Consumers' Financial Constraints and Their Use of Buy Now, Pay Later

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March 2026

Abstract

Buy now, pay later (BNPL) services have become increasingly popular among U.S. consumers over the past decade, but more recently the share of BNPL users who repay BNPL loans late has increased rapidly. We examine whether and how consumers' financial constraints and socioeconomic characteristics are correlated with the probabilities of being a BNPL user (among all consumers) and being a BNPL user who makes late payments (among BNPL users). We also assess potential effects of carrying out hard credit checks for BNPL loans on the shares of consumers who use BNPL and of BNPL users who make late payments. Using the 2024 Survey of Household Economics and Decisionmaking, we find that many of 12 financial constraint indicators created are strong predictors of both probabilities. After controlling for these indicators, several socioeconomic characteristics remain significantly correlated with BNPL use but only a few remain so with BNPL late payments, suggesting the importance of financial constraint indicators in predicting consumers' BNPL repayment behavior. We also find that hard credit checks may reduce the number of BNPL users who would not make late payments more than those who would, implying that hard credit checks may make BNPL services inaccessible not only for consumers who would overspend or overextend debt via BNPL but also for those who would be responsible BNPL users.

Keywords: Financial constraints, buy now pay later (BNPL), regulation

JEL codes: D12, D14, D18, G28

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The authors declare that they have no funding sources to report for this research. Additionally, the authors declare no financial relationships or other potential conflicts of interest.

1. Introduction

Buy now, pay later (BNPL) services have gained popularity among U.S. consumers. A common BNPL structure is four interest-free installments ("pay-in-four"), with the first installment due at the time of purchase and the remaining three are paid in three two-week cycles. BNPL services are often offered to consumers at the point of sale and typically require no credit check or only a soft credit check, making them a convenient and accessible form of credit for many consumers. According to consumer surveys, 15-20% of U.S. consumers used BNPL services in 2024 (Aidala et al. 2025; Akana and Zeballos Doubinko 2025; Board of Governors of the Federal Reserve System 2025). In the same year, gross merchandise volume sold using BNPL was estimated around $100 billion or more than 1% of the total retail sales in the United States (Broadbent 2025; Capital One Shopping Research 2026).

Despite their popularity, whether BNPL services improve or harm a consumer's financial situation is an open question. By breaking down purchases into smaller installments and providing access to interest-free credit, BNPL services may help assist consumers, especially those who may not qualify for traditional credit products, in managing financial constraints. However, the smaller interest-free installments may also lead some consumers to perceive purchases as more affordable than they really are, increasing the risk of overspending and overextending debt (Ashby et al. 2025; Maesen and Ang 2025). According to the Survey of Household Economics and Decisionmaking (SHED), the share of BNPL users who made late payments on their BNPL installments (among BNPL users) increased more recently, from 15% in 2021 to 24% in 2024, suggesting some BNPL users with late payments may have overspent or overextended their debt through BNPL.

To mitigate the risk of overspending and overextending debt via BNPL, some countries have started regulating the BNPL sector. For example, in the European Union (EU) and the United Kingdom (UK), BNPL lenders are required to carry out thorough assessments of consumers' creditworthiness before extending BNPL loans (European Parliament and Council of the European Union 2023; Financial Conduct Authority 2026; Financial IT 2026). In the United States, the BNPL sector has not been regulated at the federal level; however, some states have been considering BNPL regulations. Were states to implement BNPL regulations with a similar creditworthiness check requirement as in the EU and the UK, BNPL lenders would possibly run hard credit checks. Hard credit checks may reduce the share of BNPL users who make late

payments on BNPL purchases, but they may also reduce the share of consumers who use BNPL responsibly.

In this paper, we examine whether and how consumers' financial constraints and socioeconomic characteristics are correlated with their BNPL use and repayment behaviors. To this end, we use the 2024 SHED data and create 12 financial constraint indicators from variables that indicate credit or liquidity constraints or other financial hardships. The SHED is unique in the sense that it includes much richer information about consumers' financial situations relative to other consumer surveys, along with consumers' detailed socioeconomic characteristics as well as their BNPL use and repayment behaviors. We then run two logit models: One for BNPL use among all consumers and the other for BNPL late payments among BNPL users. By using the predicted probabilities of being a BNPL user and being a BNPL user with late payments, we assess potential effects of hard credit checks on the shares of BNPL users and BNPL users with late payments.

We find 10 out of 12 financial constraint indicators to be statistically significantly correlated with either BNPL use or late payments or both, even after controlling for other variables. Indicators of credit constraints such as "denied or given less credit" and "used alternative credit services (like payday loans)" are significantly positively associated with both probabilities of being a BNPL user (among all consumers) and being a BNPL user who makes late payments (among BNPL users). Rarely associated with both probabilities are one indicator related to financial difficulties when encountering emergencies, "no means (savings, borrowing, or selling assets) to cover three months' expenses (in case of emergency)," and one indicator related to liquidity constraint, "total spending exceeded income." An indicator related to liquidity constraints, "unable to pay bills in full," is significantly positively associated with the probability of being a BNPL user with late payments but not with the probability of being a BNPL user. After controlling for financial constraint indicators, some socioeconomic characteristics remain statistically significantly associated with the probability of being a BNPL user, but only a few characteristics remain so with the probability of being a BNPL user with late payments. These results show the importance of financial constraint indicators in predicting consumers' BNPL use and late payments.

We also find that BNPL lenders' carrying out hard credit checks may reduce both types of BNPL users, those who make late payments and those who do not. Because BNPL lenders'

hard credit checks could be as strict as credit card lenders', we assume that the predicted probabilities obtained from the regression models would be reduced to as low as zero for BNPL users who were declined or given less credit for their credit card applications. As a result, the expected share of BNPL users who make late payments among BNPL users would be reduced. However, among all consumers, the expected share of BNPL users who do not make late payments would be reduced more than the expected share of BNPL users who made late payments, implying that hard credit checks may reduce the number of BNPL users who would not make late payments more than those who would.

Our study contributes to the literature on consumers' BNPL use. While many existing studies examine the correlation between consumers' BNPL use and their socioeconomic and financial characteristics, most of them include only a few financial characteristics (Aidala et al. 2023; Akana and Zeballos Doubinko 2024, 2025; Larrimore et al. 2024; Shupe et al. 2023; Stavins 2024). In contrast, our study includes 12 financial constraint indicators and clearly demonstrates the importance of these indicators in predicting the probability that a consumer uses BNPL. Furthermore, only a few existing studies have examined the correlation between consumers who make late BNPL payments with their demographic characteristics (Akana 2022; Cooley 2025) or financial situations (Hayashi and Routh 2025). To the best of our knowledge, our study is the first to examine the correlation between BNPL late payments and both BNPL users' socioeconomic characteristics and financial constraint indicators.[1]

Our study also helps inform regulatory approaches to the BNPL sector. Our findings suggest that were BNPL lenders to carry out hard credit checks, unintended consequences could be large. Although hard credit checks may reduce the share of BNPL users who make late payments among BNPL users, they may reduce the number of BNPL users who do not make late payments more than those who do. Many BNPL users who do not make late payments may use BNPL responsibly, while some of BNPL users who do make late payments may overspend or overextend their debt via BNPL. Our findings may complement the findings of Aidala et al. (2025). They use a probabilistic stated choice survey experiment and find that including hard credit checks in the standard bundle of BNPL features would reduce overall consumer demand

[1] Shupe and Palloni (2025) examines the impact of consumers' first-time BNPL use on their non-BNPL debt and the ability to repay those debit obligations using several measures of financial distress.

for BNPL significantly but would increase demand from those with lower credit scores and lower incomes.

The rest of the paper is organized as follows. Section 2 describes the data and explains our empirical methodology. Section 3 presents the results. Section 4 discusses implications of our results for regulatory approaches to the BNPL sector and Section 5 concludes.

2. Empirical analysis

2.1 Data

To examine whether and how consumers' financial constraints and socioeconomic characteristics are correlated with their BNPL use and repayment behaviors, we use data from the 2024 SHED, which was conducted in October 2024. The SHED is an annual survey that the Board of Governors of the Federal Reserve System (Federal Reserve Board) conducts to monitor the financial circumstances of U.S. adult consumers. The SHED has a large sample size—12,295 respondents in the 2024 SHED data—and assigns a weight to each respondent so that the weighted sample is nationally representative of U.S. adults.

The 2024 SHED includes several questions pertaining to consumers' use of BNPL services. In particular, the survey asks respondents whether they have used a BNPL service to buy something in the past year and whether they have ever been late making a payment for purchases made with BNPL in the past year. Responses to these questions allow us to identify BNPL users as well as BNPL users who made late payments.

Because the SHED places great emphasis on understanding how low- and middle-income individuals are faring, the 2024 SHED data contains many variables that indicate financial constraints. Using these variables, we create 12 financial constraint indicators, listed in Table 1.[2] Indicators 1–7 capture whether a consumer faces credit, liquidity, or both constraints. Indicators 1–3 are closely related to credit constraints, especially difficulties in accessing traditional credit products, while Indicator 6–7 are closely related to liquidity constraints. Indicators 4–5 may be related to both constraints: For example, consumers who paid overdraft fees did not have sufficient liquidity to cover their expenses and may have been unable to access credit to meet

[2] Hayashi and Routh (2025) consider 11 financial constraint indicators created from variables in the 2023 SHED, we add one more for our analysis.

their credit needs.[3] The remaining indicators capture other financial hardships. Indicators 8–9 are related to financial difficulties when encountering emergencies, Indicators 10–11 capture financial difficulties in meeting their medical needs, and Indicator 12 indicates a general lack of financial resources.

Table 1: Financial constraint indicators

Indicator	Description
1	Denied credit application or approved but given less credit in the past 12 months
2	Desired credit but chose not to apply in the past 12 months
3	Used alternative credit services (payday, pawnshop, auto title loans, and tax refund advance) in the past 12 months
4	Paid overdraft fees in the past 12 months
5	Carried unpaid credit card balance regularly (all or most of the time) in the past 12 months
6	Did not pay bills in full in the past month, apart from credit card bill
7	Total spending exceeded income in the past month
8	No means (savings, borrowing, or selling assets) to cover 3 months' expenses in case of sickness, job loss, economic downturn, or other emergencies
9	Can't cover $400 emergency expenses fully with cash-equivalent methods such as funds in bank accounts, cash, or credit card without revolving
10	Could not afford needed medical care, therefore skipped
11	Had medical debt
12	Received financial assistance from government welfare programs*

Note: *Programs included in Indicator 12 are Earned Income Tax Credit, Supplemental Nutrition Assistance Program, Women, Infants, and Children (WIC) nutrition program, housing assistance programs, free or reduced-price school lunches, Supplemental Security Income, Temporary Assistance for Needy Families, and other cash assistance programs.

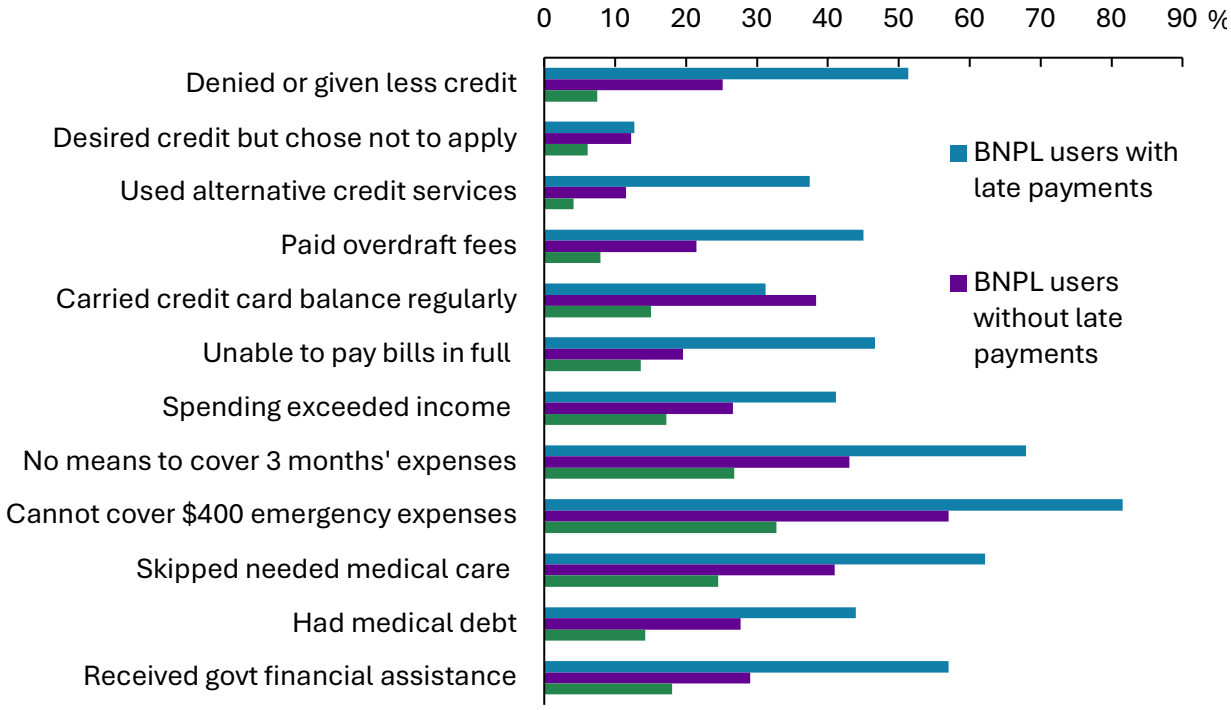
The 2024 SHED data also contains a rich set of socioeconomic variables. For our analysis, we use data on consumers' race/ethnicity, citizenship status, gender, age, household income, education level, employment status, homeownership status, census region, banking status, credit card ownership status, and self-reported credit scores.

According to the 2024 SHED data, nearly 15% of U.S. adult consumers used BNPL services in the past 12 months. Of these BNPL users, 24% made at least one late payment in 2024. Therefore, of all consumers, BNPL nonusers account for 85%, BNPL users without late payments account for 11.4%, and BNPL users with late payments account for 3.6%.

[3] Likewise, consumers who carry unpaid credit card balance regularly may do so out of necessity—because they are unable to cover their expenses using cash or cash equivalent methods or unable to obtain extended credit.

Chart 1 shows how the (weighted) share of consumers with a given financial constraint indicator varies across three groups: BNPL nonusers (green bars), BNPL users without late payments (purple bars), and BNPL users with late payments (blue bars). Clearly, both groups of BNPL users are more likely to have any given financial constraint indicator compared to BNPL nonusers. For 11 out of 12 indicators, BNPL users with late payments have higher shares than BNPL users without late payments. For one indicator, "carried credit card balance regularly," BNPL users with late payments have a *lower* share than BNPL users without late payments; however, if we limit to consumers who own credit cards, the share becomes higher for those with late payments than those without. Across all three groups, some indicators have larger shares than other indicators. For example, "cannot cover $400 emergency expenses" has the largest share across all three groups, meaning that the largest share of consumers face this financial constraint regardless of their BNPL use and repayment behaviors. "Desired credit but chose not to apply" has the smallest share for the two groups of BNPL users and the second smallest share for BNPL nonusers.

Chart 1: Financial constraints faced by BNPL users and nonusers

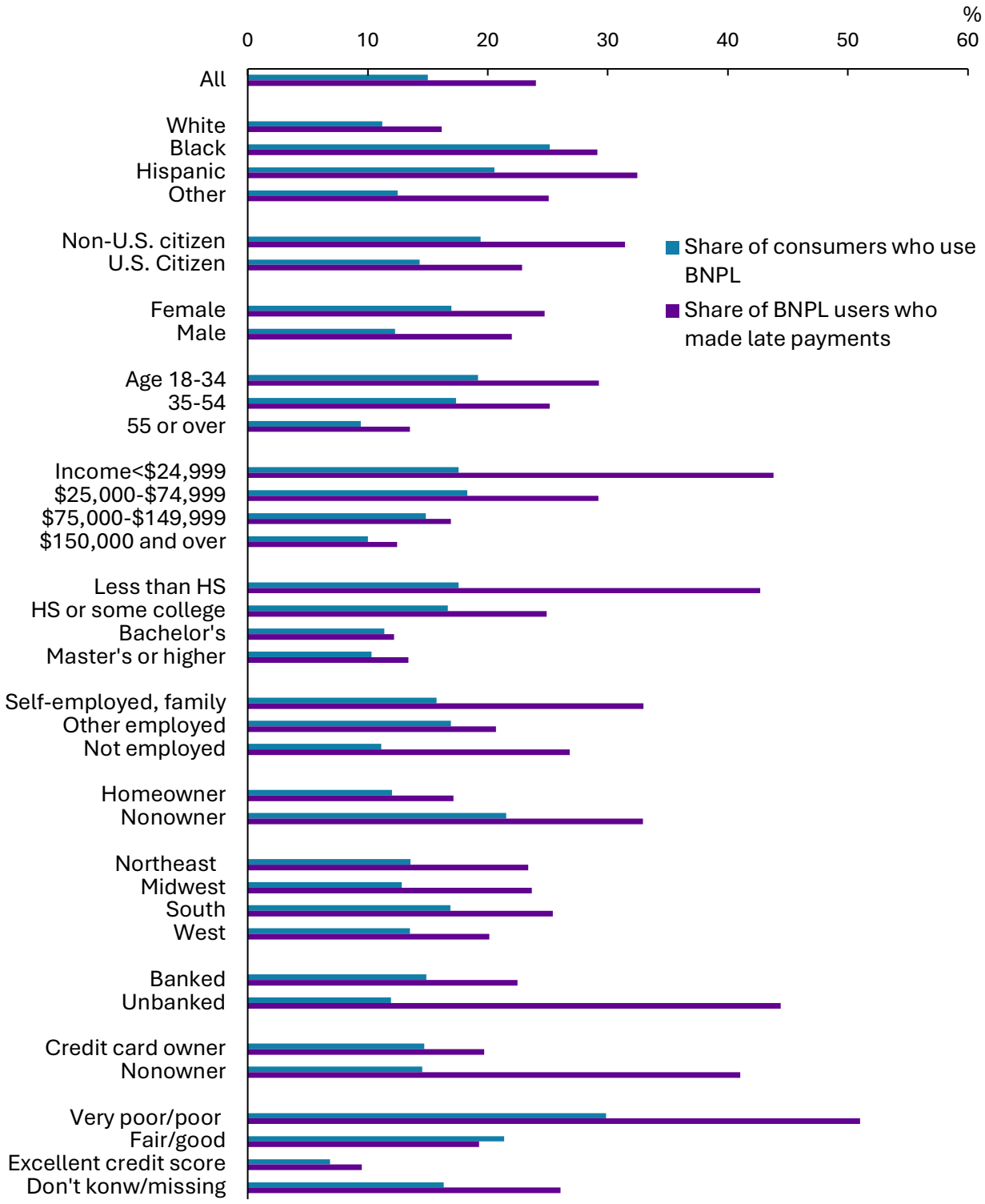


Sources: 2024 SHED and authors' calculations.

Consumers' BNPL use and repayment behaviors vary by their socioeconomic characteristics.[4] Chart 2 shows the weighted share of consumers who use BNPL among all consumers with a given socioeconomic characteristic (blue bars) and the weighted share of BNPL users who made late payments among all BNPL users with a given characteristic (purple bars). Consumers are more likely to use BNPL as well as to make late payments conditional on BNPL use, if they have the following characteristics: Black or Hispanic, non-U.S. citizen, young- or middle-age (ages 54 or younger), female, lower income (income less than $75,000), lower education level (less than high school), self-employed or work for family business, nonhomeowner, and having a very poor/poor credit score. While unbanked consumers or credit-card nonowners are less likely to use BNPL than banked consumers or credit-card owners, conditional on BNPL use, they are more likely to make late payments for BNPL.

[4] See Appendix A for how all consumers and all BNPL users are distributed across consumers' socioeconomic characteristics.

Chart 2: Share of consumers who use BNPL and share of BNPL users who made late payments by socioeconomic characteristic



Sources: 2024 SHED and authors' calculations.

2.2 Empirical methodology

We run two binomial (weighted) logit models to examine whether and how financial constraint indicators and socioeconomic characteristics are associated with BNPL use and late payments. The first model estimates BNPL use among all consumers, and the second model estimates BNPL late payments among BNPL users. For both models, we use the same set of explanatory variables, and all these variables are dummy variables.

A potential concern with estimating the second model is sample selection bias as BNPL late payments are only observable for consumers who use BNPL. If unobserved factors that influence BNPL use also affect BNPL late payments, estimates from a model using only BNPL users could be biased. To test whether sample selection is empirically relevant, we estimate the Heckman two-stage model (Heckman 1979; Van de Ven and Van Praag 1981). The results from this model indicate that sample selection bias is not a substantive concern in our empirical setting (see Appendix A for more details).

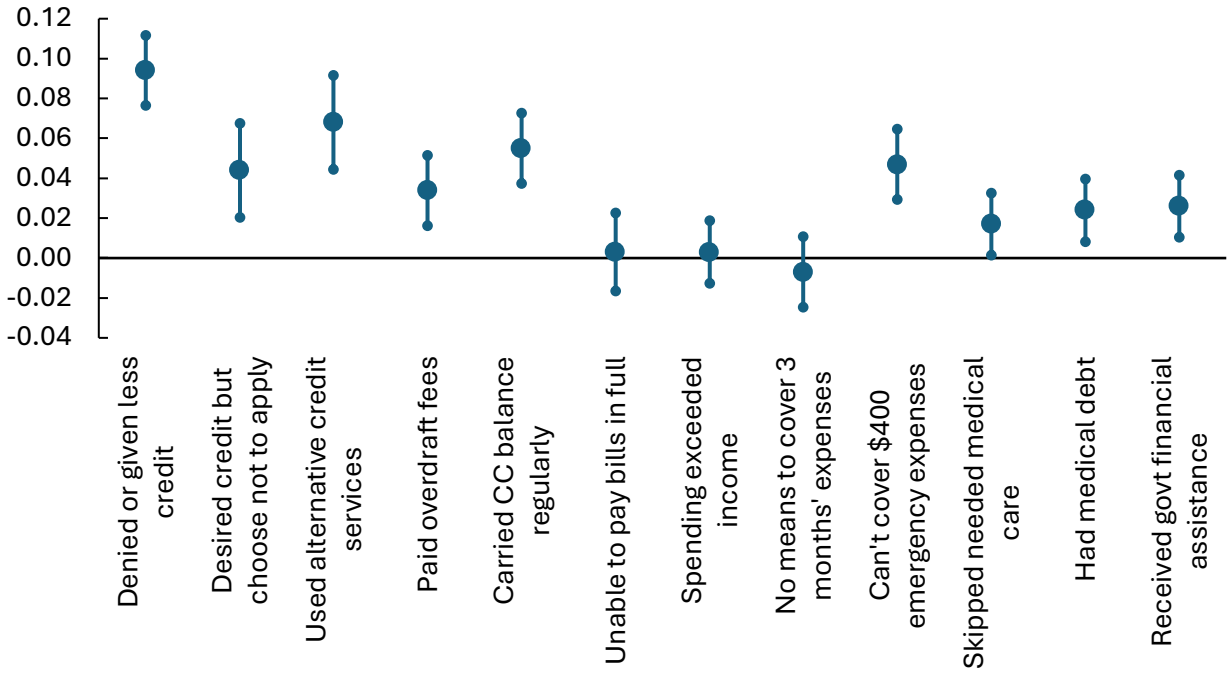
To interpret the coefficients estimated from the two logit models, we calculate the average marginal effects to quantify the degree to which each explanatory variable is individually associated with the probability of being a BNPL user (the first logit model) or with the probability of being a BNPL user who makes late BNPL payments conditional on being a BNPL use (the second logit model). The average marginal effect of an explanatory dummy variable represents the average change in each consumer's (or each BNPL user's) predicted probability across all consumers (or across all BNPL users) when only the explanatory dummy variable switches from zero to one.

3. Results

3.1 BNPL use

From the first logit model, we find 9 out of 12 financial constraint indicators to be statistically significantly positively associated with the probability of being a BNPL user among all consumers. Chart 3 plots the marginal effects of financial constraint indicators on the predicted probability of being a BNPL user. In the chart, a dot shows the average marginal effect, and a bar shows the 95-percentile range of marginal effect.

Chart 3: Marginal effects of financial constraint indicators on BNPL use



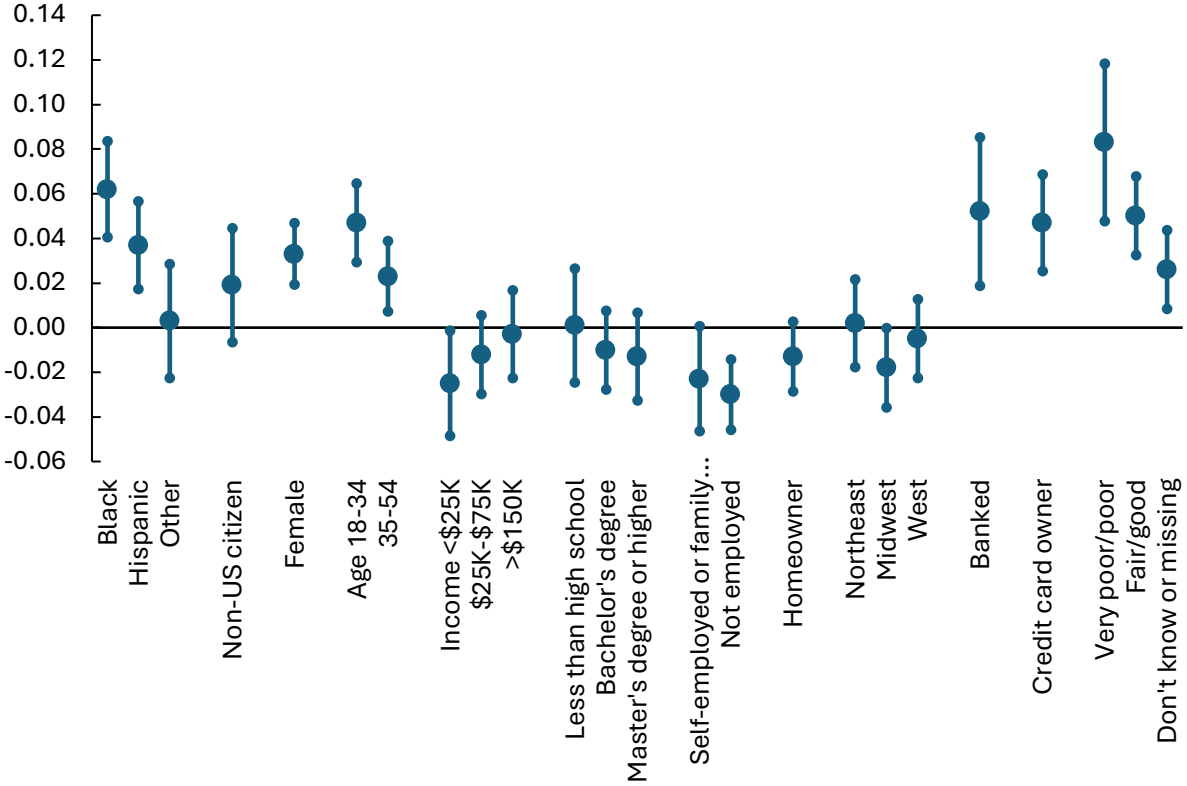
Note: A dot shows the average marginal effect, and a bar shows the 95-percentile range of marginal effect, of a given financial constraint indicator on the probability of being a BNPL user among all consumers.

Among the nine statistically significant financial constraint indicators, indicators related to credit constraints generally have larger average marginal effects than indicators related to other financial hardships. "Denied or given less credit" has the largest average marginal effect of 0.094, meaning that being denied or given less credit is associated with a 9.4 percentage points (pp) higher predicted probability of being a BNPL user. "Used alternative credit services" and "desired credit but chose not to apply" have the second and fifth largest average marginal effects (0.068 and 0.044), respectively. All these three indicators are closely related to credit constraints. "Carried credit card balance regularly" and "paid overdraft fees" have the third and sixth largest effects (0.055 and 0.034), respectively, and these indicators may be related to both credit and liquidity constraints. One indicator, "cannot cover $400 emergency expenses (fully with cash-equivalent methods)," has the fourth largest effects (0.047), which is related to financial difficulties when encountering emergencies. One indicator related to a general lack of financial resources, "received government financial assistance," has the seventh largest effect (0.026). Finally, two indicators related to financial difficulties in meeting medical needs, "had medical debt" and "skipped needed medical care," have the eighth and nineth largest effect (0.024 and 0.017), respectively.

The three statistically insignificant financial constraint indicators are related to either liquidity constraints or financial difficulties when encountering emergencies. Two indicators, "spending exceeded income" and "unable to pay bills in full," are related to liquidity constraints, and one indicator, "no means to cover 3 months' expenses" is related to financial difficulties when encountering emergencies.

In addition to the nine financial constraint indicators, we also find statistically significant differences in the predicted probability of being a BNPL user across characteristics in eight socioeconomic categories: Race/ethnicity, gender, age, employment status, census region, banking status, credit card ownership status, and self-reported credit scores. Chart 4 plots marginal effects of socioeconomic characteristics on the predicted probability of being a BNPL user.

Chart 4: Marginal effects of sociodemographic and financial characteristics on BNPL use



Notes: A dot shows the average marginal effect, and a bar shows the 95-percentile range of marginal effect, of a given characteristic, relative to the base characteristic of the same category, on the probability of being a BNPL user among all consumers. The base characteristics, which are omitted from explanatory variables, are White (race/ethnicity), U.S. citizen (citizenship), male (gender), 55 or over (age), $75K-$150K (income), other employed (employment), nonhomeowner (homeownership), South (census region), unbanked (banking status), credit card nonowner (credit card ownership), excellent (credit score).

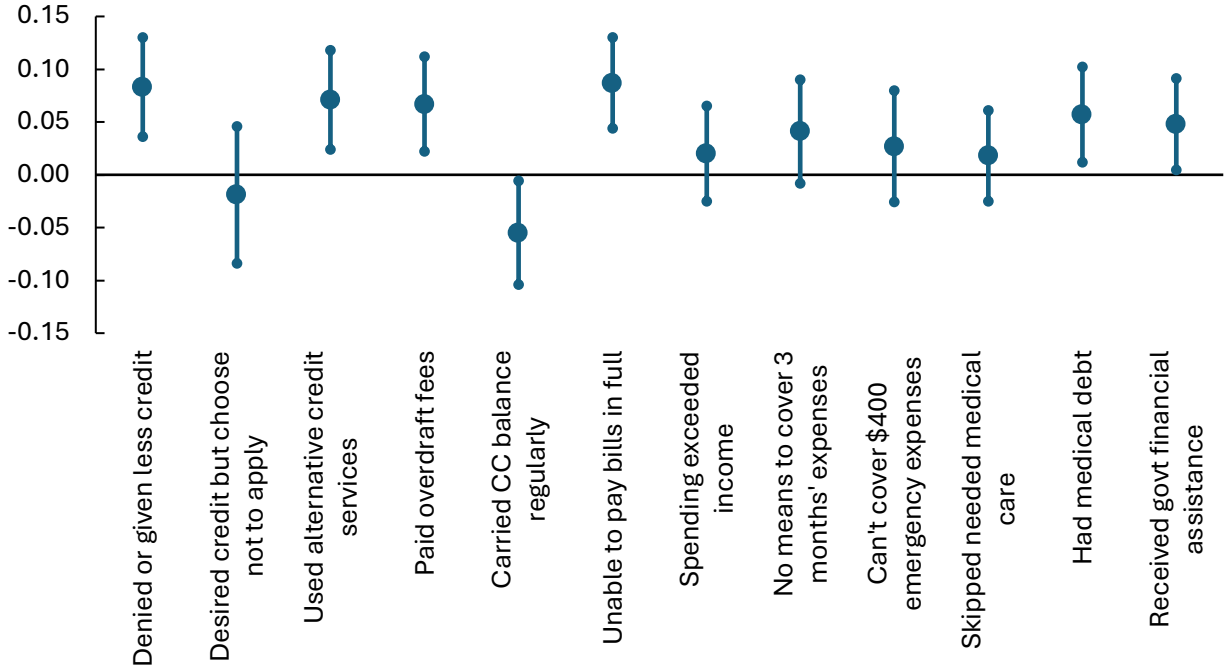
First, being a racial and ethnic minority is significantly positively associated with the predicted probability of BNPL use. Relative to being a White consumer, being a Black consumer is associated with a 6.2 pp higher predicted probability of being a BNPL user, and being a Hispanic consumer is associated with a 3.7 pp higher probability. Second, being female is associated with a 3.3 pp higher probability relative to being male. Third, age is a significant predictor of BNPL use: relative to being senior (ages 55 or older), being young (ages 18-34) or middle-aged (ages 35-54) is associated with a 4.7 pp or 2.3 pp higher probability. Fourth, being not employed is associated with a lower probability (by 3.0 pp), relative to being other employed. Fifth, relative to living in the South census region, living in the Midwest census region is associated with a slightly lower probability (by 1.8 pp). Sixth, being banked is associated with a significantly higher probability (by 5.2 pp), relative to being unbanked. Seventh, owing a credit card is also associated with a significantly higher probability (by 4.7 pp), relative to not owning a credit card. Finally, self-reported credit score is the strongest predictor of BNPL use among all socioeconomic categories: Relative to having an excellent credit score, having a very poor/poor, fair/good, or don't know or missing self-reported credit score is associated with a significantly higher probability—by 8.3 pp, 5.0 pp, and 2.8 pp, respectively.

Our results for socioeconomic characteristics are generally consistent with findings in previous studies. For example, Stavins (2024) finds that credit score is the strongest predictor of BNPL use, with a lower score being positively associated with BNPL use. Our results suggest that credit score is the second strongest predictor after the financial constraint indicator of "denied or given less credit." Stavins (2024) also finds female, Black, and Hispanic to be positively associated with the probability of using BNPL, which are consistent with our results. In other studies, younger and lower-income consumers have generally been reported to be more likely to use BNPL than their counterparts. We find that younger age is significantly positively associated with the probability of BNPL use, but lower income is not. We find that before controlling for financial constraint indicators, being a homeowner or attaining higher education (bachelor's degree or higher) is associated with a lower probability of being a BNPL user relative to being their counterparts, but these negative associations disappear after controlling for financial constraint indicators.

3.2 BNPL late payments

From the second logit model, we find six financial constraint indicators to be significantly positively correlated, and one indicator to be significantly negatively correlated, with the predicted probability of being a BNPL user who makes BNPL late payments conditional on being a BNPL user (hereafter, predicted probability of BNPL late payments). Chart 5 plots the marginal effects of the 12 financial constraint indicators on the predicted probability of BNPL late payments.

Chart 5: Marginal effects of financial constraint indicators on BNPL late payments



Note: A dot shows the average marginal effect, and a bar shows the 95-percentile range of marginal effect, of a given financial constraint indicator on the probability of being a BNPL user who makes late payments among all BNPL users.

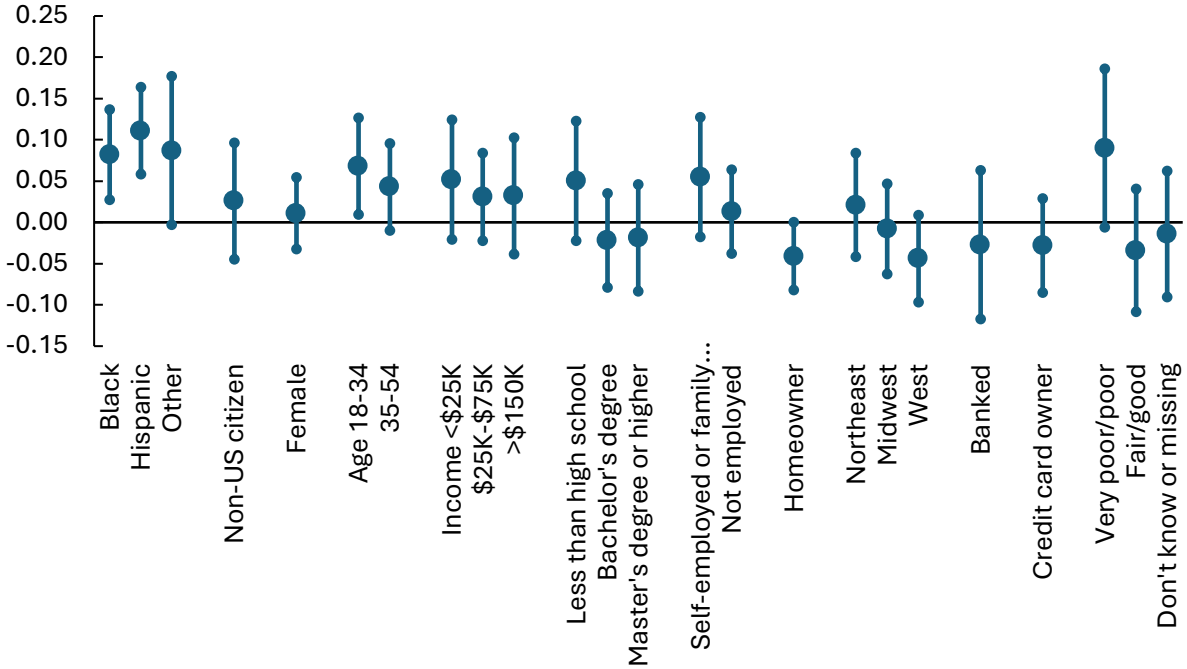
Among six indicators that are positively associated with the predicted probability of BNPL late payments, "unable to pay bills in full," which is related to liquidity constraints, has the largest average marginal effect of 0.087. Recall that this indicator has an insignificant average marginal effect on the predicted probability of being a BNPL user, while the rest five indicators have statistically significantly positive average marginal effects on that probability as well. Two indicators related to credit constraints, "denied or given less credit" and "used alternative credit services," have the second and third largest average marginal effects of 0.083 and 0.071, respectively, on the predicted probability of BNPL late payments. "Paid overdraft

fees" has the fourth largest effect of 0.067, "had medical debt" has the fifth largest effect of 0.057, and "received government financial assistance" has the sixth largest effect of 0.048.

Only one indicator, "carried credit card balance regularly," is negatively associated with the predicted probability of BNPL late payments. Recall that this indicator is significantly positively associated with the probability of being a BNPL user. However, conditional on being a BNPL user, carrying credit card balance regularly is associated with a 5.5 pp *lower* predicted probability of BNPL late payments relative to not carrying credit card balance regularly. A possible explanation may be that BNPL users who carry credit card balance regularly use BNPL loans strategically to reduce their costs for borrowing money. By allocating some of their purchases to BNPL and repaying them on time, these consumers may reduce (or avoid increasing) their credit card balance, reducing interest charges on the balance.

Unlike with the predicted probability of being a BNPL user, only a couple of demographic categories, race/ethnicity and age, are statistically significantly associated with the predicted probability of BNPL late payments (Chart 6). Relative to being a White consumer, being a Hispanic or Black consumer is associated with a 11.1 pp or 6.8 pp higher predicted probability. Relative to being a senior consumer (ages 55 or over), being a young consumer (ages 18-34) is associated with a 6.8 pp higher predicted probability.

Chart 6: Marginal effects of sociodemographic characteristics on BNPL late payments



Notes: A dot shows the average marginal effect, and a bar shows the 95-percentile range of marginal effect, of a given characteristic, relative to the base characteristic of the same category, on the probability of being a BNPL user who makes late payments among all BNPL users. The base characteristics, which are omitted from explanatory variables, are White (race/ethnicity), U.S. citizen (citizenship), male (gender), 55 or over (age), $75K-$150K (income), other employed (employment), nonhomeowner (homeownership), South (census region), unbanked (banking status), credit card nonowner (credit card ownership), excellent (credit score).

It is worth noting that without controlling for financial constraint indicators, six additional socioeconomic characteristics are statistically significantly associated with the predicted probability of BNPL late payments. Lower education level, lower income, very poor/poor credit score, nonhomeowner, and credit card nonowners are positively associated with the probability. And relative to living in the South census region, living in the West census region is associated with a lower probability. However, after controlling for financial constraint indicators, all these characteristics' average marginal effects become statistically insignificant, suggesting these characteristics act as proxy for financial constraint indicators. Therefore, observing detailed financial situations or constraints of consumers allows researchers to better predict their behavior related to financial products, such as BNPL late payments.

4. Implications for regulatory approaches to the BNPL sector

Countries, such as Australia, the UK, and EU countries, in which BNPL services were introduced before the United States, have started regulating the BNPL sector to better protect consumers from risks posed by BNPL services. Three key risks are overspending and overextending debt, high costs from missed or late BNPL repayments, and complications regarding refunds and disputes (Hayashi and Routh 2025). The EU and the UK implemented regulations that require BNPL lenders to carry out creditworthiness checks (among other things), and the intention of this requirement may be to mitigate the risk of overspending and overextending debt via BNPL (European Parliament and Council of the European Union 2023; Financial Conduct Authority 2026; Financial IT 2026). In Australia, the regulation requires BNPL providers to assess a BNPL contract's suitability for the consumer using tailored risk-based approaches rather than full (hard) credit checks (K&L Gates LLP 2025).

In the United States, the BNPL sector has not been regulated at the federal level, but at the state level, BNPL regulations have emerged. In May 2024, the Consumer Financial Protection Bureau (CFPB) adopted an interpretive rule classifying BNPL accounts as "credit cards" and requiring BNPL providers to provide the same dispute rights and protections to

consumers that credit card issuers provide, but CFPB revoked the rule in May 2025. In the same month, the State of New York enacted the Buy-Now-Pay-Later Act (Article 14-B of the Banking Law), and the state's Department of Financial Services published proposed rules in February 2026. These rules establish a BNPL-specific licensing and supervision framework, limit fees, tips, and interests, and impose a disclosure and servicing framework similar to those for credit cards (Baker McKenzie 2026). In December 2025, attorneys general from seven states (Connecticut, California, Colorado, Illinois, Minnesota, North Carolina, and Wisconsin) jointly sent letters to six largest BNPL providers (Affirm, AfterPay, Klarna, PayPal, Sezzle, and Zip) seeking detailed information regarding their pricing and repayment structures, consumer contracts, user agreements, and disclosures (Office of The Attorney General Connecticut 2025). How BNPL providers assess a consumer's financial capacity to repay BNPL loans was also a part of this inquiry. These states may consider state regulations covering the BNPL sector, as six of these seven states were part of a coalition of 19 attorneys general urging the CFPB to regulate the BNPL sector in 2022 (Office of The Attorney General Connecticut 2022). The state-level regulatory developments could result in requiring BNPL providers to assess a consumer's ability to repay BNPL loans more strictly in the future.

While hard credit checks may not be a common practice for short-term, non-interest-bearing BNPL products (such as "pay-in-four" products), BNPL providers have started sharing their data with credit bureaus. For example, Klarna began sharing loan and repayment activity for their term loan products (which do not include pay-in-four products) with TransUnion in November 2024 (Klarna 2024). Affirm began reporting all Affirm payment plans (including pay-in-four plans) and payment activities (including on-time, late, and missed payments) to Equifax in April 2025 and TransUnion in May 2025 (Affirm n.d.). In June 2025, FICO announced new credit scoring models incorporating BNPL payment data (FICO Score 10 BNPL and FICO Score 10T BNPL) but these models seem not to be available yet (as of this writing), as BNPL providers' adoption of their data furnishing to credit bureaus has remained gradual (Arkali 2026).

We simulate how requiring a more stringent assessment for consumers' ability to repay BNPL loans may affect the shares of consumers who use BNPL and of BNPL users who make late payments. The most stringent assessment may be BNPL lenders' carrying out hard credit checks similar to those of credit card lenders. We use individual consumer's predicted probability of being a BNPL user and predicted probability of being a BNPL user who makes

late payments (conditional on being a BNPL user) estimated from the two logit models in Section 3.

Our simulation is the following. First, we assume, as the most stringent case, that BNPL lenders' assessment results in the same decision as for credit cards: namely, if a consumer was denied or given less credit for credit card, the consumer would also be denied or given less credit for BNPL. Second, since our data do not allow us to distinguish those who were denied credit and those who were given less credit, we consider the case where all of those who were denied or given less credit for credit cards would be denied credit for BNPL. Third, we reduce the predicted probabilities of being a BNPL user among all consumers and of being a BNPL user who makes late payments among all BNPL users to zero for consumers who were denied or given less credit for credit cards and keep the estimated predicted probabilities for other consumers. Fourth, we calculate the expected share of consumers who use BNPL among all consumers, and the expected shares of BNPL users who make late payments among all expected BNPL users and among all consumers.

Table 2 summarizes our simulation results. BNPL lenders' hard credit checks that result in the same decision as credit card lenders' would reduce the share of BNPL users who make late payments among all (expected) BNPL users by 5.6 pp, suggesting a more stringent assessment for consumers' ability to repay BNPL loans could achieve an intended consequence—keeping some BNPL users from overspending and overextending debt. However, the same hard credit checks would reduce the shares of BNPL users and BNPL users with late payments among all consumers by 3.5 pp and 1.5 pp, respectively, implying that a 2.0 pp reduction in the share of BNPL users is from BNPL users without late payments, many of whom may use BNPL responsibly. Therefore, BNPL lenders' very stringent assessment could have a potentially larger unintended consequence—making BNPL loans less accessible for consumers who may use them responsibly—than its intended consequence.

Table 2: Potential effects of hard credit checks on BNPL use and late payments

	Current share	Possible share (lowest end)	Difference
BNPL users who made late payments among all (expected) BNPL users	23.6%	18.1%	-5.6 pp
BNPL users among all consumers	14.7%	11.1%	-3.5 pp
BNPL users who made late payments among all consumers	3.5%	2.0%	-1.5 pp

While our simulation reflects the consumers' involuntarily reduction in BNPL use because hard credit checks make some consumers inaccessible to BNPL loans, some other consumers may also reduce their demand for BNPL services voluntarily. Aidala et al. (2025) use a probabilistic stated choice survey experiment and find that including hard credit checks in the standard bundle of BNPL features would reduce overall consumer demand for BNPL but would increase demand from those with lower credit scores and lower incomes. Their results suggest that hard credit checks may reduce demand from consumers who use BNPL responsibly.

To avoid unintended consequences of stricter assessment for consumers' ability to repay BNPL loans, uncovering factors that distinguish BNPL users who use them responsibly and those who do not is critical. Our study helps inform financial constraint indicators and socioeconomic characteristics of BNPL users who made late payments, but we cannot observe how frequently BNPL users made late payments. Because BNPL users who make late payments frequently may be more likely to overspend or overextend debt via BNPL than BNPL users who make late payments only once or twice, further information about the frequency of BNPL late payments and analysis identifying factors that distinguish BNPL users who make late payments frequently and those who do so only once or twice may better inform regulatory approaches.

5. Conclusion

U.S. consumers have increasingly adopted BNPL services over the past decade and more recently the share of BNPL users who made late payments for BNPL has increased rather rapidly from 15% in 2021 to 24% in 2024. BNPL services help consumers in managing financial constraints, but they also pose risks for consumers. To mitigate the risk of overspending or overextending debt via BNPL, some countries implemented the regulation requiring BNPL lenders to carry out thorough creditworthiness checks. In the United States, regulatory developments at the state level may result in requiring BNPL lenders to make more stringent assessment for consumers' ability to repay BNPL loans. In this paper, we use the 2024 SHED data and two regression models to examine whether and how consumers' financial constraint indicators and their socioeconomic characteristics are associated with their BNPL use and late payment behaviors. We also simulate our estimation results to examine how BNPL lenders' carrying out hard credit checks would change the shares of consumers who use BNPL and of BNPL users who make late payments.

From regression model analysis, we find that many consumers' financial constraint indicators are statistically significantly associated with both probabilities of being a BNPL user (among all consumers) and being a BNPL user who makes late payments (among BNPL users). Especially, indicators related to credit constraints have larger average marginal effects than indicators related to other financial hardships. After controlling for financial constraint indicators, several socioeconomic characteristics remain statistically significantly associated with the probability of being a BNPL user, but only a few remain so with the probability of being a BNPL user who makes late payments. From the simulation, we find that BNPL lenders' hard credit checks would reduce both shares of BNPL users who make late payments and of consumers who use BNPL. Indeed, hard credit checks may reduce the number of BNPL users who do not make late payments more than those who do, suggesting hard credit checks may make BNPL inaccessible not only for those who overspend or overextend debt via BNPL but also for those who use BNPL responsibly.

Our study contributes to the literature on consumers' use of BNPL and helps inform regulatory approaches to the BNPL sector. Relative to previous studies that examine the correlation between consumers' characteristics and BNPL use, our study includes more consumer characteristics indicating various types of financial constraints in the regression models and demonstrates the importance of these financial constraint indicators to predict consumers' BNPL use. Moreover, to the best of our knowledge, our study is the first to examine the correlation between BNPL users who made late payments and their socioeconomic characteristics and financial constraint indicators. Finally, our study helps quantify both intended and unintended consequences of regulation requiring BNPL lenders to carry out hard credit checks.

While our study clearly identifies strong predictors for BNPL use or BNPL late payments, more detailed information about consumers' BNPL use and repayment behaviors, such as how frequently they use BNPL services, how much outstanding balance they have on BNPL loans, and how frequently they make late (or missed) payments, helps distinguish BNPL users who use BNPL responsibly and those who overspend or overextend debt via BNPL. Such information, along with detailed consumers' financial constraints and socioeconomic characteristics, allows researchers and policymakers to better assess benefits and risks of BNPL services and inform potential policy and regulations to address the risks.

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Appendix A: Summary statistics

Table A1: Shares of consumers and BNPL users by socioeconomic characteristics

Category	Characteristic	Share of sample (percent)	Share of BNPL users (percent)
Race/ethnicity	White	60.9	46.4
	Black	12.1	20.7
	Hispanic	17.9	25.1
	Other	9.1	7.8
Citizenship	Non-U.S. Citizen	6.7	8.9
Gender	Female	51.2	59.2
Age	18-34	26.8	35.1
	35-54	33.4	39.5
	55 or over	39.8	25.5
Annual household income	Less than $25,000	9.8	11.7
	$25,000-$74,999	29.1	36.2
	$75,000-$149,999	31.8	32.1
	More than $150,000	29.3	20.0
Education	No high school diploma	9.2	11.0
	High school diploma or some college	54.9	62.4
	Bachelor's degree	19.6	15.2
	Master's degree or higher	16.2	11.4
Employment	Self-employed or family business	9.4	10.0
	Other employed	53.9	62.2
	Not employed	36.7	27.8
Homeownership	Homeowner	72.0	58.9
Census region	Northeast	17.2	15.8
	Midwest	20.5	17.9
	South	38.7	44.4
	West	23.7	21.8
Banking status	Banked	93.5	94.7
Credit card ownership	Own	81.4	81.5
Self-reported credit score	Very Poor/poor	6.4	13.0
	Fair/good	26.0	37.8
	Excellent	40.2	18.8
	Don't know or missing	27.4	30.5

Sources: 2024 SHED and authors' calculations.

Appendix B: Heckman two-stage model

We estimate a Heckman two-stage model to test whether sample selection bias exists for a model estimating BNPL late payments among BNPL users without controlling for unobserved factors that influence BNPL use. The first stage uses a probit model to estimate BNPL use among all consumers. The second stage estimates an OLS model with the dependent variable being 1 if the BNPL user made BNPL late payments or 0 otherwise. We use credit card ownership as an exclusion criterion-variable that affects BNPL adoption (first stage) but does not directly influence late payment behavior conditional on BNPL use (second stage). Except for this credit card ownership variable, we use the same financial constraint indicators and sociodemographic characteristics as explanatory variables for both stages. We obtain the coefficient of inverse Mills ratio (λ) that is not statistically significant different from zero [λ=0.209 with p-value of 0.240], indicating that sample selection bias is not a substantive concern in our empirical setting. As an alternative to Heckman two-stage model, we use a probit model for the second stage. Despite this change, we obtain the coefficient of inverse Mill ratio that is not statistically significantly different from zero [λ=0.679 with p-value of 0.732].

Appendix C: Average marginal effects from two logit models

Table C1: Marginal effects of all variables on BNPL use and BNPL late payments

Category	Indicator/Characteristic	BNPL use		BNPL late payments	
Financial constraint indicators	Denied or given less credit	0.094***	(0.009)	0.083***	(0.024)
	Desired credit but chose not to apply	0.044***	(0.012)	-0.019	(0.033)
	Used alternative credit services	0.068***	(0.012)	0.071***	(0.024)
	Paid overdraft fees	0.034***	(0.009)	0.067***	(0.023)
	Carried credit card balance regularly	0.055***	(0.009)	-0.055**	(0.025)
	Unable to pay bills in full	0.003	(0.010)	0.087***	(0.022)
	Spending exceeded income	0.003	(0.008)	0.020	(0.023)
	No means to cover 3-months' expenses	-0.007	(0.009)	0.041*	(0.025)
	Can't cover $400 emergency expenses	0.047***	(0.009)	0.027	(0.027)
	Skipped needed medical care	0.017**	(0.008)	0.018	(0.022)
	Had medical debt	0.024***	(0.008)	0.057**	(0.023)
	Received government financial assistance	0.026***	(0.008)	0.048**	(0.022)
Race/ethnicity	Black	0.062***	(0.011)	0.082***	(0.028)
	Hispanic	0.037***	(0.010)	0.111***	(0.027)
	Other	0.003	(0.013)	0.087*	(0.046)
Citizenship	Non-U.S. citizen	0.019	(0.013)	0.026	(0.036)

Gender	Female	-0.033***	(0.007)	-0.011	(0.022)
Age	18-34	0.047***	(0.009)	0.068**	(0.030)
	35-54	0.023***	(0.008)	0.043	(0.027)
Annual household income	Less than $25,000	-0.025**	(0.012)	0.052	(0.037)
	$25,000-$74,999	-0.012	(0.009)	0.031	(0.027)
	More than $150,000	-0.003	(0.010)	0.032	(0.036)
Education	Less than high school	0.001	(0.013)	0.050	(0.037)
	Bachelor's degree	-0.010	(0.009)	-0.022	(0.029)
	Master's degree or higher	-0.013	(0.010)	-0.019	(0.033)
Employment	Self-employed or family business	-0.023*	(0.012)	0.055	(0.037)
	Not employed	-0.030***	(0.008)	0.013	(0.026)
Homeownership	Homeowner	-0.013	(0.008)	-0.041*	(0.021)
Census Region	Northwest	0.002	(0.010)	0.021	(0.032)
	Midwest	-0.018**	(0.009)	-0.008	(0.028)
	West	-0.005	(0.009)	-0.044	(0.027)
Banking status	Banked	0.052***	(0.017)	0.027	(0.046)
Credit card	Owner	0.047***	(0.011)	-0.028	(0.029)
Self-reported credit score	Very Poor/poor	0.083***	(0.018)	0.090*	(0.049)
	Fair/good	0.050***	(0.009)	-0.034	(0.038)
	Don't know/missing	0.028***	(0.009)	-0.014	(0.039)
Number of observations		12,295		1,670	

Notes: ***, **, * indicate p-value less than 0.01, 0.05, and 0.1, respectively. Standard errors are in parentheses. The base characteristics, which are omitted from explanatory variables, are White (race/ethnicity), U.S. citizen (citizenship), male (gender), 55 or over (age), $75K-$150K (income), other employed (employment), nonhomeowner (homeownership), South (census region), unbanked (banking status), credit card nonowner (credit card ownership), excellent (self-reported credit score).