Like magic: Reducing consumer credit risk with incentive contracts

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Abstract

Incentives can facilitate consumer credit that might otherwise be unavailable. We examine a quasi-natural experiment in Brazil, where a lender offers standard and incentive credit contracts. The incentive contracts carry lower interest rates and must be repaid through the electricity bill or borrowers face electricity cutoffs. Using data on loan applications and rejections, we test model-based hypotheses. We find, at origination, incentive borrowers are riskier, with 30% lower credit scores than standard borrowers. However, after origination, incentive borrowers become "like magic" safer, with 20% lower default rates than standard borrowers. Over time, the lender shifts from standard to incentive contracts.

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1. Introduction

Theory has shown that incentives can help to influence economic behavior ex ante to improve efficiency and welfare. However, in practice, it is often unclear which incentives to use, to what extent they should be applied, and under which circumstances they are truly effective. In this paper, we demonstrate, both theoretically and empirically, that incentives enable consumer credit that would otherwise be unavailable.

We study a quasi-natural experiment in Brazil, where a private consumer finance institution offers standard and incentive credit contracts. Consumers can freely choose between both contract types. The incentive credit contract bears a lower loan interest rate but must be repaid through the consumer's electricity bill. If the consumer does not pay the joint bill (electricity plus loan instalment), the electricity will be cut. The loss of electricity is a big penalty, but it comes with further negative externalities (e.g., no light, no fridge, no air condition, no telecommunication, etc.). The incentive feature is asymmetric (non-zero-sum): it is a non-pecuniary penalty that is costly for the borrower without giving a gain to the lender, following Diamond (1984). Nor does this incentive feature have any market value.

Based on this setting, we develop a model to derive theoretical predictions. The model predicts that high-risk borrowers are more likely to choose the incentive contract because they have more to gain from avoiding default than low-risk borrowers. In the model high-risk borrowers have higher incentives to exert additional effort to repay the loan and thereby effectively reduce their ex-post default risk.

We empirically test these predictions on a unique dataset consisting of 17,426 observations from consumer loans granted by a Brazilian financial institution between January 2021 and May 2023. Brazil is one of the Top 10 largest economies based on GDP and a large emerging country. It exhibits strong income and wealth inequality and its credit market is characterized by a relatively high level of asymmetric information, high default risk, high loan interest rates, and weak enforcement (Cortes and Marcondes, 2018).

We find three main results. First, incentive contract borrowers show ex ante significantly higher credit risk than standard contract borrowers. At loan origination, incentive borrowers' credit scores and income are around 30 percent lower than those of standard contract borrowers. Second, after loan origination, borrowers who choose the incentive contract exhibit "like magic" an about 20 percent lower ex-post default rate than borrowers who choose the standard contract. This incentive effect is stronger for ex ante riskier borrowers and single female borrowers. Our main finding is not due to a low discriminatory power of the ex-ante credit scores and supports the key prediction from our model: incentive borrowers exert additional effort to stay on track with their loan instalments and thereby successfully reduce their ex-post default risk. Third, the lender takes advantage of these effects and transitions over time from offering standard contracts to incentive contracts. Specifically, in period 1, the lender offers only standard contracts. In period 2, the lender offers standard and incentive contracts and borrowers can freely choose between both contract types. In period 3, the lender offers mainly incentive contracts. During this transition, the pool of approved borrowers becomes gradually riskier in terms of ex ante risk, while the ex-post risk gradually decreases. During the same period, we observe that ex-ante credit scores become less informative about ex-post defaults. The latter finding is consistent with the fact that the incentive feature indeed reduces borrower risk.

Could our findings be influenced by differences in loan characteristics - aside from the incentive feature - between standard and incentive loans? Alternatively, could sample selection biases be driving (partially) our results? To address these concerns, first, in our baseline analysis, we control for key borrower and loan characteristics as well as time and location fixed effects. We further employ different matching techniques of standard and incentive borrowers and obtain similar findings. Moreover, we estimate a Heckman Selection model on an augmented sample including approved and rejected loan applications. We show that our main finding is not affected by a sample selection bias. We find again that incentive borrowers are ex ante riskier and they become ex post safer.

Our paper contributes to several strands of literature. First, we contribute to growing research on non-physical collateral and the use of technology to enforce repayment in environments with weak formal enforcement. Gertler, Green, and Wolfram (2024) demonstrate that loans digitally secured with solar home systems significantly reduce default rates by leveraging lockout technology. In their setting, borrowers face temporary suspension of access to essential services, mirroring the enforcement mechanism in our study where non-payment of a loan leads to electricity disconnection. Both mechanisms increase borrower effort and act as commitment devices that are particularly valuable in low-income contexts. Theoretically, both interventions function as flow-based enforcement tools that reduce moral hazard and adverse selection without the high transaction costs of traditional collateral.

More broadly, our setting is part of a new class of fintech innovations that utilize non-traditional assets or services to secure credit—what the industry refers to as digital collateral. PayJoy, for example, uses smartphones as collateral by locking the device upon delinquency and has expanded this model to include cash loans in countries like Mexico and India.[1] These innovations align with Philippon's (2020) framework, which suggests that fintech can improve financial inclusion and intermediation efficiency by reducing fixed costs and exploiting big data for enforcement and credit screening. Our product design also speaks to

[1] See https://restofworld.org/2021/loans-that-hijack-your-phone-are-coming-to-india/

the World Bank's emphasis on digital financial inclusion as a means to reach underserved borrowers through behavioral incentives and automated enforcement.[2] Our setting leverages essential consumption as a lever for repayment, providing a novel contribution to the literature on contract design in fintech-driven lending markets.

Second, we contribute to the literature on access to credit and financial inclusion. High risk borrowers are often discouraged from applying for credit, face a high likelihood of being rejected if they apply, or they suffer harsh price and non-price loan terms if they receive credit. In our setting, they manage to exert additional effort, which results "like magic" in significantly lower ex post default rates. Our result complements Keys, Mukherjee, Seru and Vig (2010) who find that ex ante riskier borrowers with incomplete documentation, whose mortgages get securitized, become ex post safer through additional screening. Our result is also consistent with evidence on hidden action in credit markets. Karlan and Zinman (2009) show that repayment behavior is influenced by contract terms that affect borrowers' incentives to exert unobservable repayment effort. In our setting, borrowers under the electricity-linked contract increase their repayment likelihood through greater financial discipline or planning effort, which the threat of service disconnection likely helps motivate. The incentive contract improves access to credit, while reducing ex post credit risk. This effect is noteworthy because a democratization of credit is often accompanied by increases in consumer defaults and bankruptcies (Livshits, Mac Gee, and Tertilt, 2016).

Similar to our work, part of this literature focuses on emerging markets. Bachas et al. (2021) show enhancements in financial services can improve savings and repayment. Introducing debit cards to Mexican cash transfer recipients—who already held bank

[2] See full CGAP (Consultative Group to Assist the Poor) report available here: https://www.worldbank.org/en/topic/financialinclusion/publication/digital-financial-inclusion

accounts—led to a significant increase in formal savings, driven by reduced transaction and monitoring costs. As in our setting, the intervention did not alter income, but prompted households to better manage their finances and shift consumption patterns in ways that enhance financial outcomes. Garber, Mian, Ponticelli and Sufi (2024) provide evidence that credit expansion programs promoted by government banks in Brazil resulted in more credit to financially weaker borrowers. However, this increase is associated with higher consumption volatility and lower average consumption levels. The effects we document show that incentive contracts can effectively help to reduce default risk, increase financial inclusion, and potentially welfare.

Third, our study relates to research on commitment devices, which help individuals improve financial outcomes (for an overview, see Bryan, Karlan and Nelson, 2010). Ashraf et al. (2006) show that offering a voluntary commitment savings product significantly increases savings among Filipino clients. Casaburi and Macchiavello (2019) find that Kenyan dairy farmers are willing to accept significantly lower prices in exchange for infrequent lump-sum payments, effectively using the delayed payment schedule as a commitment device to save for lumpy expenses. Their findings underscore how individuals with time-inconsistent preferences may voluntarily choose costly contractual structures that restrict liquidity, paralleling how borrowers in our setting may value the electricity disconnection threat as a form of non-pecuniary commitment. Furthermore, our work is related to research on informal enforcement devices, where formal collateral is replaced by non-pecuniary collateral. Karlan et al. (2009) develop a theory of social collateral, showing that individuals' borrowing capacity in informal markets is shaped by the structure and strength of their social networks, which can substitute for traditional enforcement mechanisms.

Our results are in line with studies on loan covenants and the trade-off between non-price items and interest rates. Covenants help to limit borrower moral hazard and their violation may trigger default, but – unlike the incentive feature in our setting - they do not inflict an additional penalty on the borrower. Covenants can help borrowers by improving contract completeness, but they also come with costs, limiting borrower actions and reducing flexibility (Graham, 2022). When covenants tighten, the expected repayments rise, allowing the lender – just like in our data – to lower interest rates while still preserving profitability. This effect is studied in Abuzov, Herpfer and Steri (2024), who quantify the trade-off between price and non-price loan terms.

Finally, our findings align with a growing behavioral literature showing that simple reminder or salience-enhancing interventions can substantially improve borrower repayment behavior. Cadena and Schoar (2011) demonstrate that SMS reminders and financial incentives improve repayment among Ugandan borrowers, with reminders performing as well as financial discounts—suggesting frictions such as forgetfulness or poor planning as key mechanisms. Grubb et al. (2025) find that overdraft SMS alerts in the UK significantly reduce fees by prompting timely action, without major shifts in underlying budgets. Similarly, Laudenbach and Siegel (2025) show that brief phone conversations with bank agents, which convey no new information, significantly increase repayment rates among delinquent borrowers, likely by making the obligation more salient or personal. In our setting, although we do not observe the specific actions borrowers take, the strong repayment effect of the electricity-linked contract suggests that improved discipline, planning effort and salience - motivated by the threat of service disconnection - may drive the response, especially among high-risk individuals.

The remainder of the paper is organized as follows. In Section 2, we develop a stylized model and derive hypotheses. In Section 3, we describe the data and empirical strategy. In Section 4, we empirically analyze the effects of incentives on consumer credit defaults. In Section 5, we conduct further checks, address external validity concerns, and discuss welfare and policy implications. Section 6 concludes.

2. Model and hypotheses

We model the interaction between a bank and its borrowers in a two-period game.

The Bank. We do not explicitly model banking competition. Rather, we assume that the bank operates in a competitive environment, and breaks even with zero profits. The bank has access to an unlimited amount of capital at the risk-free cost of R_f. It offers a menu of two types of uncollateralized loan contracts with a fixed interest rate, $(R_i; I)$. R_i denotes the interest, rate for either safe or risky borrower type ($i = \{s, r\}$), while $I = \{0,1\}$ stands for incentives: With a standard loan contract $I = 0$, while with an incentive loan contract $I = 1$. The loan repayment is attached to the electricity bill and paying separately is not an option.

Borrowers. Without loss of generality, there are two types of borrowers. Risky borrowers have a low project success probability Q $(0 < Q < 1)$ of producing a terminal cash flow Y after one year: with probability $1 - Q$ they produce 0. Safe borrowers succeed with a probability $P,\ Q < P$ (in the data, borrower risk is measured by their credit scores at time of applying for a loan). Each borrower needs one dollar for a fixed period of one year to carry out her project in that year. Borrowers observe the two loan types and choose one of the two. We assume that borrowers, too, know their credit risk. Additionally, both banks and borrowers know the cost of effort necessary to increase success probability to 1: $C > 0$ is needed as borrowers have to forgo alternative expenses that may cause additional disutility.[3]

We assume that terminal cash flow Y is large enough to pay not only the standard contract, but the joint total of the electricity bill and loan repayment in the incentive contract. In the event that the borrower defaults, the outcome depends on the contract type: for the incentive contract, if the borrower defaults on an installment, the electricity is cut. We assume that the loss of electricity creates not only a direct negative outcome, but also other costly effects.[4] We denote these default costs by $D = F$. Finally, to focus on the interesting parameters of the model, we assume that in case of default on the standard contract, borrowers (and banks) will eventually receive nothing from the project: $D = 0$[5]. Thus, total borrower surplus for safe and risky borrowers without effort are:

$$P * (Y - R_s) - (1 - P) * D \text{ for safe borrowers, and}$$

$$Q * (Y - R_r) - (1 - Q) * D \text{ for risky borrowers,}$$

where R_s and R_r denote, respectively, interest rates offered to risky and safe borrowers. Similarly, when borrowers exert effort, they will succeed with certainty, which will be reflected in the bank's risk-free interest rate:

$$Y - R_f - C.$$

Breakeven competitive profits for the bank mean that:

$$R_r = \frac{R_f}{Q} > \frac{R_f}{P} = R_s > R_f.$$

[3] The increase of the success probability to certainty is made for simplicity and is innocuous in our model.

[4] Examples include not having a fridge or TV, no light or air condition, unable to charge phone, etc. Some of these can also necessitate costly repairs.

[5] One could assume that borrower still have some liquidation value of l. Moreover, they could also have additional costs due to further decreasing credit scores. Assuming these sum up to null, it does not have any qualitative consequences for the model.

The following assumption allows us to focus on the interesting parameter range.

Assumption. *Effort is sufficiently costly.*

$$C > (1 - Q)Y - R_r(1 - Q)$$

$$C > (1 - P)Y - R_s(1 - P)$$

This assumption states that incentives are only present in the incentive contract for both borrower types: borrowers do not consider exerting additional efforts, such as cutting down on other expenses, when they have the standard contract.

Timeline of the game:

1. The bank has access to unlimited capital at cost R_f. It observes credit risk, offers two loan types: incentive ($R_i, I = 1$) and standard ($R_i, I = 0$): R_i denotes the interest rate.
2. Borrowers know their credit risk. They observe the two loan types and choose one of the contracts.
3. After choosing the contract type, borrowers decide whether or not to exert effort with cost $C > 0$: exerting effort results in loan repayment with certainty.
4. If borrowers succeed, their project yields cash flow Y. Y is large enough to honor obligations and will be used to repay the interest rate or the joint bill (if $I = 1$).

We solve the game by backward induction as illustrated in Figure 1

Proposition.

In the parameter range where

$$C < Y(1 - P) - R_s(1 - P) + (1 - P)F \tag{1}$$

both safe and risky borrowers will choose the incentive contract and will exert more effort. In the parameter range where

$$Y(1-P)-\ R_s(1-P)+(1-P)F<C<Y(1-Q)-\ R_f(1-Q)+(1-Q)F \qquad (2)$$

only risky borrowers will choose the incentive contract and exert effort, while safe borrowers will choose the standard contract and will not exert any effort

The intuition of the model is as follows. If C is low enough (as in (1)), all borrowers will exert effort. If, by contrast, it is higher than the RHS of (1), then effort is so costly that even for risky borrowers it does not payoff to exert: increasing success probability from a very low Q to 1 is still not enough to cover the associated costs. In this case, no borrower will exert effort. If C is in the middle, then only risky borrowers will choose the incentive contract and exert effort.

(Insert Figure 1 here)

Based on the Proposition above, we state the following two hypotheses:

Hypothesis H1. *Upon accepting the incentive contract, all borrower types are less likely to default.*

Hypothesis H2. *For borrowers choosing the incentive contract, the decrease in the ex-post default rate is stronger for ex-ante riskier borrowers.*

Our Hypothesis H1 follows from the first part of the proposition: as long as effort is not too costly, all borrowers will select the incentive contract, work harder, and default less. Hypothesis H2 follows from the second part of the proposition: there is a parameter range within which only risky borrowers are affected by the incentive contract and exhibit a lower ex-post default rate. If one were to envisage a distribution of borrowers' effort costs with support across all parameter ranges, the proposition would imply that a proportion of safe borrowers choose to exert effort, while a larger proportion of risky borrowers do the same.

3. Data and empirical strategy

3.1 Data

We gather proprietary credit file data from a large, privately owned consumer finance institution in Brazil. The dataset comprises information on loan applications and rejections, with detailed monthly data on loan terms and repayment for granted loans, spanning the period from October 2020 to September 2023. A unique feature of our setting is that the lender offers two types of credit contracts: a standard contract and an incentive contract.

Standard contracts are unsecured cash loans that do not impose any additional constraints on the borrower beyond the bankruptcy law in case of default.[6] The lender started offering the standard contracts in October 2020 and charged a loan interest rate of 15 percent for these contracts. In November 2022, the interest rate was raised to 18 percents.

Incentive contracts are cash loans, where the repayment is automatically bundled with the borrower's electricity bill. Thus, if the borrower defaults or chooses only to pay the electricity costs, the electricity will be cut.[7] The lender started offering the incentive contracts

[6] According to art. 396 of the law 10.406/2002 from the Brazilian Civil Code, the institution can demand the payment of delayed values added with penalty fees and interest. Additionally, the law 8.078/1990, in its art. 52 establishes that a consumer in default can face credit score penalties, which can in turn make it more difficult to obtain additional credit in other institutions.

[7] This penalty was inflicted on all borrowers that default during our sample period. There were neither enforcement problems nor lawsuits by borrowers.

in August 2021 and charged a loan interest rate of 12.5 percent for these contracts. In November 2022, the interest rate was raised to 15 percent.

The dataset also contains information on loan characteristics such as the installment value, loan size, and default, as well as borrower characteristics such as credit score, income, age, gender, marital status, city, and state. Overall, the database consists of 29,094 observations, hereof 17,426 from approved loans (standard contracts: 9,391; incentive contracts: 8,035) and 11,668 from rejected loans. Table 1 provides summary statistics.

(Insert Table 1 here)

Panel A shows the statistics of all approved loans. The mean of credit default rate is 34%. Around 46% of all approved loans are incentive contracts. The mean maturity is 13 months and the mean loan size BRL 2,536 (around USD 500). The monthly mean borrower income is BRL 2,154 (the legal minimum salary in Brazil during our sample period ranges between BRL 1,045 and BRL 1,302 which are USD 180 and USD 225, respectively). The mean disposable income, after considering the monthly mean loan installment, is BRL 1,956. The mean borrower age is 46 years, 44% of the borrowers are men, and 82% are singles.

Panel B shows summary statistics by loan type during the overlap period (the period where both loan contracts were offered simultaneously). The mean default rate of the incentive contracts (29 percent) is lower than the one of standard contracts (34.5 percent). Incentive borrowers' mean credit score (4.26) is around 30% lower (= higher ex ante risk) than the one of standard borrowers (6.09). Moreover, incentive borrowers' mean loan maturity is longer while their mean loan size and income are lower than for standard borrowers. Standard borrowers' mean disposable income is BRL 2,083 and BRL 1,765 for incentive borrowers. 43 percent (46 percent) of the incentive contract (standard contract) borrowers are men. Finally, 82 percent of the standard borrowers are singles, while the corresponding number for the pool of incentive borrowers is 84 percent. We consider this heterogeneity between loan types by adding various borrower and loan controls as well as using matching estimators in our analysis.

3.2 Empirical strategy

Our baseline model is specified as follows:

$$Credit\ Default_{i,t} = \beta_0 + \beta_1 Loan\ Type_i + \beta_2 Credit\ Score_i + \gamma X_{i,t} + \varepsilon_{i,t} \qquad (3)$$

where i indicates the borrower and t time measured in year-months.

$Credit\ Default_{i,t}$ is a dummy variable that equals one when the borrower did not pay loan installments for three consecutive months.[8] $Loan\ Type_{i,t}$ is a dummy variable that equals one for incentive contracts and zero for standard contracts. $Credit\ Score_i$ is a continuous variable that ranges from 0 to 100 and refers to the client's external credit score at the time the loan was granted. The *Credit Score* comes from a business association, who provides this information to retailers and financial institutions in Brazil. To facilitate the interpretation, we rescale the credit score. An increase (decrease) of one point should be interpreted as an increase (decrease) of 100 points in the client's credit score. The vector $X_{i,t}$ refers to the borrower and loan control variables. $\varepsilon_{i,t}$ is the error term.

Considering that a consumer can choose between the standard and incentive contract, we are potentially facing confounding differences in ex-ante borrower characteristics. In

[8] In a robustness test (Appendix A, Table A.1), we consider different default definitions (one month past due, two months past due). The results are robust.

other words, the effects of the incentive contract we seek to analyze might be due to differences in ex ante borrower characteristics that influence their contract choice. To overcome this issue, we estimate our baseline model with different matching techniques (e.g., Chernenko and Sunderam, 2011; Acemoglu et. al., 2016). Matching techniques are a widely used strategy to control for covariates. Hence, they enable us to identify the treatment effects when the data is collected without any randomized assignment rules (Guo and Fraser, 2010). The matching variables in our analysis are key ex ante borrower characteristics such as age, disposable income, state of residence, and marital status.

4. Results

4.1 Baseline results

We test the effect of the incentive contract on credit default as shown in Equation (3). According to our model and Hypothesis H1, we expect that borrowers should, via exerting more effort, default less frequently if they have chosen the incentive contract. Table 2 reports the results of our baseline analysis, including different sets of controls and fixed effects.

(Insert Table 2 here)

We find that consumers who borrow under incentive contracts default significantly less than those who borrow under standard contracts. The effect of *Loan Type* ranges between -0.297 and -0.328 and is robust when we control for loan characteristics or borrower characteristics. Appendix A, Table A.1 demonstrates that these results are robust when we apply different default definitions (i.e., borrowers are past due one month, two months, or three months). As expected, the coefficient of *Credit Score* is negative and significant at the 1% level in all models in Table 2 and Table A.1, confirming that the measure captures consumer default risk well.

Our findings show that non-pecuniary incentives in the loan contract transform ex-ante riskier borrowers to ex post safer ones, consistent with our model and Hypothesis H1. This result sheds light on the importance of non-pecuniary incentives for reducing contracting frictions. In other words, the incentive feature in the credit contract facilitates lending to ex-ante high risk borrowers and allows the lender to grant credit that was otherwise unlikely to be approved.

4.2 Matching techniques

We acknowledge that the heterogeneity between consumers who choose standard or incentive contracts may influence their contract choices. In the baseline analysis, we control for various borrower characteristics, loan characteristics and fixed effects. We now re-estimate the baseline model using different matching techniques to isolate the effect of loan type on ex post default risk, all else equal.

We recognize that different matching techniques may yield different outcomes. For instance, while Propensity Score Matching (PSM) reduces the dimensionality of the covariates by condensing them into a single propensity score, it allows for a more straightforward comparison between treated and untreated groups. However, PSM is sensitive to the correct specification of the propensity model, and any model misspecification may lead to biased estimates (Rosenbaum & Rubin, 1983). Nearest Neighbors Matching (NNM) pairs each treated unit with the most similar untreated unit based on covariates, offering a more direct comparison. However, it requires a sufficient overlap in covariate distributions between treated and control groups. Kernel Matching applies a weighted average of control group observations, where the weights are inversely proportional to the distance between treated and control units in terms of covariates. This technique improves the efficiency of the estimation by using more information from the control group, but it can also be sensitive to the choice of bandwidth and kernel function, potentially affecting the robustness of the results (Heckman et al., 1998).

Each method offers distinct advantages and limitations. We therefore estimate the baseline model using different matching techniques to ensure that our results on the incentive effects are well-identified. The matching variables are key ex ante borrower characteristics such as age, disposable income, state, and marital status. Table 3 reports the results.

(Insert Table 3 here)

All matching techniques employed in Table 3 confirm our baseline analysis. We find again a highly significant negative effect on credit default for individuals who borrow under the incentive contract. The estimated coefficients of the variable *Loan Type* range between -0.190 and -0.242. Incentive borrowers default significantly less than the matched consumers who obtained standard credit contract. Moreover, the variable *Credit Score* is highly significant in all models, confirming that it captures consumer default risk well.

4.3 Heterogeneity by ex-ante borrower risk

In the next step, we investigate the potential heterogeneity behind our average result. In particular, we intend to shed light on the consumers' sensitivity to the incentive feature in the credit contract. Based on our model and Hypothesis H2, we expect that high-risk borrowers will be more sensitive to the incentive feature because it makes it possible for them to obtain credit and lock in a lower loan interest rate. To examine this possibility, we split the sample based on the median of the borrower credit score into high and low ex ante credit risk.

Additionally, we explore the literature on gender and analyze whether women respond to incentives differently than men. Building on previous literature that posits that women are better at repaying loans (Shahriar et al., 2020; Barthman et al., 2024), we examine whether they respond better towards incentives. To isolate the effect of gender and rule out alternative explanations regarding higher access to funds of married individuals, we analyzed a subsample of single individuals. We then estimate the baseline model from Table 2, column 3. Table 4 reports the results.

(Insert Table 4 here)

We find that the incentive feature works for high- and low-risk borrowers. However, the magnitude of the coefficient on *Loan Type* in Column (1) is 14 percent higher for high-risk borrowers, suggesting a stronger reduction of ex post default risk for these borrowers than for the low-risk borrowers in Column (2). The difference is statistically significant at the 1 percent level. Moreover, comparing Columns (3) and (4), we find that female borrowers exert greater effort in repaying their loans when provided with incentive-based structure. The findings indicate that single women default 33 percent less on incentive loans, with results significant at the 5 percent level when we add several control variables. In contrast, we do not find statistically significant results suggesting a difference in default across loan type among single male borrowers. This result confirms previous literature on gender-based loan repayment and suggest that women understand the benefits provided by the incentive and exert higher effort to meet their financial obligations.

4.4 Dynamic analysis

Until this point, our analyses are based on data from a period when the lender offered simultaneously standard and incentive contracts and consumers could freely choose the contract type. In this section we investigate what happened before and after this period.

The consumer lender started its operations in October 2020, offering exclusively standard credit contracts, effectively granting its first loan in January 2021. In August 2021, the lender started offering the new incentive credit contract in addition to the standard contract. Both contracts were offered simultaneously until May 2022. After that time, the lender decided to continue with incentive credit contracts mainly and faded out the standard credit contract only issuing under exceptional cases. We label these phases Period 1 (January 2021 - July 2021), Period 2 (August 2021 - May 2022) and Period 3 (June 2022 - May 2023).

These pre- and post-dynamics make it possible for us to analyze credit defaults in all three periods and study whether they are related to the loan type, controlling for all other observable factors such as borrower characteristics, loan characteristics and municipality and time fixed effects. Table 5 reports the corresponding results.

(Insert Table 5 here)

We obtain two key findings. First, we find that the ex-post default rate of incentive contracts in Period 2 (Column 2) and in the full sample (Column 4) is significantly lower compared to the one of standard contracts. Second, we find that the statistical and economic significance of the credit score becomes weaker when we move from Period 1 to Period 3. In Period 3, the estimated coefficient of the credit score is positive but no longer statistically significant. This effect happens because the incentive feature transforms high ex ante default risk into significantly lower ex post default risk. Borrowers prioritize loan repayment over other optional expenses to ensure that they maintain access to essential services, such as electricity. This might involve reducing non-essential spending to avoid missing payments on the loans and electricity. This highlights how the need for essential services strongly influences borrowers' financial decisions and their commitment to loan repayment.

Figure 2 illustrates these dynamic effects of contract types on credit default. We show the ex-ante risk with mean credit scores (squares and triangles) on an inverted scale on the left axis and the ex-post risk with mean default rates (+ and ×) on the right axis by contract type and period. Our main result is illustrated here: the default risk of incentive contract borrowers is significantly reduced – relative to their ex-ante risk (credit score) in Period 2 as well as relative to the ex-post risk (default rate) of standard contract borrowers in Period 2. Moreover, the default rate of the incentive contract decreased from Period 2 to Period 3. Importantly, the default rate of incentive contracts was at all times lower than the one of the standard contracts. Considering that the lender discontinued the standard contracts in Period 3 and that the default rate decreased over time suggest that the lender has learned throughout the process that incentive contracts turn ex-ante high risk into ex post low risk borrowers.

(Insert Figure 2 here)

Finally, we examine whether and how the pool of borrowers changed over time. The mean credit score in Period 1 is 5.55, in Period 2 it is 5.72, and in Period 3 it decreases to 4.21. Figure 3 displays the distributions of the ex-ante credit scores by period.

(Insert Figure 3 here)

Figure 3 shows that the distribution of ex ante credit risk is similar in Period 1 and 2, while it is very different in Period 3. We now see a significant decrease in the ex-ante credit score and a bimodal credit score distribution, which has a hump on left (high-risk) side. The change in Figure 3, Panel C indicates that the gradual transition from standard contracts to incentive contracts made it possible for the lender to grant an increased percentage of loans to ex ante high-risk borrowers and, at the same time, operate with lower ex post default rates (as shown in Figure 2). It also explains why the credit score in Period 3 (Table 5, Column 3) is no longer significant – the standard relation "the higher the ex-ante credit score, the lower the ex-post default rate" is largely offset by the incentive feature.

This effect helped to facilitate access to credit and improve financial inclusion for high-risk borrowers. We note that even if the increased focus on high-risk borrowers has crowded out some of the low-risk borrowers, it is likely that there is an increase in welfare because low-risk borrowers have relatively easy access to credit at any lender.

4.5 Selection effects due to credit approval vs. rejection

The previous analyses are all based on data from consumers who received a loan. The vast majority of related studies based on such data because usually rejections are not recorded and lenders do not keep records of rejected loan characteristics. Hence, data on approved loans may be subject to a selection effect because approved loan applicants likely show more favorable characteristics than rejected applicants.

In our analysis, we fortunately can address the concern of potential selection effects. The consumer lender provided us with additional data on those borrowers whose loan applications were rejected. Specifically, we obtained the credit scores, age, gender and income of rejected borrowers. We merge these data with our main dataset on approved loans and estimate a standard Heckman Selection model to examine whether potential selection effects influence our main finding.

We estimate one selection model on the full sample period (Period 1-3) and another one on the overlap period, when consumers can choose between standard and incentive contracts. We employ the variable gender as the exclusion restriction variable in our selection model. A key requirement of the selection model is that the exclusion restriction must influence the selection equation without exerting a direct effect on the dependent variable in the outcome equation. Consistent with this condition, the coefficient of gender is not statistically significant in the baseline outcome model (Table 2), while it is statistically significant in the selection equation about credit approval. These results support the validity of gender as an exclusion restriction in our selection model.

It is noteworthy that the coefficients associated with the gender variable are negative. This result indicates that women are more likely to have their loan applications approved than men. The literature does not find evidence of gender-based differences in loan approval rates among entrepreneurs, but instead attribute lower female participation in credit markets to self-selection as they are less likely to apply for a loan (Ongena and Popov, 2016; Moro et al., 2017). A potential explanation could be that women tend to face higher borrowing costs (Alesina et al., 2013), despite consistently demonstrating better repayment behavior (Shahriar et al., 2020; Perrin and Weill, 2022; Barthman et al., 2024).

In our sample, which is largely composed of high-risk borrowers with limited access to formal bank credit, the finding that women have a higher probability of credit approval reflects the lenders' recognition of their superior creditworthiness in a pool of high-risk loan applicants for consumer loans with fixed interest rates. Table 6 reports the estimation results for the Heckman Selection model.

(Insert Table 6 here)

The findings confirm our baseline results, both for the full sample and the overlap period. The coefficient on *Loan Type* is still negative and highly significant, though its magnitude is reduced. We further find that the Inverse Mills Ratio is not statistically significant, indicating that there is not a selection bias in our analysis.

5. Further analyses, welfare and policy implications

5.1. Further analyses

In this section, we conduct further analyses, examine the external validity of our findings and discuss potentially confounding effects.

First, one might wonder whether our main result is due to ex ante information problems (adverse selection) or ex interim/ex post information problems (moral hazard). In particular, a low discriminatory power of our measure of ex ante risk - the credit scores used by the lender – may influence the results.[9] If the credit score systematically overstates the ex-ante risk of high-risk borrowers (i.e., the borrowers are actually safer than they appear based on their credit score), then we would see lower ex post risk for these borrowers. Such effect could drive our results because high-risk borrowers choose incentive contracts with a higher likelihood than low-risk borrowers.

To investigate this possibility, we validate the discriminatory power of the credit score. Specifically, we split the credit score of all accepted borrowers with standard loans in quartiles and report the mean default rates. Figure 4 presents the results.

(Insert Figure 4 here)

Figure 4 shows that the mean default rates per credit score monotonically decline across quartiles, as expected from a well-calibrated credit scoring system. Moreover, the differences in mean ex post default rates between neighboring credit score quartiles (1 vs. 2, 2 vs. 3, and 3 vs. 4) are all statistically significant at the 0.01-level. These descriptive analyses are confirmed in a regression analysis of borrower's individual default rates on their credit

[9] As explained in Section 3.2, the lender obtains the credit scores from a third party who provides consumers' credit score to financial institutions. This institution operates independently and compiles consumers' default histories from multiple financial institutions in Brazil.

scores, which show coefficients that are negative and significant at the 0.01-level. Hence, we can rule out the concern that our result is due to a low discriminatory power of the ex-ante credit scores. In the absence of the incentive feature, ex ante credit scores and ex post default risk are well aligned. This fact also suggests that our main finding is due to the disciplining effect of the incentive contract and the corresponding additional effort that borrowers exert after receiving the incentive loans.

Second, our setting might raise the question whether the consumer lender has been able to sustain his operations. By restricting the provision of credit to incentive contracts only in Period 3, the lender might have deterred regular borrowers who prefer standard loans and/or large loan amounts. This restriction could have resulted in a reduction of revenue, potentially compromising the profitability of its operations. Based on the data analysis, the lender approved 240 standard contracts in Period 1 and 422 incentive contracts in Period 3. However, the gross revenue from lending decreased. To better understand the underlying motivations for the shift in contract types and its broader implications, we conducted an interview with the lender. According to the lender, the decision to prioritize incentive contracts in Period 3 was guided by the risk-return ratio associated with each contract type. Specifically, the monitoring costs linked to standard contracts were significantly higher compared to those incurred with incentive contracts. Despite having a lower loan amount compared to standard contracts, the lower cost and lower risk made the incentive contracts attractive from a risk-return perspective. Consequently, the lender's strategy was to offer incentive contracts as a gateway for new borrowers with no prior internal credit history. By limiting their risk exposure, the institution aimed to gather information on borrower behavior. This approach was meant to facilitate further lending, including larger standard loan contracts, and the cross-selling of other products.

Third, there is a decline in the number of loans over time, which might be due to lender's shift in contract type. From Period 2 to Period 3, the number of approved loans decreased by around 40 percent. However, the data shows a 94 percent increase in incentive contracts over the same period, leading to a loan volume growth of 103 percent. Considering these observations, we argue that the decline in the number of loans was primarily driven by macroeconomic factors rather by the lender's shift in contract type.

To further examine changes in the loan volume over time, we compare the time trend in the Brazilian credit market with the one in our dataset. For this purpose, we analyze the ESTBAN database, a publicly available database from the Central Bank of Brazil, which has been widely used in prior research (e.g., Norden et al., 2021; Fonseca and Van Doornik, 2022, Fonseca and Matray, 2024). Figure 5 displays the mean loan volume difference between the loan volume in ESTBAN and in our dataset over time.

(Insert Figure 5 here)

Figure 5 shows that the difference between the overall credit market in Brazil and our sample remains relatively stable over time. This finding supports the view that the loan volume decrease in Period 3 is mainly due to macroeconomic factors that affect overall credit and loans in our data similarly and not due to the lender's transition to incentive contracts.

Fourth, in our institutional setting, a credible enforcement of the incentive feature is critical. The incentive loans contracts are completely legal and allowed under Normative Instruction 581[10] by the energy regulator in Brazil (*Agência Nacional de Energia Elétrica*, ANEEL), but it is conceivable that the lender might still experience difficulties in enforcing

[10] The Normative Instruction 1000 of December 2021 consolidates the Normative Instruction 581 and continues to allow "atypical activities", which are economic activities performed by third parties that are interested in adding the bill to the electricity bill.

the contracts in cases of default. Specifically, borrowers could contest the terms of the contract on the grounds of unfairness, potentially securing a preliminary injunction to restore the provision of electricity.

We provide two pieces of evidence to mitigate this concern. If contract enforcement was difficult, then rational borrowers would predominantly select incentive contracts. Why? Because incentive contracts would dominate standard contracts. Considering the lower interest rates and longer maturity, all rational borrowers would opt for inventive contracts with the assurance that their electricity service would remain uninterrupted even in case of default. However, the data indicates a different outcome: over 70 percent of loans issued in Period 2 are standard contracts. This observation weakens the concern that the incentive feature was not credible because of enforcement problems.

Moreover, during our sample period, none of the incentive contract borrowers engaged in legal actions against the lender. The absence of litigation does not only reflect that the incentive contracts were legal but can be also attributed to the fact that incentive borrowers are ex-ante riskier and unable to secure credit from alternative sources. Hence, the risk of jeopardizing access to credit by suing the lender, coupled with the possibility of losing the case and, consequently, facing an electricity cut, likely discouraged incentive borrowers from contesting the contract terms.

Fifth, in our setting it is possible that the lender sheds default risk to the electricity company. This is due to two effects. On the one hand, the incentive borrowers have to pay the joint bill consisting of the electivity consumption and the loan installment, which – ceteris paribus – increases their financial burden and thereby their default risk. On the other hand, the pool of incentive borrowers is ex ante riskier than the one of standard contract. If the incentive contract works well, the lender will significantly benefit due to reduced ex post default rates. If the incentive contract does not work well, the electricity company will face higher default rates on electricity bills. The outcome essentially depends on how much the contract incentivizes borrowers to exert effort to avoid default. From the electricity company's perspective, this arrangement may be rational, as she retains the ability to disconnect electricity for defaulting customers directly.[11] Our results indicate that the incentive feature indeed works well as it significantly reduces the ex-post default rate, which is in the interest of the lender and the electricity company.

Furthermore, a review of the lender's internal policy shows a tightening of the lending standards over time. Prior to May 2022, borrowers with credit scores below 500 were accepted only under exceptional circumstances and required an approval from the office manager. In June 2022 (the time at which the lender shifted to incentive contracts), this threshold was raised to a credit score of 600. In addition, a comparison of the rejection rate (i.e., calculated as the proportion of rejected loans to total loan applications) between Period 1 and Period 3 indicates a three-percent point increase in the rejection rate. Hence, these lending policy adjustments and the increase in loan rejection rates indicate that the lender tightened its lending standards. Considering that the incentive contracts were designed to target low-income individuals, the lender's decision to tighten lending standards appears to reflect a strategy to mitigate risk, while pursuing a targeted credit expansion.

5.2. Discussion of welfare and policy implications

In the remainder, we discuss the welfare and policy implications of our experiment.

[11] The electricity company may also allow a grace period, but this decision is ultimately guided by what serves the company's best interests.

Early theoretical work has shown how contracts can address asymmetric information frictions and enforcement constraints (Stiglitz and Weiss, 1981; Grossman and Hart, 1983; Diamond, 1984; Gale and Hellweg, 1985). We document how an incentive credit contract can create benefits for borrowers and lenders. Importantly, the incentive feature - the risk of having the electricity cut in case of default - is a non-pecuniary penalty à la Diamond (1984) that harms the borrower. The feature has several advantages. It represents a credible threat to the borrower because - unlike a pecuniary penalty - it can be easily enforced on insolvent borrowers. The incentive feature differs from other mechanisms that involve redistribution of wealth. For example, physical collateral can help to reduce borrower moral hazard (risk shifting or effort aversion) such as in Boot, Thakor and Udell (1991) and Chan and Thakor (1987). Boot, Thakor and Udell (1991) show costly collateral is effective as it reduces moral hazard, and riskier borrowers may pledge more collateral, consistent with our findings. However, collateral is often not available or difficult to enforce.

Despite collateral being scarce, it is uncommon for lenders to tie loan repayments to utility bills or other non-bank obligations. In many jurisdictions, implementing such an approach may raise both practical, legal, and ethical concerns. However, our quasi-natural experiment in Brazil shows overall positive effects, with reductions in default rates and expanded credit access. Yet, there are some caveats to these potential welfare improvements. Default under the new incentive contract differs from prior defaults, as it now entails additional costs associated with electricity disconnection, complicating the welfare implications. Moreover, some defaults may remain unavoidable despite a household's efforts to pay, having already minimized non-essential expenses. Situations like job loss or urgent medical expenses may, for instance, prevent repayment. Thus, to maximize efficiency, contracts should incorporate provisions for force majeure events like these.

Furthermore, borrowers who choose the incentive loan contract may do so based on private information that they will perform better. Knowing that they still have room to exert additional effort, they commit to it, meanwhile improving their financial position by "exerting effort," such as building precautionary savings or economizing on secondary expenses. The high cost of an electricity cut-off encourages this discipline. Our findings align with this: riskier borrowers perform better (or equally well) under the incentive contracts after being matched with comparable borrowers on factors like disposable income and family status. This performance improvement among initially riskier borrowers suggests that any increased credit risk for the electricity company would likely be minimal compared to the enhanced borrower discipline.

Assuming borrowers are rational and understand the model parameters (effort costs, changes in success probability, and the costs of an electricity cut), their choice of the incentive contract may generate added welfare. The incentive contract is part of a menu of options, and borrowers select it because they expect a higher total surplus. The costly effort they exert to avoid defaults is more than offset by their improved success rates. In addition, the lower interest rate on the incentive contracts, combined with a reduced ex-post default rate compared to standard contracts, effectively lowers the bank's loan losses: this must be the case as the bank moves fully to the incentive contract. These effects contribute to higher welfare for both borrowers and the bank.

6. Conclusion

In this paper, we study a quasi-natural experiment in Brazil, where a consumer lender offers standard and incentive credit contracts. The latter bear lower interest rates but must be repaid through the consumer's electricity bill, otherwise electricity will be cut. We develop a stylized model to derive hypotheses. Based on detailed data on loan applications and rejections, we find three main results. First, at origination, incentive contract borrowers are significantly riskier, with around 30 percent lower credit scores, than standard contract borrowers. Second, after origination, the incentive borrowers become “like magic” safer, with 20 percent lower ex-post default rates than standard borrowers. This incentive effect is stronger for ex ante riskier borrowers and single female borrowers. Third, the lender takes advantage of these effects and shifts over time from standard contracts to incentive contracts, reducing consumers’ ex post default rates. These findings are robust when we apply different techniques to match standard and incentive contract borrowers and when we take into account potential selection effects due differences between approved and rejected loans. Overall, our study provides new evidence on incentive effects in consumer finance and contributes to research on contract design, access to credit and financial inclusion, and credit in emerging markets.

Appendix

Table A.1: Different credit default definitions

This table presents probit regression results of the likelihood of credit defaults on loan type and credit score. Loan type is a dummy variable that equals one for an incentive contract and zero for a standard contract. Credit Default equals one if borrowers are 1-month past due in Columns (1) and (2) and 2-months past due in Columns (3) and (4). We control for credit score, age, gender, log income, marital status, log loan size, and loan maturity. The sample period is from August 2021 until May 2022 (the period when both contract types are offered). Heteroskedasticity-robust t-statistics adjusted for clustering within loans are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Credit Default	1-month past due	1-month past due	2-months past due	2-months past due
Loan Type	-0.209***	-0.303***	-0.218***	-0.315***
	[-3.774]	[-2.723]	[-4.050]	[-2.879]
Credit Score	-0.043***	-0.041***	-0.044***	-0.043***
	[-3.032]	[-2.911]	[-3.287]	[-3.171]
Borrower controls	Yes	Yes	Yes	Yes
Loan controls	No	Yes	No	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Number of observations	7,495	7,495	7,452	7,452
Pseudo R^2	0.087	0.091	0.107	0.111

Table A.2: Matching quality

This table provides a t-test on the mean difference between matched variables using two nearest neighbors, four nearest neighbors, and propensity score matching. T-statistics are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Variables	Standard Contract	Incentive Contract	Difference (t-statistics)
Age	47.388	46.610	0.770 [1.550]
Marital Status (Single)	0.146	0.160	-0.014 [-1.040]
Marital Status (Other)	0.854	0.840	0.014 [1.040]
Disposable Income	7.389	7.382	0.007 [0.390]

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Figure 1: Model set-up

Standard denotes the branch of the tree when the standard loan contract has been chosen in the first stage. Incentive denotes the branch following the choice of the incentive contract. The upper panel is the tree with payoffs for safe borrowers, while the lower panel is one for risky borrowers. All the variables are defined in the model setup. The figure shows the scenario corresponding to the range of effort cost C as in proposition 1: in this range risky borrowers, choosing the incentive contract, will exert effort and always succeed.

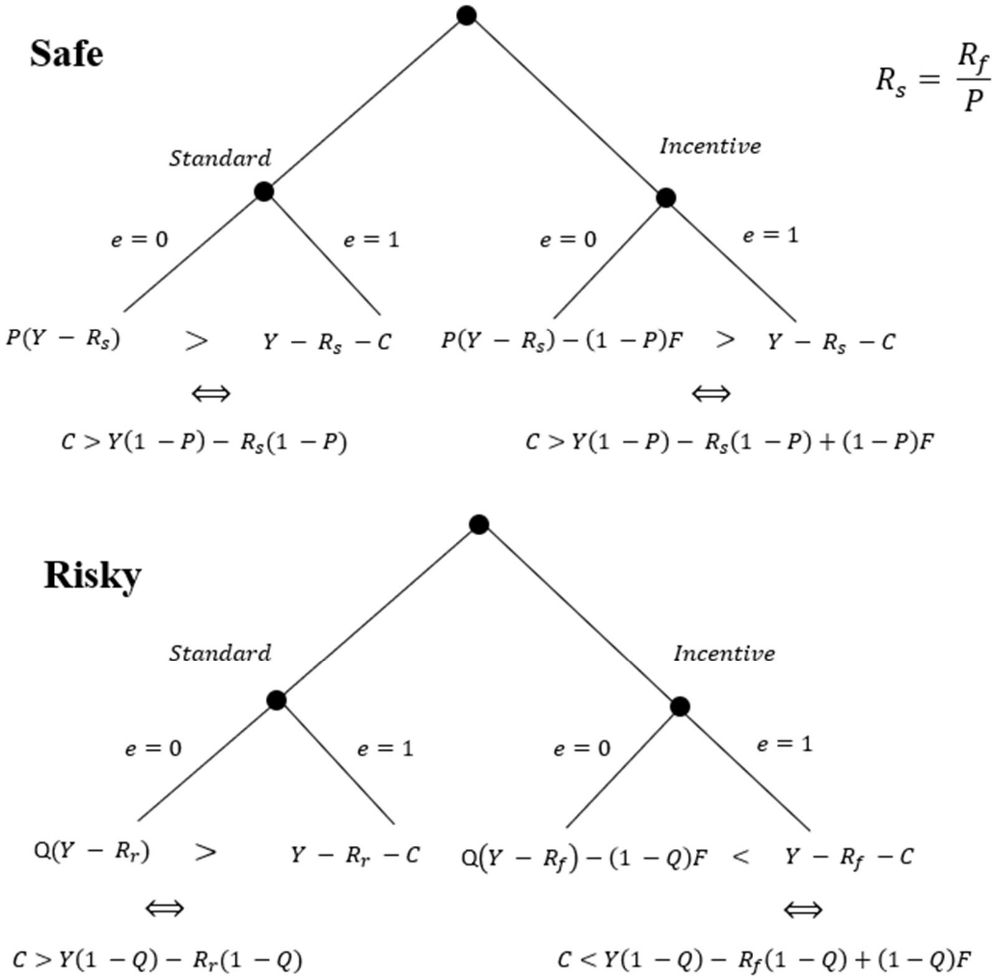


Figure 2: Dynamics of ex-ante and ex-post default risk by contract type

This figure displays the ex-ante risk with mean credit scores (squares and triangles) on an inverted scale on the left axis and ex-post risk with mean default rates (+ and ×) on the right axis by contract type and period. Period 1 presents loans granted between January 2021 until July 2021 and includes only standard contracts. Period 2 presents loans issued from August 2021 to May 2022, when both standard and incentive contracts are offered. Period 3 demonstrates loans granted from June 2022 until May 2023, when virtually all issued loans were incentive contracts.

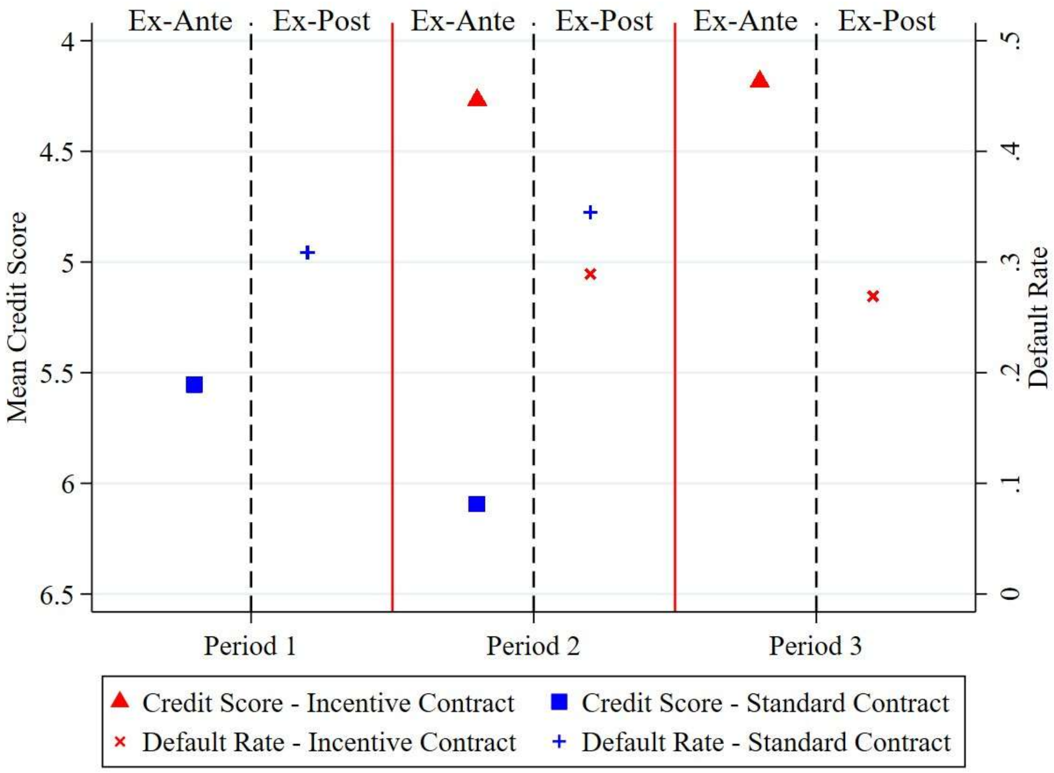
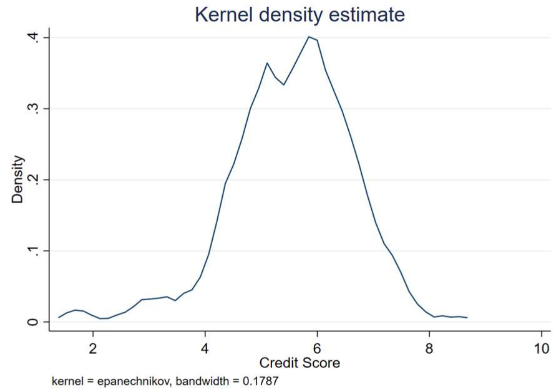


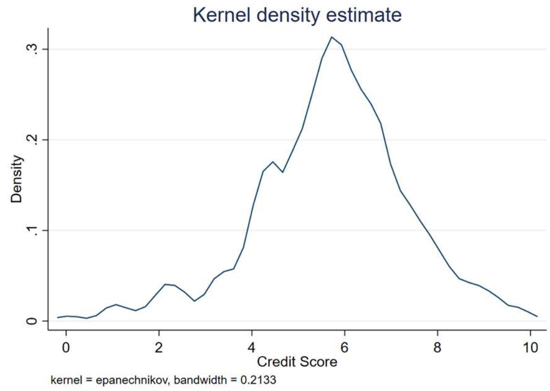
Figure 3: Credit score distributions by period

These figures demonstrate consumers' credit score distribution in each period. Panel A demonstrates consumers' credit score during period 1 (October 2020 to July 2021). During period 1, the finance institution only provided standard contracts. Panel B demonstrates the credit score distribution in period 2 (August 2021 to May 2022). In period 2, the finance institution granted both standard and incentive contracts. Panel C demonstrates consumers' credit score for all loans granted in period 3 (June 2022 until May 2023). During period 3, the finance institution mainly provided incentive contracts to consumers.

Panel A: Period 1



Panel B: Period 2



Panel C: Period 3

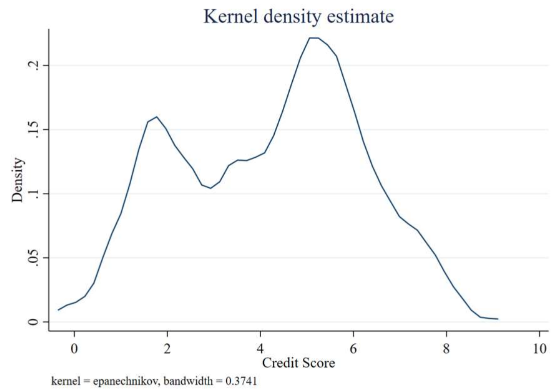


Figure 4: Default rates by credit score

This figure plots the mean default rate by credit score quartiles for all accepted standard loans in our dataset.

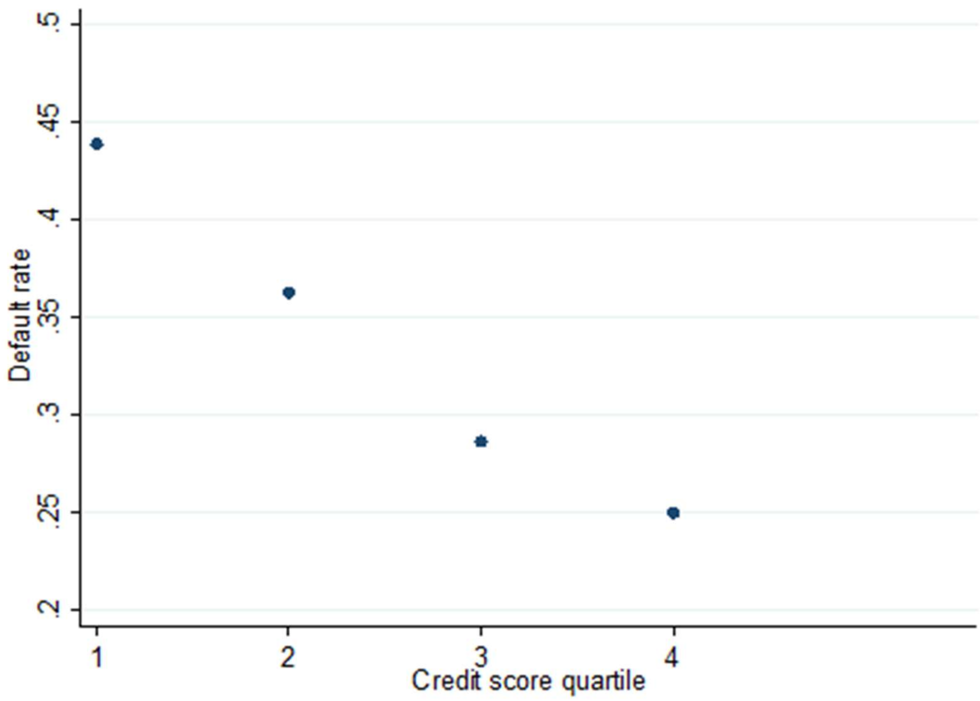


Figure 5: Mean difference in monthly loan volumes

This figure displays the mean monthly difference in loan volume between the overall credit market using the Central Bank of Brazil's ESTBAN database and the loans in our sample over time.

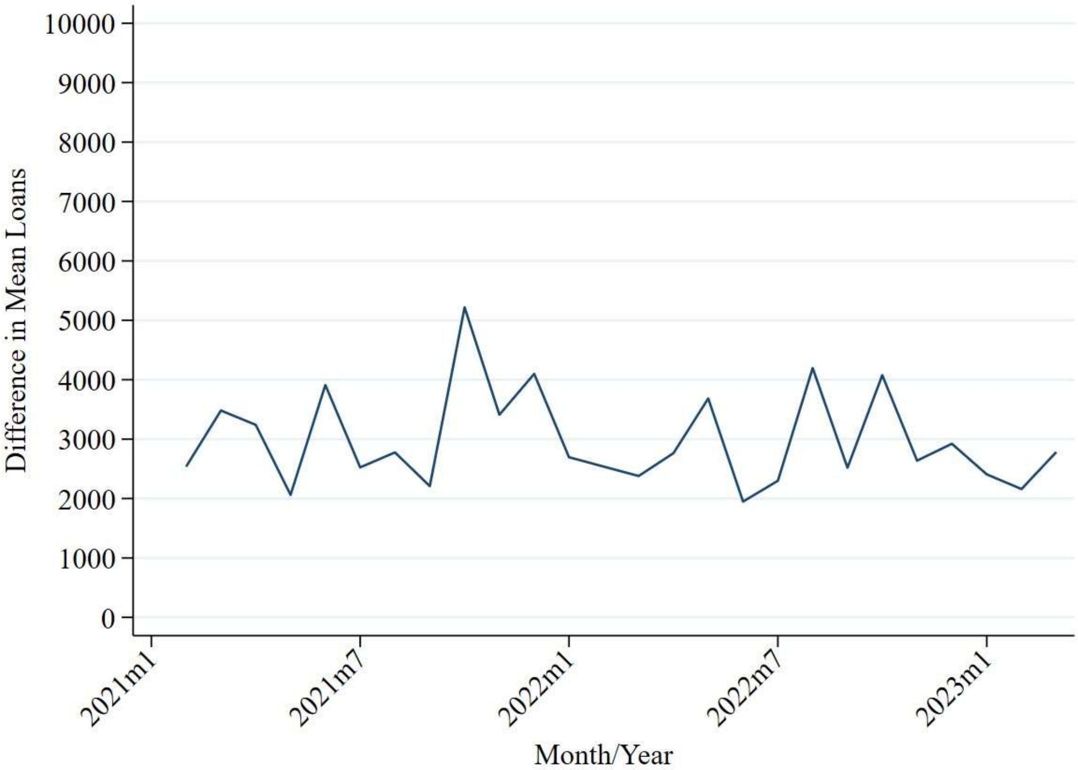


Table 1: Summary statistics

Panel A presents summary statistics of all approved loans during the period January 2021 until March 2023 (and repayment history until September 2023), based on 17,426 observations. Credit Default is a dummy variable that equals one if the borrower is in default and zero otherwise. Borrowers are in default when they are three months past due with the loan installments. The variable Income has 17,374 observations and the variable Credit Score has 12,711 observations. Panel B presents summary statistics of the approved loans by loan type (standard or incentive contract) during the overlap period where both loans were granted simultaneously. There are 6,240 observations for the standard contract and 1,578 observations for the incentive contract.

Panel A: Full sample of all approved loans

Variable	Mean	Median	Std. Dev.	P5	P95
Credit Default	0.345	0.000	0.476	0.000	1.000
Loan Type	0.461	0.000	0.498	0.000	1.000
Credit Score	5.461	5.630	1.653	2.030	7.930
Maturity	13.498	12.000	1.907	12.000	15.000
Loan Size (BRL)	2,536.92	1,970.760	1,890.726	1,114.800	6,488.880
Income (BRL)	2,154.467	1,600.000	1,506.699	1,100.000	5,000.000
Disposable Income (BRL)	1,956.425	1,425.680	1,447.484	883.700	4,629.000
Age	46.385	45.000	14.513	24.000	72.000
Gender (Men = 1)	0.444	0.000	0.497	0.000	1.000
Marital Status (Married)	0.002	0.000	0.042	0.000	0.000
Marital Status (Divorced)	0.001	0.000	0.037	0.000	0.000
Marital Status (Other)	0.173	0.000	0.378	0.000	1.000
Marital Status (Single)	0.820	1.000	0.384	0.000	1.000
Marital Status (Widow)	0.003	0.000	0.059	0.000	0.000

Panel B: Standard and incentive loans in the overlap period

	Standard contract					Incentive contract				
Variable	Mean	Median	Std. Dev.	P5	P95	Mean	Median	Std. Dev.	P5	P95
Credit Default	0.345	0.000	0.475	0.000	1.000	0.290	0.000	0.454	0.000	1.000
Credit Score	6.093	6.020	1.349	4.100	8.450	4.268	4.450	1.789	1.200	7.040
Maturity	11.878	12.000	0.934	12.000	12.000	14.795	15.000	0.758	12.000	15.000
Loan Size (BRL)	3,653.385	3,257.640	1,695.989	1,729.920	7,037.280	1,108.273	1,115.100	63.417	951.480	1,178.100
Income (BRL)	2,390.137	1,800.000	1,783.408	1,100.000	5,654.140	1,840.685	1,500.000	852.274	1,100.000	3,500.000
Disposable Income (BRL)	2,083.082	1,518.350	1,718.455	865.680	5,275.790	1,765.766	1,425.660	852.456	1,025.420	3,425.420
Age	45.880	45.000	14.890	22.000	71.000	46.610	45.000	14.259	25.000	71.000
Gender (Men = 1)	0.462	0.000	0.499	0.000	1.000	0.433	0.000	0.496	0.000	1.000
Marital Status (Married)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Marital Status (Divorced)	0.002	0.000	0.044	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Marital Status (Other)	0.167	0.000	0.373	0.000	1.000	0.160	0.000	0.366	0.000	1.000
Marital Status (Single)	0.824	1.000	0.381	0.000	1.000	0.840	1.000	0.366	0.000	1.000
Marital Status (Widow)	0.007	0.000	0.082	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 2: Baseline results

This table presents probit regression results of the likelihood of credit default on loan type and credit score. Loan type is a dummy variable that equals one for an incentive contract and zero for a standard contract. We control for credit score, age, gender, log income, marital status, log loan size, and loan maturity. The sample period is from August 2021 until May 2022 (the period when both contract types are offered). Heteroskedasticity-robust t-statistics adjusted for clustering within loans are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Credit Default	(1)	(2)	(3)
Loan Type	-0.297***	-0.225***	-0.328***
	[-3.377]	[-4.293]	[-3.061]
Credit Score	-0.035***	-0.045***	-0.044***
	[-3.554]	[-3.519]	[-3.408]
Borrower controls			
Age		-0.003***	-0.003***
		[-2.783]	[-2.726]
Gender (Men = 1)		0.018	0.020
		[0.512]	[0.588]
Income		-0.057*	-0.066*
		[-1.656]	[-1.662]
Divorced		0.178***	0.181**
		[2.598]	[2.437]
Single		-0.040	-0.045
		[-0.761]	[-0.848]
Loan controls			
Loan Size	0.007		0.017
	[0.184]		[0.335]
Maturity	0.063***		0.044**
	[3.506]		[2.173]
Municipality fixed effects	No	Yes	Yes
Time fixed effects	No	Yes	Yes
Number of observations	7,818	7,235	7,235
Pseudo R^2	0.019	0.118	0.121

Table 3: Results using different matching techniques

This table presents the probit regression results of the likelihood of credit default on loan type, credit score and loan controls for the matched sample using various matching techniques (nearest neighbors 1:2 and 1:4, PSM, and Kernel matching). Loan type is a dummy variable that equals one for an incentive contract and zero for a standard contract. The matching variables are age, gender, disposable income, state, marital status, and month/year. Loan control is loan maturity. The sample period ranges from August 2021 until June 2022 (the period when both contract types are offered). Heteroskedasticity-robust t-statistics adjusted for clustering within loans are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Credit Default	(1)	(2)	(3)	(4)
Matching technique	Nearest neighbors 1:2	Nearest neighbors 1:4	Propensity Score Matching	Kernel
Loan Type	-0.294***	-0.252***	-0.264**	-0.200***
	[-3.090]	[-2.822]	[-2.278]	[-2.685]
Credit Score	-0.048***	-0.030**	-0.047***	-0.033***
	[-3.057]	[-2.217]	[-2.794]	[-2.745]
Borrower controls	Matched	Matched	Matched	Matched
Loan controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,756	1,934	1,667	7,224
R^2	0.180	0.152	0.187	0.104

Table 4: Incentive contracts by credit score and gender

This table presents the probit regression results of the likelihood of credit default on loan type, credit score and controls for subsamples. Loan type is a dummy variable that equals one for an incentive contract and zero for a standard contract. We control for credit score, age, gender, log income, marital status, log loan size, and loan maturity. Heteroskedasticity-robust t-statistics adjusted for clustering within loans are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Credit default	(1)	(2)	(3)	(4)
Split by	Median credit score		Gender (Single Individuals)	
	High-Risk	Low-Risk	Women	Men
Loan Type	-0.454**	-0.314**	-0.337**	-0.288
	[-2.553]	[-2.064]	[-2.004]	[-1.461]
Credit Score	-0.014	-0.042	-0.070***	-0.022
	[-0.581]	[-1.431]	[-2.969]	[-1.247]
Borrower controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Number of observations	3,621	3,528	3,010	2,947
Pseudo R^2	0.121	0.161	0.164	0.123

Table 5: Dynamic analysis of credit defaults and loan type

This table presents the regression results of the likelihood of credit default on loan type, credit sore and controls in the raw sample by period. Loan type is a dummy variable that equals one for an incentive contract and zero for a standard contract. The sample period is from January 2021 until September 2023. Period 1 covers the period of loans issued from January 2021 to July 2021. Period 2 (overlap period) presents loans granted from August 2021 until May 2022. Period 3 represent the loans issued from June 2022 until May 2023. Heteroskedasticity-robust t-statistics adjusted for clustering within loans are reported in brackets. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Credit default	(1)	(2)	(3)	(4)
	Period 1	Period 2	Period 3	All periods
Contracts	Standard contracts only	Standard and incentive contracts	Incentive contracts only	Standard and incentive contracts
Loan Type		-0.328***		-0.284***
		[-3.061]		[-4.023]
Credit Score	-0.166***	-0.044***	0.015	-0.042***
	[-4.853]	[-3.408]	[0.777]	[-4.475]
Borrower controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Number of observations	2,755	7,235	1,549	12,216
Pseudo R^2	0.259	0.121	0.258	0.128

Table 6: Heckman Selection model

This table presents the results for the Heckman selection model. The first stage estimates the selection equation using the credit score, age, gender, and marital status. The second stage estimates the likelihood of credit default, excluding the variable gender for identification. Models 1-4 are estimated on the full sample from October 2020 to September 2023 (i.e., Periods 1, 2 and 3 - considering the repayment history until September 2023). Models 5-8 are estimated on the overlap period when both contracts are offered (i.e., Period 2 represents the loans issued from August 2021 to May 2022). Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Credit Default	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample				Overlap Period			
	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage
Loan Type		-0.064***		-0.237***		-0.104***		-0.169***
		[-5.987]		[-18.786]		[-7.000]		[-11.065]
Credit Score	0.132***	-0.029**	0.153***	-0.038***	0.161***	-0.032***	0.179***	-0.037***
	[18.679]	[-2.448]	[18.151]	[-8.746]	[17.574]	[-3.228]	[14.457]	[-8.982]
Borrower controls								
Age	0.001	-0.004***	-0.000	-0.003***	-0.004***	-0.002***	-0.006***	-0.003***
	[1.316]	[-11.671]	[-0.385]	[-9.869]	[-3.850]	[-5.309]	[-3.858]	[-7.541]
Gender (Men = 1)	-0.081***		-0.099***		-0.175***		-0.204***	
	[-3.418]		[-3.672]		[-5.565]		[-5.025]	
Married	0.192	-0.022	0.208	0.090	0.000	0.000	0.000	0.000
	[0.483]	[-0.146]	[0.491]	[0.631]	[.]	[.]	[.]	[.]
Divorced	0.055	0.122	0.883***	0.052	-1.102***	0.474***	-1.312**	0.361**
	[0.201]	[1.015]	[2.946]	[0.458]	[-2.963]	[2.840]	[-2.311]	[2.549]
Other	0.668***	0.147	1.038***	0.243***	-0.073	0.176**	-0.206	0.218***
	[3.537]	[1.628]	[5.267]	[3.334]	[-0.271]	[2.365]	[-0.589]	[3.115]
Single	0.607***	0.173**	0.649***	0.205***	-0.022	0.223***	-0.610*	0.185***
	[3.235]	[1.988]	[3.325]	[2.926]	[-0.082]	[3.036]	[-1.753]	[2.665]
Inverse Mills Ratio		-0.070		0.017		-0.076		-0.032
		[-0.335]		[0.241]		[-0.519]		[-0.668]
Municipality fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Time fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Number of observations	15,578	12,711	15,578	12,711	9,425	7,818	9,425	7,818