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Leveraging Private BNPL Data in Consumer Banking

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Abstract

Buy Now, Pay Later loans (BNPL) are an increasingly popular way to finance small-ticket purchases. We provide new evidence on how BNPL influences regular bank credit markets, benefiting both lenders and borrowers through information production and learning. Using data from over one million unsecured bank loan applications from a bank that also provides BNPL services, we exploit the fact that BNPL enhances the bank's ability to assess creditworthiness by incorporating transaction data beyond shared credit registers. We establish four key findings. First, BNPL users are more likely to be approved for bank loans due to lower internally assessed credit risk, while those with late BNPL payments face lower approval rates. Second, BNPL customers benefit from discounted interest rates, while the bank earns a profit margin by price discriminating among customers with a good internal payment history but differing external credit scores. Third, customers with a BNPL history exhibit better repayment behavior and lower default rates, partly driven by improved loan terms. Fourth, learning effects from prior BNPL use likely reinforce this behavior. Our findings suggest that BNPL improves risk assessment and fosters learning, enhancing credit outcomes and access for higher-risk borrowers, thereby promoting financial inclusion.

Keywords: Buy-Now-Pay-Later, Consumer Finance, Household Credit, Information Collection, Credit Risk Assessment
JEL Classifications: D14, G2, G21, G5

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1 Introduction

Buy Now, Pay Later (BNPL) is a new form of lightly regulated credit that has rapidly gained popularity with the rise of online shopping. Adoption rates are high, particularly in developed countries such as Australia and Sweden with more than 50% of the population using BNPL, followed by the US, the UK, Germany, other Nordic countries and China (Cornelli et al., 2023). In contrast to other small-scale loans such as credit cards or other forms of consumer loans, access to BNPL is quicker and easier. Unlike these traditional options, transactions do not originate through direct contract with a bank but tied to a specific purchase by the customer from a merchant where the customer is usually unaware of the financial intermediary financing the loan. Typically, the customer undergoes only a light credit check, the loan is interest free, and information about customers' repayment behavior is not shared with a credit bureau. Overall, this provides consumers with easier access to financial services and allows banks that intermediate BNPL loans to have contact with customers that might not have qualified for traditional credit products.

BNPL users have been found to be, on average, riskier and less well served than users of more conventional forms of credit (Aidala et al., 2023). Moreover, the EU has recognized that BNPL products can result in significant costs for consumers, including hidden fees, late payment penalties, and potential over-indebtedness (European Commission, 2017). A new EU Consumer Credit Directive (European Union, 2023) addresses some of these issues by extending regulatory protections to BNPL services.[1] Given BNPL's rapid adoption, easy accessibility, and growing regulatory interest, it is important to understand its impact on consumers' financial well-being.

In this paper, we study if, and through what mechanisms, the provision of BNPL loans by banks generates spillover effects on credit access and borrower behavior in the consumer loan market, specifically focusing on regular, unsecured bank loans (henceforth referred to as

[1]Key measures include stricter creditworthiness assessments, clearer advertising requirements, and expanded rights for consumers, ensuring that BNPL adheres to the same standards as traditional credit products.

bank loans or bank credit). BNPL lenders gain exclusive information about their borrowers' repayment behavior, which is not shared with other lenders. We examine whether this information impacts access to bank credit, the interest rates offered to these customers, and their repayment behavior. At the same time, BNPL offers customers a way to gain experience in repaying small loans. We examine whether this experience is associated with a learning effect when these customers later take out a regular bank loan. Moreover, we investigate whether the bank benefits from using this private information to price discriminate among customers.

Studying how the use of BNPL loans affects consumers has proven challenging. Due to the minimal regulation of these loans, no data are available in public credit registers or supervisory datasets. To address this gap, we obtain data from a large financial service provider with a banking license in the Nordics, a region where BNPL adoption has advanced most rapidly. The provider not only offers consumer loans but also acts as an intermediary for retailers offering BNPL services to their customers. This dataset is particularly valuable as it provides direct access to information on both BNPL applications and payments, alongside detailed records of bank credit applications and the corresponding decisions made by the bank. Additionally, we have access to both internal and external credit scores, as well as the terms of bank credit agreements, including loan amounts, maturities, and interest rates. Furthermore, we observe repayment behavior for bank loan customers, capturing details such as late payments and defaults. Importantly, loan applicants are not aware that the bank incorporates their prior payment history into its screening process for bank credit. Our analysis focuses on customers who apply for consumer loans through an online broker, where applicants do not target a specific bank but choose from various loan offers presented to them.

The bank classifies applicants as either "internal" or "external" customers based on the availability and recency of their BNPL transaction history. "Internal customers" are those who have made at least three BNPL transactions within the past 12 months (we will interchangeably use the terms internal customers and internal BNPL customers). By contrast, ”external customers” include those with fewer BNPL transactions, transactions that occurred further in the more distant past, or no historical BNPL data at all. For internal customers, the bank incorporates their historical BNPL information into its risk assessments. External customers’ BNPL history, if available, is disregarded by the bank.

Our identification strategy compares internal customers with all other external customers. Internal customers approved for BNPL loans are, on average, less risky, as reflected in their external credit scores. To account for this, we control for tight bins of external score fixed effects, comparing customers with the same externally assessed default risk. However, internal and external customers may still differ in unobserved ways. To address this, we use a control group consisting of applicants who had previously been approved for BNPL services within the bank but differ in transaction timing or frequency. These ”external” customers have had fewer BNPL transactions or ones occurring further in the past (e.g., two recent transactions within a year and one earlier from a previous period), leading the bank to exclude their BNPL data from internal credit assessments. This control group more closely mirrors internal customers in both observable and unobservable characteristics.

We report four main results that demonstrate how BNPL can benefit both its users and the bank. First, internal BNPL customers are nearly 30 percentage points more likely to be accepted for a bank loan than external customers. This difference persists even when comparing internal BNPL customers to observationally similar ’external’ customers whose BNPL data the bank disregards. These findings are consistent with recent studies on cross-selling, such as Basten and Juelsrud (2023) and Qi (2024), with the former reporting a similarly sized effect on credit supply for customers with long-term deposit relationships with their house bank. We provide evidence that increased credit access for internal customers is driven by the availability of their BNPL payment history, leading, on average, to significantly better internal credit scores that are approximately 8-10 points lower. Not all internal customers benefit, however, as those who past delays on their BNPL payments have a lower probability of being accepted for a bank loan.

Second, we demonstrate that private information from BNPL services impacts how the bank sets interest rates, which benefits both customers and the bank. Internal BNPL customers benefit by paying an interest rate below the market rate for their risk level, as measured by their external credit score. The discount is substantial: 1.4 percentage points, corresponding to a reduction of roughly 15% compared to the sample mean. Interestingly, this finding contrasts with evidence from the cross-selling literature, which shows that relationship customers are often offered higher interest rates on loans (Basten and Juelsrud, 2023). A possible explanation is that, in our setting, the bank-client tie is informational rather than relational - which would involve factors such as trust, loyalty, or inertia.

Furthermore, we show that the bank benefits from using private information to price discriminate among internal customers. By comparing customers categorized as low or high risk based on external credit scores and reassessed using internal data, we identify four groups: customers who are low risk in both external and internal assessments ("low risk"), those who are high risk in both assessments ("high risk"), and two groups where assessments differ. Customers deemed low risk internally but high risk externally are labeled "revealed low risk," while those assessed as high risk internally but low risk externally are "revealed high risk." We show that "revealed low risk" customers pay lower interest rates than the average internal customer, but still more than those consistently categorized as low risk. Conversely, "revealed high risk" customers face higher rates than the average internal customer, but still pay less than those consistently categorized as high risk. These findings support the notion that internal information is actively used in pricing and that BNPL data influences the competitive conditions customers face.

Third, we find no evidence that the increased access to bank credit jeopardizes the sustainability of BNPL customers' debt. When analyzing whether this group exhibits poorer repayment behavior or defaults more frequently on its bank loans, our findings indicate the opposite. Internal BNPL customers demonstrate better repayment behavior and lower default rates compared to external customers.

Fourth, we provide evidence supporting the existence of a learning mechanism through the use of BNPL. To explore this, we focus on customers with prior experience using BNPL who are not classified as internal by the bank. When compared to other external customers, with controls for both external and internal credit scores to address potential selection effects, we find that they also exhibit better bank loan repayment behavior despite receiving no interest rate advantage. We interpret these findings as suggestive evidence of a learning channel: the use of small BNPL loans can enable customers to develop the skills needed to handle regular repayments. Moreover, our result suggests that the bank may be missing potential revenue opportunities by not using the payment history of all recent BNPL users.

Our findings contribute to four strands of literature. First, we add to recent research on how BNPL credit impacts household behavior. This literature has found that BNPL stimulates shopping but has mixed effects on credit uptake and financial health. Berg et al. (2024) and Maesen and Ang (2023) show that BNPL significantly increases the likelihood of a purchase. DiMaggio et al. (2022) attribute spending increases to a "liquidity flypaper effect," where delayed payment encourages consumption of goods that can be financed through BNPL. On the credit side, Papich (2022) finds that BNPL availability improves credit scores, reduces delinquencies, and increases non-BNPL credit use, especially for riskier consumers. Bian et al. (2023) report that Chinese users increase spending but avoid credit card debt by scaling back BNPL usage when costs arise. In contrast, Guttman-Kenney et al. (2023) and deHaan et al. (2024) show that BNPL users in the UK and US accumulate high-interest debt and overdraft charges, consistent with overborrowing.

We add to this literature by providing new evidence on the connections between BNPL and regular bank credit markets and their implications for borrowers and lenders. Using unique data from a Nordic BNPL provider that also operates as a bank, we can link exactly identified BNPL transactions to bank loan applications and credit bureau reports, allowing us to explore these connections in detail and without measurement error. Our findings show that

BNPL users benefit through improved credit access, lower interest rates, better repayment practices driven by enhanced screening, and a likely learning mechanism. Furthermore, we demonstrate how banks use private BNPL data to price-discriminate and optimize strategies for different risk profiles. These insights contribute to understanding how BNPL integrates with traditional credit markets, influencing both consumer and lender behavior.

Second, we contribute to studies showing how information collection, - sharing and - asymmetries affect credit supply, pricing, and loan portfolio risk, particularly for marginal and riskier borrowers (Pagano and Jappelli, 1993, Jappelli and Pagano, 2002, Dell'Ariccia and Marquez, 2004). Information sharing tends to mitigate adverse selection, increasing lending and reducing credit risk, while private information enables lenders to charge higher rates and finance less creditworthy borrowers. Novel data sources, such as digital footprints, have been shown to further improve credit access and reduce default rates for borrowers without credit histories (Agarwal et al., 2019, Norden and Weber, 2010).[2]

We add to this literature by showing that BNPL loans generate new, private information, functioning in a similar way to digital footprints. This private information enhances credit access, improves borrower quality, but reduces borrowing costs for lower-risk customers identified through BNPL data. Additionally, we deliver suggestive evidence that the *private* character of data collected from BNPL transactions and the expansion of credit supply enable borrowers to benefit from learning by doing (BNPL), further contributing to improved credit outcomes.

Third, we contribute to studies examining how financial technology, digitization, and new payment solutions transform lending by generating novel forms of information. These innovations reduce information asymmetries, expand credit supply, and lower default rates by enhancing the information available to lenders (Liberti et al., 2022, Berg et al., 2019). Our study adds to this literature by showing how BNPL lending leverages a new credit

[2]Removing negative credit information, however, can reduce market efficiency and increase delinquency rates (Musto, 2004), while flag removals benefit defaulted consumers at modest welfare costs (Bos et al., 2018, Jansen et al., 2022).

product to generate historical payment information, creating an informational advantage for lenders. This also complements insights from Open Banking, where customers voluntarily share private data (Nam, 2022), and digital footprints collected by retailers in e-commerce contexts (Berg et al., 2019). Together, these papers demonstrate how diverse forms of digital information improve credit access, particularly for consumers less active in traditional credit markets, and potentially enhance repayment behavior.

Finally, our findings relate to the literature on financial inclusion and the drivers of credit access for underserved consumers. Consumers are often willing to invest significantly to build a good financial reputation, with evidence showing a willingness to pay up to 11 percent of monthly income to achieve this (Liberman, 2016). We contribute to this literature by providing suggestive evidence that hurdles to entering the credit market, such as low credit scores or the inability to establish a public credit track record, can potentially be mitigated through BNPL usage. Small loans like BNPL, which are not reported to general credit registers, enables consumers to build a credit reputation nearly costlessly. This improved reputation can facilitate access to bank credit, promote better repayment behavior, and simultaneously offer returns to banks.

The remainder of this paper is structured as follows. Section 2 describes the institutional setting and presents the data. Section 3 describes the empirical strategy and presents our results while Section 4 discusses results and Section 5 concludes.

2 Data

2.1 Institutional Setting

The BNPL market has experienced significant growth in the Nordic countries. In Sweden, BNPL accounts for approximately 24% of e-commerce payments, the highest rate globally. Similarly, Denmark and Norway have substantial BNPL market shares, at around 23% and 18%, respectively (Sveriges Riksbank, 2023). This widespread adoption stems from a tradition of purchasing on invoice, the presence of major BNPL providers founded in the Nordics, openness to technology, and high trust in financial institutions (Svea Bank, 2023). The rapid expansion of BNPL services, alongside rising consumer defaults (Kronofogdemyndigheten, 2024), has however also raised concerns about financial stability, prompting increased regulatory scrutiny (The Paypers, 2023).

We obtain data from a Nordic bank offering a full range of banking services, including loans, payment solutions, and other traditional banking products. The bank also provides payment services for retailers, integrating solutions for both online and in-store transactions. As an intermediary between retailers and customers, the bank manages payments tailored to retailer-specific contracts. Unsecured loans are primarily extended through online brokers, with 92.1% of loan applications in our sample originating from these platforms. Consumers usually apply to multiple banks simultaneously via such online brokers, potentially receiving several competing offers. Applicants are typically unaware that the bank has access to their BNPL payment history and do not specifically target the bank. Instead, they likely choose lenders based on the most favorable terms available rather than an existing relationship, as is common in traditional banking.

For the evaluation of loan applications, the bank considers an external credit score (ECS) purchased from a national credit bureau, which rates creditworthiness on a 0–100 scale (with lower scores indicating a lower probability of default), and an internal credit score (ICS). The ICS reweights the ECS and incorporates supplementary information, such as income, provided by the credit bureau. This internal score is tailored to the demographic applying for unsecured loans, resulting in differences between the ECS and ICS. Importantly, the bank integrates BNPL repayment behavior into its ICS model, but only for customers classified as *internal*, defined as those with at least three BNPL transactions in the past 12 months. For these customers, the ICS includes personalized BNPL repayment data, while for *external* customers, it does not. This distinction leads the bank to apply different approval thresholds for credit decisions based on a customer's classification. These thresholds vary over time to

Table 1 Summary Statistics for All Loan Applicants

The table shows summary statistics for the variables we use in our main regression analyses and background characteristics for all loan applicants. Taxable income and application amount are in thousands USD, adjusted to constant 2022 values using the Consumer Price Index and converted to U.S. dollars with the December 30, 2022 exchange rate.

	N	Mean	SD	P50	Min	Max
Internal BNPL	1,066,503	0.028	0.166	0.000	0.000	1.000
Accept	1,066,503	0.310	0.462	0.000	0.000	1.000
Internal Credit Score	1,066,503	18.62	16.11	13.30	0.03	83.43
External Credit Score	1,066,503	7.91	12.39	2.64	0.00	98.16
Married or Co-habiting	975,164	0.513	0.500	1.000	0.000	1.000
Having Children	1,066,503	0.360	0.480	0.000	0.000	1.000
Homeowner	1,066,503	0.369	0.483	0.000	0.000	1.000
Employed	1,066,503	0.880	0.325	1.000	0.000	1.000
Co-applicant	1,066,503	0.077	0.266	0.000	0.000	1.000
Taxable Income (th)	1,066,503	27.03	16.03	26.06	0.008	4,077
Application Amount (th)	1,066,503	15.50	12.25	12.47	0.847	47.95
Maturity	1,066,503	110	51	120	12	180

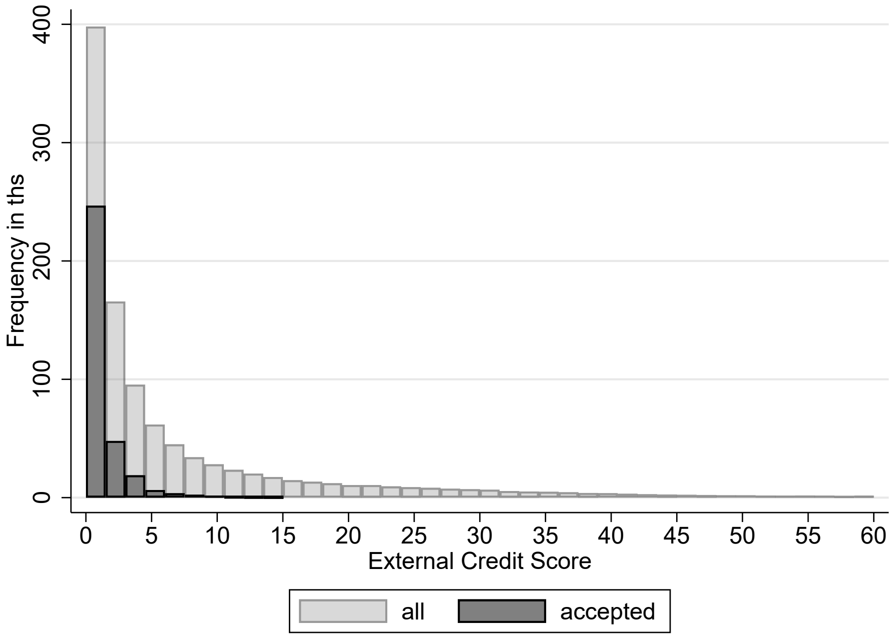
balance loan book size and risk exposure. To account for such fluctuations, we include daily time fixed effects in our analyses to control for shifting thresholds and re-calibrations of the internal credit risk model.

2.2 Datasets and Descriptive Statistics

Our dataset includes BNPL transaction records with full repayment histories, bank loan applications, loan offers made by the bank, and repayment behavior for finalized contracts.

Figure 1 Number of Applications by External Credit Score

This figure shows the distribution of loan applicants across external credit scores in light gray, and the number of applications accepted by the bank in dark gray.



Loan Application Data

The data comprise 3,583,218 loan applications filed between 2018 and 2022 and detailed information about each application, such as the date, the channel used (online platform, telemarketing, or external broker), the requested loan amount, and the bank's decision. Additionally, the dataset provides demographic and financial information about the applicants, including their income, marital status, number of children, housing type, and employment status.

In our baseline sample, we focus on first-time bank loan applicants, narrowing the dataset to 1,533,738 applications for which our main variables are available, of which 1,303,810 applications filed through an online broker.[3] We exclude internal customers with a prior relationship with the bank through other services than BNPL, such as payment solutions or

[3]External credit score, internal credit score, maturity, loan amount, income, and classification by the bank as internal or external.

existing loans, reducing the dataset to 1,066,503 loan applications. This makes up our main regression sample. Of these applicants, 30,115 (2.8%) are identified as internal BNPL customers, and 68,088 as external BNPL customers whose BNPL repayment history is excluded from the Internal Credit Score (ICS) calculation. Table 1 contains summary statistics and shows the acceptance rate averages 31%. The bank's ICS has a mean of 18.62 (SD: 16.11), ranging from 0.03 to 83.43, while the ECS averages 7.91, with a range between 0.00 and 98.16. Loan applications average a requested amount of USD 15,495 (median: USD 13,536), with a maximum of about USD 50,000. Loan maturities span from 12 to 180 months, with an average of 110 months. Demographic information shows that taxable income averages USD 27,027 (constant 2022 values), with a maximum exceeding 4 million.

Figure 1 depicts the distribution of loan applications (light gray) and accepted applications (dark gray) across external credit score levels. Most applicants have low external credit scores, and, intuitively, the bank accepts a higher proportion of applicants with low scores compared to those with high scores. Table 2 Columns 1-3 provides summary statistics for three subsets of the applicant pool: internal BNPL applicants, external BNPL applicants, and external applicants without BNPL history. The acceptance rate is highest for internal BNPL applicants (78.3%), followed by external BNPL applicants (61.7%), and lowest for external applicants without BNPL history (29.6%). This pattern is mirrored in the relative sizes of the three groups' ICS.

Notably, internal and external BNPL customers have a comparably low ECS (2.70 vs. 2.44), suggesting the latter are perceived as similarly risky externally but re-ranked by the bank's internal model. For external customers, the gap between ECS and ICS is wider and suggests the bank considers them riskier than the national credit bureau does, likely leveraging additional data or weighting its internal models differently.

Loan amounts and maturities are similar for internal and external BNPL customers (approximately USD 13,000 and 96 months) but are slightly smaller than those for external customers. Employment rates are similar across groups, but BNPL customers have higher incomes, home-ownership rates, and are twice as likely to have a co-signer. Appendix Table A1 provides historical BNPL payment data, showing that among internal BNPL customers, 38.2% were late by at least 30 days on their BNPL payments, 7.9% by 60 days, and 1.2% defaulted on their BNPL payment in the year before their loan application.

Table 2 Summary Statistics by Applicant and Borrower Sub-group

The table shows summary statistics on the regression and background variables, distinguishing between customers applying for a bank loan (Columns 1–3) and those who have taken up a bank loan (Columns 4–6). "Internal BNPL" customers have completed at least three BNPL transactions in the past 12 months; all other customers are "External". "External BNPL customers" have a prior BNPL history at the bank but fewer than three BNPL transactions over the past 12 months. Taxable income and application amount are in 2022 values using the Consumer Price Index and converted into USD with the end of 2022 exchange rate.

	(1)	(2)	(3)	(4)	(5)	(6)
	Applicant group			Customer group		
	Internal BNPL	External	External BNPL	Internal BNPL	External	External BNPL
Accept	0.78	0.30	0.62	1.00	1.00	1.00
	(0.41)	(0.46)	(0.49)	(0.00)	(0.00)	(0.00)
Interest Rate	7.32	6.90	8.01	8.51	9.71	9.05
	(2.61)	(4.68)	(3.04)	(2.04)	(2.24)	(1.79)
Late 30 days				0.272	0.395	0.286
				(0.445)	(0.489)	(0.452)
Late 60 days				0.123	0.235	0.133
				(0.329)	(0.424)	(0.340)
Default				0.068	0.163	0.072
				(0.251)	(0.369)	(0.259)
Internal Credit Score	2.25	19.10	10.40	2.81	7.46	6.16
	(3.58)	(16.08)	(11.00)	(2.66)	(3.58)	(3.52)
External Credit Score	2.70	8.06	2.44	3.76	3.58	2.99
	(5.77)	(12.50)	(5.38)	(3.44)	(3.52)	(3.15)
Female	0.443	0.408	0.428	0.530	0.426	0.516
	(0.497)	(0.492)	(0.495)	(0.499)	(0.495)	(0.500)
Age	51	47	46	49	50	51
	(15)	(15)	(14)	(17)	(16)	(18)
Married or Co-habiting	0.627	0.510	0.582	0.458	0.393	0.449
	(0.484)	(0.500)	(0.493)	(0.499)	(0.488)	(0.498)
Having Children	0.506	0.356	0.451	0.407	0.280	0.322
	(0.500)	(0.479)	(0.498)	(0.492)	(0.449)	(0.468)
Homeowner	0.632	0.361	0.579	0.397	0.404	0.478
	(0.482)	(0.480)	(0.494)	(0.490)	(0.491)	(0.500)
Employed	0.893	0.879	0.889	0.809	0.670	0.700
	(0.309)	(0.326)	(0.315)	(0.393)	(0.470)	(0.459)
Co-applicant	0.143	0.075	0.123	0.065	0.063	0.077
	(0.350)	(0.263)	(0.329)	(0.247)	(0.243)	(0.267)
Taxable Income	32,712	26,862	31,327	24,429	22,984	22,447
	(16,888)	(15,974)	(18,083)	(14,553)	(16,570)	(15,276)
Application Amount	13,416	15,556	13,789	14,045	11,974	11,940
	(10,737)	(12,290)	(10,999)	(13,761)	(13,024)	(13,201)
Maturity	96	111	96	103	102	97
	(49)	(51)	(50)	(58)	(58)	(58)
Observations	30,115	1,036,388	68,088	754	7,298	609

Loan Offers

Of the broker applicants, 31% (393,080 individuals) receive an offer from the bank, including 26,323 internal BNPL customers. Appendix Table A2 highlights key differences between internal and external customer groups who received loan offers. Internal BNPL customers pay the lowest average interest rate (7.61%), compared to 9.35% for external customers and 8.66% for external BNPL customers. While external credit scores are comparable across groups, internal BNPL customers have the lowest Internal Credit Score (1.44), reflecting the bank's richer data for screening, compared to external customers (6.31) and external BNPL customers (5.26). Loan amounts are similar across groups, though internal BNPL customers request slightly smaller amounts and shorter maturities. Taxable income is also similar, with external customers having slightly lower incomes on average. Demographically, internal BNPL customers closely resemble external BNPL customers, though the differences are less pronounced than in the broader applicant sample.

Realized Loan Contracts and Repayment Behavior

For the 8,052 customers who take the loan offer, we track repayment behavior over the subsequent months and report summary statistics in Table 2 Columns 4-6 by borrower type. Internal BNPL customers paid an average interest rate of 8.51%, compared to 9.71% for external customers and 9.05% for external BNPL customers. Late repayments on these loans are monitored at 30, 60, and 120 days, with defaults classified at 120 days. Overall, 38.5% of loans are late by 30 days, 22.6% by 60 days, and 15.5% result in default.

Loan takers exhibit slightly lower creditworthiness than those who were only offered a loan. Internal BNPL customers continue to have the lowest ICS, but interestingly, they display slightly higher ECS than external customers. Repayment behavior also varies across groups. Internal customers have 30-day late repayment rates that are over 10 percentage points lower than external customers (39.5%) and are comparable to those of external BNPL customers. This pattern holds for 60-day delays and default rates.

3 Empirical Analysis

3.1 Methodology

In our main analyses, we examine how being an internal BNPL customer influences the likelihood of being granted a regular bank loan and the interest rates offered by the bank, as well as how repayment behavior varies across groups. To address these questions, we estimate the following general regression model:

$$Y_{i,t} = \beta \times \ BNPL\,Customer_i + \boldsymbol{X_i} + \alpha_t + \epsilon_{i,t}, \tag{1}$$

where Y_{it} is the dependent variable of interest, i.e., acceptance of a loan application, the interest rate, or a payment delay. $BNPL\ Customer$ is an indicator variable that equals 1 if a customer is categorized by the bank as internal. We include a vector of individual or loan-specific controls, $\mathbf{X}_i$ that includes the external credit score, the requested loan amount and maturity, the log income of the applicant, as well as daily time fixed effects α_t. Standard errors are robust in all regressions. Our coefficient of interest is β. To account more precisely for variations in external credit risk assessments, we extend the main specification by incorporating fixed effects for 1-point bins of the external credit score. This approach allows us to compare customers with essentially the same external credit risk while accounting for differences in their internal risk estimates.

3.2 Baseline Results

3.2.1 Loan Acceptance

We first examine the determinants of loan acceptance, with a focus on the role of past BNPL information. Before presenting the results from our regression analyses, we illustrate how the probability of being accepted for a loan varies based on internal and external credit scores.

Figure 2 focuses on first-time applicants with internal scores in the range where we observe loan acceptances. The heatmap shows that applicants with lower credit scores have, as one would intuitively expect, a much higher chance of being accepted for bank credit, with acceptance rates exceeding 88 percent in the lowest risk bins and dropping below 3 percent in the highest. Acceptance rates decrease almost monotonically from the lower left (low scores) to the upper right (high scores). The internal score model, incorporating pre-application payment data, allows the bank to differentiate between customers with identical external scores. Appendix Figure A1 reveals a similar pattern for internal BNPL customers. The BNPL data that the bank holds tends to improve their internal credit scores and increase loan approval odds, even when they have mediocre external risk scores.

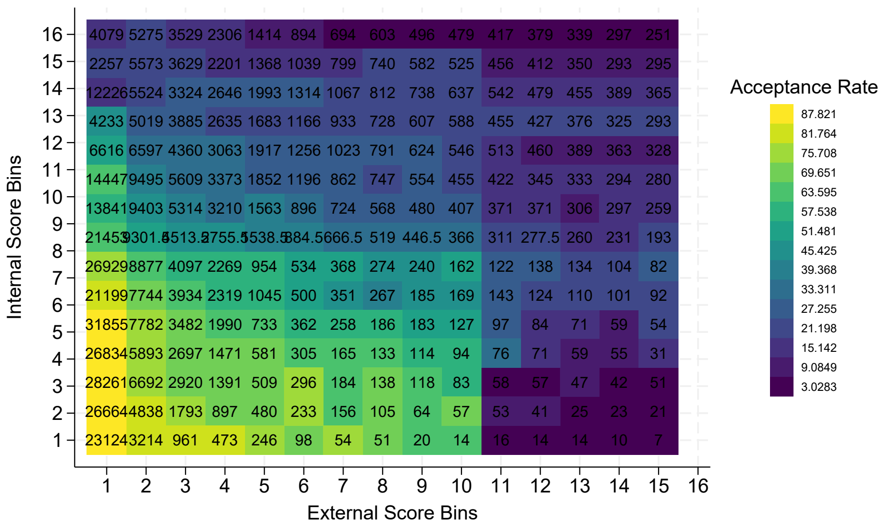


Figure 2 Acceptance Rate by External and Internal Credit Scores
This figure shows bins of external and internal credit scores, the number of applications per bin, as well as the acceptance rate. Applicants have been grouped into 1-point intervals (0-1, 1-2, 2-3, etc.). The brighter a box is, the higher the is the acceptance rate. The sample includes only first time applicants for an unsecured bank loan who apply through an online broker.

Next, we estimate how having BNPL experience with the bank affects the probability of receiving a loan. Table 3 presents results for both the full sample (columns 1-3) and for applicants with prior BNPL usage (columns 4-6). When we control for the ECS and day-fixed effects, being an internal BNPL customer significantly raises the likelihood of a loan (column 1). Adding individual-level controls (column 2) or replacing the ECS with 1-point bin fixed effects for the external score (column 3) at most slightly reduces the size of the effect. In this specification, internal BNPL applicants are about 30 pp more likely to be accepted for bank credit, a substantial increase for a sample average of 31%.

Table 3 Impact of BNPL Experience on Loan Acceptance

The table shows the impact of being an internal BNPL customer on the probability of being accepted for a consumer loan. Columns 1-3 show the impact in the whole sample of internal and external customers, and columns 4-6 in the restricted sample with customers who had previously used the BNPL service within the bank. All regressions include daily time fixed effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole Sample			BNPL Sample		
Internal BNPL	0.415***	0.376***	0.295***	0.177***	0.164***	0.172***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
External Credit Score	-0.013***	-0.012***		-0.033***	-0.029***	
	(0.000)	(0.000)		(0.000)	(0.000)	
Constant	0.402***	-0.765***	0.019**	0.697***	-0.738***	-0.136***
	(0.001)	(0.009)	(0.007)	(0.002)	(0.035)	(0.032)
Observations	1,066,503	1,066,503	1,066,502	98,203	98,203	98,199
Adj.R^2	0.179	0.225	0.387	0.202	0.240	0.309
Mean dependent	0.310	0.310	0.310	0.667	0.667	0.667
SD dependent	0.462	0.462	0.462	0.471	0.471	0.471
Controls	No	Yes	Yes	No	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	Yes	No	No	Yes

Because BNPL users may differ from non-users in several dimensions, we run a robustness test by restricting the sample to applicants with prior BNPL usage, regardless of whether they qualify as internal. By including time fixed effects, we effectively compare recent BNPL users with those who used BNPL either in the more distant past or less than three times in the past 12 months and whose past BNPL data is not used for the internal risk assessment. Columns (4)-(6) show that the coefficient on ”internal BNPL” remains significant though smaller than before, reflecting the greater similarity between recent and past BNPL users. The point estimate of 0.17 corresponds to a 26% higher likelihood of acceptance compared to the average rate.

To account for the possible gradual depreciation of experience in handling credit, we further narrow the control group to external applicants who used BNPL within either the last three years or the last year. In Appendix Table C.1, we demonstrate that the results in Table 3 are robust to varying definitions of the "aging" of external BNPL users.

Heterogeneity

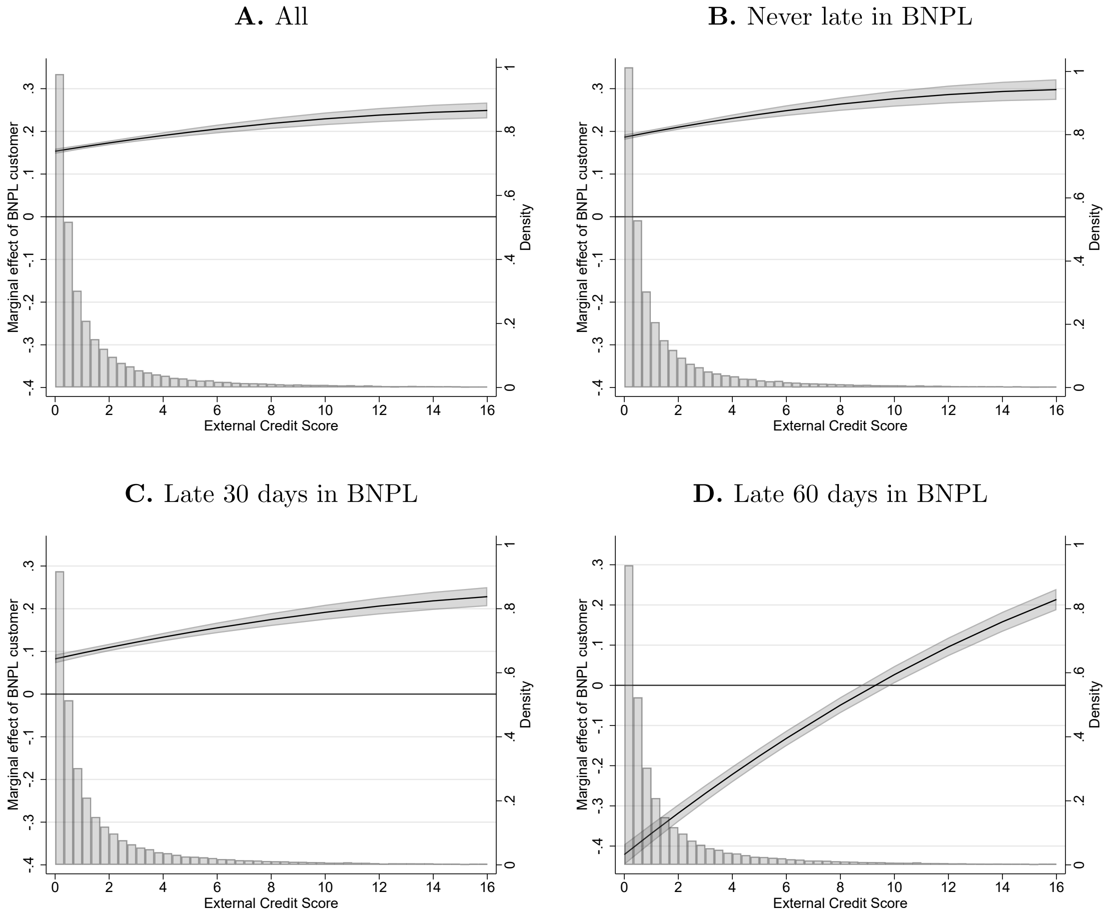
To examine which consumer groups benefit most from building BNPL experience and a payment track record, we analyze how acceptance rates vary along the external credit score distribution and across different payment performances. Presumably, customers with a history of good repayment behavior are more likely to benefit, while those with previous delinquent behavior are less likely to do so. Additionally, customers with higher external credit scores may benefit the most from a new internal assessment, as a favorable internal evaluation has the potential to significantly improve their chances of securing a loan.

We estimate the main regression while excluding the control for ECS and instead adding an interaction between the indicator for being an internal BNPL customer and a quadratic function of the ECS. This approach provides the marginal effect of being an internal BNPL customer across the full range of external credit scores, accounting for the possibility that the effect may vary more sharply at certain points along the score distribution. We estimate four separate regressions using four definitions of internal BNPL customer: (a) all internal customers, (b) internal customers without any late BNPL payments, (c) internal customers with at least one 30-day late payment, and (d) internal customers with at least one 60-day late payment. In all regressions, external BNPL customers serve as the control group.

Figure 3 presents these results, highlighting notable heterogeneity across both the ECS distribution and repayment history groups. Panel A shows that, on average, applicants benefit from being internal BNPL customers, with larger gains for those with higher ECS. Internal customers with a low ECS improve their likelihood of being accepted for bank credit by 15 percentage points (pp) compared to external customers with similar scores,

Figure 3 Acceptance of Internal BNPL customers by external credit score

In this figure we show marginal effects (solid black lines) for β over the external credit score distribution from estimating the following regression model: $Accept_{i,t} = \beta \, BNPL\,Customer_i \times Q(External\,Credit\,Score) + \cdots + \alpha_x \boldsymbol{X_i} + \alpha_t + \epsilon_{i,t}$. *Accept* is an indicator equaling 1 for applications accepted by the bank on day t, and 0 otherwise. $BNPL\,Customer$ is an indicator that equals 1 for applicants that had at least three BNPL transaction with the bank within the last 12 months. $Q(ECS)$ is a quadratic function of the *External Credit Score*. All regressions include only customers who previously had at least one BNPL contract with the bank (BNPL sample). We estimate the equation for four different treatment groups: (a) all Internal BNPL customers, (b) Internal BNPL customers that were never late on their BNPL payments, (c) Internal BNPL customers that were at least once 30 days late on their BNPL payments, and (d), Internal BNPL customers that were at least once 60 days late on their BNPL payments. Vertical bars indicate how applicants are distributed over external credit scores in each sample.



while higher ECS applicants see gains up to 25 pp. For internal customers with a completely clean BNPL payment track record (Panel B), the marginal benefit is even greater, ranging from 20 pp to 30 pp. However, for internal customers with at least one 30-day BNPL payment delay (Panel C), the positive effect is attenuated but remains positive across the range of ECS scores. Notably, Panel D demonstrates that the group of seemingly low-risk applicants (as measured by their ECS) who were more than 60 days late on a BNPL payment experience a 10-40 pp *reduction* in their acceptance probability.

Results in Appendix Table A4 reveal that the higher acceptance rates for internal BNPL customers are due to improvements in their internal credit score that stem from the inclusion of their BNPL payment data in the bank's risk assessments. On average, internal customers have an ICS that is 10 points lower than external customers and 8.3 points lower than other bank applicants with BNPL experience. Internal scores play an important role in credit approval decisions, outweighing the impact of external scores. To achieve a similar improvement in acceptance rates as the average internal BNPL customer, external applicants would on average need a 26-point reduction in their external score — equivalent to more than a two-standard-deviation improvement.

3.2.2 Interest Rates and Price Discrimination

Next, we analyze whether internal customers benefit from the bank's use of their BNPL history through the interest rate they pay on bank credit. The mean interest rates range from 8.2 percent in the sample with previous BNPL experience to 9.2 percent in the full sample. Regression results with the offered interest rate as the dependent variable in Table 4 reveal that internal BNPL customers pay 1.2 to 1.5 percentage points less compared to other applicants, a 15% reduction relative to the mean. A one-point deterioration of the ECS on average pushes up interest rates by 0.3 pp, implying that an external customer would need an ECS that is 4–5 points lower to achieve the same reduction as an internal BNPL customer. Including external score bins as controls leaves the estimated effect unchanged (columns 3 and 6).

Appendix Table C.2 also demonstrates that these results are robust to alternative sample definitions of external BNPL customers (e.g., one or two BNPL transactions in the past 12 months). We also apply a coarsened exact matching procedure to make the control group

Table 4 Impact of Having BNPL Experience on Offered Interest Rates

The table shows the impact of being an internal BNPL customer on the interest rate. Columns 1-2 show the impact in the whole sample of internal and external customers, and columns 3-4 in the restricted sample with customers who had previously used the BNPL service within the bank. All regressions include daily time fixed effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Whole Sample			BNPL Sample	
Internal BNPL	-1.483***	-1.427***	-1.434***	-1.227***	-1.205***	-1.230***
	(0.012)	(0.012)	(0.011)	(0.014)	(0.014)	(0.014)
External Credit Score	0.327***	0.280***		0.451***	0.385***	
	(0.002)	(0.002)		(0.006)	(0.006)	
Constant	8.844***	16.843***	16.224***	8.211***	17.809***	17.751***
	(0.004)	(0.092)	(0.089)	(0.009)	(0.207)	(0.201)
Observations	393,080	393,080	393,080	71,494	71,494	71,494
Adj.R^2	0.262	0.285	0.308	0.286	0.321	0.332
Mean dependent	9.232	9.232	9.232	8.277	8.277	8.277
SD dependent	2.407	2.407	2.407	2.087	2.087	2.087
Controls	No	Yes	Yes	No	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	Yes	No	No	Yes

even more similar to the internal customers.[4] We re-estimate the regression of Table 4 with the offered interest rate as the dependent variable and find a coefficient for internal BNPL customers of -1.3, within the range of our previous estimates of -1.4 in the full sample and -1.2 in the BNPL sample (see Table B.3).

So far we have shown that customers who previously used BNPL on average benefit from having their data used by the bank in regular loan applications. This average effect likely masks variation between different applicant groups. To explore in more detail which groups benefit or lose in the pricing of their bank loans from the revelation of either positive or negative information through their past BNPL payment data, we outline a simple framework in Appendix D that illustrates the bank's pricing strategy based on four types of internal customer classifications. This framework highlights the mechanisms at play when the bank adjusts loan pricing in response to information revealed by BNPL payment histories. Specif-

[4]We match Internal and External customers on year, homeownership, income, application amount and external credit score, see Appendix B for details.

ically, Table 5 summarizes how we classify customers into four types based on their external and internal scores. *High Risk* (*Low Risk*) types are those with both external and internal credit scores above (below) the median, while we label applicants with an external score below (above) the median but an internal score above (below) the median as *Revealed High Risk* (*Revealed Low Risk*).[5]

Table 5 Classification of Internal BNPL Customers Based on Credit Scores

This table shows the classification of internal customers based on their external and internal credit score rank. Medians are computed within the sample of internal BNPL customers and by year.

	Internal Score < Median	**Internal Score > Median**
External Score < Median	*Low Risk*	*Revealed High Risk*
External Score > Median	*Revealed Low Risk*	*High Risk*

We first investigate how the revelation of positive and negative information through BNPL usage data affects the price of credit for customers with the same external risk assessment. Table 6, columns (1)-(2), shows that customers who are high risk according to their external credit scores but whose BNPL data reveals them to be low risk, i.e., *Revealed Low Risk*, receive loan offers with an interest rate reduction of 2.3 to 2.4 pp compared to *High Risk* customers. This reduction is substantial, given the mean interest rate for Internal BNPL customers of 8.6%. In contrast, columns (3)-(4) make clear that if a customer's past BNPL payment history reveals them to be riskier than their external credit score suggests, i.e., they are *Revealed High Risk*, the bank charges 1.4 to 1.5 pp more in interest than what *Low Risk* customers with the same external risk profile are offered.

Second, we explore if the bank's pricing of credit depends only on its own risk assessment or also on how risky a loan applicant appears on the outside, i.e., to banks that may lack access to BNPL data. Specifically, we examine whether the bank price discriminates when customers have the same internal credit score but different external credit scores. Since external credit scores are compounded into internal risk scores, significance of the external score will reflect that the bank internalizes the information set of other banks in its price-

[5]For the analysis, medians are calculated with the sample of internal BNPL customers and by year.

Table 6 Pricing Positive and Negative Information Revelation

The table shows how information from previous BNPL payments compounded into internal credit scores (ICS) affects the offered interest rate on bank loans when ICS indicate low (high) risk while the external credit score (ECS) classifies an applicant as high (low) risk. Borrowers are classified into *(Revealed) High Risk/Low Risk* as in Table 5. In Columns (1)-(2), we check how the revelation of good information affects the pricing of credit for applicants who are classified as *High risk* based on their ECS. In Columns (3)-(4) we document how the revelation of negative information affects the pricing of credit for applicants who are classified as *Low risk* based on their ECS.

	(1)	(2)	(3)	(4)
	Sample: ECS > median		Sample: ECS < median	
Revealed Low Risk	-2.367***	-2.316***		
	(0.031)	(0.031)		
Revealed High Risk			1.398***	1.495***
			(0.023)	(0.023)
External Credit Score	0.232***		1.295***	
	(0.008)		(0.054)	
Constant	13.057***	13.596***	12.292***	13.540***
	(0.352)	(0.346)	(0.311)	(0.319)
Observations	13,115	13,115	13,111	13,111
Adj. R2	0.412	0.417	0.517	0.491
Mean dependent	8.629	8.629	6.595	6.595
SD dependent	2.245	2.245	1.168	1.168
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
External Score FE	No	Yes	No	Yes

setting. For example, if *Revealed Low Risk* borrowers pay a higher interest rate than *Low Risk* borrowers (keeping the internal credit score fixed), it would indicate that the bank does not fully adjust interest rates downwards in response to its internal risk assessment. This would be a profitable strategy when the bank knows that other banks are less likely to offer loans with lower rates because the applicant looks risky to them.

Results in Table 7, columns (1)-(2), show that *Revealed Low Risk* borrowers pay an interest rate that is 11–31 bps higher than *Low Risk* borrowers do. In Table 6 we already showed that *Revealed Low Risk* borrowers receive lower rates compared to their risk-adjusted market rate, i.e., the rate that corresponds to their external risk profile and what banks relying solely on external credit scores could offer. Table 7 reveals, however, that our bank does not lower the interest rate to the full extent justified by its internal risk assessment.

The incomplete pass-through of the internal risk assessment reflects that the bank earns a return on its private BNPL data. By offering slightly reduced rates to customers who appear low risk both externally and internally, compared to those who appear high risk externally, the bank capitalizes on its informational advantage. This strategy allows the bank to offer lower rates based on its internal assessment while retaining a competitive edge over other lenders and resembles the classic hold-up problem. When the bank has exclusive, positive information about its customers, it can exploit this informational advantage, but the extent to which it can do so will depend on what (it knows) its competitors know about those customers.

Table 7 Price Discrimination From Type Revelation vs Type Confirmation

The table shows how information from previous BNPL payments compounded into internal credit scores (ICS) affects the offered interest rate on bank loans when ICS indicate low (high) risk while the external credit score (ECS) classifies an applicant as high (low) risk. Borrowers are classified into *(Revealed) Risky/Safe* as in Table 5. In Columns (1)-(2), we compare *Revealed Low Risk* and *Low Risk* types, i.e., we investigate if borrowers whose *Low Risk* type is *confirmed* by BNPL data receive a different interest rate than those whose *Low Risk* type is *revealed* by internal BNPL data. In Columns (3)-(4), we compare *Revealed High Risk* and *High Risk* types, i.e., investigate if borrowers whose *High Risk* type is *confirmed* by BNPL data receive a different interest rate those whose *High Risk* type is *revealed* by internal BNPL data.

	(1)	(2)	(3)	(4)
	Sample: ICS < median		Sample: ICS > median	
Revealed Low Risk	0.111***	0.313***		
	(0.009)	(0.012)		
Revealed High Risk			-0.936***	-0.751***
			(0.030)	(0.029)
Internal Credit Score	1.832***		0.696***	
	(0.022)		(0.014)	
Constant	8.257***	10.563***	8.717***	10.298***
	(0.129)	(0.186)	(0.328)	(0.298)
Observations	13,062	13,062	13,155	13,154
Adj. R2	0.692	0.460	0.457	0.539
Mean dependent	6.274	6.274	8.941	8.941
SD dependent	0.719	0.719	2.097	2.096
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Internal Score FE	No	Yes	No	Yes

In columns (3) and (4), we inspect if the bank behaves symmetrically when its own risk assessments indicate an applicant is riskier than what external ratings indicate. The negative coefficient indicates that *Revealed High Risk* customers — those who appear of low risk to other banks but are judged to be high risk by the bank's internal model — receive better interest rates than customers classified as *High Risk* by both internal and external assessments. While it may seem counterintuitive, competitive dynamics can explain why the bank offers lower rates to these *Revealed High Risk* borrowers. Applicants deemed relatively risky by the bank's internal model are less likely to receive a loan offer in the first place. However, those who *do* qualify will be considered as low risk by other lenders. Consequently, the bank will face stronger competition for these borrowers and is forced to offer a lower rate than it would to applicants who are uniformly perceived as risky by both internal and external assessments.

Overall, the gain is much smaller, however, than the 2.3 pp lower rate that revealed safe customers obtain. Tables 6–7 reveal that the bank adjusts interest rates based on internal BNPL data, increasing or decreasing them depending on whether the information is positive or negative and on the bank's competitive position. When competition from lenders without BNPL data is more intense, the bank offers larger reductions in interest rates than when competition is weaker. This underscores how the bank's information advantage varies with the perceived riskiness of its clients. Borrowers deemed high risk by external credit standards benefit less from their BNPL track record than peers who appear low risk externally. Nevertheless, as we established in Section 3.2.1, nearly all borrowers with a BNPL history experience improved access to credit.

3.2.3 Repayment Behavior

Next, we analyze whether better access to bank loans and more favorable credit terms ultimately benefit internal BNPL customers or involve a trade-off where credit quality declines because marginal borrowers are riskier or increased credit uptake leads to more defaults. If greater access to credit leads internal BNPL customers to take on more debt than they can

Table 8 Impact of Having BNPL Experience on Payment Delays

The table shows how BNPL experience and external credit scores explain the likelihood of payment delays on a bank loan. Columns (1)-(3) show the impact for the full sample of internal and external customers and columns (4)-(6) for borrowers who previously used BNPL with the bank. All regressions include monthly time fixed effects. Standard errors are clustered at the individual level. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Whole Sample				BNPL Sample			
Panel A: Late 30 Days								
Internal BNPL	-0.104***	-0.118***	-0.105***	-0.105***	-0.056**	-0.067**	-0.061**	-0.055**
	(0.0174)	(0.0175)	(0.0176)	(0.0177)	(0.0259)	(0.0263)	(0.0267)	(0.0269)
External Credit Score	0.013***	0.011***	0.009***		0.016***	0.012***	0.009**	
	(0.0016)	(0.0018)	(0.0018)		(0.0039)	(0.0043)	(0.0045)	
Interest Rate			0.016***	0.017***			0.015*	0.016**
			(0.0028)	(0.0028)			(0.0078)	(0.0079)
Constant	0.347***	0.224**	-0.042	-0.006	0.253***	0.268	0.022	0.043
	(0.0078)	(0.0964)	(0.1057)	(0.1055)	(0.0214)	(0.2138)	(0.2487)	(0.2521)
Observations	8,052	7,841	7,841	7,841	1,363	1,342	1,342	1,342
Adj.R^2	0.074	0.107	0.111	0.111	0.056	0.080	0.082	0.083
Mean dependent	0.384	0.383	0.383	0.383	0.278	0.276	0.276	0.276
SD dependent	0.486	0.486	0.486	0.486	0.448	0.447	0.447	0.447
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	No	Yes	No	No	No	Yes
Panel B: Late 60 Days								
Internal BNPL	-0.097***	-0.107***	-0.087***	-0.084***	-0.032	-0.042**	-0.031	-0.025
	(0.0133)	(0.0134)	(0.0135)	(0.0136)	(0.0197)	(0.0198)	(0.0201)	(0.0201)
External Credit Score	0.011***	0.010***	0.007***		0.010***	0.008**	0.004	
	(0.0015)	(0.0016)	(0.0016)		(0.0032)	(0.0034)	(0.0036)	
Interest Rate			0.025***	0.026***			0.027***	0.028***
			(0.0025)	(0.0025)			(0.0065)	(0.0065)
Constant	0.195***	-0.007	-0.411***	-0.377***	0.111***	0.076	-0.362*	-0.359*
	(0.0069)	(0.0820)	(0.0912)	(0.0909)	(0.0164)	(0.1675)	(0.1987)	(0.1980)
Observations	8,052	7,841	7,841	7,841	1,363	1,342	1,342	1,342
Adj.R^2	0.059	0.086	0.099	0.100	0.029	0.044	0.060	0.065
Mean dependent	0.225	0.225	0.225	0.225	0.128	0.126	0.126	0.126
SD dependent	0.418	0.418	0.418	0.418	0.334	0.332	0.332	0.332
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	No	Yes	No	No	No	Yes

Impact of Having BNPL Experience on Payment Delays *-continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Whole Sample				BNPL Sample			
Panel C: Default								
Internal BNPL	-0.080***	-0.085***	-0.067***	-0.062***	-0.018	-0.029*	-0.022	-0.019
	(0.0104)	(0.0104)	(0.0105)	(0.0105)	(0.0152)	(0.0149)	(0.0149)	(0.0145)
External Credit Score	0.008***	0.007***	0.004***		0.005**	0.004	0.001	
	(0.0014)	(0.0014)	(0.0015)		(0.0025)	(0.0028)	(0.0029)	
Interest Rate			0.023***	0.024***			0.016***	0.017***
			(0.0023)	(0.0023)			(0.0050)	(0.0048)
Constant	0.134***	0.036	-0.342***	-0.311***	0.062***	0.023	-0.248*	-0.250*
	(0.0061)	(0.0695)	(0.0786)	(0.0786)	(0.0127)	(0.1158)	(0.1444)	(0.1411)
Observations	8,052	7,841	7,841	7,841	1,363	1,342	1,342	1,342
Adj.R^2	0.058	0.081	0.096	0.100	0.026	0.038	0.048	0.069
Mean dependent	0.154	0.154	0.154	0.154	0.070	0.068	0.068	0.068
SD dependent	0.361	0.361	0.361	0.361	0.255	0.252	0.252	0.252
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	No	Yes	No	No	No	Yes

manage, we would expect to observe higher default rates, as documented by deHaan et al. (2024).

For this purpose, we estimate a modified version of regression equation (1), using indicators for bank loan repayment delays of 30 days, 60 days, or a default as the dependent variable. We include demographic control variables available for the sub-sample of granted loans, such as gender and age. Because the sample size is significantly smaller for accepted loan offers, particularly for the BNPL group, we use year-month instead of daily fixed effects.

Table 8, Panel A presents evidence that internal BNPL customers are 10 to 12 pp less likely to have a 30 day payment delay than external customers, corresponding to a 27.4% reduction relative to the sample mean. This finding is robust to including time-fixed effects (column 1) and individual-level controls (column 2). Notably, the estimated effect remains virtually unchanged when we also control for the lower interest rate that internal BNPL customers pay (column 3) and external credit score fixed effects (column 4). The reduction in the frequency of late payments is not endogenously driven by the lower interest rate internal customers receive. In line with expectations, late payments rise with increasing external credit scores. In columns (5) through (8), we compare internal and external BNPL customers and observe that estimated reduction in payment delays remains highly significant but somewhat reduced in absolute size. More frequent and more recent experience in BNPL is thus associated with an improvement in payment discipline.

In Panels B and C, we extend the analysis to payment delays of 60 days and loan defaults. The results largely align with those in Panel A for the entire sample (columns 1–4). However, within the BNPL sample (columns 5–8), the relative improvement observed for internal BNPL customers compared to other BNPL customers diminishes with the duration of payment delays. To mitigate concerns about selection effects, we show in Appendix B, that our results are robust when using a control group obtained by coarsened and exact matching.

Overall, we conclude that, on average, for applicants who were accepted for a bank loan, easier access to credit and lower interest rates do not lead past BNPL users to encounter difficulties in servicing their debt. In fact, our findings indicate that they experience fewer payment delays on bank loans, even after accounting for the impact of lower interest rates.

Several factors could explain why internal BNPL customers manage debt better than the full sample but perform similarly to external BNPL customers. Controlling for interest rates rules out the possibility of better-tailored products improving repayment outcomes. While differences vanish for serious late payments (60+ days) or defaults, a gap persists for minor delays (30 days), possibly because internal BNPL customers, with recent BNPL experience, may be more attentive to their finances. This pattern is consistent with the idea that BNPL transactions might help users develop better repayment habits for larger loans, a possibility we explore further in the next section.

3.2.4 Learning as a Mechanism

A possible driver of the improvement in repayment discipline is a "learning by doing" effect, where access to small BNPL loans provides consumers with practical experience in managing credit responsibly. If some degree of learning already occurs with only a few BNPL transactions—without becoming an internal customer—comparing internal and external BNPL customers might obscure this effect. To address this, we compare external BNPL customers to the broader control group. If a lasting learning effect commences already at small numbers of BNPL transactions, we would expect external BNPL customers to demonstrate improved repayment behavior in this regression as well.

Before proceeding, we first ensure that an indirect effect of BNPL experience on interest rates does not influence repayment behavior for external BNPL customers. Appendix Table A3 replicates the regressions from Section 3.2.2 for a sample excluding internal customers and confirms that, conditional on their risk score, external BNPL customers pay the same interest rates as other external customers. We can therefore abstract from any interest rate effects when studying the repayment behavior of external customers.

Table 9 shows that external customers with BNPL experience are significantly less likely to have late payments, regardless of the regression specification. This result extends across delinquency measures: payment delays up to 30 days are 4.6 pp less likely, slightly tapering off to 4.3 pp for 60-day delays (column 5) and 3.6 pp for defaults (column 6). The consistently positive impact of BNPL usage on repayment behavior, independent of credit scores or terms, supports our earlier finding that customers appear to learn to manage credit through BNPL usage.

As a robustness check, we again apply coarsened exact matching (CEM) as an alternative for selecting our control groups. To do so, we re-estimate the regression from Table 8 with a matched sample of Internal BNPL customers and customers without BNPL experience

Table 9 Impact of BNPL experience on Late Payments

The table shows to what extent the external credit score and being an external BNPL customer explain the probability of being late on payments for a bank loan, compared to all other external customers. All regressions include monthly time fixed effects. Standard errors are clustered at the individual level. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Late 30 days				Late 60 days	Default
External BNPL	-0.055***	-0.047**	-0.045**	-0.046**	-0.043***	-0.036***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.015)	(0.011)
External Credit Score	0.009***	0.008***	0.009***			
	(0.002)	(0.002)	(0.002)			
Internal Credit Score	0.010***	0.009***	0.003	0.003	0.005*	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Interest Rate			0.013***	0.013***	0.020***	0.021***
			(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.293***	0.142	0.035	0.066	-0.319***	-0.278***
	(0.015)	(0.100)	(0.106)	(0.106)	(0.091)	(0.080)
Observations	7,298	7,102	7,102	7,102	7,102	7,102
Adj. R2	0.078	0.110	0.111	0.111	0.100	0.100
Mean dependent	0.395	0.395	0.395	0.395	0.236	0.164
SD dependent	0.489	0.489	0.489	0.489	0.425	0.370
Controls	No	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	No	Yes	Yes	Yes

with the bank.[6] Table B.3 shows that for 30-day payment delays, the coefficient for BNPL customers is -0.091, close to the earlier estimate of -0.105. Similarly, for 60-day delays, the coefficient is -0.076 (previously -0.087) and for defaults it remains unchanged at -0.067.

3.2.5 Efficiency in Use of Information

In the baseline regressions, our control group included all external customers with a previous BNPL relationship with the bank. If learning is mostly driven by recentness of BNPL experience, and less so by its intensity, then the behavior of loan applicants who recently used BNPL credit, but not frequently enough to be considered internal, will likely resemble that of internal customers. To verify this, we re-run all our main regressions using two alternative control groups. The first one includes customers who used BNPL credit during

[6] We match Internal and External customers on year, homeownership, income, application amount and external credit score, see Appendix B for details.

Table 10 Impact of BNPL on Late Payments (Alt. Control)

The table shows the impact of the external credit score and of being an internal BNPL customer on the probability of being late on payments for a consumer loan. Columns 1-3 show the impact in the whole sample of internal and external customers, and columns 4-6 in the restricted sample with customers who had previously used the BNPL service within the bank. All regressions include monthly time fixed effects. Standard errors are clustered at the individual level. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BNPL within 3yrs				BNPL last year			
Panel A: Late 30 Days								
Internal BNPL	-0.064**	-0.060*	-0.053*	-0.051	-0.032	-0.025	-0.018	-0.002
	(0.0313)	(0.0314)	(0.0320)	(0.0324)	(0.0426)	(0.0427)	(0.0431)	(0.0427)
External Credit Score	0.016***	0.010**	0.007		0.015***	0.009*	0.006	
	(0.0043)	(0.0046)	(0.0049)		(0.0047)	(0.0051)	(0.0054)	
Interest Rate			0.013	0.013			0.014	0.015
			(0.0086)	(0.0087)			(0.0092)	(0.0094)
Constant	0.270***	0.474**	0.249	0.304	0.247***	0.468*	0.220	0.287
	(0.0280)	(0.2312)	(0.2694)	(0.2728)	(0.0410)	(0.2691)	(0.3114)	(0.3205)
Observations	1,086	1,068	1,068	1,068	889	873	873	873
Adj.R^2	0.056	0.082	0.084	0.085	0.041	0.065	0.066	0.070
Mean dependent	0.281	0.278	0.278	0.278	0.273	0.270	0.270	0.270
SD dependent	0.450	0.448	0.448	0.448	0.446	0.444	0.444	0.444
Controls								
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	No	Yes	No	No	No	Yes
Panel B: Late 60 Days								
Internal BNPL	-0.034	-0.033	-0.020	-0.016	-0.048	-0.053	-0.039	-0.029
	(0.0238)	(0.0233)	(0.0236)	(0.0239)	(0.0334)	(0.0332)	(0.0328)	(0.0325)
External Credit Score	0.012***	0.008**	0.003		0.011***	0.009**	0.004	
	(0.0036)	(0.0038)	(0.0041)		(0.0039)	(0.0042)	(0.0045)	
Interest Rate			0.026***	0.027***			0.028***	0.029***
			(0.0073)	(0.0073)			(0.0078)	(0.0078)
Constant	0.110***	0.149	-0.284	-0.266	0.127***	0.180	-0.309	-0.288
	(0.0211)	(0.1862)	(0.2269)	(0.2274)	(0.0325)	(0.2253)	(0.2713)	(0.2710)
Observations	1,086	1,068	1,068	1,068	889	873	873	873
Adj.R^2	0.025	0.043	0.058	0.061	0.018	0.029	0.046	0.052
Mean dependent	0.129	0.126	0.126	0.126	0.128	0.126	0.126	0.126
SD dependent	0.335	0.332	0.332	0.332	0.335	0.332	0.332	0.332
Controls								
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	No	Yes	No	No	No	Yes

Impact of BNPL on Late Payments (Alt. Control) *-continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		BNPL within 3yrs				BNPL last year		
Panel C: Default								
Internal BNPL	-0.010	-0.016	-0.007	-0.004	-0.018	-0.027	-0.020	-0.011
	(0.0179)	(0.0169)	(0.0169)	(0.0169)	(0.0236)	(0.0229)	(0.0231)	(0.0224)
External Credit Score	0.006**	0.004	0.001		0.005*	0.004	0.002	
	(0.0028)	(0.0030)	(0.0032)		(0.0030)	(0.0033)	(0.0036)	
Interest Rate			0.017***	0.017***			0.014**	0.015***
			(0.0056)	(0.0054)			(0.0056)	(0.0054)
Constant	0.055***	0.032	-0.256	-0.241	0.064***	-0.030	-0.274	-0.242
	(0.0156)	(0.1232)	(0.1631)	(0.1592)	(0.0233)	(0.1451)	(0.1830)	(0.1800)
Observations	1,086	1,068	1,068	1,068	889	873	873	873
Adj.R^2	0.023	0.039	0.050	0.068	0.024	0.029	0.037	0.055
Mean dependent	0.069	0.066	0.066	0.066	0.069	0.065	0.065	0.065
SD dependent	0.254	0.249	0.249	0.249	0.253	0.247	0.247	0.247
Controls								
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	No	Yes	No	No	No	Yes

the past three years, the second comprises only those who did so during the 12 months.

After establishing in Tables C.1, C.2 and C.3 that even with these narrower control groups, internal BNPL customers continue to have higher acceptance rates, lower interest rates and better internal credit scores, we present in Table 10 the results for payments delays and defaults. While internal customers have fewer payment delays of 30 days than external customers with BNPL experience during the past three years (columns 1-3), we find no differences compared to externals who had BNPL experience in the most recent year (columns 4-6). For 60 days and actual defaults, internal BNPL users and other BNPL users all have equal delinquency rates.

Better repayment discipline, for example through the acquirement of greater attentiveness or experience, is thus not limited to internal customers, who are intense, recent BNPL users but extends to less frequent users. In combination with our earlier observation that internal customers have higher acceptance rates, better internal credit scores and pay lower interest rates than other BNPL users, this indicates that the bank is not using its internal BNPL data in an efficient way. While the bank's internal BNPL data show these applicants are equally creditworthy as internal applicants with similar external credit scores, they are rejected or charged higher interest rates. As a consequence, some of these loan applicants will likely accept loan offers from other banks or be excluded from mainstream bank credit.

4 Discussion

Our findings are consistent with earlier studies showing that private information can enable lenders to charge higher rates and finance less creditworthy borrowers. We provide a new perspective, however, on the mechanism through which private information affects the price and quantity of bank lending as well as the dynamic effect that incentives to collect privately held customer data have on credit market access.

Using novel data from a Nordic bank that also supplies BNPL services, we document the connections between less regulated credit, such as BNPL, and regular bank credit markets and the implications these links have for borrowers and lenders. Our results suggest that barriers for consumers to enter the market for bank credit, while preventing loan defaults in a static sense, can hamper learning by new entrants and thereby restrict lending to consumers who appear risky to banks because they lack experience or a documented track record of credit usage.

We find that a bank holding private customer data that is collected by providing BNPL services price discriminates between customers to an extent that is driven by both the type of asymmetry and the degree of asymmetry. Customers who are rated high risk in the public credit register but have proven themselves to be low risk in their BNPL transactions receive a substantial discount when applying for bank credit. However, not all borrowers who are assessed to be low risk internally receive this interest rate advantage: relative to the total pool of customers who are classified as low risk using their internal data and risk model the bank charges a markup on applicants who are rated high-risk externally. At the same time, applicants who are revealed to be risky by the bank while graded safe in the credit bureau, pay a substantial markup on their bank loans.

Overall, our research supports and extends other recent studies showing that novel data sources stemming from financial innovation, such as digital footprints, can improve credit access. Our analysis provides a dynamic perspective on the value of collecting and holding private information and suggests that the experience borrowers build up in taking small BNPL loans reduces default rates among borrowers whose public credit data may lack history and suggests they are high risk. While other research has found that lenders with privately held data charge higher rates, we explain this by documenting that higher rates reflect the revelation of new, negative, information about repayment ability as well as the degree of asymmetry. At the same time, we show that new credit on the extensive margin can both broaden the market for bank credit and improve delinquency outcomes.

5 Conclusions

We investigate the effects of short-term, easily accessible Buy-Now-Pay-Later (BNPL) credit on access to unsecured bank loans, interest rates, and repayment behavior. Our analysis draws on unique data from a Nordic BNPL provider that also operates as a bank offering traditional loans.

We show that the bank leverages BNPL transaction payment histories to evaluate credit risk when past BNPL users apply for bank loans. This approach benefits both the bank and its BNPL customers. Loan applicants with a history of using the bank's BNPL services are, on average, more likely to be approved for loans, offered lower interest rates, and have fewer late payments and defaults, consistent with a learning effect from BNPL usage. A reinforcing factor for these outcomes is that BNPL users with a positive payment history tend to receive more favorable internal credit scores compared to their external ratings and therefore better credit terms.

The bank gains from its proprietary BNPL data by implementing a price discrimination strategy, earning higher margins on customers with strong internal credit scores despite weaker external credit ratings.

By taking advantage of the fact that the bank only incorporates BNPL data from the past 12 months into its internal risk assessments, we analyze whether borrowers with prior BNPL experience perform better even when they do not receive more favorable loan terms. We provide evidence they do, consistent with the idea that small BNPL loans may facilitate financial learning, leading to improved repayment behavior and reduced default risks.

Our results provide new insights into how new types of, lightly regulated, loans affect credit market access and have important policy implications. Specifically, policymakers may face some intricate trade-offs when designing consumer protection and financial services regulation and should consider how BNPL usage influences access to credit, interest rates, and repayment behavior. On the one hand, we show that small loans with low entry thresholds can enhance financial inclusion and credit affordability for consumers with positive repayment histories. On the other hand, a strong and possibly increasing reliance by banks on proprietary data may restrict efficiency and create a potential for data sharing to increase transparency and foster competition in consumer credit markets.

Our finding that BNPL transaction data can expand credit access and improve repayment discipline raises the question of why traditional credit products, such as credit card loans, are not better tailored to these customer groups. One explanation could be BNPL's unique financing structure, where credit incentives are tied to expected returns from product sales, resembling trade credit. Additionally, the risk in BNPL transactions is often absorbed by either merchants or payment providers. Merchants can accept higher default risks because zero-interest BNPL financing increases sales by attracting customers who might otherwise be unable to purchase, effectively offsetting defaults with higher profits. Similarly, payment providers earn fees from merchants that can exceed losses from BNPL defaults, making the model viable. Another factor may be the early sharing of customer information, which lowers the returns on lending to underbanked individuals. Identifying the sources of these market frictions remains an important avenue for future research

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Appendix

Buy Now Pay (Less) Later: Leveraging Private BNPL Data in Consumer Banking

by Laudenbach, Molin, Roszbach and Sondershaus

January 30, 2025

A Additional Summary Statistics and Results

Table A1 Summary statistics Internal BNPL customers

The table shows summary statistics on repayment behavior and fees of Internal BNPL customers during 12 months preceding their consumer loan application. Fees are CPI adjusted and in 2022 Dollars.

	N	Mean	SD	P50	Min	Max
Late 30 days	30,115	0.382	0.486	0.000	0.000	1.000
Late 60 days	30,115	0.079	0.270	0.000	0.000	1.000
Default	30,115	0.012	0.108	0.000	0.000	1.000
Late fee (0/1)	30,115	0.143	0.350	0.000	0.000	1.000
Late fee amount	30,115	2.761	8.826	0.000	0.000	222.3
Late fee amount $\|_{Latefee=1}$	4,296	19.36	14.99	12.83	1.724	222.3

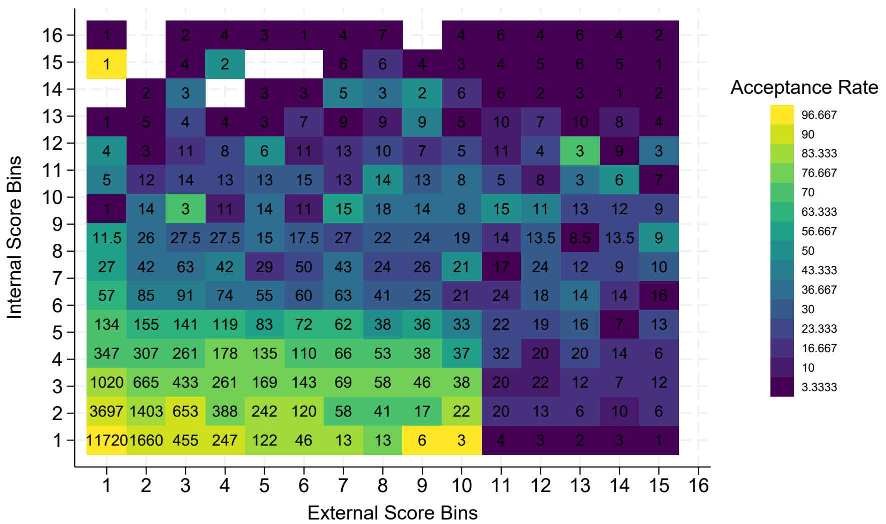

Figure A1 Acceptance Rate by ECS and ICS - Internal BNPL Applicants only

This figure shows bins of external credit scores (ECS) and internal credit scores (ICS), the number of applications per bin, as well as the acceptance rate. Applicants have been grouped into 1-point intervals (0-1, 1-2, 2-3, etc.). The brighter a box is, the higher the is the acceptance rate. The sample covers only Internal Customers who are first time applicants for an unsecured bank loan and apply through an online broker. An applicant is defined as an Internal Customer, or equivalently as an Internal BNPL Customer, if a s/he had at least three BNPL transactions with the bank over the past 12 months

Table A2 Summary Statistics Loan Offers, by Borrower Group

The table shows summary statistics on the variables used in our regression analyses as well as background characteristics in the sample of loan applicants getting a loan offer for the treatment group (Internal BNPL) and two control groups. "Internal BNPL" (or simply "Internal") customers are those who completed at least three BNPL transactions in the past 12 months All other customers are considered "external". "External BNPL customers" are those external customers who have a prior BNPL history at the bank but do not qualify as internal because their BNPL transaction frequency over the past 12 months is smaller than three. Taxable income and application amount is adjusted to constant 2022 values using the Consumer Price Index and converted to U.S. dollars based on the exchange rate as of December 30, 2022.

	Borrower group		
	Internal BNPL	External	External BNPL
Interest Rate	7.61	9.35	8.66
	(2.06)	(2.39)	(2.01)
Internal Credit Score	1.44	6.31	5.26
	(1.61)	(3.63)	(3.42)
External Credit Score	1.43	1.49	0.99
	(2.16)	(2.11)	(1.61)
Married or Co-habiting	0.642	0.568	0.631
	(0.479)	(0.495)	(0.483)
Having Children	0.516	0.398	0.488
	(0.500)	(0.489)	(0.500)
Homeowner	0.666	0.560	0.695
	(0.472)	(0.496)	(0.461)
Employed	0.894	0.871	0.884
	(0.307)	(0.335)	(0.320)
Co-applicant	0.150	0.133	0.160
	(0.357)	(0.340)	(0.367)
Taxable Income	34,029	31,385	34,760
	(16,903)	(18,576)	(18,849)
Application Amount	13,249	14,547	13,665
	(10,570)	(11,462)	(10,840)
Maturity	94	100	93
	(48)	(50)	(48)
Observations	26,323	366,757	45,172

Interest Rates for External BNPL Customers

We analyze in Table A3, if external customers with BNPL experience receives better interest rate offers than other external customers. The coefficient on BNPL External captures the interest rate difference between the external BNPL group and all other customers not classified as internal by the bank. Because this comparison is limited to external customers, we can include a control for internal credit scores to enhance the precision of our estimates. Column 1 displays the difference when controlling only for internal and external credit scores, showing a significant disparity between the groups. When additional control variables are added, the coefficient estimate shrinks and becomes only weakly significant. In the final column, we incorporate external credit score fixed effects, which causes the difference to disappear. This suggests that, when conditioned on having the same external score, these customers face equivalent interest rates.

Table A3 Impact of Having BNPL Experience on Offered Interest Rates

The table shows how being an external BNPL customer affects the offered interest rate. External BNPL applicants have BNPL experience but their BNPL data is not used in risk assessments by the bank. All regressions include daily time fixed effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
BNPL External	-0.019***	-0.010*	0.003
	(0.006)	(0.006)	(0.006)
External Credit Score	0.019***	0.018***	
	(0.001)	(0.001)	
Internal Credit Score	0.522***	0.520***	0.515***
	(0.001)	(0.001)	(0.001)
Constant	6.026***	6.634***	6.472***
	(0.004)	(0.059)	(0.058)
Observations	366,757	366,757	366,757
Adj.R^2	0.734	0.735	0.736
Mean dependent	9.348	9.348	9.348
SD dependent	2.389	2.389	2.389
Controls	No	Yes	Yes
Time FE	Yes	Yes	Yes
External Score FE	No	No	Yes

Internal Credit Score

To assess why internal BNPL customers are more likely to receive a loan offer, we examine the effect of being an internal BNPL customer on the internal credit score. This score, similar to an external credit score, reflects an individual's ability to repay a loan and ranges from 0 to 100, where a lower score indicates a lower risk of default. For internal BNPL customers, this score also incorporates their payment history related to BNPL credit usage.

Table A4 reveals that internal BNPL customers, on average, have a significantly lower internal credit score. This difference is substantial across both samples analyzed. After controlling for external score bin fixed effects, internal BNPL customers, on average, have an internal credit score that is 10 points lower than the full sample and 8.3 points lower when compared to other applicants who have also utilized BNPL services within the bank. This suggests that internal BNPL customers are more likely to have their loan applications accepted, as they have, on average, demonstrated good payment behavior, which results in lower internal credit scores.

A higher external credit score contributes to an increase in the internal credit score. As shown in columns 1-2 and 4-5, a one-point increase in the external credit score results in a less than proportional increase in the internal score, with an effect of 0.48 to 0.64 points when including the controls. External customers would thus need to improve their external credit score by 26 points and external BNPL customers by 13 points to achieve the same internal credit score as the average internal BNPL customer.

Table A4 Impact of Having BNPL Experience on Internal Credit Scores

The table shows the impact of being an internal BNPL customer on the internal credit score. Columns 1-2 show the impact in the whole sample of internal and external customers, and columns 3-4 in the restricted sample with customers who had previously used the BNPL service within the bank. All regressions include daily time fixed effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Whole Sample			BNPL Control	
Internal BNPL	-14.300***	-12.604***	-10.020***	-8.422***	-8.142***	-8.318***
	(0.028)	(0.037)	(0.049)	(0.046)	(0.045)	(0.045)
External Credit Score	0.478***	0.478***		0.720***	0.636***	
	(0.002)	(0.001)		(0.013)	(0.013)	
Constant	15.243***	26.740***	0.353	8.670***	31.796***	18.728***
	(0.016)	(0.311)	(0.275)	(0.039)	(0.754)	(0.687)
Observations	1,066,503	1,066,503	1,066,502	98,203	98,203	98,199
Adj.R^2	0.187	0.282	0.473	0.330	0.371	0.457
Mean dependent	18.621	18.621	18.621	7.902	7.902	7.901
SD dependent	16.107	16.107	16.107	10.094	10.094	10.094
Controls	No	Yes	Yes	No	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	Yes	No	No	Yes

In Appendix C, we demonstrate that these results are robust when using an alternative control group of external BNPL customers with recent experience as controls and in Appendix B when using a matched control group.

B Coarsened and Exact Matching

For the continuous variables taxed income, application amount and external credit score, we applied Sturge's rule using the Stata routine *cem*. The optimal number of cut-off points was 14 for each variable. Table B.1 displays the univariate balance of observable variables on which we match for the sample of loan offers, as used in Section 3.2.2. Column 1 shows the L1 measure (level 1 metric) that evaluates in CEM how well two groups are balanced after matching based on covariates. The L1 measure ranges from 0 to 1 and after matching, the goal is to minimize it, which indicates that the groups are similar with respect to the covariates. A L1 of 0 indicates perfect balance (the distributions of covariates between treated and control groups are identical across all strata) and a L1 of 1 indicates maximum imbalance (the distributions of covariates are entirely different between the groups). After the matching procedure, the L1 values are close to 0 for all matching variables. Internal BNPL customers still have a higher income, on average USD 2,476, but a slightly lower external credit score (-0.033). The imbalance stems mostly from higher income people; the maximum value differs by USD 178,200. Matching reduces the sample size from 393,080 to 390,701 observations. The CEM produces weights for each observation, which we then apply in the estimation.

We also perform a second CEM procedure for the third sample in our analyses, where we consider only realized loan contracts that we used in Section 3.2.3. The univariate balance of observable variables on which we match for the sample of loan offers is shown in Table B.2. Here, the L1 values are even lower and all close to zero. Internal BNPL customers still have a higher income, though only marginally and the external credit score is again lower. In this sample, the number of observations is reduces from 7,864 to 5,911. Again, CEM produces weights for each observation, which we apply in the regression analyses.

Table B.1 Univariate imbalance after CEM

This table shows the univariate imbalance of covariatates after CEM of Sample 2, i.e. offered loan contracts. The L1 measure is a summary statistic used to quantify the imbalance between the distributions of covariates across treatment groups after matching. L1 can vary between 0 and 1. After matching, the goal is to minimize the L1 measure, which indicates that the groups are similar with respect to the covariates. Income and Application amount are reported in 2024 Dollars.

	L1	mean	min	25%	50%	75%	max
Year	0.009	-0.009	0	0	0	0	0
Homeowner	0.081	0.081	0	0	0	0	0
Taxed Income	0.080	2,476	0	2,158	2,178	3,049	178,200
Application amount	0.035	26	0	0	0	0	0
External credit score	0.107	-0.033	0.000	-0.088	-0.074	0.000	-0.005

Table B.2 Univariate imbalance after CEM

This table shows the univariate imbalance of covariates after CEM of Sample 3, i.e. loan contracts. The L1 measure is a summary statistic used to quantify the imbalance between the distributions of covariates across treatment groups after matching. L1 can vary between 0 and 1. After matching, the goal is to minimize the L1 measure, which indicates that the groups are similar with respect to the covariates. Income and Application amount are reported in 2024 Dollars.

	L1	mean	min	25%	50%	75%	max
Year	0.019	-0.019	0	0	0	0	0
Homeowner	0.052	-0.052	0	0	0	0	0
Taxed Income	0.099	213	-9.9	-544.5	148.5	940.5	-1,287
Application amount	0.059	208	0	495	0	0	0
External credit score	0.064	-0.012	0.009	-0.031	-0.043	-0.066	-0.014

Table B.3 Interest Rate and Late Payments for CEM Matched Sample

The table shows the impact of being an internal BNPL customer on the offered interest rate in column 1, and late payments for 30, 60 and 120 days (default) in columns 2-4, for a sample matched with coarsened exact matching. The regression in column 1 includes daily time fixed effects, the regressions in columns 2-4 include year-month fixed effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1) Interest rate	(2) Late 30 days	(3) Late 60 days	(4) Default
BNPL Customer	-1.348***	-0.091***	-0.076***	-0.067***
	(0.012)	(0.021)	(0.016)	(0.013)
External Credit Score	0.250***	0.009**	0.009***	0.007**
	(0.004)	(0.003)	(0.003)	(0.003)
Interest Rate		0.016***	0.025***	0.019***
		(0.005)	(0.004)	(0.004)
Constant	16.309***	-0.257	-0.701***	-0.370**
	(0.133)	(0.202)	(0.168)	(0.153)
Observations	390,701	5,911	5,911	5,911
Adj.R^2	0.273	0.113	0.122	0.111
Mean dependent	9.223	0.373	0.220	0.154
SD dependent	2.401	0.484	0.414	0.361
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

C Alternative BNPL Control Group

So far, we allowed in our external BNPL control group all customers with a previous BNPL relationship with the bank. However, one might expect that loan applicants who recently obtained a BNPL credit would exhibit characteristics more similar to internal BNPL customers who completed three BNPL transactions within the last 12 months prior to their loan application, in comparison to customers whose BNPL history is further back in time. To assess this, we conduct robustness analyses for all our main results using two alternative control groups: the first group includes those who obtained a BNPL loan within the last three years, and the second group comprises those who did so within the last year.

Table C.1-C.2 present the results on the probability of loan acceptance, internal credit scores, and interest rates. Columns 1-3 use the first alternative control group, while columns 4-5 focus on the second. The results align closely with our main findings. Narrowing the control group to more recent BNPL customers slightly impacts point estimates, generally resulting in a higher loan acceptance rate, lower internal credit scores, and lower interest rates.

Table C.1 Impact of BNPL Experience on Loan Acceptance (Alt. Control)

The table shows how the external credit score and having BNPL experience affect the probability of being accepted for a consumer loan. Columns (1)-(3) restrict the control group to external BNPL customers that where accepted for a BNPL within three years from the loan application, columns (4)-(6) restricts the control group to external BNPL customers that where accepted for a BNPL less than one year from the loan application. All regressions include daily time fixed effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	BNPL within 3yrs			BNPL last year		
Internal BNPL	0.200***	0.186***	0.188***	0.237***	0.223***	0.220***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
External Credit Score	-0.032***	-0.028***		-0.031***	-0.028***	
	(0.000)	(0.000)		(0.001)	(0.001)	
Constant	0.671***	-0.649***	-0.125***	0.631***	-0.508***	-0.058
	(0.003)	(0.038)	(0.035)	(0.004)	(0.047)	(0.043)
Observations	68,130	68,130	68,123	45,970	45,970	45,961
Adj.R^2	0.219	0.251	0.315	0.239	0.264	0.322
Mean dependent	0.672	0.672	0.672	0.696	0.696	0.696
SD dependent	0.469	0.469	0.469	0.460	0.460	0.460
Controls	No	Yes	Yes	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	Yes	No	No	Yes

Table C.2 Impact of BNPL on Interest Rate (Alt. Control)

The table shows the impact of being an internal BNPL customer on the interest rate. Columns 1-3 show the impact when the control group is restricted to external BNPL customers that where accepted for a BNPL within three years from the loan application, and columns 4-6 that where accepted for a BNPL within one years from the loan application. All regressions include daily time fixed effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	BNPL within 3yrs			BNPL last year		
Internal BNPL	-1.330***	-1.290***	-1.316***	-1.381***	-1.341***	-1.370***
	(0.017)	(0.016)	(0.016)	(0.023)	(0.023)	(0.023)
External Credit Score	0.475***	0.406***		0.491***	0.425***	
	(0.006)	(0.007)		(0.007)	(0.007)	
Constant	8.296***	18.055***	17.955***	8.304***	18.334***	18.219***
	(0.013)	(0.254)	(0.245)	(0.020)	(0.303)	(0.292)
Observations	50,566	50,566	50,566	35,709	35,709	35,709
Adj.R^2	0.305	0.341	0.354	0.317	0.355	0.374
Mean dependent	8.202	8.202	8.202	7.948	7.948	7.948
SD dependent	2.198	2.198	2.198	2.154	2.154	2.154
Controls	No	Yes	Yes	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	Yes	No	No	Yes

Table C.3 Impact of BNPL on Internal Credit Scores (Alt. Control)

The table shows the impact of being an internal BNPL customer on the internal credit score. Columns 1-3 show the impact when the control group is restricted to external BNPL customers that where accepted for a BNPL within three years from the loan application, and columns 4-6 that where accepted for a BNPL within one years from the loan application. All regressions include daily time fixed effects. Robust standard errors are reported in parentheses. *, **, *** indicate significant coefficients at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	BNPL within 3yrs			BNPL last year		
Internal BNPL	-8.922***	-8.613***	-8.670***	-9.663***	-9.381***	-9.326***
	(0.058)	(0.056)	(0.053)	(0.089)	(0.086)	(0.080)
External Credit Score	0.646***	0.571***		0.556***	0.490***	
	(0.014)	(0.013)		(0.014)	(0.014)	
Constant	9.406***	32.426***	21.265***	10.425***	31.085***	22.838***
	(0.053)	(0.846)	(0.774)	(0.086)	(0.964)	(0.884)
Observations	68,130	68,130	68,123	45,970	45,970	45,961
Adj.R^2	0.362	0.395	0.470	0.415	0.440	0.497
Mean dependent	0.672	0.672	0.672	0.696	0.696	0.696
SD dependent	0.469	0.469	0.469	0.460	0.460	0.460
Controls	No	Yes	Yes	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
External Score FE	No	No	Yes	No	No	Yes

D Price Discrimination Framework

Here, we outline a simple framework for the bank's pricing strategy, categorizing internal customers into four types: *High Risk*, *Revealed High Risk*, *Low Risk*, and *Revealed Low Risk*.

In a setting of perfect price discrimination, the bank would align loan prices with each customer type's willingness-to-pay (WTP). A customer's WTP is assumed to be anchored to the market price determined by their external credit score, as this information is accessible to all loan providers. Loan applications occur via an online broker, where customers receive multiple competing offers, making the market price highly salient. However, the bank's internal credit score, which adjusts the risk assessment using payment history from Buy Now, Pay Later (BNPL) products, remains non-salient to customers. Perfect price discrimination is unlikely in this context due to competition. Customers can compare offers across banks, and the salient market price constrains the bank's ability to fully tailor rates to individual WTP. Consequently, the bank must balance competitive pricing with leveraging its internal credit score to profitably differentiate rates for various customer types.

Table D.1 summarizes the internal and external prices (interest rates) for each customer type. The internal price reflects the bank's loan offer, while the external price represents the market rate based on the customer's external credit score and corresponds to their WTP. *High Risk* and *Revealed Low Risk* customers face the same external price due to their identical external credit classifications, despite differing internal risk assessments. Similarly, *Low Risk* and *Revealed High Risk* customers share the same external price but are offered distinct internal rates, tailored to their internal credit profiles.

Table D.1 Internal and External Prices by Customer Type

Customer Type	Internal Price (IP)	External Price (EP)
High Risk	$IP_{highrisk}$	$EP_{highrisk}$
Revealed Low	$IP_{revlowrisk}$	$EP_{highrisk}$
Low Risk	$IP_{lowrisk}$	$EP_{lowrisk}$
Revealed High	$IP_{revhighrisk}$	$EP_{lowrisk}$

Low Risk Types

Low Risk customers pay an internal price IP_{low} slightly below the external (market) price for their external risk assessment,EP_{low}. This pricing strategy allows the bank to attract these customers while leveraging its informational advantage. However, IP_{low} is likely higher than what these customers would pay if the bank's private information were accessible to other lenders. By setting a price competitive enough to attract low-risk borrowers yet above their true risk-adjusted cost, the bank maintains a profit margin. This marginal profit is the difference between IP_{low} and the expected default cost.

Pricing Strategy The bank sets the internal price as:

$$IP_{lowrisk} = EP_{lowrisk} - \epsilon, \tag{A1}$$

where $EP_{lowrisk}$ is the external price based on the external credit score, and $\epsilon > 0$ is the small discount needed to attract customers. This ensures the bank remains competitive while maintaining profitability.

Marginal Cost The external and internal marginal costs for low-risk customers are:

$$EMC_{lowrisk} = EDP_{lowrisk} \times \text{Loan}, \tag{A2}$$
$$IMC_{lowrisk} = IDP_{lowrisk} \times \text{Loan}. \tag{A3}$$

Here, $EDP_{lowrisk}$ and $IDP_{lowrisk}$ are the external and internal default probabilities, respectively. The bank's informational advantage comes from $IDP_{lowrisk}$, which is lower than $EDP_{lowrisk}$, reflecting a more accurate assessment of the borrower's true risk.

Profit The bank's profit based on external and internal estimates is:

$$E\pi_{lowrisk} = EP_{lowrisk} - EMC_{lowrisk}, \tag{A4}$$
$$= EP_{lowrisk} - (EDP_{lowrisk} \times \text{Loan}), \tag{A5}$$
$$I\pi_{lowrisk} = IP_{lowrisk} - IMC_{lowrisk}, \tag{A6}$$
$$= IP_{lowrisk} - (IDP_{lowrisk} \times \text{Loan}). \tag{A7}$$

The internal profit ($I\pi_{lowrisk}$) depends on the gap between $IP_{lowrisk}$ and $IMC_{lowrisk}$.

Profitability Condition The bank's profitability condition is:

$$\pi_{internal} > 0, \quad \text{if} \tag{A8}$$
$$IP_{lowrisk} > IDP_{lowrisk} \times \text{Loan}. \tag{A9}$$

In a competitive equilibrium:

$$EP_{lowrisk} = EDP_{lowrisk} \times \text{Loan}, \tag{A10}$$

and substituting for $IP_{lowrisk}$, the condition holds if:

$$EDP_{lowrisk} - IDP_{lowrisk} > \frac{\epsilon}{\text{Loan}}. \tag{A11}$$

This inequality shows that the difference between external and internal default probabilities must exceed the scaled discount ($\frac{\epsilon}{\text{Loan}}$) for the bank to profit. Larger loans reduce the impact of the discount, making it easier for the bank to remain profitable, while smaller loans tighten the condition. Overall, the bank will profit if their internal credit assessment reveals that customers are lower risk than what the external score suggests.

Revealed Low Risk Types

Revealed Low Risk customers pay an internal price $IP_{revlowrisk}$, which is below their market price based on the external risk assessment, $EP_{highrisk}$. Due to the private information advantage, the bank only needs to slightly reduce the price (ϵ) to attract these customers. However, these customers pay a higher interest rate than they would have if the private information was shared among all banks, as competitors would have adjusted their prices downward.

It follows that *Revealed Low Risk* customers pay more than fully Low Risk customers ($IP_{lowrisk}$) because the bank does not need to reduce the price as much to secure these customers, given their external classification as higher risk.

Pricing Strategy The internal price for Revealed Low Risk customers is:

$$IP_{revlowrisk} = EP_{highrisk} - \epsilon, \tag{A12}$$

where $EP_{highrisk}$ is the market price based on their external high-risk classification, and $\epsilon > 0$ is the discount required to attract them.

Marginal Cost The marginal costs for Revealed Low Risk customers are:

$$EMC_{revlowrisk} = EDP_{highrisk} \times \text{Loan}, \tag{A13}$$

$$IMC_{revlowrisk} = IDP_{revlowrisk} \times \text{Loan}. \tag{A14}$$

Here, $EDP_{highrisk}$ and $IDP_{revlowrisk}$ are the external and internal default probabilities, respectively. As with Low Risk customers, the bank's informational advantage comes from the lower $IDP_{revlowrisk}$, reflecting a more accurate risk assessment.

Profit The profit equations for Revealed Low Risk customers are:

$$\begin{aligned}
E\pi_{revlowrisk} &= EP_{highrisk} - EMC_{highrisk}, && \text{(A15)}\\
&= EP_{highrisk} - (EDP_{highrisk} \times \text{Loan}), && \text{(A16)}\\
I\pi_{revlowrisk} &= IP_{revlowrisk} - IMC_{revlowrisk}, && \text{(A17)}\\
&= IP_{revlowrisk} - (IDP_{revlowrisk} \times \text{Loan}). && \text{(A18)}
\end{aligned}$$

The internal profit ($I\pi_{revlowrisk}$) depends on the gap between $IP_{revlowrisk}$ and $IMC_{revlowrisk}$. By leveraging its lower internal default probability ($IDP_{revlowrisk}$), the bank captures profit even when charging slightly below the external market price.

Profitability Condition The profitability condition for Revealed Low Risk customers is:

$$\pi_{internal} > 0, \quad \text{if} \tag{A19}$$

$$IP_{revlowrisk} > IDP_{revlowrisk} \times \text{Loan}. \tag{A20}$$

In a competitive equilibrium:

$$EP_{highrisk} = EDP_{highrisk} \times \text{Loan}, \tag{A21}$$

and substituting for $IP_{revlowrisk}$, the condition holds if:

$$EDP_{highrisk} - IDP_{revlowrisk} > \frac{\epsilon}{\text{Loan}}. \tag{A22}$$

This condition highlights that the bank profits if the gap between the external and internal default probabilities ($EDP_{highrisk} - IDP_{revlowrisk}$) exceeds the scaled discount ($\frac{\epsilon}{\text{Loan}}$). As with Low Risk customers, larger loans make this condition easier to satisfy, while smaller loans tighten it, as the discount becomes relatively larger.

Price Hierarchy It follows that:

$$IP_{revlowrisk} > IP_{lowrisk}, \tag{A23}$$

because $EP_{highrisk} > EP_{lowrisk}$. This reflects the higher external risk classification for Revealed Low Risk customers, allowing the bank to set a higher internal price while remaining competitive and profitable.

High Risk Types

High Risk customers are classified as high risk based on both their internal and external credit scores. These customers are typically offered higher interest rates to compensate for the increased probability of default. While the bank has less flexibility to set differentiated internal prices for these customers, it must remain competitive with the external market to attract them.

Pricing Strategy *High Risk* customers pay the internal price (interest rate) IP_{high}. On the market, they would be offered the external (market) price for their external risk assessment, EP_{high}. If the internal price is higher than their market price, these customers might choose an offer from another bank. Therefore, the bank sets:

$$IP_{highrisk} \leq EP_{highrisk}. \tag{A24}$$

This pricing strategy ensures that the bank remains competitive by offering an internal price that is at most equal to the external market price for high-risk customers.

Profitability Condition The profit for high-risk customers is:

$$I\pi_{high} = IP_{highrisk} - IMC_{highrisk}, \tag{A25}$$
$$= EP_{highrisk} - (IDP_{highrisk} \times \text{Loan}). \tag{A26}$$

Here, $IMC_{highrisk} = IDP_{highrisk} \times \text{Loan}$ is the internal marginal cost based on the bank's internal default probability ($IDP_{highrisk}$).

In a competitive equilibrium, the external price reflects the external default probability:

$$EP_{highrisk} = EDP_{highrisk} \times \text{Loan}. \tag{A27}$$

The profitability condition then becomes:

$$EDP_{highrisk} \times \text{Loan} > IDP_{highrisk} \times \text{Loan}, \tag{A28}$$

or equivalently:

$$EDP_{highrisk} > IDP_{highrisk}. \tag{A29}$$

This condition indicates that the bank profits from high-risk customers if the external risk assessment ($EDP_{highrisk}$) exceeds the bank's internal risk assessment ($IDP_{highrisk}$).

Profit Limitations If $IDP_{highrisk} > EDP_{highrisk}$, the bank may not profit from lending to high-risk customers. In such cases, the bank might choose not to lend to these customers unless $EP_{highrisk}$ is sufficiently high to cover the higher internal costs. This highlights the limited scope for leveraging the bank's informational advantage when dealing with high-risk customers.

Price Hierarchy It follows that:

$$IP_{highrisk} > IP_{revlowrisk} > IP_{lowrisk}, \tag{A30}$$

because $EP_{highrisk} > EP_{highrisk} > EP_{lowrisk}$. This hierarchy reflects the relative risk levels assessed externally, which drive differences in external prices and, consequently, the internal pricing strategy.

Revealed High Risk Types

Revealed High Risk customers are classified externally as low risk but are assessed internally by the bank as higher risk. This discrepancy arises because the bank's internal credit scoring system identifies risk factors that are not captured in external evaluations. The bank leverages this private information to set an internal price that reflects the customer's true risk profile while remaining competitive with external offers.

Pricing Strategy *Revealed High Risk* customers pay the internal price (interest rate) $IP_{revhighrisk}$. On the market, they would be offered the external (market) price for their external low-risk assessment, $EP_{lowrisk}$. The bank sets:

$$IP_{revhighrisk} \geq EP_{lowrisk}. \tag{A31}$$

This pricing strategy ensures that the internal price reflects the external low-risk assessment while accounting for the bank's internal evaluation of higher risk. By setting $IP_{revhighrisk} \geq EP_{lowrisk}$, the bank aims to cover the higher internal marginal cost associated with these customers. However, if $IP_{revhighrisk}$ exceeds $EP_{lowrisk}$, the bank risks losing customers to competitors offering loans based solely on external low-risk classifications.

Profitability Condition The profit for Revealed High Risk customers is:

$$I\pi_{revhighrisk} = IP_{revhighrisk} - IMC_{revhighrisk}, \tag{A32}$$
$$= IP_{revhighrisk} - (IDP_{revhighrisk} \times \text{Loan}). \tag{A33}$$

Here, $IMC_{revhighrisk} = IDP_{revhighrisk} \times \text{Loan}$ is the internal marginal cost based on the bank's internal default probability ($IDP_{revhighrisk}$).

In a competitive equilibrium, the external price reflects the external default probability:

$$EP_{lowrisk} = EDP_{lowrisk} \times \text{Loan}. \tag{A34}$$

The profitability condition then becomes:

$$EDP_{lowrisk} \times \text{Loan} > IDP_{revhighrisk} \times \text{Loan}, \tag{A35}$$

or equivalently:

$$EDP_{lowrisk} > IDP_{revhighrisk}. \tag{A36}$$

This condition indicates that the bank profits from Revealed High Risk customers if the external default probability ($EDP_{lowrisk}$) is greater than the internal default probability ($IDP_{revhighrisk}$).

Profit Limitations The bank's ability to profit from Revealed High Risk customers depends on its informational advantage and the pricing flexibility afforded by the external low-risk classification. If the internal default probability ($IDP_{revhighrisk}$) is significantly higher than the external default probability ($EDP_{lowrisk}$), the bank's profit margin may narrow. In such cases, the bank may choose not to lend unless $EP_{lowrisk}$ is sufficiently high to cover internal costs.

Price Hierarchy The internal price hierarchy reflects both external and internal risk assessments. In general, the expected relationship is:

$$IP_{highrisk} > IP_{revlowrisk} > IP_{revhighrisk} > IP_{lowrisk}. \tag{A37}$$

However, since *Revealed Low Risk* customers have a lower default probability than *Revealed High Risk* customers, the internal marginal cost for *Revealed High Risk* customers is higher. As a result, the hierarchy adjusts to:

$$IP_{highrisk} > IP_{revhighrisk} > IP_{revlowrisk} > IP_{lowrisk}. \tag{A38}$$

For *Revealed High Risk* customers, this implies setting $IP_{revhighrisk} > EP_{lowrisk}$ to account for their higher internal risk assessment. However, pricing above $EP_{lowrisk}$ increases the risk of losing these customers to competitors who offer loans based solely on the external low-risk classification.