expansion or digital banking in isolation, my analysis focuses on a hybrid model of collaboration between a bank and a utility company. This institutional arrangement facilitates credit provision at scale by reducing asymmetric information and transaction costs, thereby making small-value consumer lending more financially viable.

Second, this study builds on the literature that examines how new data sources and information technologies are used in the screening and monitoring of consumer loan contracts. Among this literature, some articles have analyzed the phenomenon of the "democratization of credit", which underscores how innovations in the credit market, such as credit scoring, informational technologies, and credit bureau information, have reduced operational costs for banks in the

consumer loan contract screening process (Lyons, 2003; Einav et al., 2013, 2012; Chatterjee et al., 2023; Ordoñez et al., 2019; Liberti and Petersen, 2019). Furthermore, recent studies have examined the informative level of non-traditional data. These non-traditional data include soft information in marketplace lending (Iyer et al., 2016), digital footprint (Berg et al., 2020; Agarwal et al., 2019; Rishabh, 2022), as well as information regarding friendship and social networks (Hildebrand et al., 2017; Lin et al., 2013). As technology progresses, greater volumes of concrete data become accessible, and new computer science techniques can be applied to assess the creditworthiness of clients, such as machine learning algorithms (Di Maggio et al., 2022; Fuster et al., 2022).

Relative to existing research on accessing new data and informational technologies for screening and monitoring consumer loan contracts, this study makes two contributions. First, it complements previous literature by analyzing how leveraging nontraditional data from electricity companies- such as payment history and energy consumption data of their clients- offers a novel input for estimating internal credit scores for individuals lacking a credit history in the financial system. The second contribution pertains to the "democratization of credit." While these innovations have increased credit access among previously marginalized population segments, this democratization is also associated with higher default rates, as highlighted in some literature. This study contributes to this debate by indicating that the "democratization of credit" should not only be accompanied by innovations enabling a better screening process but also by mechanisms allowing for improved monitoring and enforcement to decrease default rates.

Third, the study contributes to the literature on credit provision by non-traditional financial institutions, such as BigTech firms, telecom companies, e-commerce platforms, and payment providers (Cornelli et al., 2020; Hau et al., 2021; Gambacorta et al., 2023; Ghosh et al., 2022; Berg et al., 2022; Ouyang, 2021; Gertler et al., 2023). As a parenthesis, this lending model closely resembles companies providing short-term trade credit that have been extensively studied in existing literature (Petersen and Rajan, 1997; Biais and Gollier, 1997; Cunat, 2007). These studies show that non-traditional financial institutions have a competitive advantage in lending to their clients due to improved borrower screening or contract enforcement capabilities. Although the

company (Enel) does not directly grant credit to its customers in the CFC program, this study contributes by examining how the bank can leverage the company-client relationships indirectly. Through this approach, the bank aims to replicate the competitive advantages of non-traditional financial institutions, especially in contract enforcement, without facing the financing capacity issues that non-financial entities may encounter when offering credit to their customers.

Finally, some studies have examined specific aspects of the CFC program. The goal of such studies is to estimate the impact of this program in terms of the reduction of poverty of its beneficiaries (Restrepo et al., 2007; Riascos Villegas et al., 2013) and how sensitive the use of the credit card of this program is when there are shocks in the interest rate of the Colombian central bank (Arango et al., 2021). Although this study does not specifically focus on analyzing these topics, this study contributes to provide empirical evidence on how the structure of the CFC program can mitigate certain financial frictions. This, in turn, enhances the proper functioning of the credit market in population segments excluded from the traditional banking sector.

2 Institutional Background

2.1 Origins of the CFC Program

Crédito Fácil Codensa (CFC) is a consumer lending program jointly operated by Enel-Codensa (Enel), one of Colombia's largest electricity distributors, and DaviBank (DaviBank), one of the country's major commercial banks. Launched in 2001 by Enel, the program was designed to expand access to consumer credit among households with limited access to traditional banking services (Lobo et al., 2014).[4]

Initially, Enel directly financed purchases of household appliances and collected repayments through the monthly electricity bill. However, in 2009, Colombian financial authorities required

[4]According to Lobo et al. (2014) a key turning point occurred in 2001, when Enel-Codensa identified low ownership of home appliances among its poorest customers, many of whom lacked access to formal credit (in 2001 70% of Ene's clients lacking formal banking products and credit history, the company identified an opportunity to enhance the value of its services.

Enel to channel the loans granted to its customers through traditional banks, since its primary function was recognized as that of an energy service provider rather than a lending institution. As a result, Enel formed a partnership with DaviBank. Under this partnership, an "open book" business model was implemented, in which the bank and the company share the profits generated from the interest paid on the loans issued through credit cards. Today, the program serves more than one million customers and combines DaviBank's lending expertise with Enel's information and payment infrastructure.

2.2 How the CFC Program Operates

The CFC program differs from a conventional credit card along two institutional dimensions. First, DaviBank screens applicants using both traditional credit information and utility payment records provided by Enel. Second, approved borrowers normally repay their credit card purchases through a bundled repayment arrangement in which the monthly credit card installment is incorporated into the household's electricity bill. Figure 1 summarizes these institutional features.

The operation of the program can be divided into three stages: screening, credit provision, and repayment. Households may apply for a CFC credit card through either Enel's commercial channels or DaviBank's branch network. Regardless of the application channel, DaviBank is solely responsible for the credit decision. To evaluate applicants, the bank combines three sources of information: demographic and socioeconomic characteristics collected through the application process, credit bureau records when available, and historical electricity consumption and bill payment information provided by Enel.

Using these inputs, DaviBank assigns an internal credit score, determines whether to approve the application, and sets the corresponding credit limit. Utility payment records are particularly valuable for applicants with limited or no formal credit history, allowing the bank to evaluate borrowers who would otherwise be difficult to assess using traditional credit bureau information alone. Although financial inclusion has expanded substantially since the program's launch, approximately 30% of Colombian adults still lack a formal credit history, remaining effectively

invisible to traditional lenders. By incorporating repayment information from electricity bills into its screening process, DaviBank can evaluate applicants whose creditworthiness is only partially reflected in conventional credit bureau records.

Approved applicants receive a DaviBank credit card and may use it like any conventional credit card. Repayment, however, differs fundamentally from a standard banking product. Under the CFC program, borrowers normally repay both their electricity bill and their monthly credit card installment through a single bundled payment made to Enel. Enel subsequently transfers the corresponding credit card repayment to DaviBank. Consequently, bundled repayment constitutes the standard repayment mechanism for all borrowers enrolled in the program.

Although borrowers may exceptionally choose to pay only the electricity bill in a given month,[5] doing so requires an explicit request for a temporary payment separation. Importantly, this request cannot be made automatically or online. Instead, borrowers must visit one of the program's customer service offices in person to request the separation before the monthly billing cycle. This administrative requirement creates a non-monetary transaction cost, primarily in the form of time and effort, for borrowers wishing to deviate from the default bundled repayment arrangement.

Once the temporary separation is approved, the borrower pays only the electricity bill, while the unpaid credit card balance remains outstanding and accrues interest according to the terms of the credit card contract. If the borrower repays the outstanding credit card balance before the next billing cycle, the following electricity bill again includes only the current month's credit card installment. Otherwise, the bundled repayment arrangement is automatically reinstated, and the subsequent electricity bill incorporates both the new installment and any unpaid balance carried over from the previous billing cycle. Consequently, borrowers wishing to continue paying only the electricity bill must submit a new in-person separation request for every billing cycle.

The institutional design therefore makes temporary payment separation a costly deviation

[5]This option was introduced following a ruling of the Colombian Constitutional Court requiring that consumers retain the autonomy to pay utility and non-utility obligations separately. Consequently, borrowers may request a temporary separation of the bundled payment arrangement.

from the default repayment technology rather than an alternative repayment regime. In practice, bundled repayment remains the standard payment arrangement throughout the life of the lending relationship unless a borrower permanently leaves Enel's electricity service area, a case discussed in the following subsection.

2.3 Bundling and Permanent Unbundling of Payments

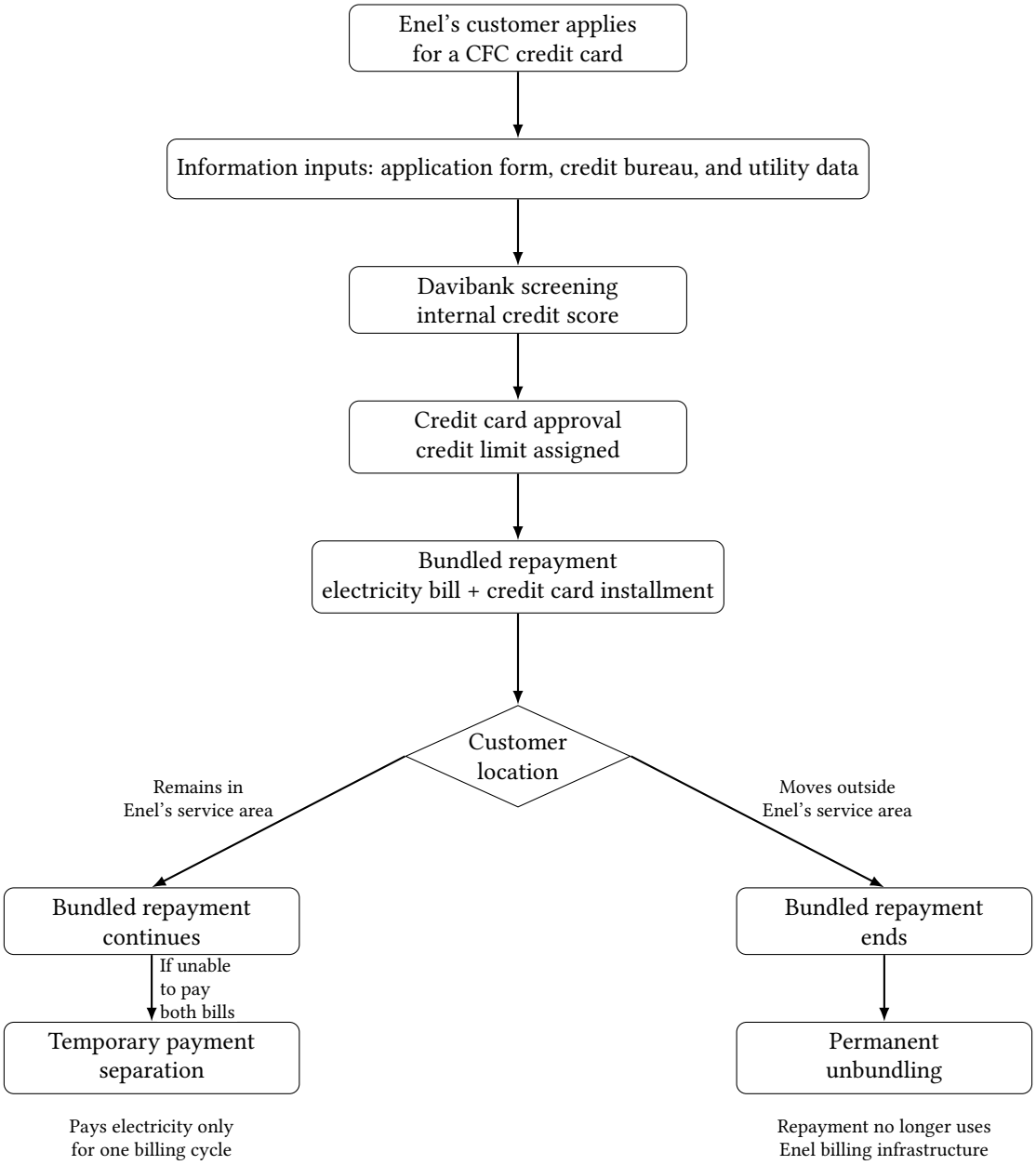
The bundled repayment arrangement described above constitutes one of the defining features of the CFC program. Under this arrangement, borrowers repay both their electricity bill and their credit card installment through Enel's billing infrastructure. As discussed in the previously, borrowers may exceptionally request a temporary payment separation for a given billing cycle. Such requests do not modify the institutional arrangement of the program, as the bundled repayment system is automatically restored in the following billing cycle unless another temporary separation is requested.

A different situation arises when borrowers permanently leave Enel's electricity distribution network. The Colombian electricity market is organized through geographically defined service territories, with each distributor operating as the exclusive residential electricity provider within its assigned municipalities. Consequently, households automatically receive electricity service from the distributor serving their municipality of residence.

When a CFC cardholder relocates to a municipality that is not served by Enel, the bundled repayment arrangement becomes infeasible because Enel no longer provides the customer's electricity service and therefore can no longer incorporate the credit card installment into the monthly electricity bill. In these situations, borrowers must permanently separate the credit card repayment from the electricity bill, a process referred to throughout the paper as unbundling. Following unbundling, the borrower remains a DaviBank customer and continues to use the same credit card, but all subsequent repayments are made directly to DaviBank rather than through Enel's billing infrastructure.

This distinction between temporary payment separation and permanent unbundling is impor-

Figure 1. How the CFC Program Works



Notes: This figure summarizes the institutional structure of the CFC program. Davibank screens applicants using application-form information, credit bureau records, and utility payment data provided by Enel. Approved borrowers normally repay credit card installments through a bundled repayment arrangement in which the credit card installment is incorporated into the monthly electricity bill. Borrowers who remain within Enel's service area may exceptionally request a temporary payment separation if they are unable to pay both bills. If a borrower permanently relocates outside Enel's service area, the bundled repayment arrangement becomes infeasible and the credit card is permanently unbundled from the electricity bill.

tant for the empirical analysis. Temporary payment separation affects only a single billing cycle and reflects a borrower's short-term payment decision, whereas permanent unbundling results from the customer's relocation outside Enel's service area and permanently removes the borrower from the bundled repayment infrastructure. The institutional features described above suggest that the partnership between DaviBank and Enel may affect lending outcomes through distinct mechanisms that will discuss later. The next section presents stylized facts on the evolution of lending and portfolio risk within the CFC program before examining these mechanisms directly.

3 Stylized Facts on Credit Expansion and Portfolio Risk

The previous section described the institutional structure of the CFC program and highlighted two distinctive features of the partnership between DaviBank and Enel: the use of utility payment information in the credit approval process and the integration of credit card repayments into the electricity billing system. Before examining these mechanisms directly, this section documents several stylized facts regarding the evolution of lending and portfolio risk in municipalities where the program operates.

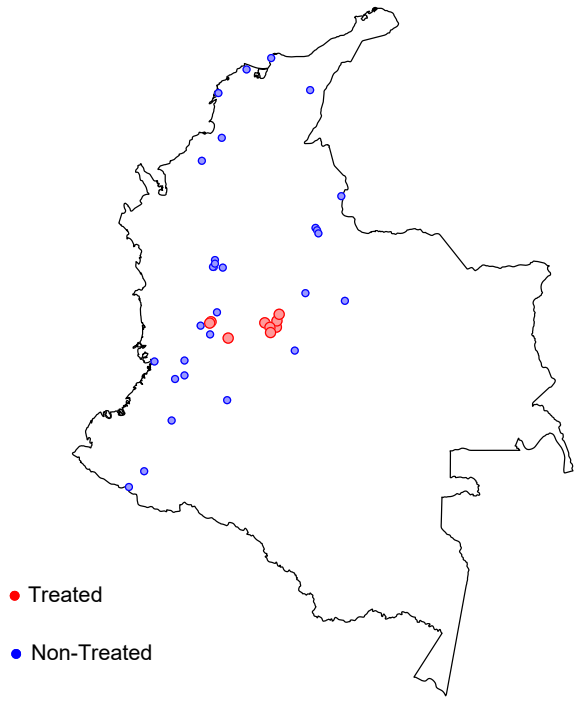
The objective of this section is not to identify the causal effect of the CFC program on financial inclusion. Rather, it aims to document broad empirical patterns that motivate the analysis of the screening and enforcement mechanisms developed in the following sections. In particular, the evidence reveals two striking facts. First, consumer lending expanded substantially in municipalities where the CFC program operates. Second, this expansion was not accompanied by a corresponding deterioration in portfolio risk.

3.1 Geographical Presence of the CFC Program

The availability of the CFC program is determined by the overlap between Enel's electricity distribution network and DaviBank's presence. As discussed in the previous section, the program can only operate in municipalities where both institutions are active. Figure 2 illustrates the

geographical distribution of municipalities where DaviBank operates in Colombia. Municipalities shown in red correspond to locations where both Enel and DaviBank are present and where the CFC program is available. Municipalities shown in blue correspond to locations where DaviBank operates but where Enel does not provide residential electricity services, making the implementation of the program infeasible.

Figure 2. Geographical distribution of the cities where DaviBank operates in Colombia (treated and non-treated cities by the CFC program).



This figure shows the geographical distribution of the cities and municipalities in which DaviBank operates in Colombia. The cities in red correspond to those where the CFC program is available, that is, where both Enel and DaviBank operate in the same city. The cities in blue represent locations where DaviBank is present, but the CFC program is not offered, due to the fact that Enel does not provide residential electricity services in these areas.

The figure highlights geographical variation in the availability of the program. While DaviBank maintains a nationwide presence, the availability of CFC is restricted by Enel's electricity distribution network. This institutional feature creates meaningful differences in the bank's ability to leverage utility information and billing infrastructure across local credit markets.

3.2 Fact 1: Consumer Lending Expanded in CFC Municipalities

To investigate if consumer lending expanded in CFC municipalities, I use administrative information from the Colombian financial regulator covering consumer lending and default outcomes at the municipality level. The analysis compares municipalities where the CFC program was introduced with municipalities where DaviBank operates but where the program cannot operate because Enel does not provide residential electricity services. As a first step, I estimate the following two-way fixed effects specification:

$$\mathrm{Y}_{it} = \alpha_i + \lambda_t + \beta \cdot \mathrm{CFC}_{it} + X_{it}'\gamma + \varepsilon_{it} \tag{1}$$

Where Y_{it} denotes the outcome variable, measuring the supply of credit exclusively from DaviBank, in municipality i and period t; α_i represents municipality fixed effects; λ_t captures time fixed effects; and CFC_{it} is a binary indicator equal to one if municipality i had access to the CFC program in period t. The vector X_{it} includes time-varying municipality-level controls, and standard errors are clustered at the municipality level. This specification exploits the staggered expansion of the CFC program generated by the geographical growth of Enel's electricity distribution network. Prior to 2016, Enel's operations were largely concentrated in Bogotá, where the CFC program was initially available. In 2016, Enel acquired the regional electricity distributor serving the municpalities of department of Cundinamarca, substantially expanding its service territory and allowing DaviBank to offer the CFC program in additional municipalities. This expansion generates plausibly exogenous variation across space and time in the bank's ability to provide the program.

Before presenting the results, it is important to clarify that the analysis focuses on consumer loans disbursed by DaviBank in municipalities where the bank operates. Because the availability of the CFC program is determined by Enel's electricity distribution network, treated municipalities may differ systematically from other municipalities in terms of demographic and economic characteristics. To improve comparability between treated and control municipalities, I construct a matched sample based on pre-treatment municipal characteristics. Because treated municipalities

are concentrated in Bogotá and Cundinamarca, they may differ systematically from control municipalities in terms of population size, economic activity, and financial development. The matching procedure and balance diagnostics are reported in Appendix A. Throughout the analysis, I present estimates for both the full sample and the matched sample.

The results presented in Table 1 indicate that the CFC program had a statistically significant and positive effect on consumer credit disbursements in the municipalities where it was implemented. Across both the matched and full samples, the interaction term *Treated* $\times$ *Post* is positive and statistically significant in all specifications. For the matched sample, the estimated effect ranges from 0.559 to 0.578 log points. In the full sample, the estimated effect is slightly lower, ranging from 0.426 to 0.428 log points, corresponding to an increase of approximately 53% in consumer loan disbursements. These estimates indicate that DaviBank substantially increased consumer lending in municipalities where the CFC program became available.

Table 1. Effect of the CFC Program on Consumer Credit Disbursements

Dependent Variable: *Ln(Consumer Loans)*	Matched Sample		Full Sample	
	TWFE (1)	TWFE (2)	TWFE (3)	TWFE (4)
Treated (CFC program) $\times$ Post	0.559^{**}	0.578^{**}	0.426^{*}	0.428^{*}
	(0.168)	(0.168)	(0.235)	(0.249)
Observations	1,176	1,176	1,960	1,960
Controls	No	Yes	No	Yes
Time FE (Quarter)	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes

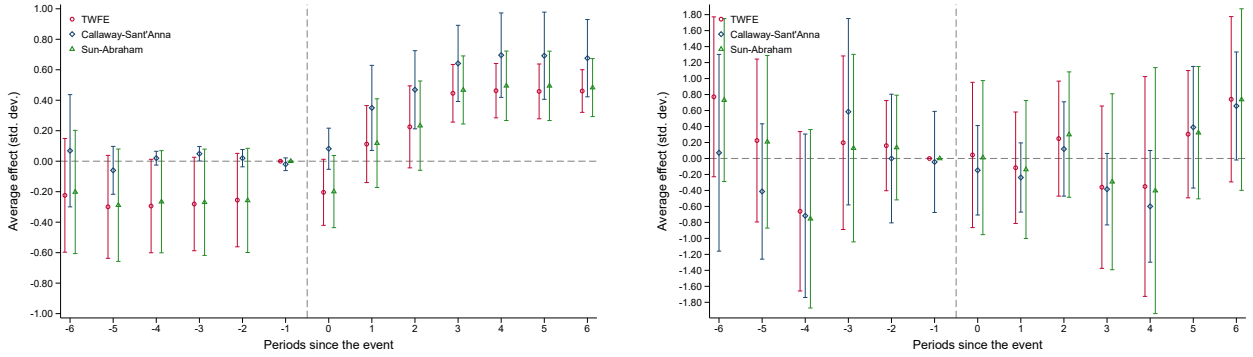
Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
TWFE: Two-Way Fixed Effects (t-test).
This table reports estimates from difference-in-differences regressions using quarterly panel data. The dependent variable is the logarithm of the total value of consumer loans disbursed by Davibank. Columns 1-2 correspond to the matched sample, while Columns 3-4 use the full sample. All regressions include municipality and time fixed effects. Standard errors are clustered at the municipality level.

In order to test the parallel trends assumption and examine the dynamics of the treatment effects, I estimate an event-study specification using alternative approaches proposed by Callaway

and Sant'Anna (2021), and TWFE. Figure 3a presents the event-study results and shows that the coefficients prior to implementation are generally close to zero, suggesting the absence of strong differential pre-trends between treated and comparison municipalities. Second, consumer lending increases steadily following the introduction of the program. Across all estimators, post-treatment coefficients become positive and economically meaningful.

The magnitude of the increase is substantial. The estimates indicate that municipalities where the CFC program becomes available experience a sustained expansion in consumer lending over the years following implementation. These results suggest that the partnership between DaviBank and Enel may have enabled the bank to serve borrowers who would otherwise have been more difficult or costly to reach through traditional lending technologies

Figure 3. Effects of the CFC Program on Consumer Credit Disbursements and Default at the Municipality Level



(a) Consumer Credit Disbursements **(b)** Default

This figure presents dynamic event-study estimates of the effects of the launch of the CFC program across municipalities where it operates. Panel A reports the effects on consumer credit disbursements, while Panel B reports the effects on defaults (measured as the value of defaulted portfolio loans in DaviBank). The figure overlays estimates obtained using traditional two-way fixed effects (TWFE), Callaway and Sant'Anna (2021), and Sun and Abraham (2021). The vertical dashed line indicates the quarter in which the CFC program was launched. The omitted category corresponds to the quarter immediately before treatment ($t = -1$). Error bars represent 95% confidence intervals.

3.3 Fact 2: Portfolio Risk Did Not Increase

Now, an expansion in lending does not necessarily imply an improvement in lending technologies. A bank could increase lending simply by relaxing underwriting standards, potentially leading to higher future default rates. To examine whether the growth in lending was accompanied

by a deterioration in portfolio quality, Figure 3b presents event-study estimates for the value of defaulted consumer loans.

In contrast to the strong increase observed for consumer lending, the value of defaulted loans remains relatively stable following the introduction of the program. Across specifications, post-treatment coefficients remain close to zero and do not display a persistent upward trend. This pattern is noteworthy because it differs from what would be expected if lending growth were driven solely by weaker screening standards. Instead, the evidence suggests that DaviBank expanded lending while maintaining relatively stable levels of portfolio risk.

3.4 Alternative Explanation: Was Credit Expansion Driven by Market Share Reallocation?

To explore whether the increase in consumer credit disbursements observed in treated municipalities of CFC program reflects genuine credit expansion or simply a reallocation of borrowers toward DaviBank, I analyze total credit disbursements at the municipality level for all banks operating in the same local credit markets. If the program merely allowed DaviBank to capture market share from competitors, one would expect little to no change in overall credit volumes. Conversely, if the CFC program facilitated access to previously underserved populations or activated latent credit demand, total disbursements across all banks should increase. To further test this distinction, I estimate a regression model that includes a triple interaction between the treatment variable, a post-treatment indicator, and a dummy for DaviBank. This approach allows me to isolate the treatment effect specific to DaviBank, controlling for trends among other banks in the same municipalities. By comparing the relative changes in disbursements, I can assess whether the program truly expanded the credit frontier or merely shifted borrowers within the existing system. Given that, I estimate the following model:

$$Y_{itb} = \alpha + \delta_1(\text{Treated}_i \times \text{Post}_t) + \delta_2(\text{Treated}_i \times \text{Post}_t \times \text{DaviBank}_b) + \mu_i + \lambda_t + \varepsilon_{itb} \quad (2)$$

Where Y_{itb} is the natural logarithm of consumer credit disbursements in municipality i, time t, and bank b. The coefficient δ_1 captures the post-treatment effect for non-DaviBank banks in treated municipalities, while δ_2 identifies the differential effect for DaviBank. Municipality fixed effects (μ_i) and time fixed effects (λ_t) are included to control for unobserved heterogeneity. The results, presented in Table 2, show that the coefficient on the interaction term *Post* $\times$ *Treated* $\times$ *DaviBank* is positive and statistically significant at the 5% level. This suggests that the increase in consumer credit disbursements is primarily driven by DaviBank itself, rather than by a reshuffling of clients across banks. The relatively small and marginally significant coefficient on the *Post* $\times$ *Treated* interaction term indicates that the increase is not attributable to other banks expanding their credit portfolios in the treated municipalities.

Table 2. Effect of CFC Program on Consumer Loans

Dependent Variable:	Ln(Consumer Loans)	
	OLS (1)	OLS (2)
Post $\times$ Treated	0.092**	0.069*
	(0.038)	(0.038)
Post $\times$ Treated $\times$ DaviBank	0.312**	0.256*
	(0.145)	(0.145)
Observations	19,894	19,894
Controls	No	Yes
Time FE (Quarter)	Yes	Yes
Municipality FE	Yes	Yes
Bank FE	Yes	Yes

This table reports OLS estimates of equation 3. The dependent variable is the logarithm of the total value of consumer loans disbursed by each bank in each municipality in which Davibank operates. Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$.

Taken together, these facts reveal a striking pattern. Municipalities where the CFC program operates experienced substantial growth in consumer lending, yet this expansion was not accompanied by higher default rates or by a reallocation of borrowers from competing banks.

These patterns suggest that the partnership between DaviBank and Enel may have relaxed important frictions that typically constrain lending to low-income and thin-file borrowers. Two mechanisms are particularly relevant. First, access to utility payment records may improve the bank's ability to identify creditworthy applicants. Second, the bundled repayment infrastructure may strengthen repayment performance after credit is granted. The next section investigates these mechanisms directly.

4 Conceptual Framework

The stylized facts presented in the previous section show that the CFC program expanded consumer lending without a corresponding increase in portfolio risk. At first glance, these two outcomes appear difficult to reconcile. Consumer lenders typically face a trade-off between expanding access to credit and maintaining portfolio quality, as lending to riskier or less observable borrowers generally increases default risk (Gross and Souleles, 2002; Zinman, 2015).

This trade-off is particularly pronounced in unsecured consumer lending. Before extending credit, banks must evaluate applicants using incomplete information about their future repayment behavior, creating information asymmetries (Stiglitz and Weiss, 1981; Jaffee and Russell, 1976) at the screening stage (Gibbs et al., 2025). Once a loan is originated, a second challenge emerges because these loans are unsecured. Without collateral, lenders cannot rely on contractual mechanisms to mitigate adverse selection and moral hazard or to recover losses in the event of default (Ioannidou et al., 2022). Instead, they must depend on borrowers' willingness and ability to repay. This makes repayment and enforcement especially costly, particularly for small consumer loans where the expected cost of collection may exceed the outstanding balance, especially when borrowers have limited assets or unstable income (Barajas et al., 2020). Together, these information and enforcement frictions reduce the expected profitability of lending and may discourage banks from extending credit even when demand from potentially creditworthy borrowers is substantial.

The partnership between DaviBank and Enel addresses these challenges by relaxing two

distinct frictions that arise over the life cycle of a consumer loan. Before loan origination, Enel contributes proprietary information on customers' utility payment behavior, improving the bank's ability to assess credit risk. After origination, Enel's billing infrastructure enables loan repayments to be bundled with electricity payments, providing an alternative repayment technology that may reduce repayment and collection frictions. Together, these institutional features provide a potential explanation for the aggregate outcomes documented in the previous section.

4.1 Information Frictions Before Loan Origination

The first friction arises during the screening stage of the lending process. Before extending credit, lenders must decide whether to approve an applicant and determine an appropriate credit limit based on imperfect information about future repayment behavior. Because repayment capacity and willingness to repay are only imperfectly observed ex ante, consumer credit markets are characterized by information asymmetries that generate adverse selection and may lead to credit rationing (Stiglitz and Weiss, 1981; Jaffee and Russell, 1976).

Traditional consumer lending relies primarily on application characteristics and credit bureau records to assess borrower risk. While these variables provide informative signals for borrowers with established credit histories, they are considerably less informative for thin-file or credit-invisible applicants. As emphasized by Liberti and Petersen (2019), the information available to lenders determines the efficiency of the screening process. When reliable information is scarce, lenders face greater uncertainty about borrowers' latent credit quality, increasing screening errors and reducing the efficiency of credit allocation.

I argue that the partnership between DaviBank and Enel relaxes these informational frictions by augmenting the bank's information production technology through the integration of alternative administrative data. In addition to conventional application and credit bureau information, the bank observes customers' electricity payment histories and consumption patterns before making its lending decision. These administrative records provide a rich and continuously updated source of information on payment discipline, liquidity management, and household financial behavior

that is largely unavailable through traditional financial databases. By transforming non-financial administrative data into economically meaningful screening signals, the partnership enables the bank to infer dimensions of borrower quality that would otherwise remain unobserved. Rather than replacing conventional credit bureau information, these alternative data complement existing information by improving the precision with which the bank evaluates applicant risk (Berg et al., 2020; Frost et al., 2019; Iyer et al., 2016).

From an economic perspective, expanding the lender's information set improves signal extraction regarding borrowers' latent credit quality and reduces information asymmetries between lenders and prospective borrowers. Better information reduces both Type I errors (rejecting creditworthy applicants) and Type II errors (approving excessively risky borrowers), allowing the bank to expand lending while maintaining portfolio quality. This mechanism provides a natural explanation for the stylized facts documented in the previous section, where the introduction of the CFC program was associated with a substantial expansion in consumer lending without a corresponding deterioration in portfolio risk. More broadly, these predictions are consistent with the literature on information production in financial intermediation, which shows that richer information sets improve screening efficiency and the allocation of credit (Liberti and Petersen, 2019).

This framework predicts that incorporating utility payment and consumption records into the bank's screening process should improve the identification of borrowers' latent credit quality beyond traditional application and credit bureau information. These informational gains are expected to be particularly important for applicants with limited or no formal credit history. Section 5 evaluates this prediction by comparing the predictive performance of alternative credit-scoring models.

4.2 Repayment Frictions After Loan Origination

A second friction arises after credit has been originated. Because unsecured consumer loans are not backed by collateral, lenders cannot rely on asset repossession to ensure repayment. Instead,

repayment depends on borrowers' willingness and ability to make periodic loan installments. For relatively small consumer loans, monitoring delinquency and collecting missed payments can be costly relative to the outstanding loan balance, reducing the profitability of lending to financially underserved households (Barajas et al., 2020).

More broadly, contract design plays a central role in shaping repayment incentives by determining how repayment obligations are structured and enforced (Bolton and Dewatripont, 2004). Recent work further shows that innovations in repayment technologies can improve loan performance even without strengthening legal enforcement or requiring collateral (Gertler et al., 2023).

I argue that the partnership between DaviBank and Enel relaxes these repayment frictions through an innovative contract design that introduces a novel repayment technology. Under the CFC program, monthly credit card installments are incorporated into the customer's electricity bill. Although borrowers may request a temporary separation of the electricity and credit card bills to prevent electricity service interruption, bundled repayment remains the standard repayment arrangement unless such a request is made. Consequently, the CFC transforms an individual credit obligation into a routine household payment embedded in the consumption of an essential household service, fundamentally changing the environment in which repayment decisions are made.

This contractual arrangement changes the repayment environment in several ways. Bundling loan installments with electricity payments may reduce transaction and compliance costs by replacing two separate payment obligations with a single recurring household bill.[6] By embedding credit card repayments into an essential household expense, the CFC may also encourage borrowers to allocate resources jointly across both obligations, effectively operating as a commitment device

[6]Under the bundled arrangement, borrowers receive a single bill, face a single payment date, and can satisfy both obligations through the same payment infrastructure. Following unbundling, borrowers must manage separate bills, payment dates, and repayment processes, increasing the administrative burden associated with debt repayment. Even relatively small administrative frictions have been shown to affect household financial decisions and repayment outcomes (Agarwal et al., 2009; Keys and Wang, 2019).

that strengthens repayment discipline.[7] Finally, because electricity is jointly consumed within the household, failure to pay the bundled bill without requesting a temporary separation may affect all household members rather than only the cardholder, making repayment decisions more visible within the household.[8] Overall, this repayment technology illustrates how contractual innovations can improve the performance of unsecured consumer lending without relying on stronger legal enforcement or collateral.

This framework predicts that borrowers should exhibit stronger repayment performance while enrolled in the bundled repayment system than after permanently losing access to it. Section 5 evaluates this prediction by exploiting borrowers' relocation outside Enel's electricity service territory, which permanently removes bundled repayment while leaving the underlying credit contract unchanged.

5 Empirical Evidence on the Economic Channels

The conceptual framework argues that the partnership between DaviBank and Enel relaxes complementary frictions through two complementary contractual technologies that operate at different stages of the lending relationship. Before loan origination, the partnership expands the bank's information production technology by incorporating utility payment and consumption records into the credit evaluation process. After loan origination, it introduces a bundled repayment technology that changes the contractual environment in which repayment decisions are made by embedding loan installments into the payment of an essential household service.

This section evaluates the empirical relevance of these two economic channels using a unique administrative dataset constructed from the internal records of DaviBank and Enel. I first examine whether alternative utility data improve the prediction of borrowers' repayment outcomes beyond

[7] Even in the absence of stronger legal enforcement, integrating debt repayment into a routine household bill may help borrowers follow through on intended repayment decisions and facilitate self-control (Ashraf et al., 2006; Thaler and Benartzi, 2004).

[8] Bundling may also increase the salience of debt repayment because electricity bills are among the most visible and routinely monitored household financial obligations. Incorporating credit card installments into the same bill may reduce inattention and facilitate financial planning (Chetty et al., 2009; Hastings and Shapiro, 2013).

traditional application and credit bureau information. I then analyze the repayment channel by exploiting borrowers' permanent loss of bundled repayment following relocation outside Enel's electricity service territory, which allows me to identify the causal effect of the repayment technology on subsequent loan performance.

5.1 Administrative Data

To evaluate the two contractual technologies introduced by the CFC program, I construct a unique administrative dataset from the internal records of DaviBank and Enel, the two institutions participating in the partnership. The integrated database combines information on credit card applications, credit card repayment behavior, and household electricity consumption and payment records, making it possible to study both the information production and repayment technologies described in the conceptual framework.

The core of the dataset consists of all individuals who applied for and were approved for a CFC credit card between 2010 and 2019. DaviBank provided detailed information collected during the credit application process, including demographic and socioeconomic characteristics, internal credit assessments, and credit bureau information when available. In addition, the bank supplied monthly account-level information on outstanding balances, installment payments, fees, delinquency, and default outcomes throughout the life of each credit card.

To complement the bank's information, the credit records were merged with Enel's administrative database using the residential unit identifier reported by applicants at the time of application. This merge provides detailed information on household electricity consumption and bill payment behavior both before and after credit origination. The matching procedure was successful for approximately 91% of approved applicants. Unmatched observations are primarily attributable to inconsistencies or typographical errors in residential unit identifiers.

Table 3 reports the annual number of approved CFC credit cards and the proportion successfully matched with Enel's administrative records. Between 2010 and 2019, a total of 943,281 credit cards were granted through the CFC program, of which 860,869 (91.3%) were successfully linked to

electricity consumption and payment information.

The resulting database combines three complementary sources of information. First, it contains the traditional variables typically available to lenders, including application characteristics and credit bureau records. Second, it incorporates alternative administrative data derived from electricity consumption and bill payment histories. Third, it provides detailed longitudinal information on subsequent repayment outcomes, including balances, installment payments, delinquency, and default over the life of each account.

Table 3. Construction of the CFC-Enel Administrative Dataset

Year	Credit Cards Granted	Matched with Energy Information	Percentage
2010	150,431	137,042	91.1%
2011	97,879	88,403	90.3%
2012	142,135	131,047	92.2%
2013	113,835	104,974	92.2%
2014	153,932	135,812	88.2%
2015	72,876	67,249	92.3%
2016	72,484	66,847	92.2%
2017	82,515	75,550	91.6%
2018	77,743	71,680	92.2%
2019	92,028	85,313	92.7%
Total	943,281	860,869	91.26%

Notes: This table reports the number of credit cards approved under the CFC program and the number successfully matched with electricity consumption and payment records from Enel. The final row presents cumulative totals for the 2010–2019 period.

The integrated structure of the database is central to the empirical analysis because it links information available before loan origination with repayment outcomes observed throughout the life of the loan. This allows me to evaluate the two contractual technologies developed in the conceptual framework. First, I examine whether incorporating utility payment and consumption records into the bank's information set improves the prediction of borrowers' subsequent repayment performance beyond traditional application and credit bureau information. Second, I exploit the monthly panel structure to identify the causal effect of the bundled repayment technology

following borrowers' permanent transition from bundled to separate billing arrangements after relocating outside Enel's electricity service territory.

Although both empirical analyses rely on the same underlying administrative database, the estimation samples differ. The screening analysis focuses on approved CFC applicants for whom subsequent repayment outcomes can be observed, whereas the repayment analysis uses a monthly panel of active CFC cardholders and exploits variation generated by the permanent loss of bundled repayment.

5.2 Evidence on Information Production Technology: Screening Channel

The conceptual framework argues that the partnership between DaviBank and Enel expands the bank's information production technology by incorporating utility payment and consumption records into the credit evaluation process. This section evaluates that prediction by examining whether utility information improves the prediction of future repayment outcomes beyond traditional application and credit bureau information.

From the bank's perspective, consumer lending is fundamentally a screening problem. At the time of the credit application, the bank must decide whether to extend credit without directly observing the applicant's future repayment behavior. Because repayment capacity and willingness to pay are latent characteristics, the bank instead relies on observable signals of applicant quality, such as demographic characteristics, financial history, and other available information. These signals are combined into an internal credit score that summarizes the applicant's predicted probability of default and guides the bank's lending decision.

Formally, the bank's information production technology can be represented as

$$Y_i = f(X_{1i}, X_{2i}, X_{3i}) + \varepsilon_i, \tag{3}$$

where Y_i denotes a future credit outcome, X_{1i} contains information collected through the application form, X_{2i} corresponds to the applicant's credit bureau information, and X_{3i} represents

electricity consumption and bill payment history provided by Enel. The function $f(\cdot)$ maps these observable signals into a predicted probability of default, which summarizes the applicant's estimated credit risk at the time of the lending decision.

The predicted probability of default, denoted by p_i, constitutes the key output of the bank's credit-scoring model. The bank compares this predicted probability with an internal approval threshold, δ, and grants credit whenever $p_i < \delta$. Applicants whose predicted default probability exceeds this threshold are rejected. As shown formally in Section 6, the approval threshold δ corresponds to the bank's profit-maximizing lending rule. Consequently, improvements in predictive accuracy can change borrower rankings around the approval threshold, affecting both lending decisions and the bank's expected profitability.

The central empirical question is whether utility payment and electricity consumption records improve the estimation of borrowers' default risk beyond the information already contained in traditional data sources. If utility payment behavior captures dimensions of financial discipline, liquidity management, or repayment capacity that are not fully reflected in application characteristics or credit bureau records, incorporating this information should improve the predictive performance of the credit-scoring model. Better predictions allow the bank to distinguish more accurately between high- and low-risk applicants, thereby improving lending decisions around the approval threshold.

To evaluate this hypothesis, I estimate a sequence of credit-scoring models that progressively expand the bank's information set. The first specification uses only information available from the credit application. The second adds the applicant's credit bureau score. The third further incorporates electricity consumption and utility payment records provided by Enel. Comparing the predictive performance across these specifications isolates the incremental contribution of utility information to the bank's information production technology. The analysis is conducted separately for applicants with and without credit bureau records. This distinction allows me to assess whether utility information complements existing credit histories or substitutes for missing credit information among applicants with limited access to the formal financial system.

Following the traditional credit-scoring literature, I estimate these models using logistic regression. Logistic models remain widely used in consumer credit risk assessment because they produce directly interpretable estimates of default probabilities and provide a transparent framework for evaluating the incremental contribution of new information sources to credit risk prediction (Board of Governors of the Federal Reserve System, 2007; Duarte et al., 2025). This transparency is particularly valuable for the purposes of this paper, which seeks to quantify the informational value of utility payment records rather than develop the prediction algorithm that maximizes classification accuracy.[9] Specifically, the probability of default is estimated as

$$Pr(Y_i = 1) = F\left(\beta_0 + \boldsymbol{\beta}_1 \mathbf{X}_{1i} + \beta_2 X_{2i} + \boldsymbol{\beta}_3 \mathbf{X}_{3i}\right), \tag{4}$$

where $F(\cdot)$ denotes the logistic cumulative distribution function. The dependent variable Y_i equals one if borrower i experiences a default event during the observation period and zero otherwise.

The predictive performance of each specification is evaluated using the Area Under the Receiver Operating Characteristic Curve (AUC). The AUC measures the probability that the model assigns a higher predicted default probability to a borrower who subsequently defaults than to one who does not. Higher AUC values indicate greater discriminatory power and therefore a more informative information production technology. Following Berg et al. (2020) and Iyer et al. (2016), an AUC above 0.70 is interpreted as evidence of meaningful predictive content in the underlying information set.[10]

Although the primary outcome of interest is default, I also estimate analogous models using delinquency as the dependent variable. Delinquency captures earlier repayment difficulties and provides an additional robustness check of the incremental informational value of utility payment

[9]The empirical analysis is conducted within the bank's secure computing environment, which imposes restrictions on software installation and computational resources. As a result, the implementation of more computationally intensive machine-learning algorithms, such as Random Forest or Gradient Boosting, is not feasible in this setting.

[10]The Receiver Operating Characteristic (ROC) curve plots the true positive rate (sensitivity) against the false positive rate for all possible classification thresholds. As discussed in the conceptual framework, the objective of the bank's information production technology is to improve the identification of high- and low-risk borrowers. The AUC summarizes this ability by measuring the model's discriminatory power across all possible approval thresholds.

records. These results are presented as complementary evidence, while the main analysis focuses on default because it is the outcome most directly related to credit risk and expected lending losses.

A limitation of this exercise is that repayment outcomes are observed only for approved applicants. Consequently, default outcomes are unavailable for rejected applicants, giving rise to the selective-label problem commonly encountered in consumer lending markets (Blattner and Nelson, 2021). Because rejected applicants are never observed ex post, the analysis cannot assess how utility payment information would have ranked these borrowers. As a result, the estimated improvement in predictive performance should be interpreted as a conservative estimate, or lower bound, of the incremental informational value of utility payment records in the full applicant population.

5.2.1 Information Production Technology: Results

The empirical analysis evaluates the bank's information production technology using three sources of information that enter the credit-scoring models described in (4): application-form information (X_1), credit bureau information (X_2), and electricity consumption and bill payment information provided by Enel (X_3).

The application form includes information on income, age, employment status, education, gender, household composition, housing tenure, and the socioeconomic stratum of the applicant's residence.[11] The utility dataset provides information on electricity consumption levels, payment delays, and indicators of payment irregularities, such as red flags and consecutive red flags. For applicants with previous participation in the formal financial system, DaviBank additionally provided the applicant's credit bureau score at the time of application.

Table 4 reports summary statistics separately for applicants with and without prior credit history. Approximately 62.5% of approved applicants had an existing credit history, while the

[11] In Colombia, the socioeconomic stratum is an official classification of residential properties used to determine pricing and subsidies for household public services. It ranges from 1 (lowest) to 6 (highest) and reflects neighborhood and housing characteristics rather than household income.

remaining 37.5% had no previous credit bureau records. Applicants without credit history tend to be older, have lower reported income, and are more likely to lack a permanent employment contract. In contrast, applicants with prior credit histories exhibit higher average income levels and lower default rates.

Several utility-payment variables also differ across groups. Applicants without credit history display higher average payment delays and a greater incidence of payment irregularities, suggesting that electricity bill payment behavior may contain valuable information about repayment capacity and financial discipline. At the same time, electricity consumption levels are broadly similar across both groups, highlighting that the predictive content of utility data is likely driven more by payment behavior than by consumption levels alone. For applicants without a formal credit history, no credit bureau score is available. Taken together, these descriptive patterns are consistent with the conceptual framework, which predicts that utility payment behavior reveals dimensions of borrower quality that are not fully captured by traditional financial information. The following analysis evaluates whether these differences translate into economically meaningful improvements in credit risk prediction.

Table 5 evaluates the central prediction of the conceptual framework: whether incorporating utility payment and consumption records into the bank's information production technology improves the identification of borrower risk beyond traditional application and credit bureau information. The table reports the predictive performance of alternative credit-scoring models using the area under the ROC curve (AUC). The analysis is conducted separately for applicants without prior credit history and applicants with existing credit histories

Panel A reports the main results using default as the outcome variable. For applicants without prior credit history, the baseline model using only application information achieves an AUC of 0.682. Incorporating utility payment and consumption information from Enel increases the AUC to 0.732, an improvement of 5.1 percentage points. The corresponding DeLong test strongly rejects the equality of ROC curves ($\chi^2 = 79.79$). These results support the prediction that utility information expands the bank's information production technology by improving the identification

Table 4. Applicant Characteristics by Credit History

	No Credit History			Credit History		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.
A. Applicant Characteristics						
Income (COP)	1,077,337	900,000	1,098,317	1,225,526	953,010	855,742
Age (years)	38.02	36.00	13.27	35.51	32.00	13.04
No permanent contract	0.26	0.00	0.44	0.15	0.00	0.36
College	0.27	0.00	0.44	0.31	0.00	0.46
Female	0.55	1.00	0.50	0.53	1.00	0.50
Dependents	1.15	1.00	1.16	1.58	1.00	1.03
Rented housing	0.10	0.00	0.30	0.16	0.00	0.37
B. Utility Payment and Consumption Information						
Avg. energy consumption	164.34	136.58	131.96	159.58	133.01	137.03
Avg. bill payment	0.05	0.03	0.05	0.02	0.02	0.02
Red flags	0.02	0.00	0.05	0.02	0.00	0.06
Consecutive red flags	0.06	0.00	0.47	0.06	0.00	0.47
Last-month consumption	161.74	153.00	93.83	156.77	135.00	101.63
SD consumption	101.24	58.23	85.42	94.37	45.98	84.58
Minimum consumption	214.84	141.00	182.38	175.39	122.00	157.52
Maximum consumption	299.52	201.00	227.49	248.07	177.00	195.56
C. Socioeconomic Strata						
Strata 1	0.17	0.00	0.37	0.18	0.00	0.38
Strata 2	0.40	0.00	0.49	0.56	1.00	0.50
Strata 3	0.21	0.00	0.41	0.24	0.00	0.43
Strata 4	0.02	0.00	0.15	0.02	0.00	0.13
Strata 5	0.01	0.00	0.07	0.00	0.00	0.05
D. Credit Bureau Information						
Credit Score	–	–	–	814.73	931.00	193.65
E. Default and Delinquency Information						
Default	0.03	0.00	0.17	0.02	0.00	0.15
Delinquency	0.04	0.00	0.20	0.03	0.00	0.18
Observations		266,905			613,696	

Notes: This table reports summary statistics separately for applicants without prior credit history and applicants with credit history. Utility variables are computed using historical electricity consumption and bill payment records from Enel. Default and delinquency outcomes are measured during the post-origination period.

of repayment risk among thin-file borrowers.

For applicants with existing credit histories, the model including traditional credit bureau scores achieves an AUC of 0.718, while the model using only Enel information reaches an AUC of 0.709. Although the bureau score performs slightly better in absolute terms, the difference is not statistically significant according to the DeLong test ($p = 0.256$). This finding indicates that utility information alone provides discriminatory power comparable to traditional credit bureau information. Combining application information, bureau scores, and Enel variables further increases the AUC to 0.748, the highest value across all specifications and an improvement of 7.6 percentage points relative to the application-only model. Overall, utility information substitutes for missing financial information among thin-file applicants and complements traditional credit bureau information for borrowers with established credit histories.

Panel B reports similar results using delinquency as the outcome variable. Although the improvements in AUC are slightly smaller, the overall pattern remains unchanged. Among borrowers without prior credit history, incorporating Enel information increases the AUC from 0.635 to 0.671. For borrowers with existing credit histories, the combined model including bureau scores and utility information achieves the highest AUC (0.679), while the model using only utility information (AUC = 0.652) performs statistically as well as the model using only credit bureau scores (AUC = 0.659), as the DeLong test fails to reject equality between the two ROC curves ($p = 0.304$). The consistency of the results across default and delinquency indicates that the informational value of utility payment records is robust across alternative measures of repayment performance. Overall, the evidence shows that utility information expands the bank's information production technology, particularly for applicants without prior credit histories, while continuing to add value for borrowers already integrated into the formal financial system.

While Table 5 shows that incorporating utility information improves the bank's ability to identify borrower risk, it does not reveal which dimensions of the Enel data generate these improvements. Table 6 therefore reports the coefficient estimates from the baseline Logit models

Table 5. Incremental Predictive Value of Utility Information

Group	Model	AUC	ΔAUC	χ^2
Panel A. Default				
No Credit History	Application	0.682	–	–
	+ Enel	0.732	0.051	79.79***
With Credit History	Application	0.672	–	–
	+ Score	0.718	0.046	85.03***
	+ Enel	0.709	0.037	51.82***
	+ Score + Enel	0.748	0.076	141.48***
Panel B. Delinquency				
No Credit History	Application	0.635	–	–
	+ Enel	0.671	0.036	44.02***
With Credit History	Application	0.627	–	–
	+ Score	0.659	0.032	61.42***
	+ Enel	0.652	0.025	61.69***
	+ Score + Enel	0.679	0.053	134.29***

Notes: The table reports the area under the ROC curve (AUC) for different predictive models. ΔAUC corresponds to the increase relative to the application-only model within each group. χ^2 statistics correspond to DeLong tests of equality of ROC curves. Panel A reports results for default prediction, while Panel B reports results for delinquency prediction. *** denotes significance at the 1% level.

used to construct the ROC curves.[12]

The estimates show that both utility payment behavior and electricity consumption contain useful information for identifying repayment risk. Late bill payments, red flags, and consecutive red flags are consistently associated with a higher probability of default, suggesting that persistent repayment difficulties signal household financial distress. Electricity consumption patterns, including volatility and recent consumption dynamics, are also significant predictors of default and likely capture dimensions of household economic conditions not reflected in application forms or credit bureau records. Importantly, these variables remain significant after controlling for applicant characteristics, regional and month-year fixed effects and, for borrowers with prior credit histories, the credit bureau score. This evidence indicates that utility information contributes additional information beyond traditional financial data.

An important concern is whether the improvements documented in Tables 5 and 6 reflect overfitting. Table 7 addresses this issue by comparing in-sample and out-of-sample performance using 5-fold and 10-fold cross-validation. The out-of-sample results closely match the in-sample estimates across all specifications. For example, among borrowers with prior credit histories, the AUC of the model combining application information, bureau scores, and Enel variables declines only from 0.748 in-sample to 0.745 under 5-fold cross-validation. Similar patterns are observed for borrowers without prior credit histories. These results indicate that the additional information contained in utility records generalizes well out of sample and is unlikely to reflect overfitting.

Table 8 examines whether the contribution of utility information differs across borrower characteristics. The results show that incorporating Enel information improves borrower risk identification across all subgroups. The gains are particularly large among older borrowers, higher socioeconomic strata, and borrowers with stronger credit bureau scores. For example, among borrowers with relatively high bureau scores, adding Enel information increases the AUC by more than 8 percentage points. At the same time, utility information also improves borrower classification among applicants without prior credit histories and those from lower socioeconomic

[12]Results using delinquency as the dependent variable are reported in Appendix Table A4.

Table 6. Determinants of Default in the Credit Scoring Models

	(1)	(2)	(3)	(4)	(5)	(6)
	No Credit History			With Credit History		
Credit Score				-0.002***		-0.003***
				(0.000)		(0.000)
Avg. energy cons.		-0.043			0.082***	0.207***
		(0.027)			(0.019)	(0.022)
Avg. bill payment		-4.106***			-1.839***	-1.311***
		(0.708)			(0.548)	(0.662)
Red flags		2.361***			1.496***	2.132***
		(0.176)			(0.116)	(0.121)
Consecutive red flags		0.248***			0.364***	0.309***
		(0.015)			(0.009)	(0.010)
Cons. last month		0.002***			0.001***	0.001***
		(0.000)			(0.000)	(0.000)
SD consumption		0.002***			0.004***	0.004***
		(0.000)			(0.000)	(0.000)
Min. consumption		0.003***			-0.002***	-0.002***
		(0.000)			(0.000)	(0.000)
Max. consumption		-0.004***			-0.001***	-0.001***
		(0.000)			(0.000)	(0.000)
Strata 1		0.147***			0.375	0.119
		(0.059)			(0.340)	(0.342)
Strata 2		0.136***			0.297	0.069
		(0.055)			(0.339)	(0.342)
Strata 3		0.150***			0.357	0.144
		(0.059)			(0.339)	(0.342)
Strata 4		0.009			0.127	0.021
		(0.107)			(0.347)	(0.349)
Strata 5		0.201			-0.610	-0.605
		(0.210)			(0.441)	(0.442)
Observations	266,905	266,905	613,696	613,696	613,696	613,696
Applicant characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Credit score included	No	No	No	Yes	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
AUC	0.682	0.732	0.672	0.718	0.709	0.748

Notes: The table reports Logit coefficients. Columns (1)–(2) correspond to individuals without credit history; columns (3)–(6) correspond to individuals with credit history. Energy consumption variables are measured over the previous 12 months unless otherwise indicated. AUC corresponds to the area under the ROC curve. Standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. In-Sample and Out-of-Sample Predictive Performance

			Out-of-Sample AUC	
Group	Model	In-Sample AUC	5-fold CV	10-fold CV
No Credit History				
	Application	0.6820	0.6807	0.6820
			(0.0092)	(0.0010)
	+ Enel	0.7320	0.7312	0.7330
			(0.0065)	(0.0009)
With Credit History				
	Application	0.6720	0.6677	0.6720
			(0.0093)	(0.0008)
	+ Score	0.7180	0.7147	0.7180
			(0.0059)	(0.0006)
	+ Enel	0.7090	0.7053	0.7090
			(0.0089)	(0.0010)
	+ Score + Enel	0.7480	0.7445	0.7480
			(0.0052)	(0.0007)

Notes: The table compares in-sample and out-of-sample predictive performance. Out-of-sample AUCs are computed using 5-fold and 10-fold cross-validation. Standard deviations across folds are reported in parentheses. The similarity between in-sample and out-of-sample AUCs suggests that the predictive gains are not driven by overfitting.

strata. These findings reinforce the earlier evidence that utility information substitutes for missing financial information while complementing traditional credit bureau information.

Table 8. Heterogeneity in the Predictive Value of Utility Data

Panel A. No Credit History				
Subsample	Observations	App.	App.+Enel	Δ(p.p.)
Female	143,098	0.686	0.736	4.97
Male	118,817	0.660	0.716	5.61
Young	96,205	0.642	0.693	5.06
Older	163,599	0.646	0.721	7.44
Low SES	152,529	0.676	0.725	4.89
High SES	57,622	0.703	0.764	6.07
Panel B. With Credit History				
Subsample	Observations	App.	App.+Enel	Δ(p.p.)
Female	309,727	0.715	0.746	3.11
Male	288,238	0.706	0.736	3.06
Young	277,089	0.687	0.719	3.16
Older	316,785	0.720	0.755	3.50
Low score	203,171	0.688	0.725	3.76
High score	203,995	0.703	0.783	8.05

Notes: The table reports the area under the ROC curve (AUC) across borrower subgroups. Panel A focuses on borrowers without prior credit history. In this panel, the baseline model uses application and socioeconomic characteristics, while the enriched model additionally includes Enel utility information. Panel B focuses on borrowers with credit history. In this panel, the baseline model includes application characteristics and the credit bureau score, while the enriched model additionally incorporates Enel information. ΔAUC is expressed in percentage points and corresponds to the difference between the enriched and baseline models within each subgroup. Young borrowers are defined as individuals below 30 years old. Low- and high-score groups are defined using terciles of the credit bureau score distribution. Low SES corresponds to socioeconomic strata 1–2, while High SES corresponds to strata 5–6.

5.3 Repayment Technology: Enforcement Channel

The conceptual framework argues that the partnership between DaviBank and Enel improves loan performance not only by expanding the bank's information production technology before loan origination, but also by introducing a bundled repayment technology after credit is granted. Under the CFC program, borrowers normally repay both their electricity bill and their monthly credit card installment through a single bundled payment. By embedding loan repayment into one

of the household's most routine financial obligations, this contractual arrangement may strengthen repayment discipline and reduce frictions associated with debt repayment. This section evaluates that prediction by examining whether losing access to bundled repayment affects subsequent repayment performance.

The institutional design of the CFC program provides a unique source of variation to identify this mechanism. Borrowers who permanently relocate outside Enel's electricity service territory can no longer repay their credit card installments through the electricity bill and must instead make payments directly to DaviBank. Importantly, these borrowers retain the same credit card, remain clients of the same bank, and continue under the same contractual conditions. The principal institutional change is therefore the loss of the bundled repayment technology rather than a modification of the underlying lending relationship. This setting allows the analysis to isolate the contribution of the repayment technology to subsequent loan performance.

The empirical analysis focuses on borrowers who submitted permanent unbundling requests between January 2018 and February 2020. Requests submitted after February 2020 are excluded to avoid potential confounding effects associated with the COVID-19 pandemic, which may have influenced both residential mobility and borrowers' ability to submit in-person unbundling requests. Restricting the treatment cohort to the pre-pandemic period also provides a sufficiently long post-treatment window to evaluate repayment outcomes.

An important institutional feature further strengthens the empirical design. Borrowers are allowed to request permanent unbundling only if they are not officially in default at the time of the request. Consequently, accounts must have fewer than 90 days past due and cannot have been charged off, reducing concerns that unbundling is mechanically driven by severe repayment problems. Under the identifying assumption that, conditional on borrower fixed effects, calendar-time fixed effects, and time-varying controls, the timing of unbundling is unrelated to unobserved changes in repayment behavior other than those generated by the loss of bundled repayment, the baseline specification is:

$$Y_{it} = \alpha_i + \lambda_t + \beta\, Unbundling_{it} + \gamma X_{it} + \varepsilon_{it}, \tag{5}$$

Where Y_{it} denotes repayment outcomes for borrower i in month t. $Unbundling_{it}$ is an indicator equal to one from the month in which the borrower permanently loses access to bundled repayment and zero otherwise. The specification includes borrower fixed effects (α_i), month-year fixed effects (λ_t), and time-varying controls (X_{it}), including the logarithm of the monthly installment plus interest and the logarithm of fees. The coefficient of interest, β, captures the average change in repayment outcomes following unbundling relative to the borrower's own pre-unbundling period. If the repayment technology embedded in the CFC program improves loan performance, losing access to bundled repayment should increase delinquency and default, implying positive estimates of β.

Although permanent unbundling is primarily driven by residential relocation outside Enel's service territory, borrowers requesting unbundling may differ systematically from those who remain within the bundled repayment system. Table 9 therefore characterizes the observable pre-treatment characteristics associated with permanent unbundling requests using a Logit model. The estimates indicate that borrowers requesting unbundling tend to be younger, have higher incomes, are substantially more likely to live in rented housing, and exhibit stronger repayment histories before treatment. Across alternative measures of repayment performance, they are less likely to have experienced delinquency, accumulate fewer delinquent months, and record fewer days past due.

These descriptive patterns suggest that borrowers requesting unbundling are not characterized by deteriorating repayment behavior prior to treatment. This is important for the identification strategy because it reduces concerns that borrowers select into unbundling in response to worsening financial conditions or an already declining repayment trajectory. Instead, treated borrowers enter the post-unbundling period with stronger observable economic and repayment characteristics, making it less likely that any subsequent deterioration in repayment outcomes

Table 9. Observable Characteristics Associated with Permanent Unbundling Requests

	(1) Avg. Days Past Due	(2) Delinquent Months	(3) Ever Delinquent
Panel A. Borrower Characteristics			
Income	0.423***	0.423***	0.423***
	(0.016)	(0.016)	(0.016)
Age	-0.025***	-0.025***	-0.025***
	(0.001)	(0.001)	(0.001)
Female	-0.162***	-0.162***	-0.162***
	(0.038)	(0.038)	(0.038)
Married	-0.449***	-0.449***	-0.449***
	(0.043)	(0.043)	(0.043)
College	-0.137***	-0.137***	-0.137***
	(0.038)	(0.038)	(0.038)
High School	0.280***	0.280***	0.280***
	(0.033)	(0.033)	(0.033)
Strata 1	-0.088	-0.088	-0.088
	(0.088)	(0.088)	(0.088)
Strata 2	-0.138	-0.138	-0.138
	(0.089)	(0.089)	(0.089)
Strata 3	-0.167	-0.167	-0.167
	(0.089)	(0.089)	(0.089)
Strata 4	-0.289*	-0.289*	-0.289*
	(0.136)	(0.136)	(0.136)
Strata 5	-0.204	-0.204	-0.204
	(0.257)	(0.257)	(0.257)
Rented	0.765***	0.765***	0.765***
	(0.026)	(0.026)	(0.026)
Public Employee	-0.262	-0.262	-0.262
	(0.177)	(0.177)	(0.177)
Retired	-0.541***	-0.541***	-0.541***
	(0.111)	(0.111)	(0.111)
Credit History	-0.109***	-0.109***	-0.109***
	(0.028)	(0.028)	(0.028)
Energy Consumption	0.048***	0.048***	0.048***
	(0.014)	(0.014)	(0.014)
Panel B. Pre-Treatment Repayment History			
Average Days Past Due	-0.006***		
	(0.001)		
Number of Delinquent Months		-0.188***	
		(0.030)	
Ever Delinquent			-0.297***
			(0.046)
Observations	495,430	495,430	495,430
Pseudo R^2	0.0390	0.0390	0.0389

Notes: The table reports Logit coefficient estimates. The dependent variable equals one if the borrower submitted a permanent unbundling request. Each specification includes a different measure of pre-treatment repayment history. Robust standard errors are reported in parentheses. The intercept is estimated but not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

is driven by pre-existing financial distress rather than by the removal of the bundled repayment technology.

Nevertheless, the existence of observable differences between borrowers who request unbundling and those who remain in the bundled repayment system motivates the construction of a more comparable control group. To address this concern, the following subsection implements a propensity-score matching procedure based on pre-treatment borrower characteristics before estimating the effects of unbundling on repayment outcomes.

5.3.1 Matching Strategy

A potential concern is that borrowers who request unbundling may differ systematically from those who remain within Enel's service territory. Although unbundling typically occurs when customers relocate to municipalities where Enel does not provide residential electricity services, the decision to move is unlikely to be random. Relocation may be associated with economic or household shocks, such as changes in employment, income, family structure, or housing conditions, which may also affect subsequent repayment behavior. Consequently, borrowers who request unbundling may face different underlying financial conditions than those who continue repaying through Enel's billing infrastructure.

To improve comparability between treated and control borrowers, I construct a propensity-score matched sample using nearest-neighbor matching. Following the logic of Agarwal et al. (2020), the objective is to compare individuals who are observationally similar prior to treatment but differ in whether they eventually request unbundling. Matching is performed using pre-treatment characteristics that are likely to influence both relocation decisions and repayment outcomes, including income, age, gender, education, credit history, and electricity consumption.

Table 10 reports balance statistics before and after matching. Prior to matching, borrowers who eventually request unbundling differ significantly from non-requesters across several observable characteristics. After matching, these differences become substantially smaller and are generally no longer statistically significant, indicating that the procedure successfully improves comparability

between the two groups.

Table 10. Covariate Balance Before and After Matching

	Control		Treated		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Difference
Panel A. Before Matching					
Income	808,721	14,353	1,026,822	8,777	218,101***
Energy Consumption	161.00	99.14	167.00	107.33	-5.46***
Credit History	0.706	0.456	0.747	0.435	-0.040***
Age	37.25	13.17	32.53	11.28	4.72***
Female	0.552	0.497	0.484	0.500	0.068***
College Education	0.2757	0.4469	0.2523	0.4343	0.0234***
Married	0.1532	0.3601	0.0883	0.2838	0.0648***
Rented	0.1465	0.3536	0.2955	0.4563	-0.1488***
Observations	484,011		11,419		
Panel B. After Matching					
Income	1,025,447	10,221	1,025,365	10,118	-82
Energy Consumption	165.58	104.98	166.64	107.33	-1.067
Credit History	0.745	0.435	0.746	0.435	-0.0006
Age	32.46	10.97	32.52	10.21	-0.0646
Female	0.472	0.499	0.484	0.499	-0.0115*
College Education	0.247	0.431	0.252	0.434	-0.004
Married	0.082	0.275	0.088	0.283	-0.005
Rented	0.284	0.450	0.295	0.456	-0.011*
Observations	11,199		11,419		

This table reports summary statistics for the treatment and control groups before and after propensity score matching. The matched sample is obtained using nearest-neighbor propensity score matching. The last column reports the difference in means between the control and treated groups. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Importantly, the matched-sample estimates should not be interpreted as replacing the baseline difference-in-differences results. Rather, they serve as a robustness exercise designed to assess whether the estimated effects are driven by observable differences associated with the decision to relocate. If the results remain similar after matching, this would provide additional evidence that the deterioration in repayment outcomes following unbundling is not solely explained by differences in observable borrower characteristics.

5.3.2 Results of Unbundling Request

Table 11 reports the baseline difference-in-differences estimates of the effect of permanently losing access to the bundled repayment arrangement on borrowers' subsequent repayment performance. The dependent variables are monthly indicators for delinquency and default measured at the cardholder-month level. Columns (1) and (2) present estimates for the full sample of CFC cardholders, while Columns (3) and (4) report the corresponding estimates for the propensity-score matched sample described in the previous subsection.

The results provide strong evidence that permanently separating credit card repayments from the electricity bill significantly worsens repayment performance. In the full sample, an unbundling request increases the probability of monthly delinquency by 5.5 percentage points and the probability of default by 7.4 percentage points. Both estimates are statistically significant at the one percent level and economically large. Relative to average delinquency and default rates of approximately 4 percent and 3 percent, respectively.

The results remain remarkably similar after restricting the analysis to the matched sample. Following matching, unbundling increases delinquency by 2.4 percentage points and default by 4.9 percentage points, both statistically significant at the one percent level. Relative to the corresponding baseline rates, these effects represent increases of approximately 60 percent in delinquency and 163 percent in default. Although the estimated effects become somewhat smaller after matching, particularly for delinquency, they remain economically meaningful. This pattern suggests that observable differences between borrowers who eventually request unbundling and those who remain under the bundled repayment arrangement explain part of the raw differences in repayment outcomes, but cannot account for the substantial deterioration observed after unbundling.

An important feature of the results is that the estimated effect on default remains consistently large across specifications. While delinquency captures temporary repayment difficulties, default reflects a more severe and persistent breakdown of the lending relationship. The stability of the

default estimates therefore suggests that the bundled repayment arrangement does more than reduce short-term payment frictions. Instead, it appears to play an important role in preventing borrowers from transitioning into prolonged financial distress.

Table 11. The Enforcement Effect of Bundling on Loan Repayment

	Full Sample		Matching Sample	
	(1) Delinquency	(2) Default	(3) Delinquency	(4) Default
Unbundling request	0.055***	0.074***	0.024***	0.049***
	(0.004)	(0.002)	(0.002)	(0.000)
Ln(Loan installment + Interest)	0.071***	0.002**	0.074***	0.009***
	(0.003)	(0.001)	(0.002)	(0.000)
Ln(Fee)	-0.090***	0.009***	0.050*	-0.006**
	(0.003)	(0.001)	(0.024)	(0.002)
Constant	0.063***	-0.072***	-1.146***	-0.036*
	(0.002)	(0.003)	(0.198)	(0.016)
Observations	28,639,232	28,639,232	474,112	474,112
R^2	0.261	0.048	0.274	0.049
Cardholder controls	Yes	Yes	Yes	Yes
Cardholder FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the results from linear probability models estimating the relationship between unbundling requests and credit risk outcomes among CFC cardholders. Columns (1) and (2) report estimates for the full sample of cardholders, while columns (3) and (4) report estimates for the propensity-score matched sample. The dependent variable in columns (1) and (3) is a monthly delinquency indicator equal to one if the cardholder is at least one day past due in a given month. The dependent variable in columns (2) and (4) is a default indicator equal to one if the cardholder reaches 90 or more days past due. The main explanatory variable, *Unbundling request*, is a dummy equal to one after the cardholder requests the separation of the electricity bill and the credit card payment. All specifications additionally control for the logarithm of the loan installment plus interest payment and the logarithm of fees. Cardholder controls include age, income, liabilities, credit score, and credit history. All specifications include cardholder fixed effects and month-year fixed effects. Standard errors are clustered at the cardholder level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Overall, the evidence strongly supports the repayment mechanism proposed in the conceptual framework. Borrowers who permanently lose access to Enel's billing infrastructure become substantially more likely to experience repayment problems, despite continuing to hold the same DaviBank credit card under the same contractual conditions. Since the primary institutional change following relocation is the disappearance of the bundled repayment technology, these

findings indicate that the repayment infrastructure itself contributes to loan performance beyond its role in facilitating payment processing. More broadly, the results suggest that contractual innovations that simplify repayment can improve the performance of unsecured consumer lending even without relying on stronger legal enforcement or collateral.

5.3.3 Dynamic Effects

A remaining concern is that borrowers who eventually request unbundling may already be on a deteriorating repayment path before the separation of the electricity bill and the credit card installment occurs. For example, relocation decisions may be associated with adverse economic or household shocks that affect repayment outcomes independently of the loss of the bundled repayment arrangement. To examine this possibility, I estimate an event-study specification around the month of the unbundling request.

Figures 4a and 4b present the dynamic effects of unbundling on default and delinquency, respectively. The figures compare repayment outcomes before and after the unbundling request, normalizing the month immediately preceding the request ((t=-1)) to zero. To assess the robustness of the results, I report estimates obtained using traditional two-way fixed effects, Callaway and Sant'Anna (2021), and Sun and Abraham (2021).

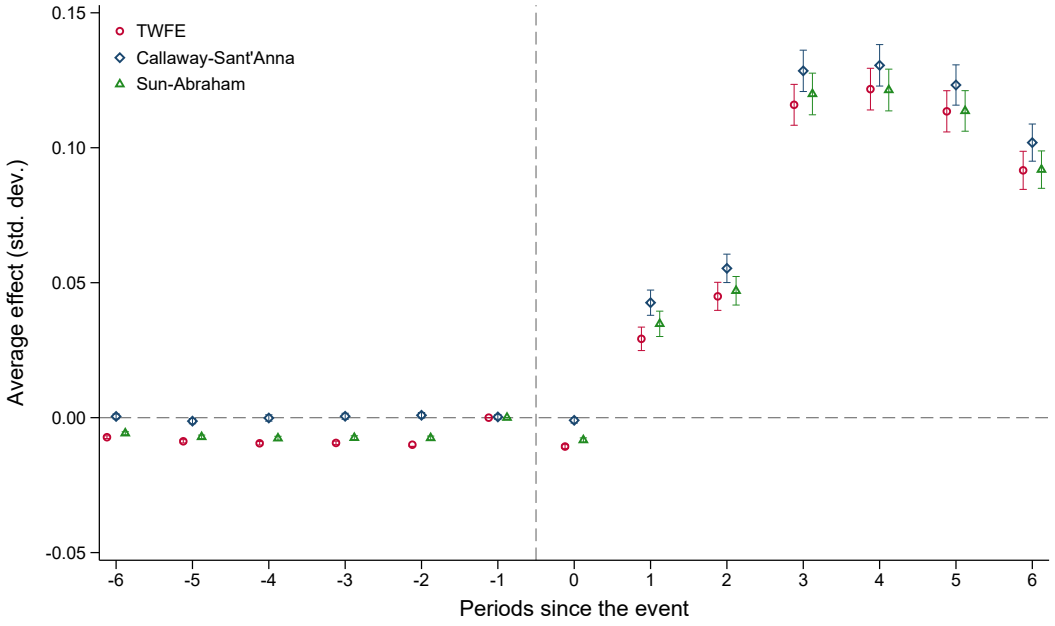
The event-study estimates provide little evidence of differential pre-trends. For both delinquency and default, the coefficients in the months preceding the unbundling request remain relatively stable and close to zero across the three estimators. This pattern suggests that borrowers who eventually request unbundling do not exhibit a systematic deterioration in repayment performance prior to the separation of the two obligations.

Following the unbundling request, repayment outcomes deteriorate noticeably. Both delinquency and default increase after borrowers lose access to Enel's billing infrastructure, and the post-treatment effects remain positive across all estimators. The increase in repayment problems emerges shortly after the separation occurs and persists over time, indicating that the deterioration in loan performance is not merely a temporary adjustment associated with relocation.

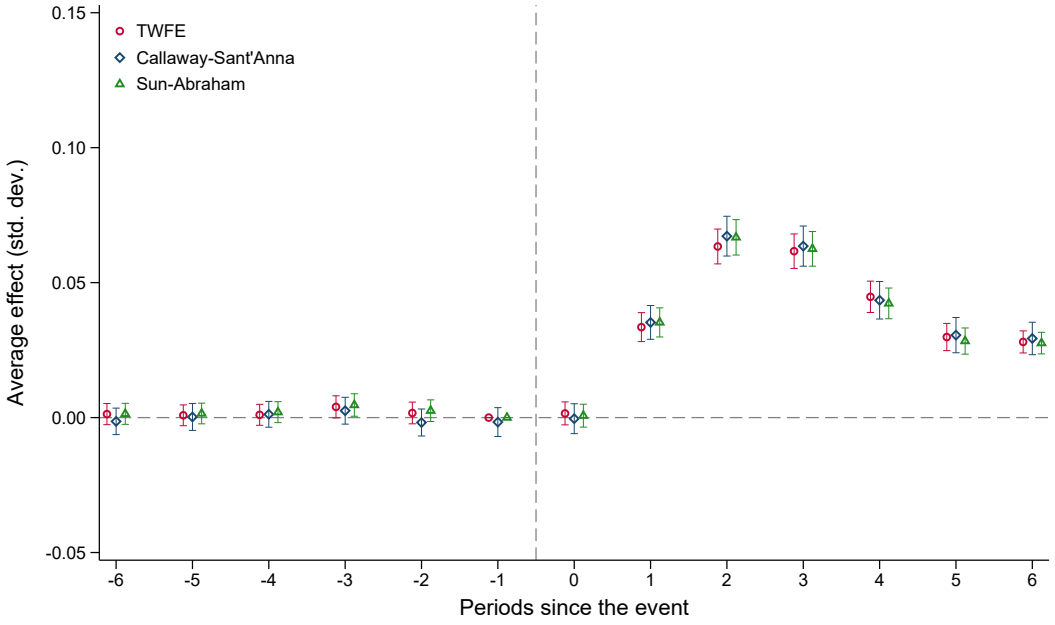
The dynamic patterns are particularly informative because they help distinguish the repayment effects of unbundling from alternative explanations based on pre-existing borrower characteristics. If borrowers who requested unbundling had already been experiencing worsening financial conditions before the move, one would expect to observe an upward trend in delinquency and default prior to treatment. Instead, the figures show that repayment performance remains relatively stable before the request and deteriorates only after the bundled repayment arrangement is removed.

Overall, the event-study evidence reinforces the baseline difference-in-differences results. The absence of strong pre-trends and the emergence of repayment difficulties following unbundling are consistent with the interpretation that bundled repayment contributes to loan performance by strengthening repayment discipline and reducing frictions associated with debt repayment.

Figure 4. Event Study of the Unbundling Effect on Repayment Outcomes



(a) Default



(b) Delinquency

This figure presents dynamic event-study estimates of the effect of unbundling requests on repayment outcomes. Panel A reports the effects on default, while Panel B reports the effects on delinquency. The figure overlays event-study estimates obtained using traditional two-way fixed effects (TWFE), Callaway and Sant'Anna (2021), and Sun and Abraham (2021). The vertical dashed line indicates the month of the unbundling request. The omitted category corresponds to the month immediately before the request ($t = -1$). Error bars represent 95% confidence intervals.

6 Economic Value of Utility Information and the Bundled Repayment Technology[13]

The previous sections show that the partnership between DaviBank and Enel affects consumer lending through two distinct mechanisms. First, utility payment and consumption information improve the bank's ability to identify creditworthy borrowers. Second, the bundled repayment arrangement improves loan performance by reducing delinquency and default rates. While these findings establish the existence of economically meaningful screening and enforcement effects, they do not quantify the economic value of these mechanisms from the lender's perspective.

This section quantifies the economic value of the two mechanisms underlying the DaviBank–Enel partnership through a simulation exercise. The analysis consists of two parts. Building on Lee et al. (2025), Einav et al. (2013), and Fuster et al. (2022),[14] the first part quantifies the economic value of utility information by evaluating how improvements in screening affect the bank's approval policy and expected profits. The second part quantifies the economic value of the bundled repayment technology by measuring how the reduction in delinquency and default translates into higher expected profitability. Together, these exercises provide a unified assessment of the economic value created by combining superior borrower screening with a repayment technology that improves loan performance.

[13] This section presents work in progress. The current version reports an initial calibration of the economic value of utility information. Ongoing work will further refine the calibration, explore alternative simulation periods and assumptions, and extend the framework to quantify the economic value of the bundled repayment technology.

[14] Lee et al. (2025) argue that improvements in predictive performance should be evaluated according to the economic value they generate through better decisions rather than predictive accuracy alone. Einav et al. (2013) show that the value of credit-scoring models arises from improving the allocation of credit across borrowers through more efficient approval decisions. Fuster et al. (2022) demonstrate how advances in predictive technologies reshape credit allocation by improving lenders' assessment of borrower risk. Together, these studies provide the conceptual foundation for the first simulation, which evaluates the economic value of utility information through its effect on lending decisions.

6.1 Economic Value of Utility Information

The empirical results presented in Section 5 show that electricity consumption and bill payment records substantially improve the prediction of future repayment performance, particularly among applicants without formal credit histories. However, greater predictive accuracy does not necessarily imply greater economic value. Following Lee et al. (2025) and Einav et al. (2013), the relevant question is whether more informative predictions improve lending decisions and ultimately increase expected profits.

To formalize this idea, consider a bank that receives a pool of credit card applications. Let $\mathcal{I}$ denote the information available to the lender when evaluating applicant i. Based on $\mathcal{I}$, the bank assigns a credit score $s_i^{\mathcal{I}} \in [0, 1]$, where higher values indicate lower predicted default risk and therefore higher expected profitability. The credit score summarizes all information relevant for predicting repayment and serves as the basis for the bank's lending decision. If a loan is approved, one of two repayment outcomes is realized,

$$\omega_i \in \{N, D\}, \tag{6}$$

where N denotes the non-default state and D denotes the default state. From the bank's perspective, the repayment state is unknown at the time the lending decision is made. The role of the credit-scoring model is to transform the information available at origination into an estimate of the applicant's repayment risk. Let $p^{\mathcal{I}}(s)$ denote the probability that an applicant with score s does not default. Since higher scores indicate lower repayment risk, $p^{\mathcal{I}}(s)$ is increasing in s.

Higher default risk reduces expected profits through greater expected credit losses and higher monitoring, collection, and provisioning costs (Cuesta and Sepúlveda, 2021). Consequently, applicants with higher scores generate higher expected profits and are therefore more likely to satisfy the bank's profitability criterion and be approved (see Appendix C).

Additionally, let π^N denote the profit generated by a non-defaulting borrower and π^D the

profit generated by a defaulting borrower[15]. I assume that $\pi^N > \pi^D$, which reflects the fact that borrowers who repay generate interest income and fees, whereas defaulting borrowers generate losses through unpaid balances and collection costs. The expected payoff associated with approving an applicant with score s is therefore:

$$m^{\mathcal{I}}(s) = p^{\mathcal{I}}(s)\pi^N + \left[1 - p^{\mathcal{I}}(s)\right]\pi^D. \tag{7}$$

This Equation (7) expression illustrates the fundamental trade-off faced by the lender. Approving a borrower with score s generates profits when repayment occurs but may generate losses if default occurs. Consequently, the profitability of a loan depends on both the payoffs associated with each repayment state and the probability that each state is realized. Expected profits increase with the probability of repayment because non-defaulting borrowers generate interest income, fees, and other revenues, whereas defaulting borrowers generate losses through unpaid balances and collection costs.

Proposition 1 (Monotonicity of Expected Profits)**.** *Suppose $\pi^N > \pi^D$ and $\partial p^{\mathcal{I}}(s)/\partial s > 0$. Then $m^{\mathcal{I}}(s)$ is strictly increasing in s. See Appendix D.1 for the proof.*

Proposition 1 establishes that applicants with higher scores always generate higher expected profits. Consequently, ranking applicants according to their scores is equivalent to ranking them according to expected profitability. This monotonicity result provides the theoretical justification for the bank's cutoff rule. Given that, the bank follows a cutoff rule and approves all applicants whose score exceeds a threshold $\delta^{\mathcal{I}}$:

$$Approve_i = \begin{cases} 1 & \text{if } s_i^{\mathcal{I}} \geq \delta^{\mathcal{I}}, \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

Let $f_S^{\mathcal{I}}(s)$ denote the density of scores among applicants under information set $\mathcal{I}$. The bank's

[15]The profit associated with the default state should be interpreted broadly as net profits after accounting for expected losses, collection expenses, provisioning requirements, and other costs associated with credit risk.

expected profit from adopting approval threshold $\delta^{\mathcal{I}}$ is given by

$$\Pi(\delta^{\mathcal{I}} \mid \mathcal{I}) = \int_{\delta^{\mathcal{I}}}^{1} m^{\mathcal{I}}(s) f_S^{\mathcal{I}}(s)\, ds. \tag{9}$$

The integral can be interpreted as the total expected profit generated by all applicants whose scores exceed the approval threshold. Lower approval thresholds expand lending but expose the bank to riskier borrowers. Higher thresholds reduce default risk but may reject profitable applicants. The optimal cutoff balances these two considerations. Substituting the expression for expected profits yields

$$\Pi(\delta^{\mathcal{I}} \mid \mathcal{I}) = \int_{\delta^{\mathcal{I}}}^{1} \left[p^{\mathcal{I}}(s)\pi^N + \left(1 - p^{\mathcal{I}}(s)\right)\pi^D \right] f_S^{\mathcal{I}}(s)\, ds. \tag{10}$$

For simplicity, I assume that the bank behaves as a risk-neutral lender and chooses the approval policy that maximizes expected portfolio profits. This assumption is reasonable in the present setting because the analysis focuses on a large and highly diversified portfolio of consumer loans, where idiosyncratic repayment risk is largely diversified away. Consequently, the bank's lending decision can be approximated by the maximization of expected profits. Given that, the optimal approval threshold solves:

$$\delta^{\mathcal{I},*} = \arg\max_{\delta^{\mathcal{I}} \in [0,1]} \Pi(\delta^{\mathcal{I}} \mid \mathcal{I}). \tag{11}$$

Proposition 2 (Optimal Approval Threshold)**.** *Suppose $f_S^{\mathcal{I}}(s) > 0$ for all $s \in [0,1]$. At an interior optimum, the marginal approved borrower generates zero expected profit:*

$$m^{\mathcal{I}}(\delta^{\mathcal{I},*}) = 0. \tag{12}$$

Equivalently, the threshold repayment probability satisfies:

$$p^{\mathcal{I}}(\delta^{\mathcal{I},*}) = \frac{-\pi^D}{\pi^N - \pi^D} \equiv \bar{p}, \tag{13}$$

and $\bar{p}$ is independent of the information set $\mathcal{I}$. *See Appendix D.2 for the proof.*

Proposition 2 shows that the bank approves applicants only if their predicted repayment probability exceeds a minimum profitability threshold. Importantly, this threshold depends only on the profitability of lending, summarized by (π^N, π^D), and not on the information available to the lender. Consequently, introducing additional information does not relax lending standards. Instead, it improves the bank's ability to identify applicants whose repayment probabilities exceed the existing profitability threshold. The value of utility information can therefore be measured by comparing the maximal profits obtained under alternative information sets.

6.1.1 Alternative Information Sets

To quantify the economic value of utility information, I compare the bank's optimal approval policy under two alternative information environments.

The first information set corresponds to the traditional information available to lenders in consumer credit markets, including the demographic and socioeconomic characteristics collected through the application form (A) and, when available, the applicant's credit bureau information (B). Since credit bureau records are unavailable for borrowers without a formal credit history, the information available to the lender varies across applicants. Formally,

$$\mathcal{I}^{Tra} = \{A, B\}. \tag{14}$$

The second information set augments the traditional information environment with utility information provided by Enel (E), including historical measures of electricity consumption and bill payment behavior. As shown in Section 4.1, these variables improve the prediction of default, particularly among applicants without formal credit histories.

$$\mathcal{I}^{Tra+E} = \{A, B, E\}. \tag{15}$$

For each information set, the bank estimates a credit-scoring model and selects the profit-maximizing approval threshold. Let $\Pi(\delta^{Tra,*} \mid \mathcal{I}^{Tra})$ and $\Pi(\delta^{Tra+E,*} \mid \mathcal{I}^{Tra+E})$ denote the maximal expected profits obtained under the traditional and enriched information environments, respectively. The economic value of utility information is therefore defined as

$$V^{Enel} = \underbrace{\Pi(\delta^{Tra+E,*} \mid \mathcal{I}^{Tra+E})}_{\text{Profit with utility information}} - \underbrace{\Pi(\delta^{Tra,*} \mid \mathcal{I}^{Tra})}_{\text{Profit without utility information}} > 0. \tag{16}$$

The definition above can be related to the theory of information developed by Blackwell (1953). In this framework, one information structure is more informative than another if it allows the decision maker to achieve weakly higher expected payoffs in every decision problem. Applied to the present setting, the enriched information set $\mathcal{I}^{Tra+E}$ is more informative than the traditional information set $\mathcal{I}^{Tra}$ if the signals observed under $\mathcal{I}^{Tra}$ can be obtained from those observed under $\mathcal{I}^{Tra+E}$ through an information-reducing transformation.

Proposition 3 (Blackwell Dominance)**.** *Suppose $\mathcal{I}^{Tra}$ is a less informative version of $\mathcal{I}^{Tra+E}$ in the sense of Blackwell (1953) — that is, the signals observed under $\mathcal{I}^{Tra}$ can be obtained from those under $\mathcal{I}^{Tra+E}$ through an information-reducing transformation. Then for any (π^N, π^D) with $\pi^N > \pi^D$:*

$$\Pi(\delta^{Tra+E,*} \mid \mathcal{I}^{Tra+E}) \geq \Pi(\delta^{Tra,*} \mid \mathcal{I}^{Tra}), \tag{17}$$

so $V^{Enel} \geq 0$. See Appendix D.3 for the proof.

Proposition 3 provides the central prediction of the model. Utility payment records create value not because they alter the bank's approval standard, but because they improve borrower classification. Holding the profitability threshold fixed, a richer information set allows the lender to identify profitable borrowers more accurately and therefore allocate credit more efficiently. This prediction follows directly from Blackwell's theory of information, according to which a more informative information structure cannot reduce the expected payoff of an optimal decision maker.

The magnitude of utility information gains, however, depends on the extent to which utility payment records improve borrower ranking and on the profitability associated with lending decisions. The next section quantifies these gains through a simulation that compares optimal lending policies under the two information environments.Because the availability of credit bureau information differs across applicants, the analysis is conducted separately for borrowers with and without prior credit histories.

6.1.2 Calibration

This subsection describes the empirical implementation of the model developed above. The objective is to quantify the economic value of utility information by comparing the profitability of lending decisions under the traditional information environment, $\mathcal{I}^{Tra}$, and the enriched information environment, $\mathcal{I}^{Tra+E}$. Implementing the model requires calibrating four objects: (i) repayment probabilities, (ii) profits associated with each repayment state, (iii) the approval threshold, and (iv) expected portfolio profits.

Calibration Sample

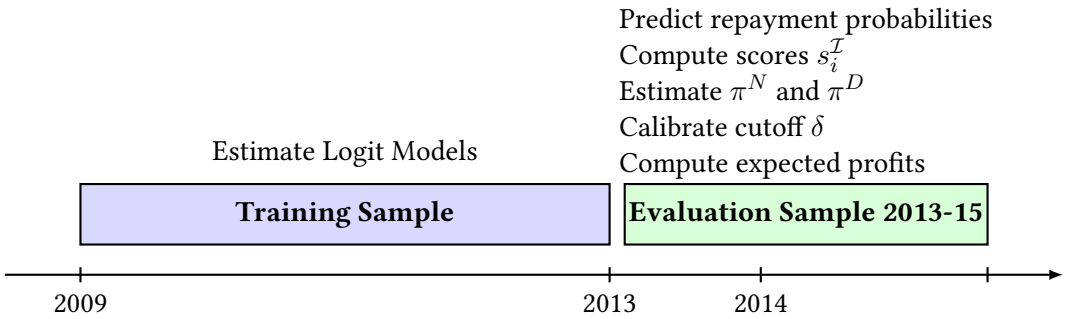
The calibration is conducted using borrowers originated during 2014 and 2015. This year is particularly suitable because both the consumer-credit usury rate and the monetary policy rate remained relatively stable throughout the period (see: Appendix A1). Stability in the usury rate is important because changes in the maximum permissible lending rate may alter the profitability of extending credit to riskier borrowers and therefore affect the lender's optimal approval threshold. Similarly, changes in the monetary policy rate may modify funding costs and expected loan profitability. More specifically, variation in lending rates may affect the values of π^N and π^D, thereby shifting the optimal approval threshold $\delta^{\mathcal{I},*}$ derived in the previous subsection (see Appendix E, where there is short analysis about the optimal threshold and cap rate). By focusing on a period with relatively stable lending conditions, differences in profitability are more likely to reflect improvements in borrower selection rather than changes in loan pricing or funding costs.

To mimic the information available to the lender at the time credit decisions are made, repay-

ment probabilities are estimated out-of-sample. Specifically, the prediction models are estimated using borrowers originated between 2009 and 2013 and are subsequently applied to applicants originated during 2014 and 2015. This procedure follows the approach of Lee et al. (2025) and avoids using future information when predicting repayment outcomes.

Restricting the analysis to a single origination cohort also avoids survivorship bias that would arise from including borrowers originated in earlier years who remained active in the portfolio during 2014-2015. Because the objective of the simulation is to evaluate the value of information at the time of loan origination, focusing on a single cohort provides a cleaner comparison between alternative information environments.

Figure 5. Timeline of the Calibration Procedure



Notes: Logistic models are estimated using borrowers originated between 2009 and 2014. The estimated coefficients are then applied to borrowers originated during 2015 to generate out-of-sample repayment probabilities. These predictions are subsequently used to calibrate scores, approval thresholds, and expected profits under alternative information environments.

Repayment Probabilities

The first object required for the calibration is the repayment probability associated with each applicant. Following the credit-scoring framework developed in Section 4.2, I estimate the probability of default using the Logit models described in Equation (4) under each information environment. Let $\hat{q}_i^{\mathcal{I}} = Pr(Y_i = 1 \mid X_i, \mathcal{I})$ denote the predicted probability of default for applicant i, where Y_i is an indicator equal to one if the borrower defaults during the observation period. The corresponding repayment probability is then given by

$$p_i^{\mathcal{I}} = 1 - \hat{q}_i^{\mathcal{I}}. \tag{18}$$

The analysis considers the two information sets defined in the previous subsection, namely the traditional information environment $\mathcal{I}^{Tra}$ and the enriched information environment $\mathcal{I}^{Tra+E}$. The variables included in each specification are identical to those used in the screening analysis. For simplicity, I define the applicant's score as the predicted repayment probability:

$$s_i^{\mathcal{I}} = p_i^{\mathcal{I}}. \tag{19}$$

Under this normalization, higher scores indicate a greater likelihood of repayment and therefore higher expected profitability for the lender. These scores constitute the key input used to rank applicants, calibrate the approval threshold, and compute expected profits under the alternative information environments considered in the simulation.

Repayment-State Profits

The second object required for the calibration is the profit associated with each repayment state. Using administrative records provided by DaviBank, I follow Einav et al. (2013) to compute the cumulative interest payments, fees, and outstanding balances generated by each borrower in the 2014-15 origination cohort. All monetary values are expressed in constant 2014 Colombian pesos. Funding and operational costs are allocated using information from DaviBank's monthly income statements reported to the Colombian financial regulator. Profits in the non-default state are given by:

$$\pi_i^N = R_i - FC_i - OC_i, \tag{20}$$

where R_i denotes total revenues generated by borrower i, including interest income, fees, and penalty interest accrued on delinquent balances that are ultimately repaid. The terms FC_i and OC_i denote the funding and operational costs allocated to the account. For defaulting borrowers, profits are given by

$$\pi_i^D = \pi_i^N - LGD_i, \tag{21}$$

whereas LGD_i denotes the loss given default associated with borrower i. The resulting borrower-level payoffs are combined with the predicted repayment probabilities to compute expected profits under each information environment.

Approval Threshold

The third object required for the calibration is the approval threshold. The theoretical framework assumes that the bank approves applicants whose expected profits exceed a minimum cutoff. To isolate the value of utility information from changes in lending standards, I follow Lee et al. (2025) and hold the approval threshold fixed across information environments. For each applicant, expected profits under the traditional information environment are computed as:

$$m_i^{\mathcal{I}^{Tra}} = \hat{p}_i^{\mathcal{I}^{Tra}} \pi_i^N + \left(1 - \hat{p}_i^{\mathcal{I}^{Tra}}\right) \pi_i^D, \tag{22}$$

where $\hat{p}_i^{\mathcal{I}^{Tra}}$ denotes the predicted repayment probability obtained from the baseline credit-scoring model. Because the administrative data contain only approved CFC applicants, the bank's exact approval threshold is not directly observed. Following Lee et al. (2025), I recover the implicit threshold as the lowest expected profit observed among approved borrowers:

$$\delta = \min_i \left\{ m_i^{\mathcal{I}^{Tra}} \right\}. \tag{23}$$

The same threshold is subsequently applied when utility information is incorporated. Thus, applicant i is approved under information set $\mathcal{I}$ whenever

$$m_i^{\mathcal{I}} \geq \delta. \tag{24}$$

The calibration is performed separately for borrowers with and without prior credit histories. Consequently, repayment probabilities, expected profits, and approval thresholds are estimated independently for each group. Holding the cutoff fixed ensures that differences in approval decisions and expected profits reflect only improvements in borrower ranking generated by utility

information, rather than changes in the lender's approval policy.

Economic Value of Utility Information

To quantify the economic value of utility information, I compare lending outcomes under two alternative information environments: one based solely on traditional information available to the bank and another that additionally incorporates utility consumption and payment records from Enel. For each environment, borrowers are ranked according to their predicted repayment probabilities and approved whenever their expected profitability exceeds the bank's lending threshold. Total expected profits are then obtained by aggregating the expected profits generated by all approved applicants.

The economic value of utility information is measured as the difference in total expected profits between the environment that includes Enel information and the environment based only on traditional data. A positive difference indicates that utility information improves the bank's ability to identify profitable borrowers, leading to a more efficient allocation of credit and higher expected profits. In this sense, the exercise provides a direct measure of the economic benefits associated with incorporating alternative data into the screening process.

6.1.3 Results[16]

To better understand the economic implications of utility data, this section presents first how the winners and losers are from the use of Enel during the screening process. I follows the approach proposed by Fuster et al. (2022) and examines the distributional consequences of incorporating new information into the screening process. Specifically, I first identify the borrowers who gain and lose access to credit when utility information from Enel is incorporated into the lender's information set. This exercise is based on changes in borrowers' predicted default probabilities ($\hat{q}$), which determine their relative ranking in the credit allocation process. While Fuster et al. (2022) study winners and losers arising from the adoption of a more accurate prediction technology, I apply a

[16]The results presented in this section are preliminary and should be interpreted with caution. Ongoing work is refining the methodology used to estimate operational costs and expected profits, which may affect the magnitude of the estimates reported below.

similar framework to evaluate the consequences of incorporating a new source of information. After characterizing the borrowers whose creditworthiness improves or deteriorates when utility information is added, I quantify the economic value of this information by comparing lending outcomes under alternative information environments. This approach allows me to move beyond statistical measures of predictive performance and evaluate whether the additional information translates into economically meaningful improvements in credit allocation.

Winners and Losers

Table 12 examines how the incorporation of electricity consumption and bill-payment information changes the assessment of borrower risk. Following Lee et al. (2025), I define a borrower as a winner when the predicted probability of default decreases after utility information is incorporated into the credit-scoring model. Formally, winners are borrowers for whom $\Delta\hat{q} < 0$, where $\Delta\hat{q}$ denotes the difference between the predicted probability of default obtained from the enriched model and that obtained from the benchmark model.

The results indicate that utility information substantially improves the assessment of borrowers without a formal credit history. Among these applicants, 79.8% are classified as winners, and the average predicted probability of default declines by 1.11 percentage points. The effect is particularly pronounced among economically vulnerable households. For example, 84.4% of low-income applicants are classified as winners, compared with 72.8% among higher-income borrowers. Moreover, the average reduction in predicted default risk reaches 1.67 percentage points for low-income applicants, more than six times the corresponding effect observed among higher-income individuals.

These findings suggest that utility information primarily benefits borrowers for whom traditional screening information is limited. In particular, electricity payment records appear to reveal dimensions of repayment capacity and financial discipline that are not fully captured by application-form variables alone. As a result, many applicants who would otherwise be assessed as relatively risky under the traditional information environment receive more favorable risk assessments once utility information is incorporated.

Table 12. Winners and Losers from the Inclusion of Electricity Information (2014-2015)

Characteristic	N	% Winners	Mean $\Delta\hat{q}$	SD $\Delta\hat{q}$
Panel A. Borrowers Without Credit History				
Full sample	91,426	79.82	-1.11	3.23
Female	50,453	80.76	-1.06	3.00
Male	40,973	78.67	-1.18	3.49
Low income (Bottom 50%)	55,379	84.40	-1.67	3.06
High income (Top 50%)	36,047	72.79	-0.26	3.29
Strata 1	7,703	71.19	-0.93	3.52
Strata 2	30,147	80.60	-1.62	3.77
Strata 3	9,599	77.39	-0.93	3.84
Strata 4	899	59.34	-0.18	3.73
Strata 5	157	79.29	-0.28	1.77
Panel B. Borrowers With Credit History				
Full sample	111,635	66.10	0.04	2.97
Female	60,510	66.76	0.04	2.74
Male	51,125	65.32	0.05	3.23
Low income (Bottom 50%)	48,865	66.95	-0.03	2.50
High income (Top 50%)	62,770	65.45	0.06	3.30
Strata 1	20,753	63.49	-0.05	1.67
Strata 2	63,040	67.82	0.01	2.75
Strata 3	26,102	63.64	0.18	3.90
Strata 4	1,469	70.33	0.15	5.01
Strata 5	210	88.05	-0.41	1.11

Notes: Winners are defined as borrowers whose predicted probability of default decreases after incorporating electricity consumption and bill-payment information into the credit-scoring model. $\Delta\hat{q}$ is defined as the difference between the predicted probability of default from the enriched model and that from the benchmark model. Values of $\Delta\hat{q}$ are reported in percentage points.

The results are markedly different for borrowers with an existing credit history. Although 66.1% of applicants are classified as winners, the average change in predicted default risk is economically negligible, amounting to only 0.04 percentage points. This pattern suggests that utility information mainly redistributes risk assessments within this group rather than systematically improving borrower evaluations. Taken together, the evidence indicates that the informational value of utility records is concentrated among applicants lacking traditional credit information, precisely the segment targeted by financial inclusion initiatives.

Economic Value of Utility Information

While the previous analysis shows that utility information improves risk prediction, the key question for lenders is whether these improvements translate into more profitable lending decisions. Table 13 addresses this question by comparing simulated profits under the traditional and enriched information environments.

The results indicate that utility information reallocates expected profitability toward borrowers who ultimately repay and away from borrowers who eventually default. Among applicants without a prior credit history, the incorporation of utility information increases simulated profits by approximately COP 209,000 for borrowers who never default, while reducing expected profitability by more than COP 740,000 for borrowers who eventually default. A similar pattern emerges among applicants with credit histories, where profits increase by approximately COP 266,000 for non-defaulting borrowers and decrease by roughly COP 750,000 for defaulting borrowers.

These results provide direct evidence that utility information improves the allocation of credit. Rather than simply increasing predictive accuracy, the enriched model systematically shifts expected profitability toward borrowers who subsequently perform well and away from borrowers who generate losses. In this sense, utility information allows the lender to better distinguish profitable from unprofitable lending opportunities.

The aggregate implications are economically meaningful. For borrowers without a formal credit history, incorporating utility information increases expected profits by 6.74%. Among borrowers with credit histories, the corresponding increase equals 2.80%. Consistent with the winners-and-

Table 13. Simulated Profit Reallocation from the Inclusion of Electricity Information

Group	N	Mean $\Delta\Pi$	SD $\Delta\Pi$
Panel A. Borrowers Without Credit History			
Never Default	95,274	208,999	135,463
Default	3,323	-740,073	152,882
Average Profit Increase with Enel Data			6.74%
Panel B. Borrowers With Credit History			
Never Default	115,925	266,174	175,675
Default	4,467	-750,214	165,047
Average Profit Increase with Enel Data			2.80%

Notes: $\Delta\Pi$ denotes the change in simulated profits obtained by incorporating electricity consumption and bill-payment information into the credit-scoring model. Positive values indicate that the enriched model assigns higher expected profitability to a borrower, while negative values indicate lower expected profitability. Borrowers are classified ex post according to their realized repayment outcomes. The last row reports the average percentage increase in simulated profits generated by the enriched model relative to the benchmark model.

losers analysis, the gains are substantially larger among applicants without traditional credit information. This finding suggests that utility records are particularly valuable in environments where conventional screening tools provide limited information about borrower quality.

Overall, the results imply that the value of utility information extends beyond improvements in statistical prediction. By improving borrower classification and reallocating credit toward more profitable applicants, utility information generates economically significant gains for lenders while potentially expanding access to credit among underserved households.

7 Conclusion

This paper studies how partnerships between financial institutions and non-financial firms can help overcome key frictions that limit access to consumer credit among low-income and financially underserved households. Using the case of the CFC program in Colombia, I analyze how a commercial bank leverages both the information and the billing infrastructure of an electricity company to expand unsecured consumer lending.

I first document that municipalities where the CFC program operates experienced a substantial expansion in consumer credit supplied by DaviBank. Importantly, this increase was not accompanied by a corresponding rise in portfolio risk, nor does the evidence suggest that it was driven by a simple reallocation of borrowers from competing banks. These patterns motivate the analysis of the mechanisms through which the partnership may have relaxed lending frictions.

The paper identifies two complementary channels. First, utility payment and consumption information significantly improves the screening of potential borrowers. For individuals without prior credit histories, incorporating utility data increases the predictive performance of credit-scoring models by approximately five percentage points in terms of AUC. Even among borrowers with existing credit histories, utility information performs similarly to traditional credit bureau scores and provides additional predictive power when combined with them. These findings suggest that routine payment behavior observed outside the financial system contains valuable information about repayment capacity and financial discipline.

Second, the paper shows that the repayment infrastructure itself plays an important role. Exploiting variation generated by borrowers who lose access to the bundled repayment arrangement, I find that unbundling electricity and credit card payments increases both delinquency and default rates. Because Colombian regulation prohibits electricity disconnection for non-payment of credit obligations, these effects cannot be explained by direct enforcement threats. Instead, the evidence is consistent with mechanisms related to payment salience, lower transaction costs, and commitment effects generated by integrating debt repayment into one of the household's most routine financial obligations.

Taken together, the results suggest that the success of the CFC program cannot be explained solely by access to alternative information. The combination of alternative data and non-traditional repayment infrastructure appears to be crucial for expanding lending while maintaining portfolio quality. More broadly, the findings highlight that collaborations between banks and non-financial firms can create value not only through better borrower screening but also through innovations in contract enforcement and repayment technologies.

These results have important implications for financial inclusion policies. As financial institutions increasingly rely on alternative data sources and partnerships with utility companies, digital platforms, telecommunications firms, and other non-financial entities, understanding the mechanisms through which these collaborations affect lending outcomes becomes increasingly relevant. The evidence presented in this paper suggests that expanding access to credit may require not only better information about borrowers but also institutional arrangements that facilitate repayment and reduce the costs of maintaining lending relationships.

Several avenues for future research remain open. First, while this paper focuses on screening and enforcement mechanisms, future work could examine the long-term welfare effects of access to credit through programs such as CFC, including impacts on consumption, asset accumulation, and financial resilience. Second, the growing availability of alternative data sources raises important questions regarding consumer privacy, data ownership, and the optimal regulation of information sharing between financial and non-financial institutions. Understanding these trade-offs will become increasingly important as financial inclusion strategies continue to rely on partnerships between banks and non-traditional firms.

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Appendix

A Matching Analysis of Stylized Facts

I implement a parsimonious matching procedure, following Fonseca and Matray (2024), to construct a control group of untreated cities that closely resembles the treated cities across a wide range of observable characteristics.

The matching process begins by considering city population. Specifically, the 38 municipalities where DaviBank operates in Colombia are divided into quintiles according to their population size. Each city treated by the CFC program is then matched, with replacement, to all control cities within the same population quintile. The matched sample consists of municipalities located in Quintiles 1, 2, and 5, which are the only groups where both treated and non-treated municipalities are present (see Table A1). This selection ensures that comparisons between treated and control units are made within strata of similar population size, thereby reducing confounding bias associated with city size.

Table A1. Distribution of Treated and Control Cities by Population Quintile

Population Quintile	Non-Treated	Treated	Total
1	5	3	8
2	6	2	8
3	7	0	7
4	8	0	8
5	3	4	7
Total	**29**	**9**	**38**

This table shows the results of ranking municipalities according to their population size. Population data correspond to the data reported in the Colombian Population Census for the year prior to the implementation of the CFC program, in 2009. Source: DANE (2009 Census).

Table A2 shows a comparison of pre-treatment characteristics between treated and control municipalities, both in the unmatched and matched samples. In the unmatched sample, significant differences are observed across various covariates, including population size, local government expenditures, inequality (GINI), informality, and financial inclusion indicators. After matching, these differences are substantially reduced, and most covariates exhibit improved balance, with lower standardized differences and increased standard errors. This suggests that the matching procedure successfully constructs a more comparable control group, thereby enhancing the credibility of the empirical identification strategy. Nevertheless, given that the pool of municipalities available for matching is relatively small, the main estimations will be conducted using both the full sample and the matched subsample.

Table A2. Comparison Between Treated and Matched Groups

Variable	Unconditional		Matched	
	Treated	S.E.	Treated	S.E.
Population	0.387**	(0.196)	0.338	(0.681)
Distance to State Capital	0.075	(0.343)	0.117	(0.406)
GDP per Capita	0.092	(0.343)	-0.114	(0.365)
Government Expenditures	0.676**	(0.339)	0.645	(0.576)
GINI	-0.017**	(0.008)	-0.016**	(0.007)
Labor Informality	-0.740**	(0.338)	-0.620	(0.602)
Energy Service Coverage	-0.644*	(0.340)	-0.823	(0.604)
Water Service Coverage	0.431	(0.341)	0.294	(0.280)
% GDP Agriculture	-0.532	(0.341)	-0.400	(0.319)
% GDP Industry	-0.412	(0.342)	-0.175	(0.348)
% GDP Services	0.389	(0.342)	0.236	(0.418)
Private Loans	2.096***	(0.305)	2.044*	(1.008)
Private Deposits	2.087***	(0.305)	2.055*	(1.059)
Consumer Credit per Capita	2.050***	(0.307)	1.983*	(0.955)
Credit Cards per Capita	1.767***	(0.316)	1.742*	(0.922)

This table presents coefficient estimates of the differences between treated and control cities across various variables. "Unconditional" refers to the comparison between treated cities and the full sample of untreated cities. "Matched" refers to the subsample in which treated cities are matched with untreated cities within the same pre-reform population quintile. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Finally, Table A3 presents summary statistics for the two samples: matched and full (unconditional), which are used to estimate the baseline model (Equation 1). It is important to note that, in this version, the dependent variable is the natural logarithm of consumer credit disbursements by DaviBank during the quarter. Since financial inclusion is proxied by increases in credit supply, future versions will include additional variables, such as the number of new credit cards granted, to capture broader dimensions of the bank's credit provision.

Table A3. Summary Statistics for Matched and Full Samples

Variable	Obs	Mean	Std. Dev.	Min	Max
Matched Sample					
Ln(Consumer loans)	1,176	22.453	2.780	14.274	29.286
Ln(bank employees)	1,176	3.226	1.528	1.099	8.823
Ln(deposits)	1,176	24.101	1.799	18.865	29.676
Ln(population)	1,176	12.821	1.142	11.085	15.905
Full Sample					
Ln(Consumer loans)	1,960	20.977	3.118	14.274	29.286
Ln(bank employees)	1,960	2.966	1.330	1.098	8.823
Ln(deposits)	1,960	23.949	1.930	17.564	30.121
Ln(population)	1,960	12.605	1.199	10.986	16.105

This table reports summary statistics from the dataset provided by the Financial Superintendency of Colombia (SFC). The unit of observation is the municipality. All monetary variables are expressed in natural logarithms of millions of Colombian pesos at 2006 constant prices.

B Supplementary Tables, Figures, and Variable Definitions

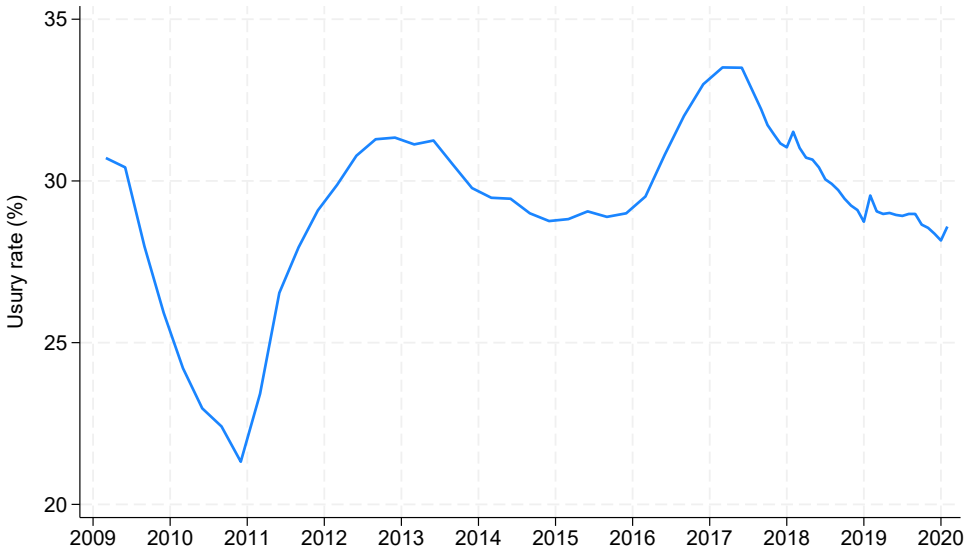


Figure A1. Evolution of the Colombian Cap Rate (*Tasa de Usura*), 2009–2020

Notes: This figure plots the Colombian cap rate (*usury rate*) from March 2009 to February 2020. The usury rate represents the maximum legal interest rate that financial institutions can charge on consumer loans and is determined by the Financial Superintendency of Colombia. Source: Financial Superintendency of Colombia.

Table A4. Logit Estimates of Delinquency Risk

	(1)	(2)	(3)	(4)	(5)	(6)
	No Credit History			With Credit History		
Credit Score				-0.002***		-0.002***
				(0.000)		(0.000)
Avg. energy cons.		-0.052**			0.070***	0.168***
		(0.024)			(0.017)	(0.019)
Avg. bill payment		-2.531***			-0.699	-0.537
		(0.577)			(0.485)	(0.561)
Red flags		1.889***			1.330***	1.805***
		(0.161)			(0.106)	(0.109)
Consecutive red flags		0.238***			0.322***	0.279***
		(0.014)			(0.009)	(0.009)
Cons. last month		0.001***			0.001***	0.001***
		(0.000)			(0.000)	(0.000)
SD consumption		0.002***			0.003***	0.003***
		(0.000)			(0.000)	(0.000)
Min. consumption		0.002***			-0.001***	-0.002***
		(0.000)			(0.000)	(0.000)
Max. consumption		-0.003***			-0.000***	-0.001***
		(0.000)			(0.000)	(0.000)
Strata 1		0.122**			0.507*	0.309
		(0.048)			(0.304)	(0.304)
Strata 2		0.101**			0.461	0.285
		(0.045)			(0.304)	(0.304)
Strata 3		0.104**			0.499	0.336
		(0.048)			(0.304)	(0.304)
Strata 4		-0.006			0.396	0.313
		(0.087)			(0.309)	(0.309)
Strata 5		0.076			0.008	0.010
		(0.173)			(0.356)	(0.356)
Observations	266,905	266,905	613,696	613,696	613,696	613,696
Applicant characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Credit score included	No	No	No	Yes	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
AUC	0.635	0.671	0.627	0.659	0.652	0.679

Notes: The table reports Logit coefficients for delinquency. Columns (1)–(2) correspond to individuals without credit history; columns (3)–(6) correspond to individuals with credit history. Energy consumption variables are measured over the previous 12 months unless otherwise indicated. AUC corresponds to the area under the ROC curve. Standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Why Higher Scores Generate Higher Expected Profits

The framework presented in Section 5 assumes that applicants with higher credit scores generate higher expected profits for the lender. This appendix provides a simple justification for this assumption.

Recall that the expected profit associated with approving an applicant with score s is given by

$$m^{\mathcal{I}}(s) = p^{\mathcal{I}}(s)\pi^N + \left[1 - p^{\mathcal{I}}(s)\right]\pi^D. \tag{A1}$$

where $p^{\mathcal{I}}(s)$ denotes the probability that the applicant repays the loan, π^N denotes the profit generated by a non-defaulting borrower, and π^D denotes the profit generated by a defaulting borrower.

The score is constructed so that higher values indicate lower repayment risk. Therefore,

$$\frac{\partial p^{\mathcal{I}}(s)}{\partial s} > 0. \tag{A2}$$

Moreover, non-defaulting borrowers generate higher profits than defaulting borrowers. Thus,

$$\pi^N > \pi^D. \tag{A3}$$

This assumption reflects the fact that repaying borrowers generate interest income and fee revenues, whereas defaulting borrowers generate lower profits due to unpaid balances, collection expenses, provisioning requirements, and other costs associated with credit risk.

Differentiating expected profits with respect to the score yields

$$\frac{\partial m^{\mathcal{I}}(s)}{\partial s} = \frac{\partial p^{\mathcal{I}}(s)}{\partial s}\left(\pi^N - \pi^D\right). \tag{A4}$$

Since

$$\frac{\partial p^{\mathcal{I}}(s)}{\partial s} > 0, \tag{A5}$$

and

$$\pi^N - \pi^D > 0, \tag{A6}$$

it follows that

$$\frac{\partial m^{\mathcal{I}}(s)}{\partial s} > 0. \tag{A7}$$

Therefore, expected profits are increasing in the applicant's score. Applicants with higher scores are expected to generate larger profits because they have a higher probability of repayment and are less likely to enter the default state.

This result provides the economic rationale for the approval rule analyzed in the main text. Since expected profits are increasing in the score, the lender can rank applicants according to profitability and implement a threshold rule that approves all borrowers whose scores exceed a

given cutoff. Because expected profits are strictly increasing in the score, the bank's optimization problem admits a threshold rule. There exists a cutoff score $\delta^{\mathcal{I},*}$ such that approving all applicants with $s^{\mathcal{I}} \geq \delta^{\mathcal{I},*}$ maximizes expected profits.

D Proof of Proposition

D.1 Proof of Proposition 1

Proof. Differentiating equation (7) with respect to s:

$$\frac{\partial m^{\mathcal{I}}(s)}{\partial s} = \frac{\partial p^{\mathcal{I}}(s)}{\partial s}\Big(\pi^N - \pi^D\Big).$$

By assumption, $\partial p^{\mathcal{I}}(s)/\partial s > 0$ and $\pi^N > \pi^D$, so both factors are strictly positive and therefore $\partial m^{\mathcal{I}}(s)/\partial s > 0$. □

D.2 Proof of Proposition 2

Proof. Differentiating (**??**) with respect to $\delta^{\mathcal{I}}$:

$$\frac{\partial \Pi(\delta^{\mathcal{I}} \mid \mathcal{I})}{\partial \delta^{\mathcal{I}}} = -\, m^{\mathcal{I}}(\delta^{\mathcal{I}})\, f_S^{\mathcal{I}}(\delta^{\mathcal{I}}).$$

At an interior optimum the first-order condition gives:

$$-\, m^{\mathcal{I}}(\delta^{\mathcal{I},*})\, f_S^{\mathcal{I}}(\delta^{\mathcal{I},*}) = 0.$$

Since $f_S^{\mathcal{I}}(\delta^{\mathcal{I},*}) > 0$ by assumption, it follows that $m^{\mathcal{I}}(\delta^{\mathcal{I},*}) = 0$. Substituting (7):

$$p^{\mathcal{I}}(\delta^{\mathcal{I},*})\,\pi^N + \Big[1 - p^{\mathcal{I}}(\delta^{\mathcal{I},*})\Big]\,\pi^D = 0.$$

Rearranging yields $p^{\mathcal{I}}(\delta^{\mathcal{I},*}) = -\pi^D/(\pi^N - \pi^D) \equiv \bar{p}$. Since $\bar{p}$ depends only on (π^N, π^D) and not on $\mathcal{I}$, the threshold repayment probability is information-set invariant. □

D.3 Proof of Proposition 3

Proof. Since $\mathcal{I}^{Tra}$ is a garbling of $\mathcal{I}^{Tra+E}$, the lender can always replicate any decision rule based on $\mathcal{I}^{Tra}$ by using $\mathcal{I}^{Tra+E}$ and then applying the same information-reducing transformation M. Formally, the feasible set of decision rules under $\mathcal{I}^{Tra+E}$ contains the feasible set under $\mathcal{I}^{Tra}$ as a subset. By Blackwell (1953), a more informative experiment yields weakly higher expected utility in any decision problem with a convex loss function. The lender's expected profit maximization satisfies this condition because $m^{\mathcal{I}}(s)$ is linear in $p^{\mathcal{I}}(s)$. Therefore:

$$\max_{\delta^{\mathcal{I}}} \Pi(\delta^{\mathcal{I}} \mid \mathcal{I}^{Tra+E}) \geq \max_{\delta^{\mathcal{I}}} \Pi(\delta^{\mathcal{I}} \mid \mathcal{I}^{Tra}),$$

which gives $V^{Enel} \geq 0$. □

E Interest Rate Caps and the Approval Threshold

This appendix shows why changes in the usury rate may affect the bank's optimal approval threshold. The main model defines the expected profit from approving an applicant with score s as

$$m^{\mathcal{I}}(s) = p^{\mathcal{I}}(s)\pi^N + \left[1 - p^{\mathcal{I}}(s)\right]\pi^D, \tag{A8}$$

where $p^{\mathcal{I}}(s)$ is the probability of repayment, π^N is the profit generated in the non-default state, and π^D is the profit generated in the default state.

Suppose that the bank charges an interest rate r on the loan, subject to a regulatory cap $\bar{r}$. Therefore,

$$r \leq \bar{r}. \tag{A9}$$

The profit in the non-default state depends positively on the interest rate charged by the bank:

$$\pi^N = \pi^N(r), \qquad \frac{\partial \pi^N(r)}{\partial r} > 0. \tag{A10}$$

For simplicity, assume that π^D does not increase with the lending rate, or increases less than π^N. The expected profit from approving an applicant with score s can then be written as

$$m^{\mathcal{I}}(s; r) = p^{\mathcal{I}}(s)\pi^N(r) + \left[1 - p^{\mathcal{I}}(s)\right]\pi^D. \tag{A11}$$

The bank approves an applicant whenever expected profits are non-negative. Therefore, the marginal approved applicant satisfies

$$m^{\mathcal{I}}(\delta^{\mathcal{I},*}; r) = 0, \tag{A12}$$

where $\delta^{\mathcal{I},*}$ denotes the optimal approval threshold.

Using the implicit function theorem,

$$\frac{\partial \delta^{\mathcal{I},*}}{\partial r} = -\frac{\frac{\partial m^{\mathcal{I}}(\delta^{\mathcal{I},*};r)}{\partial r}}{\frac{\partial m^{\mathcal{I}}(\delta^{\mathcal{I},*};r)}{\partial s}}. \tag{A13}$$

The numerator is positive because higher interest rates increase profits in the non-default state:

$$\frac{\partial m^{\mathcal{I}}(s; r)}{\partial r} = p^{\mathcal{I}}(s)\frac{\partial \pi^N(r)}{\partial r} > 0. \tag{A14}$$

The denominator is also positive because expected profits are increasing in the score:

$$\frac{\partial m^{\mathcal{I}}(s; r)}{\partial s} = \frac{\partial p^{\mathcal{I}}(s)}{\partial s}\left[\pi^N(r) - \pi^D\right] > 0. \tag{A15}$$

It follows that

$$\frac{\partial \delta^{\mathcal{I},*}}{\partial r} < 0. \tag{A16}$$

Thus, when the lending rate decreases, the approval threshold increases. Intuitively, a lower usury cap reduces the interest income that the bank can obtain from approved borrowers. As a result, some marginal applicants who were profitable at a higher interest rate may no longer generate non-negative expected profits. The bank therefore raises the approval threshold and rejects riskier applicants. This result explains why the calibration focuses on a period in which the consumer-credit usury rate remained stable. If the usury rate changed during the evaluation period, variation in expected profits could reflect changes in pricing constraints rather than improvements in borrower selection generated by utility information.