What Matters for Consumer Credit Choice? Evidence from the Philippine Digital Credit Market*

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Abstract

Digital credit—short-term, high-interest loans offered via mobile channels—has surged over the past decade, reaching millions in the developing world. However, much like payday loans in developed economies, it remains unclear whether its liquidity benefits outweigh the risks of overindebtedness and financial distress. Using an online discrete choice experiment with digital credit users in the Philippines, we examine how disclosures about price and non-price attributes affect consumer choice. Standardizing contract terms across products leads consumers to choose loans with lower interest rates and higher probability of approval at the expense of longer time to disburse and higher documentation requirements. Presenting interest rates in effective (compounded) or nominal terms makes no difference but, ranking by an attribute leads to the choice of products that are more favorable on that attribute. While on average, consumers are responsive to disclosures about late payment fees, overconfident consumers are not. We argue that overconfidence can reduce the effectiveness of attention-based interventions and how much consumers' choices reveal about their risk profiles.

JEL Codes: D12, D14, D18, G41, G51

Keywords: Digital credit, Consumer protection, Overconfidence, Choice experiment

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1 Introduction

Digital credit, typically offered as short-term, high-interest loans through mobile channels, has surged over the last 10 years with millions of registered users across the developing world. By removing traditional barriers to access, digital credit allows consumers to obtain funds quickly, bypassing physical and procedural constraints (Francis et al., 2017). However, much like payday loans in developed economies, it is not clear if the benefits of providing liquidity in times of need (Morse, 2011; Allcott et al., 2022) outweigh the risk of overindebtness and financial distress (Melzer, 2011). These risks are particularly pronounced in this market, since, on the one hand, many consumers are new to credit and often unaware of their loan terms (Brailovskaya et al., 2024), and, on the other hand, sophisticated providers, aware of this, may have incentives to obfuscate loan terms (Gabaix and Laibson, 2006; Ru and Schoar, 2016).

A common policy intervention to help borrowers understand the terms and costs of a loan are standardized disclosures(Garz et al., 2021; Chien, 2018). In traditional credit markets with relatively homogeneous products a case has been made that disclosures centered around the cost of credit can improve welfare by helping borrowers select more affordable options (e.g., Loewenstein et al., 2014; Johnson et al., 2012).[1] However, in digital credit markets, where loans can vary significantly beyond cost (e.g., in disbursement speed, approval requirements, and documentation requirements), consumers may prioritize non-price attributes and, consequently, firms have an incentive to differentiate on those. For instance, digital borrowers often value quick disbursement for urgent needs. Further, minimal documentation requirements with high approval rates can justify high interest rates for those with limited options. In a market where both firms and consumers care about attribute heterogeneity, standardized disclosures based purely on cost could inadvertently create barriers to the best product match, limiting their potential benefits.

In this paper, we study how various disclosures of price and non-price attributes impact consumer choice in the Philippine digital credit market. We first conduct a census of digital credit products to identify the extent of price shrouding in the market. We then present results from a pre-registered online discrete choice experiment with 4,000 prospective digital credit users in which we examine how information standardization and ranking by various price and non-price attributes influence choices and estimate the trade-offs consumers make between these attributes.

In the experiment, participants were randomly assigned to one of eight treatment arms or the control group, and then asked to choose their most preferred option from six hypothetical digital credit products. The products vary across a number of price and non-price attributes,

[1] In contrast to digital credit products, traditional credit products tend to have similar (e.g. monthly) repayment schedules, predictable underwriting requirements based on credit scores and income, and application processes that allows for asking questions (typically in person at a bank branch).

namely: effective interest rate, late payment fee per day, time to disbursement, number of documentary requirements, and probability of approval. The control group, inspired by how digital loans are marketed to consumers in the Philippines, requires participants to hover the mouse over short lines of marketing advertisements to access information on product attributes. In contrast, for all eight treatment arms, the product attributes are presented in a standardized format (i.e., tabular form). The first two treatment arms test the impact of standardization, which involves providing information on product attributes that a regulator might request be presented in fine print. They differ, however, in how the cost of credit is presented: one shows the nominal interest rate and processing fee separately, while the other presents the total cost of credit by collapsing the costs into an effective interest rate. In both treatment arms, the six products are displayed in random order. In the next five treatment arms products are rank-ordered according to one of five attributes. The final treatment arm allows the participant to choose the attribute to rank.

Our analysis uncovers four main findings. First, standardizing information leads consumers to choose products with more favorable terms compared to information displayed through traditional marketing campaigns. Specifically, consumers choose digital loans with lower effective interest rate and higher probability of approval, at the expense of longer time to disbursement and additional loan documents. On average, standardizing reduces the chosen effective interest rate by 2.70 percentage points (a 17% reduction from base). Further, when information is displayed in a standardized format, there is no statistically significant difference between presenting interest rates in effective or nominal terms: when the costs are presented as an effective interest rate, the average effective interest rate chosen decreases by 2.94 percentage points (an 18% reduction from base).

Second, we find that the arrangement of products influences consumer choice. Relative to the condition in which information is standardized but products are presented in random order, displaying products in a rank-ordered manner results in consumers choosing products with more favorable terms on the ranking attribute. For example, ranking the products by effective interest rate results in further 1.54 percentage points decline (a 12% reduction from base) in effective interest rate. Similarly, the average treatment effect of ranking products by late payment fee per day is a Php 2.63 reduction (a 9% reduction from base) in late fee. Our analysis allows us to quantify how consumers trade off various price and non-price attributes under different rankings. When ranking by late payment fee, consumers are willing to accept a Php 1 reduction in late fee for a 0.66 percentage points increase in effective interest rate. When products are ranked by number of documents, consumers are willing to trade off 1 additional loan document for a 7.62 percentage points reduction in effective interest rate. When ranking by time to disbursement, consumers are willing to accept a 1-hour increase in time to disbursement for a .03 percentage points reduction in the effective interest rate. When ranking by probability of approval, consumers are willing to accept a 1 percentage point increase in the probability of approval for a 0.29 decrease in the effective interest rate.

Third, after eliciting overconfidence at the individual level, we find that overconfident consumers do not respond to ranking by late payment fee. We measure overconfidence by asking three general knowledge or three financial literacy questions from Lusardi and Mitchell (2014) and comparing participants' self-assessed scores to their actual scores. In both cases, participants who overestimate their scores are flagged as overconfident (Pfäuti et al., 2024; Balasubramnian and Sargent, 2020; Pikulina et al., 2017) and, for them, there is no response to ranking by late payment fees, despite reporting a higher probability of past late payments.

Fourth, consistent with the predictions of behavioral contract theory (Gabaix and Laibson, 2006), the census of digital credit products reveals that firms choose not to advertise high-price attributes that arguably are relevant for consumer choice: 36% of products do not explicitly advertise loan fees and 64% do not explicitly advertise how late fees are calculated. If consumers were updating according to Bayes rule, they would infer high levels for all hidden prices and firms would then have an incentive to unshroud them and compete on them. Instead, the standard practice seems to be the obfuscation of expensive prices. Further, while the speed of approval and the likelihood of being approved are alluded to in advertisements, the advertisements are generally non-informative about the actual levels of these attributes.

In all our regression analyses, we account for multiple hypothesis testing and report both sharpened q-values (Anderson, 2008) and Romano-Wolf stepdown adjusted p-values (Clarke, 2021). A drawback of our design, as with any stated preference method, is hypothetical bias. For example, the choices are made in an artificial environment, the choice sets may not resemble real-life options, and the decisions participants make do not have any real-world consequences. We employ several techniques in our experiment to mitigate hypothetical bias. First, one of the eligibility criteria we set is that a participant must be looking to apply for a digital loan, as existing evidence shows that familiarity with the product and context alleviates hypothetical bias (Schläpfer and Fischhoff, 2012). Second, participants were presented with a "cheap talk" script (Cummings and Taylor, 1999) at the beginning of the experiment to motivate them to provide honest and unbiased answers.[2] Third, the hypothetical digital credit products were curated based on extensive market research to ensure that they closely resemble real-world products.

This paper contributes to the literature in three ways. First, in the context of the effect of disclosures on consumer behavior (Bertrand and Morse, 2011; Wang and Burke, 2022; Seira et al., 2017; Agarwal et al., 2015; Giné et al., 2017; Carpenter et al., 2021), we extend the literature in two distinct directions. First, this paper disentangles the individual effects of (*i*) standardizing information, (*ii*) reducing the attribute space by presenting total cost of credit, and (*iii*) increasing the salience of an attribute through ranking. Our approach differs to

[2] A "cheap talk" script is an ex-ante approach to reduce hypothetical bias. It attempts to persuade and remind participants to give more thoughtful answers prior to the choice task, so that their responses will more closely reflect their true preferences in a real purchasing decision.

Giné et al. (2017) and Carpenter et al. (2021) as their laboratory experiments focus on "choice overload" and "attribute overload", respectively.[3] Second, our research design allows us to estimate how consumers trade off between price and non-price attributes. The attributes examined in Giné et al. (2017) and Carpenter et al. (2021) are all price-related (interest rate and upfront fees), whereas in this study we present both price (effective interest rate) and non-price attributes (e.g., late payment fee, time to disbursement, etc.).

Second, this paper contributes to the literature on effectiveness of choice architecture interventions in changing consumer behavior (Münscher et al., 2016; Johnson et al., 2012; Loewenstein et al., 2014). Decision structure interventions (e.g., presenting products in a rank-ordered manner) have shown promise in other domains such as health (Dayan and Bar-Hillel, 2011; Pope, 2009) and education (Luca and Smith, 2013), but is still understudied in consumer finance.

Third, our results contribute to studies about the role of overconfidence on financial choices and its impact on the effectiveness of consumer protection policies. Although previous studies have documented the pervasiveness of overconfidence among digital credit users (Brailovskaya et al., 2024; Garz et al., 2021), there is no work, to our knowledge, on its impact on the effectiveness on consumer protection policies, such as disclosures. Overconfidence could mitigate the effectiveness of financial disclosures about contingent fees when it leads consumers to ignore relevant information they incorrectly believe is not relevant for them (Ausubel, 1991). Our results about the interaction of overconfidence and disclosures ranking by late payment fees support this contention.

Finally, our results are also relevant for the literature on behavioral industrial organization in two ways. First, we document behavior consistent with attribute shrouding (Gabaix and Laibson, 2006), building on the work of Ru and Schoar (2016). Second, we provide empirical support to the main premise of models for screening consumers with incorrect beliefs (Heidhues and Kőszegi, 2018; Spinnewijn, 2015). When borrowers have accurate beliefs about their probability of missing a payment, late payment fees allow lenders to induce borrowers to self-select into contracts that are appropriate for their risk profile. This allows lenders to profitably serve high-risk borrowers who would otherwise be excluded (Bester, 1985, 1987). However, when high-risk individuals overestimate their ability to avoid missed payments, they may respond less to late payment fees, reducing their effectiveness as a screening tool. Our findings on the diminished impact of late fee disclosures on overconfident consumers supports this premise.

[3] Giné et al. (2017) and Carpenter et al. (2021) also test the impact of standardized format. However, the treatment arms of Giné et al. (2017) test the concept of "choice overload", while the idea of "attribute overload" is central to the interventions of Carpenter et al. (2021). We also touch on "attribute overload" as one of our interventions consolidates fees (processing fee and monthly nominal interest rate) into effective interest rate. We do not study "choice overload" as the number of hypothetical products across all treatment arms in our experiment is fixed.

2 Setting and Product Census

2.1 Institutional Setting

The Philippine digital lending market is projected to reach USD 488.8 million in 2023, growing by 45.4% from USD 336 million in 2022 (Domingo, 2023). The country is experiencing a remarkable increase in the adoption of digital credit mobile applications. In 2023, the total number of digital loan app downloads reached 89.66 million (a 52% increase from previous year), while the number of unique users stood at 47.46 million (a 25% increase from previous year) (Ta-Asan, 2024).[4] Furthermore, the country is expected to see continued growth in demand for digital credit due to its large unbanked population, nearly universal mobile penetration, high internet usage, and the under-investment of traditional banks in digital offerings (McKinsey, 2023; Bangko Sentral ng Pilipinas, 2021).

Based on the latest national financial inclusion survey, 44% of the total adult population (or 34.3 million) is unbanked (Bangko Sentral ng Pilipinas, 2021).[5] Of the 34.3 million unbanked Filipino adults, 68% (or 23.3 million) has access to both mobile phone and internet. The average Filipino spends a staggering 10 hours on the internet per day and nearly 4 hours on social media, the highest worldwide (Diop et al., 2020). Consequently, this extensive online presence lends itself to being targeted by digital credit providers because many lenders use social media sites like Facebook and Tiktok to promote their products (Foundation for Media Alternatives, 2021).

Borrowing is the main coping mechanism of Filipinos in managing liquidity, defined as meeting regular spending needs, followed by the use of income and then savings. Fifty percent of adults with outstanding loan disclosed that it was used to meet day-to-day expenses, while 10% said it was used as payment for another loan (Bangko Sentral ng Pilipinas, 2021). Additionally, 76% of the country's banking system total loan portfolio is allocated to corporate/wholesale lending (one of the largest worldwide), while retail lending of traditional banks is heavily concentrated in a narrow band of wealthy households (McKinsey, 2023). Thus, fintech companies are well-positioned to overtake traditional banks in unsecured lending (Cigaral, 2021).[6]

The most popular form of digital credit in the Philippines is short-term (ranging from 7 to 30 days), high-interest (implied Annual Percentage Rate of more than 500%), small loans (minimum of Php 1,000 or approximately USD 20 for first-time borrowers) made directly to consumers (Foundation for Media Alternatives, 2021; The Manila Times, 2019).[7] Due to

[4]The statistics reported in Ta-Asan (2024) is based on a study conducted by Digido (a digital credit provider in the Philippines) and the analysis covers 70 online lending applications.

[5]"Unbanked" refers to adult Filipinos who do not own any type of formal account in a bank, e-money issuer, non-stock savings and loan association, cooperative, or microfinance institution.

[6]There are three types of digital credit business models in the Philippines, namely: mobile network operator plus regulated financial institution ("MNO + FI"), mobile money operator plus regulated financial institution ("MMO + FI"), and app/internet-based unregulated lender ("Fintech companies") (Alliance for Financial Inclusion, 2017).

[7]Annual Percentage Rate (APR) of digital credit in other countries are also sizeable: 478.8% in Mexico (Burlando

a surge in customer complaints concerning inadequate disclosures, misrepresentations, high interest rates, and unreasonable collection practices, the Securities and Exchange Commission (SEC) issued cease-and-desist orders against 58 digital lenders from September 2019 to April 2020 (Foundation for Media Alternatives, 2021). In addition, the Bangko Sentral ng Pilipinas's Consumer Empowerment Group reported a 63.3% year-on-year increase in complaints in 2020 (Tamayo, 2021). These factors, among others, prompted regulators in the Philippines to implement a ceiling on interest rates and other fees charged by digital credit providers through SEC Memorandum Circular No. 3, Series of 2022, effective March 3, 2022.[8]

Despite the caps on interest rates and late payment fees, digital credit in the Philippines remains costly, with interest rates approximately five times higher than credit cards.[9] Additionally, the census we conducted one year after the memorandum circular took effect reveals that some digital credit providers are still advertising interest rates and late payment fees above the prescribed ceiling. Our findings are supported by news stories about regulatory violations (Samaniego, 2023; Manabat, 2023; Duplito, 2023).

2.2 Census of Digital Credit Providers

We obtained a list of registered online lending platforms from the Securities and Exchange Commission (updated as of November 29, 2021).[10] The list contained the universe of financing and lending companies that conduct lending activities through websites or mobile applications. There were 238 online lending platforms registered under 124 companies. For an online lending platform to be considered as a digital credit provider, we follow Francis et al.'s (2017) definition of digital credit. Thus, the following criteria must be met: loan application is done remotely (via website or mobile application); short term (less than one year); no collateral requirements; and cash is disbursed directly to consumers (i.e., 'buy now, pay later' is excluded). Out of 238 registered online lending platforms, we identified 72 eligible digital credit platforms. Then, for each digital credit platform, we hand collected product attributes from advertisements via three sources, namely: online website (company website only), Google play, and homepage of mobile application (downloaded from Google play). We limited our data collection to the homepage of the mobile applications because, beyond that point, the applications require personal details such as a mobile number and access to phone records (e.g., gallery and contacts). We decided not to proceed further for privacy reasons. Of the 166 which were not classified as digital credit platforms, 7 (or

et al., 2023), 138% for M-Shwari in Kenya, and over 1000% for Kutchova in Malawi (Francis et al., 2017).

[8]SEC Memorandum Circular No. 3, Series of 2022 - Implementation of Bangko Sentral ng Pilipinas Circular No. 1133 Series of 2021 on the Ceiling/s on Interest Rates and Other Fees Charged by Lending Companies, Financing Companies, and their Online Lending Platforms. The structure of the caps on interest rates and fees are as follows: nominal interest rate (6% per month), effective interest rate (15% per month), and late payment fee (5% on outstanding scheduled amount per month).

[9]The maximum interest rate or finance charge on the unpaid outstanding credit card balance of a cardholder is 3 percent per month or 36 percent per year (Bangko Sentral ng Pilipinas, 2023).

[10]Accessed on January 16, 2023

4%) had cease and desist orders or lending licenses were revoked; 107 (or 64%) do not have company websites, Google play advertisements, or downloadable mobile applications from Google play; 32 (or 19%) offer business or auto loans that require collateral; and 10 (or 6%) offer 'buy now, pay later' financing.[11] Figure 1 summarizes the reasons why the 166 lending platforms were excluded in the final census.

Next, we examine the content of the advertisements from the 72 digital credit platforms and assess whether the focal loan attributes are inaccessible or obfuscated. We consider an attribute to be inaccessible if its value or detail is not explicitly advertised.[12] Product attribute obfuscation occurs when digital credit providers make the overall cost or other attributes difficult to understand or compare with competitor products.

2.2.1 Inaccessible Loan Terms

Figure 2 shows whether the loan attributes were explicitly advertised. Only 36% explicitly advertised late payment fee. For most products, late payment fee is not explicitly advertised; when it is, details about the fee and how it is computed are buried in fine print or placed outside the main page. Furthermore, only 64% explicitly advertised loan fees (e.g., loan set-up fee, insurance, notarial fee, etc.). All digital credit platforms explicitly advertised loanable amount, while 96% advertised both an interest rate (nominal, annual, or effective interest rate) and documentary requirements.

Only 6% and 7% explicitly advertised time to disbursement and probability of approval, respectively. However, we observed that both attributes were prominently mentioned across advertisements, but in a non-informative, persuasive manner.[13] In summary, evidence of inaccessible loan terms can be seen from the fact that 64% of digital providers did not advertise late payment fees, while other loan fees were only visible after uploading identification documents.

2.2.2 Price Obfuscation

Figure 3 summarizes our findings on price obfuscation. We find significant heterogeneity in how interest rates are advertised, which makes it difficult for consumers to compare products. Among the platforms that advertised any interest rate, panel (a) shows considerable variation in format: 92% in nominal annualized rate, 64% in nominal daily or monthly rate, and 6% in effective interest rate. It is noteworthy that only 6% presented in effective interest terms despite the fact that 64% of digital credit platforms advertised other fees (e.g., loan

[11] The extent of missing data is not surprising as the SEC has issued numerous cease and desist orders against online lending applications from 2019-2023. See for example: SEC orders 12 more online lenders to stop operations (Philippine News Agency, 2019); SEC stops new online lending apps as loan sharks shame Filipinos (Rivas, 2021); and SEC removes 33 online lending platforms from Google Play Store (Tabile, 2023).

[12] We consider this threshold the lower bound for shrouding because even when the loan attribute is explicitly advertised, some digital credit providers may increase or downplay the salience of a particular attribute.

[13] For example, a common advertisement might state: "Fast approval and high pass rate".

set-up fee). Panel (b) depicts significant heterogeneity in how the late payment fees are computed among the platforms that advertised late fee: 40% charge a daily penalty based on a percentage of the loan amount; 32% charge a one-time fee based on a percentage of the loan amount plus a daily penalty based on a percentage of the loan amount; 8% charge a one-time fee based on a percentage of the loan amount; 8% charge a monthly fee based on a percentage of the loan amount; and 4% charge a fixed amount monthly. The census suggests that in the absence of a regulated information space, the heterogeneity in how interest rate and late fee are presented makes it extremely challenging for consumers to compare products based on their true cost.

The summary statistics of loan attributes from the census are presented in appendix table A.1. Overall, we provide descriptive evidence that shrouding of loan attributes occurs. If consumers were updating their beliefs about prices based on Bayes rule, they would infer that firms who do not explicitly advertise relevant attributes have high prices on them, which in turn would give firms an incentive to advertise them and compete on them. The prevalence of inaccessible or obfuscated terms, along with a large fraction of consumers entering credit contracts without knowing important contract terms (Brailovskaya et al., 2024), is consistent with the Shrouded Prices Equilibrium of Gabaix and Laibson (2006).

3 Experimental design and Descriptive statistics

In partnership with the Philippine Competition Commission, we conducted an online discrete choice experiment in the Philippines. The study was implemented using Qualtrics through a survey firm utilizing their panel to recruit $n \approx 4,000$ prospective digital credit borrowers.[14] The experiment ran for one month, from December 1, 2023 to January 4, 2024, and it was available in both English and Filipino.

At the beginning of the survey, participants were screened based on the following criteria: (*i*) Filipino citizen with age between 18 and 65 years, and (*ii*) must be planning to take out digital credit in the next 12 months.[15] After passing the screening questions, the eligible participants were asked questions related to digital financial services usage and socio-demographic characteristics. Participants proceeded to the choice experiment and they were randomly assigned to one of the nine equally-sized groups: eight treatment arms and one control group. Before proceeding to the choice task, participants were asked to imagine that they were taking out a new loan and to choose a product as they would in real life. Importantly, they were informed that there are no right or wrong answers. The participants were instructed that their task is to choose their most preferred option (similar to Giné et al., 2017; Carpenter et al., 2021) from six hypothetical digital credit products. These

[14] In section 3.3, we compare our sample with the nationally representative financial inclusion survey conducted by the Bangko Sentral ng Pilipinas.

[15] The screening questions are designed in a similar fashion to the online discrete choice experiments of Chung et al. (2024) and Carroll et al. (2022).

products were representative of real products in the marketplace and differ in five attributes, namely: effective interest rate, late payment fee per day, time to disbursement, number of documentary requirements, and probability of approval.[16] The definition of each attribute was also provided. In addition, we indicated that all products have the same loan amount (Php 1,000), maturity date (30 days full payment), and disbursement/repayment channels (any bank, e-wallet, or padala center) to ensure that the participants only consider the focal loan attributes when choosing a product.[17] These instructions remained throughout the experiment.

After completing the experiment, participants were asked questions related to financial literacy, late payment history, liquidity, and behavioral characteristics. We also conducted an attention check, and participants who failed are excluded in the empirical analysis.[18] Participants who successfully completed the survey were compensated Php 150 (USD 3). The online survey took approximately 25 minutes to complete.

3.1 Hypothetical digital credit products

The choice experiment is unlabelled (i.e., use generic names for the products) and involves choosing the most preferred option from six hypothetical digital credit products. The five loan attributes being studied and their respective levels were curated based on the census we conducted between February and April 2023, the pilot testing conducted in October 2023, and the national financial inclusion survey which reports the main loan attributes considered by Filipinos when taking out loans (Bangko Sentral ng Pilipinas, 2021).

3.1.1 Attribute levels

In determining the attribute levels, we considered the range of each attribute from our product census. We decided the attribute levels should be whole numbers, spaced evenly to reduce complexity when participants evaluate the products. This approach also ensures that the study has sufficient power to detect meaningful differences. Table 1 summarizes the key product attributes and the corresponding attribute levels. There are five attributes and each attribute has three levels (worst, medium, and best). Each attribute level is presented an equal number of times, with each level appearing six times in total. By construction, there is no dominated product because all products have equal total assigned attribute scores (see appendix A.2 for more details).

[16] The details of hypothetical products and treatment arms are discussed in sections 3.1 and 3.2, respectively.

[17] Loan amount, tenor, amount of regular payments and amortization, and convenience of payment methods are among the top 10 attributes considered by borrowers when taking out loans (Bangko Sentral ng Pilipinas, 2021).

[18] As part of the robustness check, we report estimates using the unrestricted sample in the appendix.

3.2 Treatment arms and hypotheses tested

Our treatment arms test the impact of consumer disclosure formats on loan choice. We present the same number of hypothetical digital credit products (six) in both control and treatment groups. For all eight treatment arms, the product attributes are presented in a standardized format (i.e., tabular form). Treatment 1 tests the effect of standardization, while treatment 2 tests the combined effect of standardization and presentation of total cost of credit (i.e., effective interest rate). In treatments 3 to 7, we introduce a choice architecture enhancement by presenting the products in a rank-ordered manner according to one of the five attributes (e.g., ranked by effective interest rate, ranked by late payment fee, etc.). Treatment 8 allows the participant to choose the attribute to rank. Below we discuss the details of each treatment arm and the hypotheses we aim to test.

Control group "Marketing advertisements": The control group mirrors how digital loans are marketed to consumers in the Philippines. The six hypothetical digital credit products are described using short lines taken from typical advertisements, without explicitly presenting detailed information about product attributes upfront. The respondents need to hover the mouse over the advertisement to access information on attributes such as nominal interest rates, processing fees, etc. As is typical in the market, the total cost of credit is not presented with the product attributes. Using Qualtrics's randomizer function, the products are presented in a random order and they are randomized evenly. Appendix figure 4 shows how the digital credit products are presented in the control group.

Treatment 1 "Standardized - no EIR, random order": This experimental arm shows the nominal interest rates and the processing fees, instead of presenting the effective interest rates (EIR). As such, a total of six attributes are shown per product, namely: nominal interest rate, processing fee, late payment fee per day, number of loan documents, time to disbursement, and probability of approval. The products are presented in a random order and they are randomized evenly, similar to the control group. Appendix figure 5 shows how the digital credit products are presented in treatment 1. We hypothesize that providing information in a standardized format even without total cost of credit will reduce the effective interest rate chosen (Control vs T1).

Treatment 2 "Standardized - with EIR, random order": Unlike treatment 1, effective interest rate is presented instead of nominal interest rate and processing fee. As such, the total number of attributes to compare is reduced from six to five, namely: effective interest rate, late payment fee per day, number of loan documents, time to disbursement, and probability of approval. As with the control group and treatment 1, the products are presented in a random order. Appendix figure 6 shows how the digital credit products are presented in treatment 2. We hypothesize that providing information in a standardized format with total cost of credit will reduce the effective interest rate chosen (Control vs T2).

Treatment 3 "Ranked by effective interest rate": Using the same set of attributes

from treatment 2 (effective interest rate, late fee per day, number of loan documents, time to disbursement, and probability of approval), this experimental arm ranks the products by effective interest rate (%, lowest to highest). By design, we have two products with the "best" level of effective interest rates. Through the software's randomization function, we randomize the presentation of top two products evenly. Appendix figure 7 shows how the digital credit products are presented in treatment 3. We hypothesize that ranking products based on effective interest rate will lead to a reduction in effective interest rate chosen (T2 vs T3). The randomization procedure implemented in treatment 3 also applies to treatments 4 to 7.

Treatment 4 "Ranked by late payment fee per day": Using the same set of attributes from treatment 2, this experimental arm ranks the products by late payment fee per day (Philippine Peso, lowest to highest). Appendix figure 8 shows how the digital credit products are presented in treatment 4. We hypothesize that ranking products based on late payment fee per day will lead to a reduction in late fee chosen (T2 vs T4).

Treatment 5 "Ranked by number of documents": Using the same set of attributes from treatment 2, this experimental arm ranks the products by number of documents (lowest to highest). Appendix figure 9 shows how the digital credit products are presented in treatment 5. We hypothesize that ranking products based on number of loan documents will lead to a reduction in number of documents chosen (T2 vs T5).

Treatment 6 "Ranked by time to disburse": Using the same set of attributes from treatment 2, this experimental arm ranks the products by time to disbursement (hours, fastest to slowest). Appendix figure 10 shows how the digital credit products are presented in treatment 6. We hypothesize that ranking products based on time to disbursement will lead to a reduction in time to disbursement chosen (T2 vs T6).

Treatment 7 "Ranked by probability of approval": Using the same set of attributes from treatment 2, this experimental arm ranks the products by probability of approval (%, highest to lowest). Appendix figure 11 shows how the digital credit products are presented in treatment 7. We hypothesize that ranking products based on probability of approval will lead to an increase in probability of approval chosen (T2 vs T7).

Treatment 8 "Personal ranking": This experimental arm allows the respondents to decide how the products are ranked based on one of the five attributes (e.g., by effective interest rate, or by late fee per day, etc.). First, on the landing page, respondents are asked how they want to rank the products. Then, products are presented based on the attribute they chose. For this treatment arm, a back button is enabled as an option to allow the respondent to change how products are ranked. This treatment arm mimics the loan comparison tools online. Appendix figure 12 shows an example of landing page in treatment 8. We hypothesize that allowing respondents to rank loan products based on the attribute

of their choice will lead to a difference in effective interest rate, late payment fee per day, time to disbursement, number of loan documents, and probability of approval chosen (T2 vs T8).

3.3 Descriptive Statistics

The participants in the experiment are prospective digital credit borrowers. Our total sample of 4,486 reduces to 4,018 after restricting the sample to only include those who passed the attention check. In other words, 10% of the eligible participants failed the attention check. The attention check is placed halfway through the survey, and the multiple choice question reads as follows: "*This is not a trick question. It is designed to ensure that you are reading instructions carefully.* $2 + 2 =$ *?*"[19]

Table 2 reports summary statistics for participants in both treatment and control groups. The average age is 31 and almost half of the sample earn less than 15,000 Philippine Peso (or less than 269 USD) per month. In terms of experience with financial services, almost 40% have taken more than one digital credit loan in the last 12 months and 35% have incurred late payment penalty for missing a loan payment (any loan). Forty-three percent consider themselves as liquidity-constrained, while almost 60% at one point in the last 12 months delayed paying some essential bills (e.g., electricity, water, rent) due to lack of funds. Less than 10% of our sample is financially literate, as measured by whether the participant provided correct answers to all "Big 3" financial literacy questions (Lusardi and Mitchell, 2014).

Overconfidence about financial knowledge is a dummy variable that equals one if the participant's self-assessment of how many questions she thinks she got right is higher than her actual correct answers to the "Big 3" financial literacy questions, and equals zero otherwise. Fifty-five percent of the sample exhibit overconfidence about their own financial knowledge. Adapting Allcott et al.'s (2022) test for perceived time inconsistency, the awareness of time inconsistency variable is a dummy variable that equals one if the participant's reward chosen for avoiding late fee is above median, and equals zero otherwise.[20] Sixteen percent of the sample perceive themselves to be time inconsistent.

We formally test if the randomization process was successful in balancing observable characteristics across control and treatment groups. Appendix table A.3 shows that we can reject the null hypothesis of joint orthogonality across all experimental arms for three variables: age, gender (female), and educational attainment (with bachelors degree). In other words, the three covariates (out of ten) are not balanced across experimental arms.

[19] The choices, which are randomized, for the correct answer are : a) 22 b) 4 c) 2 and d) 0.

[20] The (hypothetical) reward amount accepted by the participant if she does not incur late fee can be viewed as a commitment device. Participants who are aware of their time inconsistency will have a higher valuation for the commitment device than people who are not aware of their time inconsistency (i.e., they are more sophisticated) (O'donoghue and Rabin, 1999).

As specified in our pre-analysis plan, we will select controls in our main analysis using a data-driven approach through a double-selection lasso linear regression (Belloni et al., 2014). As a robustness check, we will also control for the three imbalanced covariates.

We also compare the characteristics of our sample to the 2021 Financial Inclusion Survey, a nationally representative survey conducted by the Bangko Sentral ng Pilipinas (BSP) (see appendix table A.4). Our study sample has a higher percentage of respondents who are: living in the National Capital Region, younger, living in the urban area, working, single, and college-educated. These characteristics are in line with our expectations, and they also align with the typical profile of digital credit users in the Philippines (McKinsey, 2023; Bangko Sentral ng Pilipinas, 2021). The level of financial literacy in our sample, based on the percentage of participants who correctly answered all of BSP's six financial literacy questions, is comparable to the national survey (3% in this study versus 2% in national survey). The six financial literacy question of BSP includes the "Big 3" financial literacy questions by Lusardi and Mitchell (2014) plus three questions pertaining to knowledge about division, investment risk, and simple interest computation.

4 Methodology

In this section, we discuss how we estimate the causal effects of the experimental treatments on the level of loan attribute chosen. Since we use the attribute levels of the selected product as dependent variables, we have five outcome variables, namely: effective interest rate (%), late payment fee per day (Philippine Peso), time to disbursement (hours), number of loan documents, and probability of approval (%). In our pre-analysis plan, we specified that for each treatment arm there is one main outcome variable of interest. For example, the outcome variable of interest for T1, T2, and T3 is the effective interest rate as these interventions are choice architecture enhancements focused on the price attribute. For T4, T5, T6, and T7, the main outcome variable of interest is late payment fee, number of documents, time to disbursement, and probability of approval, respectively. For T8, we consider all five attributes as primary outcomes of interest. Nevertheless, we correct for multiple hypothesis testing and report both sharpened q-values (Anderson, 2008) and Romano-Wolf stepdown adjusted p-values (Clarke, 2021) in all our regression tables.

To determine the effects of treatments 1 to 3 on loan choice, we estimate

$$Attribute_j \;=\; \alpha \;+ \sum_{k=1}^{3} \beta_k \times T_{k,j} \;+\; \gamma Z \;+\; \epsilon_j \tag{1}$$

where *Attribute* is the level of attribute of the hypothetical digital credit product chosen by participant j. β_k represents the average treatment effect of treatment k which is calculated as the difference in loan attribute level (e.g., effective interest rate) between treatment k and

the control group; specifically, β_1, β_2, and β_3 are the average treatment effects of T1, T2, and T3, respectively. Z is a set of controls selected through a double-selection lasso linear regression (Belloni et al., 2014) and γ is a vector with the corresponding coefficients. The potential control variables specified in the regression are *socio-demographic characteristics* and *experience with financial services* variables reported in table 2. The double-selection lasso linear regression by Belloni et al. (2014) selects the control variables by running two lasso regressions. First, it performs a linear lasso of the outcome variable on all predictors (i.e., finding those that predict the outcome variable). Second, it performs a linear lasso of the explanatory variable of interest on potential controls (i.e., finding those that predict the explanatory variable of interest). Then, it identifies the union of variables estimated to have non-zero coefficient in steps 1 and 2, and run a post-lasso OLS regression. All of the estimates use heteroskedasticity-robust standard errors.

To examine the effects of treatments 4 to 8 on loan choice, we estimate

$$Attribute_j \;=\; \alpha \;+ \sum_{k=4}^{8} \beta_k \times T_{k,j} \;+\; \gamma Z \;+\; \epsilon_j \tag{2}$$

where the regression specifications and parameters are analogous to equation 1, except for the base category being T2 (Standardized - with EIR, random order) instead of the control group (marketing advertisements).

The main results presented in section 5 are estimated using double-selection lasso linear regression. For robustness check, we also estimate OLS regression and control for the three covariates (age, gender, and with bachelors degree) that are not balanced across experimental arms.

5 Results

5.1 Effects of standardization and ranking on effective interest rate

Table 3 reports the average treatment effects of T1, T2, and T3, estimated using equation 1. We present the five attributes as dependent variables, but the main outcome variable of interest is the effective interest rate, so we focus on column 1. There are four key results from this table. Firstly, column 1 shows that standardization (T1) reduces the effective interest rate chosen by 2.70 percentage points (or 17% reduction from base). Similarly, the combined effects of standardization and presentation of total cost of credit (T2) leads to a 2.94 percentage points reduction (18% reduction from base) in effective interest rate. The direction of the effects of T1 and T2 are consistent with Carpenter et al. (2021) and Giné et al. (2017) who find that presenting information in a standardized format, relative to market-designed disclosures, increases the likelihood of choosing the cheapest financial product. Secondly, we

find that standardizing information (T1 and T2) results in consumers choosing loan products with more "favorable" terms compared to information displayed through traditional marketing campaigns. Specifically, we find on average that consumers choose digital loans with lower effective interest rate and higher probability of approval, at the expense of longer time to disbursement and additional loan document. We argue that this is likely "favorable" not only because of the lower cost of credit, but also because evidence suggests that extending loan approval times reduces the likelihood of default among digital credit borrowers (Burlando et al., 2023). This extended time gives borrowers the opportunity to reconsider and adjust their intended use of the loan in a way that improves the chances of repayment.

Thirdly, the treatment effects of T1 and T2 are not statistically different from each other. This indicates that when the information is standardized, there is no statistically significant difference between presenting interest rates in effective or nominal terms. Finally, ranking the products by effective interest rate (T3) results in a 4.47 percentage points decline (28% reduction from base) in effective interest rate. T3 has the largest average treatment effect among the interventions, and it is statistically different from T1 and T2. We argue that differences in effect sizes between T3 and the standardization treatments (T1 and T2) indicates that ranking increases the attention allocated to the effective interest rate, leading consumers to choose digital credit products with a significantly lower (statistically speaking) total cost. The coefficient estimates for T1, T2, and T3 in column 1 are significant at 1% level, and remain robust after accounting for multiple hypothesis testing.

For regulators a deeper questions remains. Given that consumers value each of the five digital credit attributes to different extents, can consumer welfare be improved through standardization or ranking by effective interest rate. We argue that providing full information for improved product comparison is welfare improving (full product information in our experiment lowers EIR of chosen product), however it is not clear that ranking by EIR would improve consumer welfare. It may well be the case that a particular consumer, at a particular moment in time, may value very highly, due to immediate liquidity constraints, probability of approval or time to disbursement, and a circumspect regulator may deem it inappropriate to nudge a consumer towards a lower price loan at the expense of these other attributes. We suspect regulators with different regulatory philosophies may take different perspectives on this point.

5.2 Effects of ranking by non-price attributes

Table 4 reports the average treatment effects of ranking on the corresponding outcome variable of interest, estimated using equation 2. Columns 1, 2, 3, and 4 show the respective effects of T4 (ranking by late fee), T5 (ranking by number of documents), T6 (ranking by time to disbursement), and T7 (ranking by probability of approval). Column 5 shows the effects of T4 to T7 on the effective interest rate, and the purpose of reporting these estimates is to demonstrate our calculations of how consumers trade off between effective interest rate

and non-price attributes.

Column 1 of table 4 shows that ranking by late payment fee (T4) reduces the average late fee chosen by Php 2.63 (9% reduction from base). When ranking by late payment fee, consumers are willing to accept a Php 1 reduction in late fee for a 0.66 percentage points ($1.733/-2.631$) increase in effective interest rate. Similarly, column 2 shows that when products are ranked by number of loan documents (T5), consumers are more likely to choose products with lesser documentary requirements. When ranking by number of documents, consumers are willing to trade off 1 additional loan document for a 7.62 percentage points reduction in effective interest rate.

Column 3 of table 4 demonstrates that the average time to disbursement decreases by 8.23 hours (28% reduction from base) when products are ranked by time to disbursement (T6). When ranking by time to disbursement, consumers are willing to accept a 1-hour increase in time to disbursement for a .03 percentage points reduction in the effective interest rate. Column 4 shows that when products are ranked by probability of approval (T7), the average probability of approval selected increases by 4.45 percentage points (7% increase from base). When ranking by probability of approval, consumers are willing to accept a 1 percentage point increase in the probability of approval for a 0.29 decrease in the effective interest rate. The coefficient estimates in columns 1 to 4 are significant at least at 5% level, and remain robust after accounting for multiple hypothesis testing. The corresponding full tables for each column (with all five attributes as outcome variables) are in appendix tables A.5 to A.8.

Overall, the results in table 4 demonstrate that when digital credit products are ranked based on non-price attribute, consumers are more likely to choose the products that rank highly on that non-price attribute. This is consistent with what we find in table 3 (T3-ranking by effective interest rate), and with existing evidence that the position of product attributes could influence how attention is allocated, which in turn is likely to influence choices (Orquin et al., 2018).

Finally, table 5 shows that when consumers are allowed to rank the products based on their preferred attribute, their attribute choices are not statistically different from when the products are presented in a random order (treatment 2). There are two potential explanations: either there is no effect, or the effects on different consumers who value different attributes cancel out. The finding suggests that consumers are consistent in their choice between a random order list and when they have choice of ranking attribute.

5.3 Heterogeneity of treatment effects

We test whether overconfident and liquidity-constrained individuals respond to the treatments differently compared to those who are not. We estimate heterogeneous treatment

effects by augmenting equation 2 with interaction term between the treatment status and the covariate of interest. For each pre-specified binary covariate X, we estimate the following regression equation:

$$Attribute_j \;=\; \alpha \;+\sum_{k=3}^{7} \beta_k \times T_{k,j} \;+\; \delta X_j \;+\sum_{k=3}^{7} \omega_k (T_{k,j} \times X_j) \;+\gamma Z \;+\; \epsilon_j \tag{3}$$

where δ is a coefficient capturing level differences in the outcome when X equals one. ω_k is a vector of coefficients which represents how the effect of treatment group k on outcome variable varies when X takes the value of one. The base category is treatment 2.

5.3.1 Overconfidence

Column 1 of table 6 shows that, while on average consumers are responsive to ranking by late payment fee (treatment 4), those who are overconfident about their financial knowledge do not respond to that ranking. The result is robust to using an alternative definition of overconfidence, that is overconfidence in one's general knowledge (appendix table A.9).[21]

The insensitivity of overconfident consumers to late-fee disclosures does not appear to be driven by them having a better risk profile. Overconfident individuals in our sample are more likely to have missed a loan payment in the last 12 months, more likely to have incurred a late payment fee in the last 12 months.

The result highlights the limits of consumer disclosures of attributes that are contingent on consumer behavior and over which consumers may have incorrect beliefs.[22] Late payment fees are only relevant for individuals who expect to pay late. Even if their price is highlighted by disclosures and made salient by lenders, borrowers may still be insensitive to it if they underestimate the probability of paying late.

5.3.2 Liquidity-constrained

Column 1 of table 7 shows that consumers who are liquidity-constrained do not respond to ranking by effective interest rate (T3). The result aligns with previous studies which show that when liquidity constraints are binding, they reduce borrowers' sensitivity to loan prices (see Zinman, 2015, for review). We argue that for liquiditiy-constrained individuals, choice architecture enhancement making effective interest rate salient is not effective because their need for funds outweighs concerns about the cost of borrowing. For them, it is possible that the high prices are outweighed by a high marginal utility of consumption.

[21] Appendix table A.10 shows that our measures of overconfidence are also correlated with naivete about self control, as measured by Allcott et al. (2022).

[22] These contingent fees can also be thought of as add-ons of a base credit product, in which the ability to pay late is an optional attribute for which consumers can pay a price if they want it.

5.4 Robustness checks

We employ different regression specifications to verify the robustness of our results First, we run the same regression specifications on the unrestricted sample (i.e., include those who failed the attention check). Our main results remain robust as reported in appendix tables C.1 to C.6. Second, instead of using double-selection lasso linear regression to select covariates from potential control variables, we estimates an OLS regression and control for the three covariates (age, gender, and with bachelors degree) that are not balanced across experimental arms. In appendix tables D.1 to D.6, we show that our main results still remain robust, except for table 7 (Ranking by effective interest rate (T3) $\times$ Liquidity-constrained).

6 Conclusion

Our findings feed into the long standing discussion of how far regulators should go in shaping the information space for consumers. In the case of the Philippines, the degree of product attribute shrouding (inaccessibility and obfuscation) and what some might call misdirection in marketing, provides a strong case for regulators to ensure standardization of product attributes. There are examples around the world of such interventions by financial regulators and in some incidences price comparison websites. We suspect a similar case can be made for product attribute standardization for digital credit products around the world, not least in low income and emerging economies.

For financial products where effective interest rate is all that matters to the consumer, a case has been made by others that ranking by cost could be welfare improving (e.g., Loewenstein et al., 2014; Johnson et al., 2012). In the case of digital credit, where the consumer may value many different attributes at a particular point in time, prescribing a cost based ranking may not be welfare improving. Our results provide quantitative estimates of how individuals trade-off price and non-price attributes when facing different information structures.

Our results also show that unshrouding is not straightforward. Even when typically hidden but relevant contingent prices or add-ons, such as late-payment fees, are made salient, consumers may still fail to factor them into their decisions. This underscores the limitations of attention-based interventions in improving decision-making and has implications for what firms can infer about their clients from their choices.

Ultimately a regulator may choose to be open minded about the value of non-price attributes of digital credit products to customers while at the same time improve product attribute transparency, encourage price competition, and help customers navigate the information space shaped by sophisticated marketing teams in digital credit firms. For any given individual it may not be possible to say that their welfare has been improved by a ranking intervention. For circumstances where a regulator wishes to give the power to the consumer to

rank products by their preferred attribute, our study does not provide any evidence against or for this approach. However, we suspect that such a feature may help improve competition between digital credit providers as each attempts to stand out from the crowd by topping the ranking for particular attributes.

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Tables and Figures

Figure 1: Reasons excluded in the final census

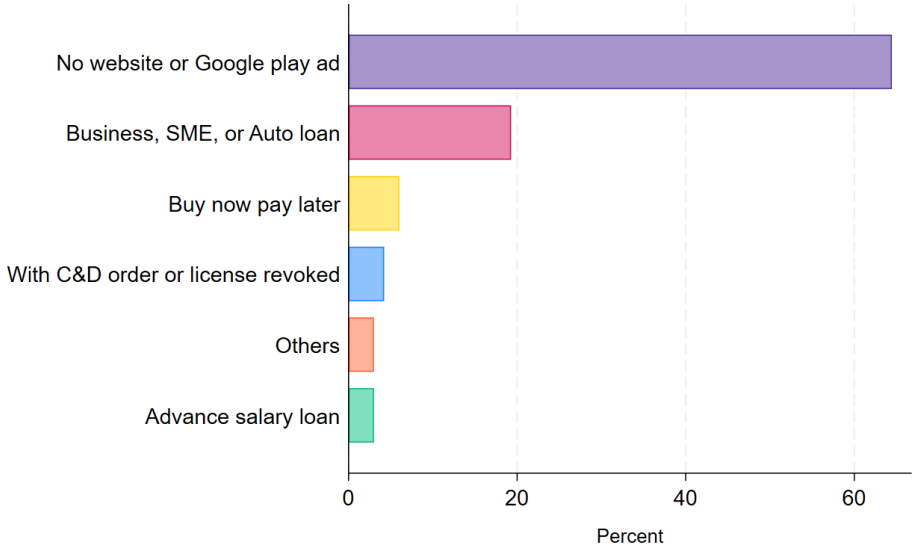


Figure 1 shows why the 166 platforms (out of 238 registered online lending platforms) were excluded in the final census: 107 (or 64%) do not have company websites, Google play advertisements, or downloadable mobile applications from Google play; 32 (or 19%) offer business or auto loans that require collateral; 10 (or 6%) offer 'buy now, pay later' financing; 7 (or 4%) had cease and desist orders or lending licenses were revoked; and 5 (or 3%) offer advance salary loans.

Figure 2: Explicit advertisement of attributes

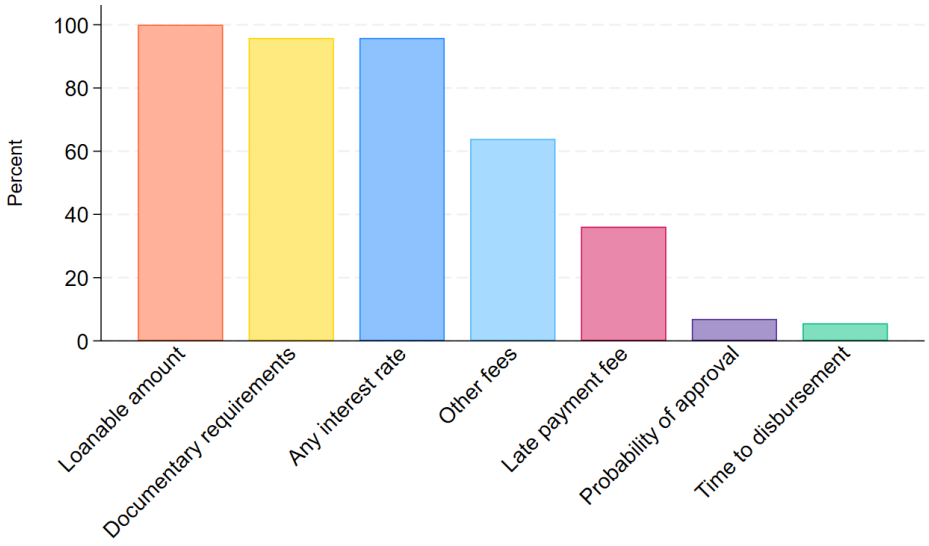
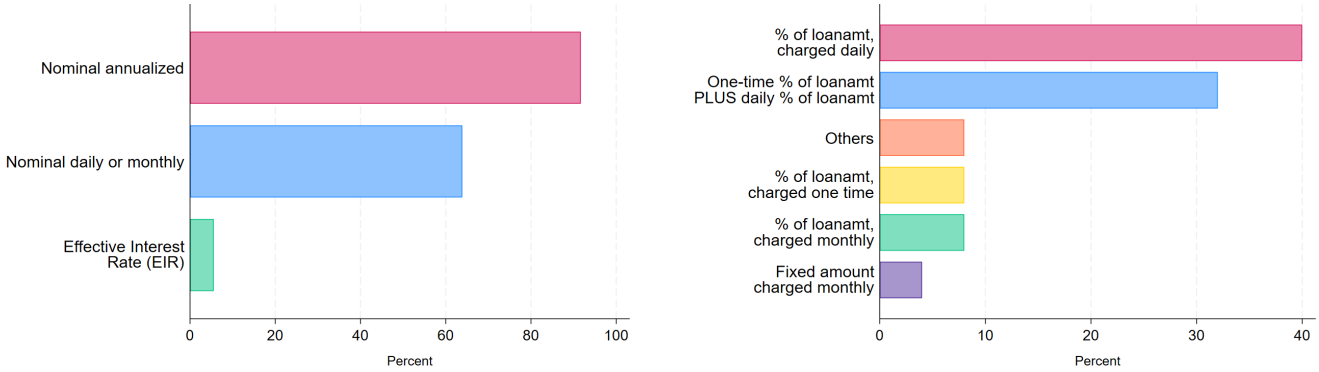


Figure 2 shows whether the loan attributes were explicitly advertised. An attribute is considered explicitly advertised if its value is specified in the advertisement. All eligible digital credit platforms explicitly advertised loanable amount. 69 (or 96%) advertised either documentary requirements or any interest rates. 46 (or 64%) advertised loan fees and only 26 (or 36%) advertised late payment fees. 5 (or 7%) and 4 (or 6%) advertised probability of approval and time to disbursement, respectively.

Figure 3: Content of advertisements



(a) Presentation of interest rate

(b) Late payment fee computation

Figure 3 presents the key findings on price obfuscation. Panel (a) illustrates the heterogeneity in how interest rates are presented among digital credit platforms that advertise them: 92% use nominal annualized rate, 64% use nominal daily or monthly rate, and 6% use effective interest rate. Similarly, panel (b) depicts the heterogeneity in how late payment fees are computed among the platforms that advertise them: 40% charge a daily penalty based on a percentage of the loan amount; 32% charge a one-time fee based on a percentage of the loan amount plus a daily penalty based on a percentage of the loan amount; 8% charge a one-time fee based on a percentage of the loan amount; 8% charge a monthly fee based on a percentage of the loan amount; and 4% charge a fixed amount monthly.

Table 1: Attributes and levels

	Levels		
	1 (Worst)	2 (Medium)	3 (Best)
Product attributes			
Effective interest rate (%)	25	15	5
Late payment fee per day (Philippine peso)	50	30	10
Time to disbursement (hours)	48	24	1
Number of documentary requirements	3	2	1
Probability of approval (%)	30	60	90

Table 1 presents the key attributes of the hypothetical digital credit products and their corresponding levels. There are five attributes and each attribute has three levels: worst, medium, and best. The specific attribute levels of the six hypothetical digital credit products are listed in appendix table A.2.

Table 2: Summary statistics

	Mean	Std. Dev	Min.	Max.
Socio-demographic characteristics				
Age	31.41	8.81	18.00	65.00
Female (=1)	0.59	0.49	0.00	1.00
Married (=1)	0.36	0.48	0.00	1.00
With bachelors degree (=1)	0.49	0.50	0.00	1.00
Formal employment (=1)	0.43	0.50	0.00	1.00
Urban (=1)	0.75	0.43	0.00	1.00
Invidual monthly net income (=1)				
Less than ₱15,000	0.44	0.50	0.00	1.00
₱15,000-₱29,999	0.32	0.47	0.00	1.00
₱30,000-₱44,999	0.14	0.35	0.00	1.00
₱45,000-₱59,999	0.06	0.25	0.00	1.00
₱60,000 or more	0.04	0.19	0.00	1.00
Experience with financial services (=1)				
Mobile banking app user	0.74	0.44	0.00	1.00
E-wallet app user	0.97	0.17	0.00	1.00
Experienced digital credit user	0.39	0.49	0.00	1.00
Behavioral and other characteristics (=1)				
Financially literate	0.09	0.28	0.00	1.00
Overconfident (financial knowledge)	0.55	0.50	0.00	1.00
Awareness of time inconsistency	0.16	0.36	0.00	1.00
Incurred late fee last 12 months	0.35	0.48	0.00	1.00
Delay pay essential bills last 12 months	0.58	0.49	0.00	1.00
Liquidity-constrained	0.43	0.49	0.00	1.00
Observations	4,018			

Notes: Table 2 presents the summary statistics. Variables with (=1) are dummy variables. Formal employment is defined as being employed in the private or public sector. Mobile banking app user is equal to 1 if the respondent performed a transaction on mobile banking app in the last 90 days. E-wallet app user is equal to 1 if the respondent sent or received payments using e-money or e-wallet account in the last 90 days. Experienced digital credit user is defined as taking out more than 1 (sample median) digital loan in the last 12 months. Financially literate is equal to 1 if the respondent answered all the Big 3 financial literacy questions correctly. Overconfidence is equal to 1 if the participant's self-assessment of how many questions she thinks she got right is higher than her actual correct answers to the Big 3 financial literacy questions. Awareness of time inconsistency is equal to 1 if the participant's reward chosen for avoiding late fee is above the sample median. Delay pay essential bills last 12 months is equal to 1 if the respondent delayed paying any essential bills due to lack of funds. Incurred late fee last 12 months is equal to 1 if the respondent incurred late payment fee for a missing a loan payment. Liquidity-constrained is equal to 1 if respondent answered *A great deal* or *A lot* to the question *"On a scale of 1 (A great deal) to 5 (None at all), to what extent do you perceive yourself as cash-constrained?"*. The average annual exchange rate in 2023 was 1 USD = 55.63 Php (source: Central Bank of the Philippines).

Table 3: Effect of T1, T2, and T3 on Effective Interest Rate

	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T1 Standardized-no EIR, random	-2.696	1.049	0.342	3.251	7.775
	(0.527)	(1.106)	(0.056)	(1.253)	(1.674)
	[0.000]***	[0.343]	[0.000]***	[0.009]***	[0.000]***
	{0.001}***	{0.086}*	{0.001}***	{0.005}***	{0.001}***
	{{0.001}}***	{{1.000}}	{{0.001}}***	{{0.001}}***	{{0.001}}***
T2 Standardized-with EIR, random	-2.936	0.361	0.327	3.632	6.071
	(0.535)	(1.100)	(0.057)	(1.236)	(1.712)
	[0.000]***	[0.743]	[0.000]***	[0.003]***	[0.000]***
	{0.001}***	{0.175}	{0.001}***	{0.002}***	{0.001}***
	{{0.001}}***	{{1.000}}	{{0.001}}***	{{0.001}}***	{{0.001}}***
T3 Ranked by EIR	-4.476	3.987	0.371	0.775	4.511
	(0.541)	(1.075)	(0.054)	(1.293)	(1.725)
	[0.000]***	[0.000]***	[0.000]***	[0.549]	[0.009]***
	{0.001}***	{0.001}***	{0.001}***	{0.134}	{0.005}***
	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{1.000}}	{{0.001}}***
Mean of control group	16.22	27.68	1.87	25.69	58.06
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	1,784	1,784	1,784	1,784	1,784
p-value(T1=T2)	0.649	0.524	0.790	0.772	0.325
p-value(T1=T3)	0.001	0.005	0.590	0.070	0.062
p-value(T2=T3)	0.005	0.001	0.417	0.035	0.382

Table 3 reports the average treatment effects of T1, T2, and T3 on: effective interest rate (in percentage points), late fee per day (in Philippine Peso), number of documents, time to disbursement (in hours), and probability of approval (in percentage points). All columns are estimated using the double-selection lasso linear regression (equation 1). In columns 1-5, there are no covariates selected from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2). Respondents who failed the attention check are excluded in the analysis. Control group (marketing advertisements) is the base category for all columns. In the bottom panel, we report the p-value from testing the equality of two coefficients, where the null hypothesis is that the coefficients are equal. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Effect of T4 to T7 on non-price attributes

	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)	Outcome Variable: Effective interest rate (%)
	(1)	(2)	(3)	(4)	(5)
T4 Ranked by late fee	-2.631				1.733
	(1.094)				(0.528)
	|0.016|**				|0.001|***
	{0.023}**				{0.003}***
	{{0.001}}***				{{0.001}}***
T5 Ranked by number of documents		-0.263			2.003
		(0.059)			(0.521)
		|0.000|***			|0.000|***
		{0.001}***			{0.001}***
		{{0.001}}***			{{0.001}}***
T6 Ranked by time to disbsurse			-8.234		0.254
			(1.349)		(0.556)
			|0.000|***		|0.647|
			{0.001}***		{0.276}
			{{0.001}}***		{{1.000}}
T7 Ranked by probability of approval				4.448	-1.304
				(1.788)	(0.523)
				|0.013|**	|0.013|**
				{0.010}***	{0.016}**
				{{0.001}}***	{{1.000}}
Mean of control group	28.04	2.20	29.32	64.13	13.29
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	901	896	903	901	2,251

Columns 1-4 of table 4 report the average treatment effects of T4 (ranked by late fee), T5 (ranked by number of documents), T6 (ranked by time to disbursement), and T7 (ranked by probability of approval) on their respective outcome variable: late fee per day (in Philippine Peso), number of documents, time to disbursement (in hours), and probability of approval (in percentage points). In column 5, we report the average treatment effects of T4-T7 on the effective interest rate to derive how consumers trade-off between the effective interest rate and non-price attributes. All columns are estimated using the double-selection lasso linear regression (equation 2). In column 1, the double-selection method selected monthly net income from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2). There are no covariates selected from the potential controls in other columns. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of T8 (own ranking) on price and non-price attributes

	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T8 own ranking	-0.021	0.385	-0.013	-0.673	-0.738
	(0.548)	(1.076)	(0.056)	(1.316)	(1.789)
	|0.969|	|0.720|	|0.816|	|0.609|	|0.680|
	{1.000}	{1.000}	{1.000}	{1.000}	{1.000}
	{{1.000}}	{{1.000}}	{{1.000}}	{{1.000}}	{{1.000}}
Mean of control group	13.29	28.04	2.20	29.32	64.13
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	883	883	883	883	883

Table 5 reports the average treatment effects of T8 on: effective interest rate (in percentage points), late fee per day (in Philippine Peso), number of documents, time to disbursement (in hours), and probability of approval (in percentage points). All columns are estimated using the double-selection lasso linear regression (equation 2). In columns 1-5, there are no covariates selected from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2). Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Heterogeneous analysis - T4 × Overconfidence-financial knowledge

	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: No. of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T4 Ranked by late fee	-5.140	2.916	-0.204	1.466	-3.266
	(1.568)	(0.750)	(0.082)	(1.802)	(2.562)
	[0.001]***	[0.000]***	[0.013]**	[0.416]	[0.202]
	{0.005}***	{0.002}***	{0.036}**	{0.301}	{0.203}
	{{0.010}}***	{{0.010}}***	{{0.010}}***	{{1.000}}	{{1.000}}
Overconfident-financial knowledge	-2.231	0.921	-0.053	1.942	0.350
	(1.509)	(0.757)	(0.079)	(1.838)	(2.506)
	[0.139]	[0.224]	[0.502]	[0.291]	[0.889]
T4 × Overconfident	4.879	-2.299	0.125	-2.770	0.765
	(2.184)	(1.055)	(0.115)	(2.504)	(3.567)
	[0.025]**	[0.029]**	[0.279]	[0.268]	[0.830]
	{0.045}**	{0.045}**	{0.211}	{0.211}	{0.509}
	{{0.010}}***	{{0.010}}***	{{1.000}}	{{1.000}}	{{1.000}}
Mean of control group	28.04	13.29	2.20	29.32	64.13
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	901	901	901	901	901
Linear combination: T4 + Interaction term	-0.261	0.617	-0.079	-1.304	-2.502
p-value	0.864	0.405	0.326	0.453	0.314

Table 6 reports treatment effect heterogeneity by interacting T4 (ranked by late fee) with overconfidence-financial knowledge. The dummy variable overconfidence-financial knowledge is equal to 1 if the participant's self-assessment of how many questions she thinks she got right is higher than her actual correct answers to the "Big 3" financial literacy questions, and equals zero otherwise. All columns are estimated using the double-selection lasso linear regression (equation 3). In column 1, the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): monthly net income. There are no covariates selected from the potential controls in other columns. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Heterogeneous analysis - T3 × Liquidity-constrained

	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: No. of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T3 Ranked by EIR	-2.500	3.856	0.102	-1.084	-0.106
	(0.684)	(1.341)	(0.070)	(1.773)	(2.331)
	[0.000]***	[0.004]***	[0.148]	[0.541]	[0.964]
	{0.003}***	{0.019}**	{0.262}	{0.511}	{0.628}
	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{1.000}}	{{1.000}}
Liquidity-constrained	0.899	-2.801	-0.003	0.511	-0.924
	(0.780)	(1.551)	(0.082)	(1.875)	(2.583)
	[0.249]	[0.071]*	[0.975]	[0.785]	[0.720]
T3 × Liquidity-constrained	2.378	-0.578	-0.134	-4.338	-3.275
	(1.099)	(2.156)	(0.110)	(2.751)	(3.642)
	[0.030]**	[0.789]	[0.221]	[0.115]	[0.369]
	{0.089}*	{0.584}	{0.348}	{0.252}	{0.421}
	{{0.001}}***	{{1.000}}	{{1.000}}	{{0.001}}***	{{1.000}}
Mean of control group	13.29	28.04	2.20	29.32	64.13
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	893	893	893	893	893
Linear combination: T3 + Interaction term	-0.122	3.278	-0.033	-5.423	-3.382
p-value	0.888	0.051	0.699	0.010	0.227

Table 7 reports treatment effect heterogeneity by interacting T3 (ranked by late EIR) with liquidity-constrained. The dummy variable liquidity-constrained is equal to 1 if respondent answered *A great deal* or *A lot* to the question *"On a scale of 1 (A great deal) to 5 (None at all), to what extent do you perceive yourself as cash-constrained?"*, and equals zero otherwise. All columns are estimated using the double-selection lasso linear regression (equation 3). In all columns (1-5), the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): age, urban, and experienced digital credit user. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Appendix

A Tables

Table A.1: Census advertised loan attributes

	Mean	Std. Dev	Min.	Max.
Any interest rates (%)				
Nominal daily interest rate	0.35	0.75	0.02	5.00
Nominal annualized rate	42.98	49.62	0.20	194.00
Effective interest rate	13.64	2.72	9.56	15.00
Late payment fee				
Percentage of loan amount, charged one-time (%)	5.50	2.59	2.00	10.00
Percentage of loan amount, charged monthly (%)	5.00	0.00	5.00	5.00
Percentage of loan amount, charged daily (%)	2.35	1.11	0.16	4.25
Fixed amount in Peso, charged monthly (in Php)	500.00	.	500.00	500.00
Time to disbursement				
Approval to disbursement (hours)	27.46	21.49	0.03	72.00
Documentary requirements (dummy)				
Government-issued ID	0.97	0.17	0.00	1.00
Proof of employment	0.07	0.26	0.00	1.00
Proof of income	0.16	0.37	0.00	1.00
Proof of billing	0.04	0.21	0.00	1.00
Bank account	0.10	0.30	0.00	1.00
Social media account	0.01	0.12	0.00	1.00
Probability of approval				
Probability of approval (%)	88.00	4.47	85.00	95.00

Table A.1 presents the summary statistics of loan attributes from the census.

Table A.2: Attributes, levels, and product scores

	Effective interest Rate (%)	Late fee per day (Php)	Number of loan documents	Time to disburse (hours)	Probability of approval (%)	Product score
Product name						
Loan OR	25 [1]	10 [3]	1 [3]	24 [2]	30 [1]	[10]
Loan GN	25 [1]	30 [2]	2 [2]	1 [3]	60 [2]	[10]
Loan BL	5 [3]	30 [2]	3 [1]	48 [1]	90 [3]	[10]
Loan PR	5 [3]	50 [1]	2 [2]	1 [3]	30 [1]	[10]
Loan YL	15 [2]	50 [1]	1 [3]	24 [2]	60 [2]	[10]
Loan WH	15 [2]	10 [3]	3 [1]	3 [1]	90 [3]	[10]

Notes: There are five attributes and each attribute has three levels. The numbers in brackets [ ] are attribute scores, which range from 1 to 3 corresponding to the three attribute levels. The worst attribute level is assigned a value of 1 while the best is assigned 3. Product score is derived as the sum of attribute scores.

Table A.3: Balance table

Variable	(1) Control Mean/SE	(2) T1 Full information Mean/SE	(3) T2 With EIR, random Mean/SE	(4) T3 Sorted by EIR Mean/SE	(5) T4 Sorted by Late fee Mean/SE	(6) T5 Sorted by No. docs Mean/SE	(7) T6 Sorted by Time disburse Mean/SE	(8) T7 Sorted by Probability app. Mean/SE	(9) T8 Own ranking Mean/SE	T-test Difference (1)-(2)	(1)-(3)	(1)-(4)	(1)-(5)	(1)-(6)	(1)-(7)	(1)-(8)	(1)-(9)	F-test for joint orthogonality
Age	32.307	31.557	30.122	31.068	31.792	31.016	31.570	31.809	31.425	0.751	2.185***	1.240**	0.516	1.292**	0.738	0.498	0.882	2.484**
	(0.416)	(0.430)	(0.374)	(0.407)	(0.436)	(0.406)	(0.408)	(0.438)	(0.432)									
Female	0.548	0.590	0.622	0.578	0.570	0.619	0.567	0.603	0.591	-0.043	-0.074**	-0.030	-0.022	-0.071**	-0.019	-0.055*	-0.043	1.122
	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)									
Married	0.396	0.376	0.347	0.357	0.324	0.334	0.347	0.361	0.430	0.021	0.050	0.040	0.073**	0.062*	0.050	0.035	-0.033	2.023**
	(0.023)	(0.023)	(0.022)	(0.023)	(0.022)	(0.022)	(0.022)	(0.023)	(0.024)									
Employed in formal sector	0.457	0.410	0.453	0.420	0.388	0.422	0.428	0.452	0.469	0.047	0.003	0.037	0.069**	0.035	0.028	0.004	-0.012	1.261
	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)									
With bachelors degree	0.497	0.439	0.489	0.510	0.481	0.489	0.525	0.435	0.527	0.058*	0.008	-0.013	0.016	0.008	-0.029	0.062*	-0.030	1.967**
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)	(0.023)	(0.024)									
Urban	0.757	0.756	0.769	0.740	0.747	0.753	0.764	0.747	0.725	0.002	-0.012	0.017	0.010	0.004	-0.007	0.010	0.032	0.393
	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)									
Ind. month net income (discretized)	1.998	1.941	1.916	1.930	1.980	1.937	1.956	1.958	1.945	0.057	0.082	0.068	0.018	0.061	0.042	0.040	0.053	0.247
	(0.052)	(0.052)	(0.048)	(0.053)	(0.051)	(0.051)	(0.053)	(0.052)	(0.051)									
Mobile banking app user	0.777	0.731	0.773	0.727	0.745	0.717	0.722	0.738	0.741	0.047	0.004	0.050*	0.032	0.060**	0.055*	0.039	0.036	1.101
	(0.020)	(0.021)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)									
E-wallet app user	0.967	0.980	0.964	0.975	0.962	0.978	0.962	0.976	0.979	-0.013	0.002	-0.009	0.004	-0.011	0.004	-0.009	-0.013	0.846
	(0.008)	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.007)									
Experienced digital credit user	0.390	0.376	0.358	0.402	0.381	0.451	0.371	0.395	0.370	0.014	0.032	-0.012	0.008	-0.061*	0.019	-0.005	0.020	1.357
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)	(0.023)	(0.023)									
N	449	442	450	443	451	446	453	451	433									
F-test of joint significance (F-stat)										1.070	2.304**	1.209	1.058	2.933***	0.906	1.128	1.237	
F-test, number of observations										891	899	892	900	895	902	900	882	

Notes: The value displayed for t-tests are the differences in the means across the groups. The value displayed for F-tests are the F-statistics. Standard errors are robust. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A.4: Comparison of study sample with 2021 BSP Financial Inclusion Survey (FIS)

Variable	BSP FIS	Experiment	
		Full sample	Restricted sample
Area			
National Capital Region	13%	43%	44%
North and Central Luzon	22%	24%	23%
South Luzon	23%	24%	24%
Visayas	19%	6%	6%
Mindanao	23%	3%	3%
Age			
15-19	13%	3%	4%
20-29	28%	45%	43%
30-39	20%	35%	36%
40-49	18%	13%	13%
50-59	15%	3%	4%
60 above	7%	1%	1%
Locale			
Urban	52%	75%	75%
Rural	48%	25%	25%
Gender			
Male	50%	43%	41%
Female	50%	57%	59%
Employment status			
Working	62%	70%	69%
Non-working	38%	30%	31%
Marital status			
Married	50%	35%	36%
Single	30%	62%	61%
Separated	2%	2%	2%
Widowed	5%	1%	1%
Educational attainment			
None/some/completed elementary	12%	6%	7%
Some/completed high school	60%	44%	45%
Some/completed vocational	12%	-	-
Some/completed college or postgraduate degree	16%	50%	49%
Correct answers to financial literacy questions			
Division	91%	78%	77%
Diversification of portfolio	61%	26%	24%
Investment risk	58%	81%	82%
Inflation	42%	42%	41%
Simple interest	32%	56%	56%
Compound interest	30%	34%	35%
All 6 questions	2%	3%	3%

Notes: The 2021 Financial Inclusion Survey (FIS) is a nationally representative survey conducted by the Bangko Sentral ng Pilipinas (BSP). The full sample includes all respondents from the experiment, while the restricted sample excludes those who failed the attention check.

Table A.5: Effect of T4 (Ranked by late fee) on Late fee

	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Number of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T4 Ranked by late fee	-2.631	1.733	-0.140	0.046	-2.869
	(1.094)	(0.528)	(0.058)	(1.251)	(1.781)
	[0.016]**	[0.001]***	[0.015]**	[0.971]	[0.107]
	{0.023}**	{0.006}***	{0.023}**	{0.241}	{0.057}*
	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{1.000}}	{{1.000}}
Mean of control group	28.04	13.29	2.20	29.32	64.13
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	901	901	901	901	901

Table A.5 reports the average treatment effects of T4 (ranked by late fee) on: late fee per day (in Philippine Peso), effective interest rate (in percentage points), number of documents, time to disbursement (in hours), and probability of approval (in percentage points). As specified in our pre-analysis plan, the outcome variable of interest for this treatment arm is late fee per day (column 1). All columns are estimated using the double-selection lasso linear regression (equation 2). In column 1, the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): monthly net income. There are no covariates selected from the potential controls in other columns. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table A.6: Effect of T5 (Ranked by number of documents) on Number of documents

	Outcome Variable: Number of documents	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T5 Ranked by number of documents	-0.263	2.002	-0.600	0.375	-2.183
	(0.059)	(0.517)	(1.113)	(1.207)	(1.730)
	[0.000]***	[0.000]***	[0.589]	[0.756]	[0.207]
	{0.001}***	{0.001}***	{0.528}	{0.528}	{0.262}
	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{1.000}}	{{0.001}}***
Mean of control group	2.20	13.29	28.04	29.32	64.13
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	896	896	896	896	896

Table A.6 reports the average treatment effects of T5 (ranked by number of documents on) on: number of documents, effective interest rate (in percentage points), late fee per day (in Philippine Peso), time to disbursement (in hours), and probability of approval (in percentage points). As specified in our pre-analysis plan, the outcome variable of interest for this treatment arm is number of documents (column 1). All columns are estimated using the double-selection lasso linear regression (equation 2). In column 2, the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): with bachelors degre. There are no covariates selected from the potential controls in other columns. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: Effect of T6 (Ranked by time to disbursement) on Time to disbursement

	Outcome Variable: Time to disburse (hours)	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T6 Ranked by time to disbsurse	-8.234	0.254	3.368	-0.034	-5.789
	(1.349)	(0.556)	(1.062)	(0.052)	(1.739)
	[0.000]***	[0.647]	[0.002]***	[0.505]	[0.001]***
	{0.001}***	{0.350}	{0.003}***	{0.338}	{0.002}***
	{{0.001}}***	{{1.000}}	{{0.001}}***	{{1.000}}	{{0.001}}***
Mean of control group	29.32	13.29	28.04	2.20	64.13
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	903	903	903	903	903

Table A.7 reports the average treatment effects of T6 (ranked by time to disbursement) on: time to disbursement (in hours), effective interest rate (in percentage points), late fee per day (in Philippine Peso), number of documents, and probability of approval (in percentage points). As specified in our pre-analysis plan, the outcome variable of interest for this treatment arm is time to disbursement (column 1). All columns are estimated using the double-selection lasso linear regression (equation 2). There are no covariates selected from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2). Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table A.8: Effect of T7 (Ranked by probability of approval) on Probability of approval

	Outcome Variable: Probability of approval (%)	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Time to disburse (hours)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents
	(1)	(2)	(3)	(4)	(5)
T7 Ranked by probability of approval	4.448	-1.304	3.835	-1.814	0.208
	(1.788)	(0.523)	(1.293)	(1.051)	(0.054)
	[0.013]**	[0.013]**	[0.003]***	[0.084]*	[0.000]***
	{0.010}***	{0.010}***	{0.007}***	{0.018}**	{0.001}***
	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{0.001}}***
Mean of control group	64.13	13.29	29.32	28.04	2.20
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	901	901	901	901	901

Table A.8 reports the average treatment effects of T7 (ranked by probability of approval) on: probability of approval (in percentage points), effective interest rate (in percentage points), time to disbursement (in hours), late fee per day (in Philippine Peso), and number of documents. As specified in our pre-analysis plan, the outcome variable of interest for this treatment arm is probability of approval (column 1). All columns are estimated using the double-selection lasso linear regression (equation 2). There are no covariates selected from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2). Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table A.9: Heterogeneous analysis - T4 × Overconfidence-general knowledge

	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: No. of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T4 Ranked by late fee	-5.741	2.908	-0.157	1.975	-1.901
	(1.806)	(0.850)	(0.097)	(2.029)	(3.002)
	[0.001]***	[0.001]***	[0.106]	[0.330]	[0.527]
	{0.007}***	{0.007}***	{0.175}	{0.309}	{0.491}
	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{1.000}}
Overconfident-general knowledge	-2.120	1.752	-0.069	-1.080	-1.238
	(1.590)	(0.775)	(0.083)	(1.929)	(2.635)
	[0.183]	[0.024]**	[0.402]	[0.575]	[0.638]
T4 × Overconfident	4.883	-1.812	0.025	-3.111	-1.586
	(2.268)	(1.083)	(0.121)	(2.575)	(3.730)
	[0.031]**	[0.094]*	[0.837]	[0.227]	[0.671]
	{0.092}*	{0.175}	{0.609}	{0.270}	{0.594}
	{{0.001}}***	{{0.001}}***	{{1.000}}	{{0.001}}***	{{1.000}}
Mean of control group	28.04	13.29	2.20	29.32	64.13
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	901	901	901	901	901
Linear combination: T4 + Interaction term	-0.858	1.096	-0.132	-1.136	-3.487
p-value	0.532	0.102	0.064	0.474	0.115

Table A.9 reports treatment effect heterogeneity by interacting T4 (ranked by late fee) with overconfidence-general knowledge. The dummy variable overconfidence-general knowledge is equal to 1 if the participant's self-assessment of how many questions she thinks she got right is higher than her actual correct answers to the general knowledge questions, and equals zero otherwise. All columns are estimated using the double-selection lasso linear regression (equation 3). In column 1, the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): monthly net income. There are no covariates selected from the potential controls in other columns. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table A.10: Correlates of Overconfidence

	Outcome Variable: Missed loan payment last 12 mths	Outcome Variable: Incurred late fee last 12 mths	Outcome Variable: Awareness of time inconsistency
	(1)	(2)	(3)
Panel A: Financial Knowledge			
Overconfident-financial knowledge	0.117***	0.120***	-0.050**
	(0.032)	(0.032)	(0.025)
Panel B: General knoweldge			
Overconfident-general knowledge	0.082**	0.081**	-0.056**
	(0.034)	(0.033)	(0.027)
Obersvations	901	901	901

Table A.10 shows the correlates of overconfidence. The outcome variables are dummy indicators as defined in table 2. Both measures of overconfidence are dummy variables equal to 1 if the self-perceived number of correct answers exceeds the actual number of correct answers on financial or general knowledge questions. The OLS regression is based on a subsample consisting of respondents assigned to T2 (Standardized-with EIR, random) and T4 (ranked by late fee). Respondents who failed the attention check are excluded in the analysis. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

B Figures

Figure 4: Example Control group "Marketing advertisements" page

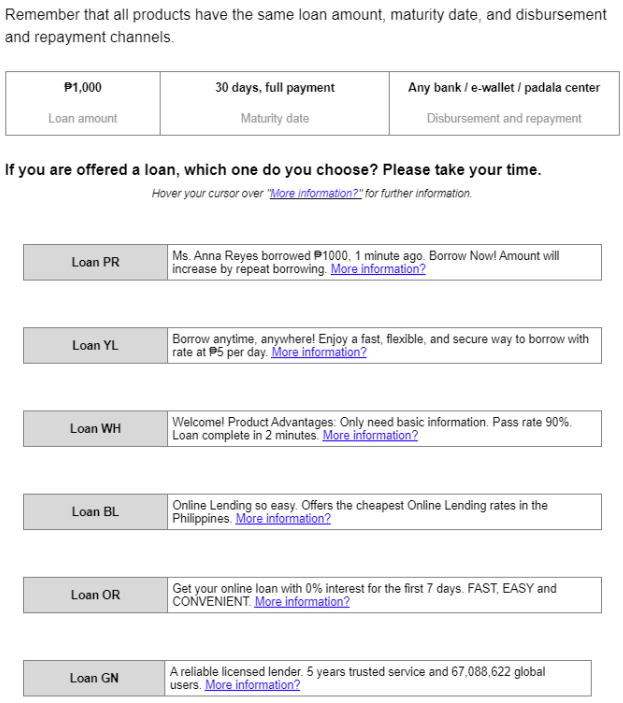
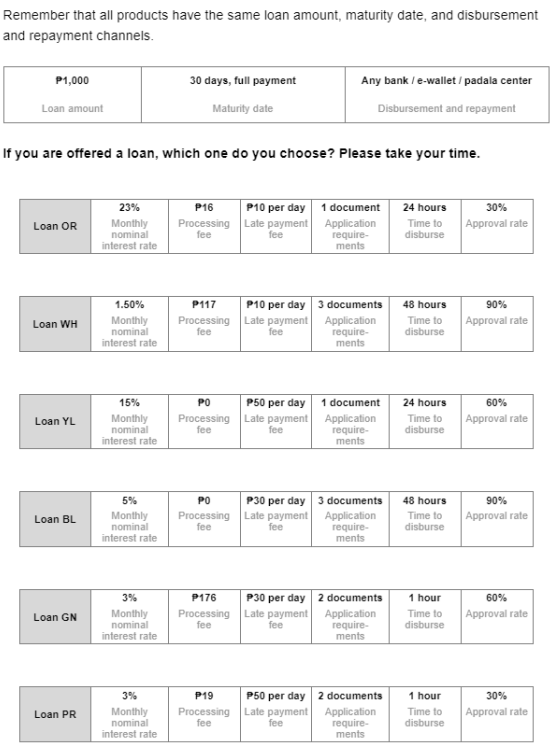


Figure 5: Example Treatment 1 "Standardized - no EIR, random order" page



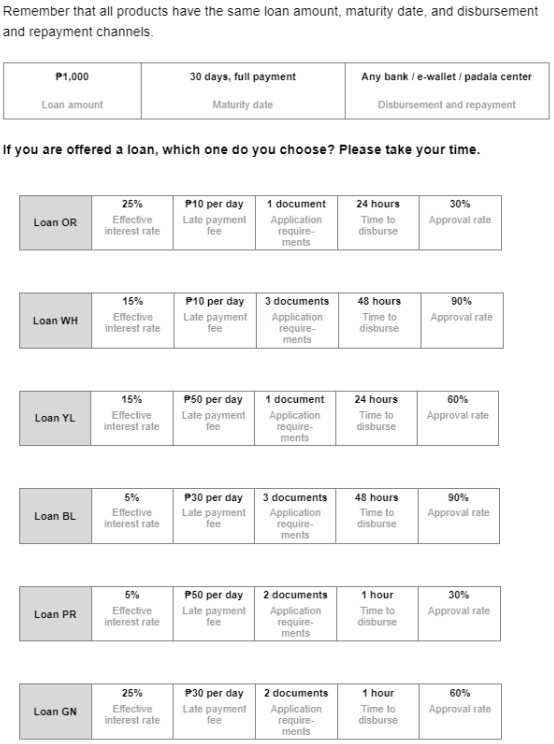
Remember that all products have the same loan amount, maturity date, and disbursement and repayment channels.

₱1,000	30 days, full payment	Any bank / e-wallet / padala center
Loan amount	Maturity date	Disbursement and repayment

If you are offered a loan, which one do you choose? Please take your time.

Loan OR	23% Monthly nominal interest rate	₱16 Processing fee	₱10 per day Late payment fee	1 document Application require-ments	24 hours Time to disburse	30% Approval rate
Loan WH	1.50% Monthly nominal interest rate	₱117 Processing fee	₱10 per day Late payment fee	3 documents Application require-ments	48 hours Time to disburse	90% Approval rate
Loan YL	15% Monthly nominal interest rate	₱0 Processing fee	₱50 per day Late payment fee	1 document Application require-ments	24 hours Time to disburse	60% Approval rate
Loan BL	5% Monthly nominal interest rate	₱0 Processing fee	₱30 per day Late payment fee	3 documents Application require-ments	48 hours Time to disburse	90% Approval rate
Loan GN	3% Monthly nominal interest rate	₱176 Processing fee	₱30 per day Late payment fee	2 documents Application require-ments	1 hour Time to disburse	60% Approval rate
Loan PR	3% Monthly nominal interest rate	₱19 Processing fee	₱50 per day Late payment fee	2 documents Application require-ments	1 hour Time to disburse	30% Approval rate

Figure 6: Example Treatment 2 "Standardized - with EIR, random order" page



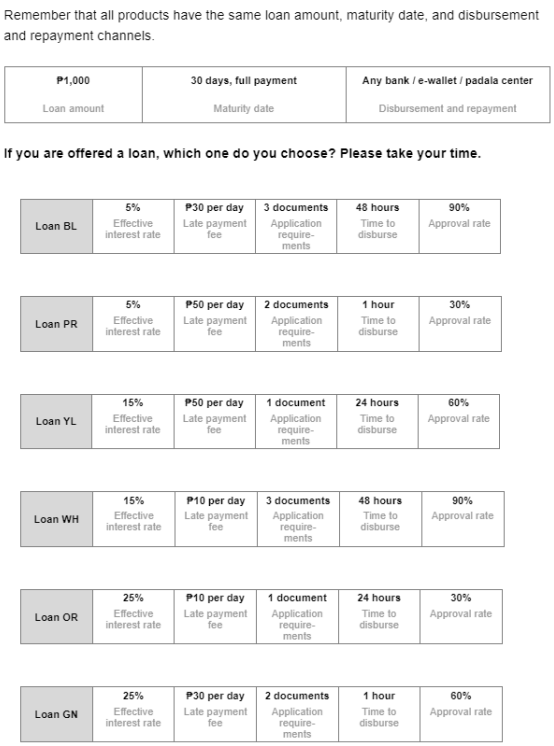
Remember that all products have the same loan amount, maturity date, and disbursement and repayment channels.

₱1,000	30 days, full payment	Any bank / e-wallet / padala center
Loan amount	Maturity date	Disbursement and repayment

If you are offered a loan, which one do you choose? Please take your time.

Loan OR	25% Effective interest rate	₱10 per day Late payment fee	1 document Application require-ments	24 hours Time to disburse	30% Approval rate
Loan WH	15% Effective interest rate	₱10 per day Late payment fee	3 documents Application require-ments	48 hours Time to disburse	90% Approval rate
Loan YL	15% Effective interest rate	₱50 per day Late payment fee	1 document Application require-ments	24 hours Time to disburse	60% Approval rate
Loan BL	5% Effective interest rate	₱30 per day Late payment fee	3 documents Application require-ments	48 hours Time to disburse	90% Approval rate
Loan PR	5% Effective interest rate	₱50 per day Late payment fee	2 documents Application require-ments	1 hour Time to disburse	30% Approval rate
Loan GN	25% Effective interest rate	₱30 per day Late payment fee	2 documents Application require-ments	1 hour Time to disburse	60% Approval rate

Figure 7: Example Treatment 3 "Ranked by effective interest rate" page



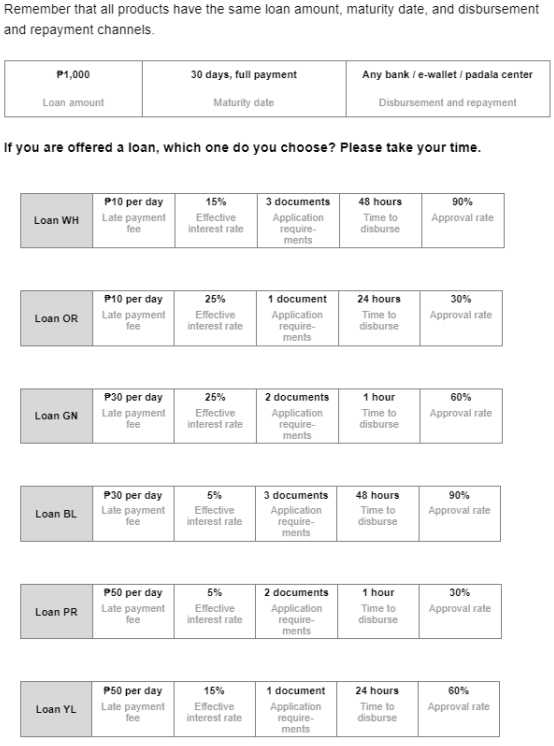
Remember that all products have the same loan amount, maturity date, and disbursement and repayment channels.

₱1,000	30 days, full payment	Any bank / e-wallet / padala center
Loan amount	Maturity date	Disbursement and repayment

If you are offered a loan, which one do you choose? Please take your time.

Loan BL	5% Effective interest rate	₱30 per day Late payment fee	3 documents Application require-ments	48 hours Time to disburse	90% Approval rate
Loan PR	5% Effective interest rate	₱50 per day Late payment fee	2 documents Application require-ments	1 hour Time to disburse	30% Approval rate
Loan YL	15% Effective interest rate	₱50 per day Late payment fee	1 document Application require-ments	24 hours Time to disburse	60% Approval rate
Loan WH	15% Effective interest rate	₱10 per day Late payment fee	3 documents Application require-ments	48 hours Time to disburse	90% Approval rate
Loan OR	25% Effective interest rate	₱10 per day Late payment fee	1 document Application require-ments	24 hours Time to disburse	30% Approval rate
Loan GN	25% Effective interest rate	₱30 per day Late payment fee	2 documents Application require-ments	1 hour Time to disburse	60% Approval rate

Figure 8: Example Treatment 4 "Ranked by late payment fee per day" page



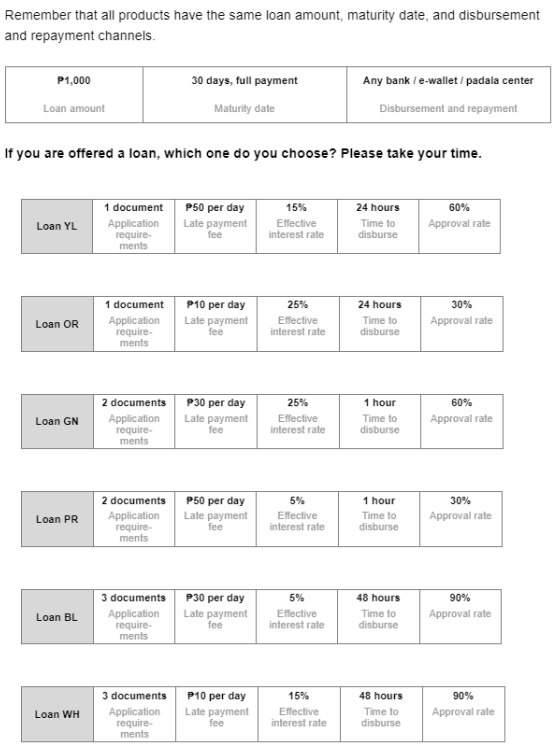
Remember that all products have the same loan amount, maturity date, and disbursement and repayment channels.

₱1,000	30 days, full payment	Any bank / e-wallet / padala center
Loan amount	Maturity date	Disbursement and repayment

If you are offered a loan, which one do you choose? Please take your time.

Loan WH	₱10 per day Late payment fee	15% Effective interest rate	3 documents Application require-ments	48 hours Time to disburse	90% Approval rate
Loan OR	₱10 per day Late payment fee	25% Effective interest rate	1 document Application require-ments	24 hours Time to disburse	30% Approval rate
Loan GN	₱30 per day Late payment fee	25% Effective interest rate	2 documents Application require-ments	1 hour Time to disburse	60% Approval rate
Loan BL	₱30 per day Late payment fee	5% Effective interest rate	3 documents Application require-ments	48 hours Time to disburse	90% Approval rate
Loan PR	₱50 per day Late payment fee	5% Effective interest rate	2 documents Application require-ments	1 hour Time to disburse	30% Approval rate
Loan YL	₱50 per day Late payment fee	15% Effective interest rate	1 document Application require-ments	24 hours Time to disburse	60% Approval rate

Figure 9: Example Treatment 5 "Ranked by number of documents" page



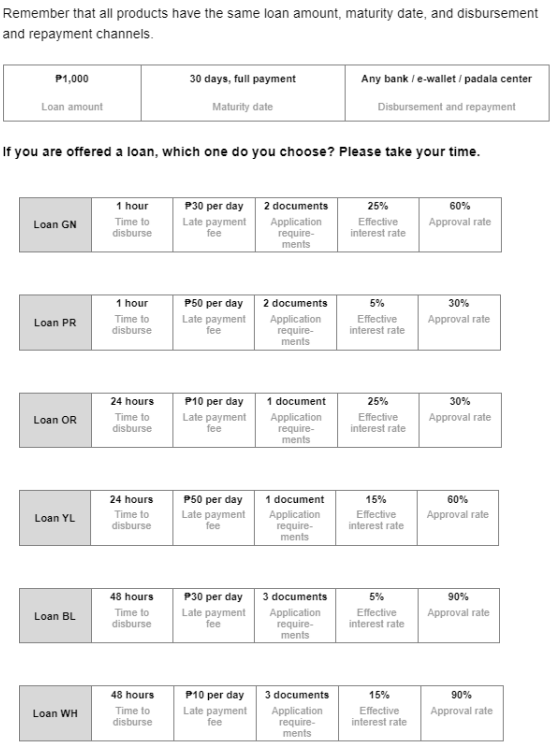
Remember that all products have the same loan amount, maturity date, and disbursement and repayment channels.

₱1,000 Loan amount	30 days, full payment Maturity date	Any bank / e-wallet / padala center Disbursement and repayment

If you are offered a loan, which one do you choose? Please take your time.

Loan YL	1 document Application require-ments	₱50 per day Late payment fee	15% Effective interest rate	24 hours Time to disburse	60% Approval rate
Loan OR	1 document Application require-ments	₱10 per day Late payment fee	25% Effective interest rate	24 hours Time to disburse	30% Approval rate
Loan GN	2 documents Application require-ments	₱30 per day Late payment fee	25% Effective interest rate	1 hour Time to disburse	60% Approval rate
Loan PR	2 documents Application require-ments	₱50 per day Late payment fee	5% Effective interest rate	1 hour Time to disburse	30% Approval rate
Loan BL	3 documents Application require-ments	₱30 per day Late payment fee	5% Effective interest rate	48 hours Time to disburse	90% Approval rate
Loan WH	3 documents Application require-ments	₱10 per day Late payment fee	15% Effective interest rate	48 hours Time to disburse	90% Approval rate

Figure 10: Example Treatment 6 "Ranked by time to disburse" page



Remember that all products have the same loan amount, maturity date, and disbursement and repayment channels.

₱1,000 Loan amount	30 days, full payment Maturity date	Any bank / e-wallet / padala center Disbursement and repayment

If you are offered a loan, which one do you choose? Please take your time.

Loan GN	1 hour Time to disburse	₱30 per day Late payment fee	2 documents Application require-ments	25% Effective interest rate	60% Approval rate
Loan PR	1 hour Time to disburse	₱50 per day Late payment fee	2 documents Application require-ments	5% Effective interest rate	30% Approval rate
Loan OR	24 hours Time to disburse	₱10 per day Late payment fee	1 document Application require-ments	25% Effective interest rate	30% Approval rate
Loan YL	24 hours Time to disburse	₱50 per day Late payment fee	1 document Application require-ments	15% Effective interest rate	60% Approval rate
Loan BL	48 hours Time to disburse	₱30 per day Late payment fee	3 documents Application require-ments	5% Effective interest rate	90% Approval rate
Loan WH	48 hours Time to disburse	₱10 per day Late payment fee	3 documents Application require-ments	15% Effective interest rate	90% Approval rate

Figure 11: Example Treatment 7 "Ranked by probability of approval" page

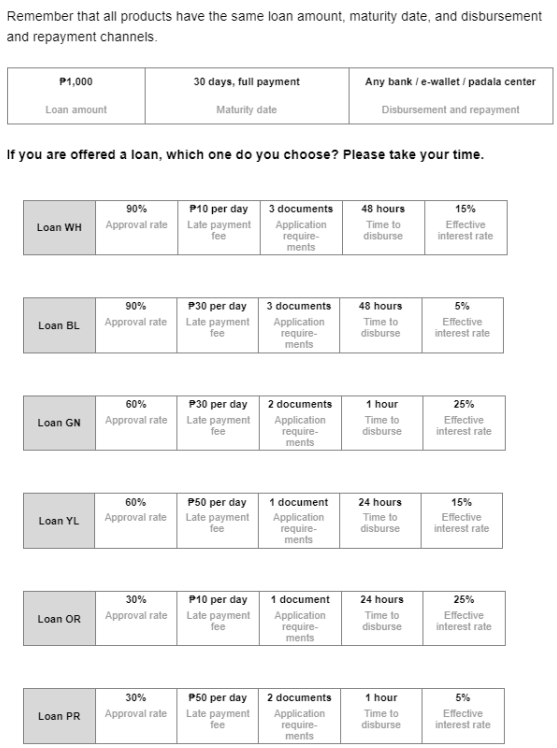
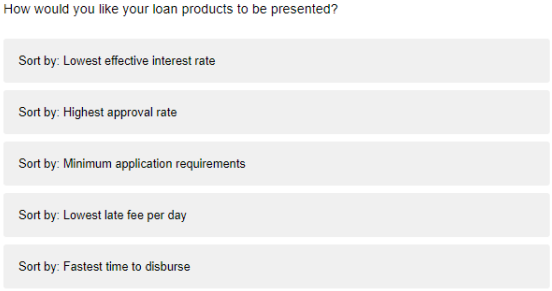


Figure 12: Example Treatment 8 "Personal ranking" landing page



C Robustness checks - unrestricted sample

Table C.1: Robustness check (unrestricted sample) - Effect of T1, T2, and T3 on Effective Interest Rate

	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T1 Standardized-no EIR, random	-2.783	-0.013	0.417	4.139	9.281
	(0.493)	(1.052)	(0.053)	(1.178)	(1.573)
	[0.000]***	[0.990]	[0.000]***	[0.000]***	[0.000]***
	{0.001}***	{0.153}	{0.001}***	{0.001}***	{0.001}***
	{{0.001}}***	{{1.000}}	{{0.001}}***	{{0.001}}***	{{0.001}}***
T2 Standardized-with EIR, random	-3.064	0.455	0.373	3.017	6.406
	(0.511)	(1.047)	(0.053)	(1.183)	(1.617)
	[0.000]***	[0.664]	[0.000]***	[0.011]**	[0.000]***
	{0.001}***	{0.150}	{0.001}***	{0.004}***	{0.001}***
	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{0.001}}***
T3 Ranked by EIR	-4.700	3.544	0.427	1.919	6.301
	(0.511)	(1.014)	(0.052)	(1.211)	(1.618)
	[0.000]***	[0.000]***	[0.000]***	[0.113]	[0.000]***
	{0.001}***	{0.001}***	{0.001}***	{0.027}**	{0.001}***
	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{0.001}}***
Mean of control group	16.42	27.96	1.83	25.30	57.30
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	1,992	1,992	1,992	1,992	1,992
p-value(T1=T2)	0.573	0.649	0.404	0.373	0.079
p-value(T1=T3)	0.000	0.000	0.846	0.085	0.069
p-value(T2=T3)	0.002	0.002	0.292	0.395	0.950

Table C.1 reports the average treatment effects of T1, T2, and T3 on: effective interest rate (in percentage points), late fee per day (in Philippine Peso), number of documents, time to disbursement (in hours), and probability of approval (in percentage points). All columns are estimated using the double-selection lasso linear regression (equation 1). In columns 1-5, the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): age. Respondents who failed the attention check are included in the analysis. Control group (marketing advertisements) is the base category for all columns. In the bottom panel, we report the p-value from testing the equality of two coefficients, where the null hypothesis is that the coefficients are equal. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table C.2: Robustness check (unrestricted sample) - Effect of T4 to T7 on non-price attributes

	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)	Outcome Variable: Effective interest rate (%)
	(1)	(2)	(3)	(4)	(5)
T4 Ranked by late fee	-2.293				1.316
	(1.039)				(0.508)
	[0.027]**				[0.010]***
	{0.033}**				{0.020}**
	{{0.001}}***				{{0.001}}***
T5 Ranked by number of documents		-0.247			1.876
		(0.055)			(0.498)
		[0.000]***			[0.000]***
		{0.001}***			{0.001}***
		{{0.001}}***			{{0.001}}***
T6 Ranked by time to disbsurse			-6.872		0.143
			(1.298)		(0.531)
			[0.000]***		[0.788]
			{0.001}***		{0.188}
			{{0.001}}***		{{0.001}}***
T7 Ranked by probability of approval				3.299	-1.078
				(1.696)	(0.509)
				[0.052]*	[0.034]**
				{0.041}**	{0.036}**
				{{0.001}}***	{{0.001}}***
Mean of control group	28.31	2.20	28.43	63.86	13.39
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	989	1,000	993	997	2,485

Columns 1-4 of table C.2 report the average treatment effects of T4 (ranked by late fee), T5 (ranked by number of documents), T6 (ranked by time to disbursement), and T7 (ranked by probability of approval) on their respective outcome variable: late fee per day (in Philippine Peso), number of documents, time to disbursement (in hours), and probability of approval (in percentage points). In column 5, we report the average treatment effects of T4-T7 on the effective interest rate to derive how consumers trade-off between the effective interest rate and non-price attributes. All columns are estimated using the double-selection lasso linear regression (equation 2). In columns 1 and 5, the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): monthly net income. There are no covariates selected from the potential controls in other columns. Respondents who failed the attention check are included in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table C.3: Robustness check (unrestricted sample) - Effect of T8 (own ranking) on attributes chosen

	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T8 own ranking	0.023	-0.798	0.046	1.002	1.648
	(0.512)	(0.997)	(0.052)	(1.255)	(1.656)
	[0.964]	[0.423]	[0.376]	[0.425]	[0.320]
	{1.000}	{1.000}	{1.000}	{1.000}	{1.000}
	{{1.000}}	{{1.000}}	{{1.000}}	{{1.000}}	{{1.000}}
Mean of control group	13.39	28.31	2.20	28.43	63.86
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	1,005	1,005	1,005	1,005	1,005

Table C.3 reports the average treatment effects of T8 on: effective interest rate (in percentage points), late fee per day (in Philippine Peso), number of documents, time to disbursement (in hours), and probability of approval (in percentage points). All columns are estimated using the double-selection lasso linear regression (equation 2). In column 1, the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): monthly net income. There are no covariates selected from the potential controls in other columns. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table C.4: Robustness check (unrestricted sample) - Heterogeneous analysis - T4 × Overconfidence-financial knowledge

	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: No. of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T4 Ranked by late fee	-4.763	2.277	-0.194	2.443	-3.254
	(1.480)	(0.735)	(0.078)	(1.749)	(2.441)
	[0.001]***	[0.002]***	[0.013]**	[0.162]	[0.182]
	{0.010}***	{0.010}***	{0.036}**	{0.159}	{0.159}
	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{0.001}}***
Overconfident-financial knowledge	-1.396	0.212	-0.055	1.914	-0.606
	(1.425)	(0.728)	(0.074)	(1.785)	(2.364)
	[0.327]	[0.771]	[0.458]	[0.283]	[0.798]
T4 × Overconfident	4.718	-1.775	0.112	-3.323	1.197
	(2.073)	(1.019)	(0.109)	(2.427)	(3.398)
	[0.023]**	[0.081]*	[0.302]	[0.171]	[0.725]
	{0.046}**	{0.109}	{0.202}	{0.159}	{0.296}
	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{0.001}}***	{{1.000}}
Mean of control group	28.31	13.39	2.20	28.43	63.86
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	989	989	989	989	989
Linear combination: T4 + Interaction term	-0.045	0.502	-0.082	-0.879	-2.057
p-value	0.975	0.477	0.281	0.601	0.384

Table C.4 reports treatment effect heterogeneity by interacting T4 (ranked by late fee) with overconfidence-financial knowledge. The dummy variable overconfidence-financial knowledge is equal to 1 if the participant's self-assessment of how many questions she thinks she got right is higher than her actual correct answers to the "Big 3" financial literacy questions, and equals zero otherwise. All columns are estimated using the double-selection lasso linear regression (equation 3). In column 1, the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): monthly net income. There are no covariates selected from the potential controls in other columns. Respondents who failed the attention check are included in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table C.5: Robustness check (unrestricted sample) - Heterogeneous analysis - T4 × Overconfidence-general knowledge

	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: No. of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T4 Ranked by late fee	-4.960	2.480	-0.157	1.799	-2.390
	(1.742)	(0.826)	(0.093)	(2.001)	(2.899)
	[0.004]***	[0.003]***	[0.092]*	[0.369]	[0.410]
	{0.023}**	{0.023}**	{0.197}	{0.414}	{0.414}
	{{0.001}}***	{{0.001}}***	{{1.000}}	{{1.000}}	{{1.000}}
Overconfident-general knowledge	-1.378	1.759	-0.097	-2.381	-2.721
	(1.539)	(0.746)	(0.079)	(1.885)	(2.529)
	[0.371]	[0.018]**	[0.217]	[0.206]	[0.282]
T4 × Overconfident	4.100	-1.708	0.029	-1.776	-0.517
	(2.170)	(1.047)	(0.114)	(2.510)	(3.574)
	[0.059]*	[0.103]	[0.801]	[0.479]	[0.885]
	{0.186}	{0.197}	{0.794}	{0.428}	{0.794}
	{{1.000}}	{{1.000}}	{{1.000}}	{{1.000}}	{{1.000}}
Mean of control group	28.31	13.39	2.20	28.43	63.86
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	989	989	989	989	989
Linear combination: T4 + Interaction term	-0.860	0.772	-0.128	0.023	-2.908
p-value	0.505	0.231	0.056	0.988	0.164

Table C.5 reports treatment effect heterogeneity by interacting T4 (ranked by late fee) with overconfidence-general knowledge. The dummy variable overconfidence-general knowledge is equal to 1 if the participant's self-assessment of how many questions she thinks she got right is higher than her actual correct answers to the general knowledge questions, and equals zero otherwise. All columns are estimated using the double-selection lasso linear regression (equation 3). In all columns (1-5), the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): monthly net income. Respondents who failed the attention check are included in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table C.6: Robustness check (unrestricted sample) - Heterogeneous analysis - T3 × Liquidity-constrained

	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: No. of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T3 Ranked by EIR	-2.879	3.538	0.112	1.004	1.261
	(0.653)	(1.269)	(0.067)	(1.703)	(2.204)
	[0.000]***	[0.005]***	[0.095]*	[0.556]	[0.567]
	{0.001}***	{0.017}**	{0.154}	{0.423}	{0.423}
	{{0.001}}***	{{0.001}}***	{{1.000}}	{{1.000}}	{{1.000}}
Liquidity-constrained	0.131	-1.851	0.010	1.037	-0.749
	(0.758)	(1.471)	(0.077)	(1.837)	(2.455)
	[0.863]	[0.208]	[0.894]	[0.572]	[0.760]
T3 × Liquidity-constrained	2.953	-1.071	-0.133	-4.933	-3.030
	(1.047)	(2.008)	(0.103)	(2.613)	(3.413)
	[0.005]***	[0.594]	[0.196]	[0.059]*	[0.375]
	{0.017}**	{0.423}	{0.236}	{0.116}	{0.366}
	{{0.001}}***	{{1.000}}	{{1.000}}	{{0.001}}***	{{1.000}}
Mean of control group	13.39	28.31	2.20	28.43	63.86
Lasso PDS controls	✓	✓	✓	✓	✓
Observations	995	995	995	995	995
Linear combination: T3 + Interaction term	0.074	2.467	-0.022	-3.929	-1.769
p-value	0.928	0.111	0.781	0.048	0.497

Table C.6 reports treatment effect heterogeneity by interacting T3 (ranked by late EIR) with liquidity-constrained. The dummy variable liquidity-constrained is equal to 1 if respondent answered *A great deal* or *A lot* to the question *"On a scale of 1 (A great deal) to 5 (None at all), to what extent do you perceive yourself as cash-constrained?"*, and equals zero otherwise. All columns are estimated using the double-selection lasso linear regression (equation 3). In all columns (1-5), the double-selection method selected the following covariates from the potential controls (*socio-demographic characteristics* and *experience with financial services* variables reported in table 2): monthly net income, age, urban, experienced digital credit user, and female. Respondents who failed the attention check are included in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

D Robustness checks - control for imbalanced covariates

Table D.1: Robustness check (covariate imbalance) - Effect of T1, T2, and T3 on Effective Interest Rate

	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T1 Standardized-no EIR, random	-2.685	1.065	0.342	3.202	7.786
	(0.527)	(1.106)	(0.056)	(1.257)	(1.676)
	[0.000]***	[0.336]	[0.000]***	[0.011]**	[0.000]***
	{0.001}***	{0.085}*	{0.001}***	{0.006}***	{0.001}***
	{{0.001}}***	{{0.670}}	{{0.001}}***	{{0.055}}*	{{0.001}}***
T2 Standardized-with EIR, random	-2.981	0.484	0.324	3.535	5.904
	(0.537)	(1.103)	(0.057)	(1.242)	(1.721)
	[0.000]***	[0.661]	[0.000]***	[0.004]***	[0.001]***
	{0.001}***	{0.153}	{0.001}***	{0.003}***	{0.001}***
	{{0.001}}***	{{0.822}}	{{0.001}}***	{{0.021}}**	{{0.005}}***
T3 Ranked by EIR	-4.493	4.061	0.367	0.706	4.387
	(0.538)	(1.074)	(0.055)	(1.295)	(1.728)
	[0.000]***	[0.000]***	[0.000]***	[0.586]	[0.011]**
	{0.001}***	{0.001}***	{0.001}***	{0.144}	{0.006}***
	{{0.001}}***	{{0.002}}***	{{0.001}}***	{{0.822}}	{{0.055}}*
Mean of control group	16.22	27.68	1.87	25.69	58.06
Controls	✓	✓	✓	✓	✓
Observations	1,784	1,784	1,784	1,784	1,784
p-value(T1=T2)	0.578	0.592	0.739	0.800	0.279
p-value(T1=T3)	0.001	0.005	0.641	0.069	0.052
p-value(T2=T3)	0.005	0.001	0.417	0.037	0.395

Table D.1 reports the average treatment effects of T1, T2, and T3 on: effective interest rate (in percentage points), late fee per day (in Philippine Peso), number of documents, time to disbursement (in hours), and probability of approval (in percentage points). All columns are estimated using OLS regression controlling for the 3 imbalanced covariates: age, gender, and with bachelors degree. Respondents who failed the attention check are excluded in the analysis. Control group (marketing advertisements) is the base category for all columns. In the bottom panel, we report the p-value from testing the equality of two coefficients, where the null hypothesis is that the coefficients are equal. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table D.2: Robustness check (covariate imbalance) - Effect of T4 to T7 on non-price attributes

	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)	
	(1)	(2)	(3)	(4)	(5)
T4 Ranked by late fee	-2.369				1.648
	(1.111)				(0.528)
	[0.033]**				[0.002]***
	{0.047}**				{0.004}***
	{{0.087}}*				{{0.031}}**
T5 Ranked by number of documents		-0.262			1.961
		(0.059)			(0.518)
		[0.000]***			[0.000]***
		{0.001}***			{0.001}***
		{{0.001}}***			{{0.002}}***
T6 Ranked by time to disbsurse			-8.463		0.237
			(1.352)		(0.555)
			[0.000]***		[0.669]
			{0.001}***		{0.288}
			{{0.001}}***		{{0.987}}
T7 Ranked by probability of approval				4.421	-1.412
				(1.810)	(0.527)
				[0.015]**	[0.007]***
				{0.012}**	{0.011}**
				{{0.031}}**	{{0.073}}*
Mean of control group	28.04	2.20	29.32	64.13	13.29
Controls	✓	✓	✓	✓	✓
Observations	901	896	903	901	2,251

Columns 1-4 of table D.2 report the average treatment effects of T4 (ranked by late fee), T5 (ranked by number of documents), T6 (ranked by time to disbursement), and T7 (ranked by probability of approval) on their respective outcome variable: late fee per day (in Philippine Peso), number of documents, time to disbursement (in hours), and probability of approval (in percentage points). In column 5, we report the average treatment effects of T4-T7 on the effective interest rate to derive how consumers trade-off between the effective interest rate and non-price attributes. All columns are estimated using OLS regression controlling for the 3 imbalanced covariates: age, gender, and with bachelors degree. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table D.3: Robustness check (covariate imbalance) - Effect of T8 (own ranking) on attributes chosen

	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Number of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T8 own ranking	0.045	0.138	-0.007	-0.526	-0.531
	(0.550)	(1.077)	(0.057)	(1.326)	(1.795)
	[0.934]	[0.898]	[0.906]	[0.692]	[0.767]
	{1.000}	{1.000}	{1.000}	{1.000}	{1.000}
	{{0.997}}	{{0.997}}	{{0.997}}	{{0.978}}	{{0.987}}
Mean of control group	13.29	28.04	2.20	29.32	64.13
Controls	✓	✓	✓	✓	✓
Observations	883	883	883	883	883

Table D.3 reports the average treatment effects of T8 on: effective interest rate (in percentage points), late fee per day (in Philippine Peso), number of documents, time to disbursement (in hours), and probability of approval (in percentage points). All columns are estimated using OLS regression controlling for the 3 imbalanced covariates: age, gender, and with bachelors degree. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table D.4: Robustness check (covariate imbalance) - Heterogeneous analysis - T4 × Overconfidence-financial knowledge

	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: No. of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T4 Ranked by late fee	-5.004	2.810	-0.197	1.386	-3.109
	(1.573)	(0.753)	(0.082)	(1.807)	(2.582)
	[0.002]***	[0.000]***	[0.017]**	[0.443]	[0.229]
	{0.007}***	{0.003}***	{0.041}**	{0.327}	{0.222}
	{{0.013}}**	{{0.004}}***	{{0.094}}*	{{0.659}}	{{0.557}}
Overconfident-financial knowledge	-2.307	0.963	-0.056	1.939	0.255
	(1.510)	(0.757)	(0.079)	(1.840)	(2.511)
	[0.127]	[0.204]	[0.478]	[0.292]	[0.919]
T4 × Overconfident	5.115	-2.317	0.122	-2.800	0.733
	(2.183)	(1.054)	(0.115)	(2.503)	(3.575)
	[0.019]**	[0.028]**	[0.290]	[0.264]	[0.838]
	{0.041}**	{0.048}**	{0.222}	{0.222}	{0.570}
	{{0.094}}*	{{0.111}}	{{0.578}}	{{0.578}}	{{0.826}}
Mean of control group	28.04	13.29	2.20	29.32	64.13
Controls	✓	✓	✓	✓	✓
Observations	901	901	901	901	901
Linear combination: T4 + Interaction term	0.110	0.493	-0.074	-1.414	-2.375
p-value	0.943	0.507	0.361	0.419	0.343

Table D.4 reports treatment effect heterogeneity by interacting T4 (ranked by late fee) with overconfidence-financial knowledge. The dummy variable overconfidence-financial knowledge is equal to 1 if the participant's self-assessment of how many questions she thinks she got right is higher than her actual correct answers to the "Big 3" financial literacy questions, and equals zero otherwise. All columns are estimated using OLS regression controlling for the 3 imbalanced covariates: age, gender, and with bachelors degree. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table D.5: Robustness check (covariate imbalance) - Heterogeneous analysis - T4 × Overconfidence-general knowledge

	Outcome Variable: Late fee per day (PhP)	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: No. of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T4 Ranked by late fee	-5.204	2.706	-0.147	1.879	-1.614
	(1.845)	(0.861)	(0.098)	(2.037)	(3.030)
	[0.005]***	[0.002]***	[0.134]	[0.357]	[0.594]
	{0.023}**	{0.018}**	{0.232}	{0.368}	{0.543}
	{{0.033}}**	{{0.018}}**	{{0.421}}	{{0.682}}	{{0.856}}
Overconfident-general knowledge	-1.610	1.666	-0.076	-1.377	-1.433
	(1.609)	(0.775)	(0.083)	(1.931)	(2.641)
	[0.317]	[0.032]**	[0.360]	[0.476]	[0.587]
T4 × Overconfident	4.431	-1.680	0.019	-3.069	-1.782
	(2.286)	(1.085)	(0.121)	(2.575)	(3.734)
	[0.053]*	[0.122]	[0.876]	[0.234]	[0.633]
	{0.165}	{0.232}	{0.638}	{0.368}	{0.543}
	{{0.254}}	{{0.421}}	{{0.888}}	{{0.548}}	{{0.856}}
Mean of control group	28.04	13.29	2.20	29.32	64.13
Controls	✓	✓	✓	✓	✓
Observations	901	901	901	901	901
Linear combination: T4 + Interaction term	-0.773	1.025	-0.128	-1.190	-3.395
p-value	0.574	0.125	0.075	0.455	0.127

Table D.5 reports treatment effect heterogeneity by interacting T4 (ranked by late fee) with overconfidence-general knowledge. The dummy variable overconfidence-general knowledge is equal to 1 if the participant's self-assessment of how many questions she thinks she got right is higher than her actual correct answers to the general knowledge questions, and equals zero otherwise. All columns are estimated using OLS regression controlling for the 3 imbalanced covariates: age, gender, and with bachelors degree. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1

Table D.6: Robustness check (covariate imbalance) - Heterogeneous analysis - T3 × Liquidity-constrained

	Outcome Variable: Effective Interest Rate (%)	Outcome Variable: Late fee per day (PhP)	Outcome Variable: No. of documents	Outcome Variable: Time to disburse (hours)	Outcome Variable: Probability of approval (%)
	(1)	(2)	(3)	(4)	(5)
T3 Ranked by EIR	-2.392	3.842	0.091	-1.196	-0.267
	(0.686)	(1.351)	(0.070)	(1.774)	(2.332)
	[0.001]***	[0.005]***	[0.198]	[0.500]	[0.909]
	{0.006}***	{0.021}**	{0.384}	{0.601}	{0.833}
	{{0.008}}***	{{0.037}}**	{{0.565}}	{{0.813}}	{{0.967}}
Liquidity-constrained	0.780	-2.672	-0.002	0.678	-0.851
	(0.777)	(1.554)	(0.081)	(1.867)	(2.576)
	[0.316]	[0.086]*	[0.981]	[0.716]	[0.741]
T3 × Liquidity-constrained	2.127	-0.561	-0.113	-4.047	-3.010
	(1.101)	(2.177)	(0.110)	(2.757)	(3.655)
	[0.054]*	[0.797]	[0.305]	[0.143]	[0.410]
	{0.168}	{0.795}	{0.553}	{0.333}	{0.554}
	{{0.255}}	{{0.967}}	{{0.716}}	{{0.484}}	{{0.796}}
Mean of control group	13.29	28.04	2.20	29.32	64.13
Controls	✓	✓	✓	✓	✓
Observations	893	893	893	893	893
Linear combination: T3 + Interaction term	-0.265	3.281	-0.022	-5.243	-3.277
p-value	0.758	0.053	0.790	0.013	0.242

Table D.6 reports treatment effect heterogeneity by interacting T3 (ranked by late EIR) with liquidity-constrained. The dummy variable liquidity-constrained is equal to 1 if respondent answered *A great deal* or *A lot* to the question *"On a scale of 1 (A great deal) to 5 (None at all), to what extent do you perceive yourself as cash-constrained?"*, and equals zero otherwise. All columns are estimated using OLS regression controlling for the 3 imbalanced covariates: age, gender, and with bachelors degree. Respondents who failed the attention check are excluded in the analysis. Treatment 2 (Standardized - with EIR, random order) is the base category for all columns. Robust standard errors in round parentheses ( ). Unadjusted p-values in brackets [ ]. Sharpened q-values in curly brackets { }. Romano-Wolf stepdown adjusted p-values in double curly brackets {{ }}. *** p<0.01, ** p<0.05, * p<0.1