Buy Now Pay (Pain?) Later

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Abstract

"Buy Now Pay Later" (BNPL) is a largely unregulated FinTech innovation that provides consumers with easy access to credit for retail purchases. BNPL spending is projected to reach $1 trillion by 2025, but we know little about its effects. Using banking data for 10.6 million U.S. consumers, we investigate the effects of BNPL on leading indicators of users' financial health. We find that new BNPL users experience rapid increases in bank overdraft charges and credit card interest and fees, as compared to non-users. An instrumental variable exploiting consumers' pre-BNPL shopping habits increases the credibility of BNPL having a causal negative effect. Our results directly inform current regulatory investigations into the effects of BNPL on users' financial health, and expand the academic literature's understanding of a major new development in consumer credit.

Keywords: BNPL, FinTech, consumer credit, household accounting and finance, regulation

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1. Introduction

"Buy Now Pay Later" (BNPL) is a largely unregulated FinTech innovation that provides consumers with easy access to credit for retail purchases. A typical purchase on BNPL requires an up-front payment followed by three bi-weekly payments, and has no fees or interest if paid on time. Missed payments typically incur a late charge from the BNPL provider and an overdraft fee from the consumer's bank. BNPL credit decisions are made nearly instantly using alternative data and without a hard credit check, and spending limits can dynamically adjust to changes in risk. Thus, BNPL is often available to consumers who have limited traditional credit. Total BNPL loans issued by the largest providers in the U.S. increased from roughly $8.3 billion in 2020 to $24.2 billion in 2021 (CFPB 2022c) and the global market is forecasted to reach $1 trillion by 2025 (CB Insights 2021), primarily due to new BNPL offerings from financial and tech companies.[1] Despite its popularity and growth, archival research on BNPL is scarce. We provide an early investigation of the effects of BNPL on consumers' financial health.

The likely effects of BNPL on consumers' financial health are unclear.[2] On the one hand, a consumer can use BNPL to smooth liquidity constraints or substitute from more expensive credit, and therefore end up materially better off. For example, using BNPL could reach consumers without other credit access, replace high-rate credit cards or payday loans, or help consumers avoid temporary bank overdrafts or missed credit card payments (e.g., Jappelli & Pistaferri 2010; Agarwal & Qian 2014; Di Maggio et al. 2021; Dooley & Gallagher 2021). Moreover, market pressures are plausibly sufficient to cause BNPL providers to self-regulate

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[1] In additional to the original FinTech BNPL providers (e.g., Afterpay and Klarna), new market entrants include American Express's "Pay It Plan It," Chase Bank's "My Chase Plan," PayPal's "Pay-in-4," Apple's "Apple Pay Later," and many more. Section 2 for further discusses BNPL loans, providers, and market.

[2] CFPB (2022b) overviews the BNPL industry and potential positive/negative effects on financial health. Reviews of consumer credit literature include: Guiso & Sodini (2013); Zinman (2015); Campbell (2017); Agarwal & Zhang (2020).

credit limits to avoid reputation damage and unsustainable bad debt expenses.

On the other hand, there are several reasons why BNPL plausibly allows consumers to over-spend and experience negative financial consequences. First, easy access to credit is often found to cause increased consumption and declines in financial health.[3] Second, BNPL providers are plausibly willing to extend riskier credit than other lenders (e.g., credit cards) because BNPL providers also earn substantial commission and advertising revenues from retailers, and because consumers often prioritize BNPL payments over other credit.[4] Third, BNPL providers seldom report to credit score agencies (Akana 2022; Andriotis 2022), which increases the risk that users obtain excessive credit. Fourth, BNPL avoids many consumer disclosure requirements and regulatory protections, so the risks of serious negative consequences from over-use are likely especially high (CFPB 2021, 2022c).

Practitioner surveys indicate that BNPL indeed changes spending behaviors and risks. For example: 70% of BNPL users report spending more via BNPL than they would have paid otherwise (LendingTree 2022); 38% have used BNPL to make a purchase that would not fit in their budget (CB Insights 2021); up to 42% have missed payments (LendingTree 2022; Credit Karma 2021); and 25% adopted BNPL to avoid a hard credit check (CB Insights 2021).

We investigate BNPL and financial health using a dataset of bank and credit card transactions for 10.6 million U.S. consumers from 2015 through 2021. Consumers are anonymized but uniquely identified, allowing us to track consumers across accounts. 1.37 million consumers (13%) use BNPL at least once in our sample. As shown in Figure 1, BNPL

[3] E.g.: Gross & Souleles (2002); Melzer (2011); Carrell & Zinman (2014); Gathergood et al. (2019); Argawal et al. (2009); Gerrans et al. (2021); Stango & Zinman (2011); Laibson (1997); O'Donoghue & Rabin (2006); Brunnermeier & Parket (2009); Trueblook & Sussman (2021); Werthschult (2020).

[4] BNPL repayments are prioritized over other credit because BNPL providers typically require that users set up automatic repayments from a bank account or credit card (CFPB 2022c), and because BNPL providers quickly reduce credit limits upon a missed payment.

usage increases sharply in recent years, and by 2021 the average user makes roughly 12 BNPL payments per quarter, totaling over $500.

BNPL users in our sample are more likely to have student debt, are less likely to have a mortgage, and are more likely to pay bank overdraft fees and credit card interest. These data are consistent with survey evidence that BNPL users tend to be younger people without well-established credit (e.g., Akana 2022; LendingTree 2021; TransUnion 2021). Users tend to shop in areas (and so likely live in areas) with lower proportions of college education, higher poverty rates, and less access to traditional banks, as compared to non-users.

We examine changes in BNPL users' financial health over the four quarters before and after BNPL adoption, as compared to non-users over the same period. We create a balanced event-time panel by matching each user to a non-user in the same state and with similar pre-adoption levels and trends in financial health. After requiring complete data in the year before and after adoption and imposing the matching criteria, our final sample includes 572,475 pairs of users and non-users.

Our primary measure of financial health is the number of overdraft charges on a consumer's bank accounts, which happen when a payment (including a BNPL repayment) exceeds available funds. Overdraft fees are ubiquitous in the U.S., totaling $32 billion in 2012, or roughly $178 per checking account (Liu et al. 2018). Overdrafts are expensive unto themselves and are a primary driver of bank account closures, after which consumers are often left with limited and expensive banking alternatives (Campbell et al. 2012). Overdraft charges also lead consumers to seek expensive credit such as payday loans (Di Maggio et al. 2021), which in turn predicts bankruptcies and broad welfare declines (Melzer 2011, 2018; Skiba & Tobacman 2019;

Carrell & Zinman 2014).[5]

We also measure financial health based on credit card interest payments and late fees. Credit cards are the largest consumer lending product in the U.S, and the costs of credit card interest and late fees are substantial. For example, in recent years the average U.S. household had $6,300 in credit card debt and paid roughly $1,000 of interest and late fees per year (Vasan & Zhang 2022; Federal Reserve 2019). Credit card borrowing is also considered a key driver of bankruptcy filings (e.g., Domowitz & Sartain 1999; Stavins 2000; White 2007).

Bank overdraft charges and credit card interest and fees should capture short-term changes in financial health after BNPL adoption. Overdraft charges will increase if BNPL repayments divert funds from paying other bills or if BNPL repayments bounce (most BNPL repayments are automatic bank withdrawals). Alternatively, overdraft charges will plausibly decrease if BNPL allows users to smooth liquidity constraints. Similarly, credit card interest and late fees will increase if BNPL diverts funds from paying-down credit card debt or if BNPL repayments are charged to credit cards.

Difference-in-differences (DID) plots in Figure 2 reveal similar trends in overdrafts, credit card interest, and credit card late fees between users and non-users prior to adoption, followed by increases in the first quarter after BNPL adoption. DID regressions indicate that BNPL users have 4.0% higher overdraft charges, 1.1% higher credit card interest, and 2.3% higher credit card late fees in the one-year post-adoption period. These results indicate that BNPL adopters experience declines in financial health relative to non-adopters. However, the results cannot differentiate between a causal effect of BNPL versus consumers experiencing a coinciding shock (e.g., a layoff) that causes both BNPL adoption and declines in financial health.

[5] Some studies of high-interest loans and financial health have found mixed or positive effects. For example, Karlan & Zinman (2010), Morse (2011), and Allcott et al. (2022).

We use an instrumental variable (IV) to abstract from a consumer's endogenous decision to adopt BNPL when she experiences a negative financial shock. The intuition behind our instrument is that consumers are more likely to adopt BNPL when the retailers they frequently shop at partner with a BNPL provider. For example, Adidas partnered with a BNPL provider in July 2020. We expect that a frequent Adidas store shopper is more likely to adopt BNPL after July 2020 than a less frequent Adidas shopper because the frequent shopper has more exposure to BNPL as a payment choice and because she has a greater incentive to take the time to sign up for BNPL. At the same time, it seems unlikely that frequent shopping at Adidas over the trailing year directly predicts post-adoption declines in financial health (the exclusion condition). Based on this intuition, our instrument is the number of transactions each BNPL user and matched non-user have at BNPL retail partners in the year before adoption.

First stage IV regressions confirm that partner spending is a powerful predictor of BNPL adoption, and second stage regressions find that instrumented adoption is associated with an 8.9% increase in overdraft charges, a 2.5% increase in credit card interest, and an 8.4% increase in credit card late fees. The similar inferences from our DID and IV analyses lend credibility to our results plausibly capturing a causal effect of BNPL adoption on financial health.

Our inferences are robust to several sensitivity tests. We investigate the concern that consumers increase their shopping at BNPL stores when they know they are approaching financial distress, in which case transactions at BNPL retailers plausibly predict declines in financial health (violating the IV exclusion condition). We find that transactions at BNPL retailers are highly consistent over the year before BNPL adoption. We further address this concern by lagging our instrument by six months before adoption, assuming that BNPL adopters are unlikely to precisely predict declines in financial health more than six months ahead. We find similar results. We also find similar results when examining changes in financial health just one-quarter pre/post-adoption, when excluding the COVID period, and in a variety of other sensitivity tests.

Supplementary analyses find that: 1) heavy users of BNPL have larger declines in financial health; 2) BNPL users' total spending increases after BNPL adoption, consistent with BNPL motivating consumers to spend more; and 3) BNPL adopters partially substitute away from credit card spending, consistent with the conjecture that BNPL is disrupting traditional forms of consumer credit.[6]

Our collection of findings is consistent with BNPL having a plausibly causal negative impact on leading indicators of users' financial health, and motivates numerous questions for future research. First, future research can investigate whether BNPL-related increases in overdraft and credit card charges portend more serious longer-term consequences (e.g., bankruptcies). Second, research can investigate whether BNPL has offsetting positive effects (e.g., allowing consumers to pay for necessary healthcare), in which case BNPL could have neutral or positive overall welfare effects. Third, our findings only speak to the current state of the BNPL market, and BNPL lending and effects will likely evolve as the industry matures. Fourth, our sample includes consumers with relatively extensive banking data, so research can examine whether findings differ among consumers who use banks less frequently. Finally, future research can reexamine BNPL using alternative designs to further reduce endogeneity concerns.

Our study offers among the first evidence of the effects of BNPL on consumers' financial

[6] Higher credit card interest payments and lower credit card spending after BNPL adoption are not contradictory findings. When a consumer partially substitutes to BNPL, credit card interest payments will continue to increase if over-spending diverts cash from paying-down existing card balances and paying-off new card charges.

health, and provides meaningful insights for several stakeholders.[7] Our findings are likely of immediate interest to regulators in the U.S. and abroad as they collaborate in ongoing inquiries into the welfare effects of BNPL (CFPB 2021, 2022c). For example, CFPB's recent investigative report on BNPL laments that they were unable to "measure the impact of BNPL payments on borrowers' checking accounts, including non-sufficient funds or overdraft fees, or on borrowers' capacity to repay other expenses or obligations" (CFPB 2022c, p8). Our study directly informs CFPB and international regulators about these outcomes. For similar reasons, our findings are also likely of interest to credit agencies and FinTech BNPL providers, and to the many tech companies and financial institutions that recently introduced BNPL products.

We also contribute to the large literature on the determinants and consequences of consumer credit, including the growing literature on the roles of FinTech.[8] BNPL has already begun to supplant the mainstay of short-term consumer financing, the credit card, and is forecasted to reach $1 trillion in spending by 2025. While true growth in the industry is difficult to predict, it seems clear that BNPL has the potential to become a significant component of households' debt portfolios, so it is useful to study the downstream impacts of BNPL borrowing.

2. About BNPL

Here we describe the prototypical BNPL provider and loan. Many variations exist, although the differences generally do not alter our predictions and inferences.

BNPL is (typically) a short-term, zero-interest loan used to finance a specific purchase at

[7] To our knowledge, other archival research on the effects of BNPL is limited to a contemporaneous working paper by Di Maggio et al. (2022), which uses similar data and draws similar inferences. Other working papers investigate the determinants of BNPL usage (Guttman-Kenney et al. 2022; Boshoff et al. 2022; Akana 2022).
[8] Example papers not cited elsewhere include Butler et al. (2017), Gurun et al. (2016), Chava et al. (2021), D'Acunto et al. (2019), Gargano & Rossi (2021).

a BNPL retail partner. Once a retailer partners with a BNPL provider, consumers can use BNPL at the retailer's physical and online stores, and can usually purchase the retailer's products via the BNPL provider's app. First-time BNPL users sign-up by providing basic information such as their name, contact details, and debit/credit card number (for automatic repayments). BNPL providers then use algorithms to profile applicants based on soft credit checks and alternative data.[9] Approval and credit limit decisions are made within seconds.

The typical BNPL loan splits the purchase into four installments; one at the initial purchase, and the remaining three every second week.[10] Most BNPL providers charge a late fee for missed payments (e.g., $7 per payment, sometimes capped at 25% of the purchase value) (Akana 2022) and limit access to additional credit. BNPL repayments are usually automatic bank withdrawals, so the consumer's bank also charges an overdraft fee when funds are insufficient (averaging around $35, per CFPB (2022a)). If BNPL repayments are charged to a credit card, then repayments increase the card balance and can result in higher interest and fees. BNPL providers seldom report to credit bureaus, which impairs providers' abilities to monitor debt across other providers, and prevents non-BNPL lenders from observing BNPL debt.[11]

BNPL providers make money by charging commissions on BNPL sales (e.g., 6%, paid by the retailers), from targeted advertising on the BNPL app or webstore (paid by the retailers), and from late payment fees (paid by the consumer). Retailers are willing to pay commissions

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[9] Per one BNPL provider: "By utilizing our unique risk model predicated on sophisticated machine learning algorithms, proprietary data, and product-level underwriting, we can serve consumers across the credit spectrum and price risk across transaction types" (Affirm 2021, p5).

[10] Longer-term BNPL loans can bear interest, and the interest rate is usually on par with credit cards (average APR of 20%) and lower than payday loans (average APR close to 400%).

[11] Credit reporting practices vary across BNPL providers and across credit bureaus. According to credit bureaus' announcements, Experian has a special bureau for BNPL while Equifax and TransUnion will include BNPL payment history into consumer credit profile, but allow lenders to filter it out. However, Andriotis (2022) reports that the major BNPL providers still opt not to report to credit bureaus due to concerns about negatively impacting BNPL users' credit scores. Delinquent accounts that are referred to credit collection agencies are likely reported to credit bureaus.

because BNPL is estimated to increase sales conversion rates by 20-30% and increase the average purchase size by 18-50% (Reagan 2021; CFPB 2022b). One major BNPL provider reported $22.4 billion in BNPL sales in 2021, which generated $925 million in net revenues (Afterpay 2021). Of those revenues, roughly 9.5% were from late fees.

While the BNPL market was developed by FinTech companies that solely offer BNPL, traditional financial institutions and major tech companies have recently entered the market. BNPL loans from non-dedicated providers (e.g., American Express) are generally similar to those from dedicated BNPL providers. One difference is that BNPL from financial institutions can often be used at any retailer where the institution's payments are already accepted, so do not require a partnership with each retailer. During our sample, few non-dedicated BNPL providers had yet to enter the market.

Verified data on BNPL is scarce, but surveys generally find that BNPL users tend to be young and financially constrained, and that approximately one-third of users use BNPL at least once per month.[12] CFPB (2022c) reports that the users skew towards Millennials and Gen Z, and that consumers increasingly use BNPL to buy a diverse range of both discretionary and essential products. Users' reasons for using BNPL include convenience and also dissatisfaction with traditional credit products. Consistent with the popularity of BNPL, the five providers we study have over 2.8 million reviews in the Apple App Store as of June 2022, with an average rating of 4.9 out of 5.

Given that many BNPL users are thought to have limited access to other credit, it is reasonable to question why BNPL providers choose to extend credit to individuals that credit

[12] Surveys include: PYMNTS.com & PayPal (2020); CFPB (2021); McKinsey & Company (2021); TransUnion (2021); Credit Karma (2021, 2022); Akana (2022); LendingTree (2022); Morning Consult (2022); Motley Fool (2022); CB Insights (2021).

card providers do not serve. Several explanations are plausible. First, BNPL providers earn higher sales commissions and advertising revenues, which likely offset higher bad debt expenses. Second, BNPL providers' credit assessments are plausibly superior and their credit limits are more nimble, which plausibly allows them to accept quality borrowers that credit card providers overlook. Third, many consumers plausibly prioritize BNPL repayments over credit cards; for example, because BNPL repayments occur quickly, because BNPL providers restrict credit after a missed payment, and because BNPL repayments can even be charged to a credit card. Fourth, BNPL is largely unregulated, which plausibly lowers compliance costs and gives BNPL greater flexibility. Fifth, because FinTech BNPL providers are growth-stage firms, capital providers are plausibly willing to sustain short-term accounting losses in exchange for market share and longer-term profit potential.

3. Data and descriptive statistics

3.1. Sample and Data

Our sample is based on consumer bank account and credit card transactions, obtained from a service-provider that processes transaction data for major financial institutions. Consumers' names and personal information are removed, but identifiers allow us to link transactions made by the same consumer across institutions and accounts. For each transaction, we observe the consumer identifier, time, amount, counterparty, location when available, and a brief description, much like a user would see when viewing her account online. The data vendor categorizes each transaction based on the counterparty and description. The vendor approximates each consumer's home state using transaction locations, putting heavy weight on payments such as routine spending. Finally, the vendor uses income deposits and spending to assign each consumer an estimated income tier ranging from 1 (annual income \$0 – 25,000) to 7 (above \$150,000). Home states and income tiers are updated monthly.

We identify BNPL users based on payments to the five major FinTech BNPL providers in the U.S. during our sample period: Affirm, Afterpay, Klarna, Zip (formally QuadPay), and Sezzle. A consumer is considered a BNPL user when she makes at least one payment to a BNPL provider during our sample period, and other consumers are considered non-users.[13] BNPL purchases require one up-front payment, so we use the date of a BNPL user's first payment to identify her initial BNPL adoption date.

Several caveats are warranted about our identification of BNPL users. First, although we consider the major BNPL providers during our sample, consumers who use other BNPL providers are erroneously classified as non-users. Second, we do not observe BNPL payment schedules so cannot identify BNPL late payments or delinquencies. As such, we under-count BNPL use intensity (as quantified by the dollar amount or the number of BNPL payments) when users do not make their BNPL repayments in a timely manner. This aspect is not a concern in examining initial BNPL adoptions, though, because adoptions require one up-front payment. Third, we cannot observe BNPL usage if a consumer pays the BNPL provider from an account that is not included in our data. To mitigate concerns about incomplete data, the data vendor provides a score to help identify which consumers have relatively complete banking data available. Following the vendor's guidance, we only include consumers with a score that equates to roughly 56 transactions per month on average.[14]

[13] Many other financial institutions have also begun offering BNPL but are not identified in our sample. Any BNPL users who use an omitted BNPL provider are classified as a non-user in our data, so our analyses likely provide a lower bound on the estimates of BNPL usage and its consequences.
[14] This requirement excludes roughly 20% transactions. We have not assessed the sensitivity of our results to alternative cutoffs. Prior literature sometimes uses five transactions per month to select consumers with sufficient transactions (e.g., Ganong & Noel 2019; Baker et al. forthcoming).

An initial (untabulated) review of our data indicates that there are a small number of extreme outliers in consumers' total quarterly consumption (defined below). These outliers could be extremely wealthy individuals, people who use their personal accounts to pay for reimbursed expenses, or data errors. We mitigate the effects of these outliers by dropping consumers who fall in the top 1% of consumption.

Table 1 shows that our sample includes 10.6 million unique consumers that meet the data selection criteria for at least one quarter from 2015 to 2021, of which 1.37 million consumers (or 13%) use BNPL at least once. This ratio is in the ballpark of statistics reported in recent surveys.[15]

3.2. Trends in BNPL usage

Figure 1 shows considerable growth in BNPL usage from 2015 through 2021. Panel A shows that the aggregate value of BNPL transactions (i.e., payments made to BNPL providers) grows from approximately $0.8 million during Q1 of 2015 to $358 million during Q4 of 2021. Individual BNPL payments approach 8.2 million transactions by Q4 of 2021. Growth accelerates sharply during the COVID pandemic, from roughly $121 million during Q1 of 2020 to $358 million during Q4 of 2021. This 296% increase is similar to the growth documented in the recent CFPB report (CFPB 2022c, p31), which increases confidence in the validity and representativeness of our data. As another validity check, our time trends are also similar to downloads of BNPL apps tracked by Apptopia (Swaminathan 2021).

Panel B of Figure 1 plots the intensive margin (i.e., the average number of BNPL

[15] For example, Cornerstone Advisors report that 7% of Americans made a BNPL purchase through the first nine months of 2020, based on a sample of 3,016 US consumers (Shevlin 2020). Morning Consult (2022) reports that 18% of 2,200 adults surveyed in 2022 January are BNPL users. In contrast, Credit Karma's 2021 survey reports that 44% of respondents have used BNPL, up slightly from December 2020 (Credit Karma 2021). Morning Consult and Credit Karma report a higher ratio probably due to differences in sample and the scope of BNPL (for example, Akana (2022) reports that survey respondents count other point-of-sale installment loans as BNPL).

payments by each user per quarter). It indicates that the average dollar value of BNPL payments per user-quarter reaches over $500 by the end of 2021, which amounts to roughly 3.7% of a user's quarterly consumption (as defined below). The number of BNPL payments per user-quarter steadily increases from about 2 to 12 over the sample period. 12 payments per quarter means one payment per week, indicating that the average BNPL user makes regular BNPL purchases, potentially across different BNPL providers.

3.3. Descriptive Statistics on BNPL Adopters versus Non-Adopters

Panel A of Table 2 presents descriptive information for BNPL users versus non-users. The unit of observation is one consumer, with values averaged over the sample. Naturally, the descriptive statistics for BNPL users reflect the characteristics of consumers who both apply for, and are approved for, BNPL credit. Applying for BNPL typically requires a web-enabled computer or smartphone, and a bank account or credit card to make repayments.

The upper rows provide approximated demographic information on the consumers in our sample. Because we do not know consumers' identities or addresses, we report the average demographic information of the zip codes of their transactions, where available.[16] Assuming that consumers do most of their shopping close to home, these demographic statistics are our best approximation of the demographics of the consumers in our sample (Begley & Purnanandam 2021). Several economically meaningful differences are apparent. BNPL users shop in less educated areas (-7% in university attendance), where more people live in poverty (4% higher), that have less access to traditional banks (4% fewer bank branches), and that have more complaints about banking regulators (19% higher CFPB complaints). We do not see economically meaningful differences in terms of area senior population and computer access,

[16] Zip codes are not provided for most online retailers, so online purchases are largely excluded from these data.

although t-tests show they are statistically different.

The lower rows of Panel A of Table 2 report consumers' financial characteristics. As mentioned in Section 1, BNPL users are more likely to have a student loan, are less likely to have a mortgage, and are more likely to have a wage direct deposit (e.g., are less likely to be retired or unemployed).

Consumption is our estimate of a consumer's total spending, calculated as their logged total spending excluding debt and tax payments, account transfers, and savings (in $ thousands, see Appendix A for details). *Consumption* includes spending that is later reimbursed or returned, so is a high estimate of consumers' net spending. BNPL users have higher *Consumption* than non-users.[17]

Overdraft, *Interest*, and *Late_Fee* are our three proxies for consumers' financial health. *Overdraft* is the logged number of overdraft charges on bank accounts per quarter, *Interest* is the logged dollar value of credit card interest payments in $ thousands, and *Late_Fee* is the logged count of credit card late payment charges. BNPL users have higher values of all three variables, consistent with BNPL users having poorer financial health. These data are averaged over the whole sample, though, so are not informative about changes before/after BNPL adoption.

3.4. Matched Sample

Our tests below examine changes in BNPL users' financial health one-year before and after their initial BNPL adoption, relative to non-users over the same period. Aligning users and non-users in event time requires us to match each BNPL user to one non-user in the quarter of

[17] The median unlogged consumption for BNPL users is $10,830 per quarter, which is similar to the consumption reported by Ganong et al. (2022). Untabulated data show that consumption accounts for roughly 66% of their total cash inflows (which includes wage income and non-wage inflows like freelance income, parental subsidies, investment income, tax refunds, etc. but excludes bank transfers). These statistics are generally consistent with low savings rates in the U.S. For example, St. Louis Fed data (accessed August, 2022) shows that the median national savings rate was 7.6% during our sample period.

BNPL adoption. Matching users also helps to homogenize our sample and improve common support between users and non-users. As shown in Table 1, requiring one-year of data after BNPL adoption eliminates 520,447 (or 38%) of BNPL users, nearly all of which adopted BNPL in 2021 (the last year of our sample).

We match with replacement using several criteria. In the adoption quarter, we require that the consumers are in the same state and income tier, and have the same values for student loans, mortgage, wage direct deposit, and credit card indicators. We then match on the pre-adoption values of variables that are plausibly affected by BNPL. We require that the match has within plus/minus 2.5% of *Consumption* averaged over the trailing year, and that they have the same tercile rankings of *Overdraft*, *Interest*, and *Late_Fee* in the pre-adoption period. To further reduce concerns about pre-adoption differences in trends in financial health, we also require that the match is in the same tercile of trend in *Overdraft*, *Interest*, and *Late_Fee* from *t*-4 through *t*-1. When multiple non-users meet the above criteria, we choose one at random. Table 1 shows that our matching process eliminates another 21% of BNPL users, either due to missing matching data or to a lack of qualifying matches. Our final sample includes 572,475 BNPL users and 572,475 matched non-users. Sensitivity analyses below using relaxed matching requirements have larger samples and yield similar inferences.

Panel B of Table 2 compares BNPL users prior to adoption to their matched non-users in the same period. Compared to the unmatched sample reported in Panel A, BNPL users' financial characteristics are more similar to non-users, especially for the characteristics we match on. Nevertheless, some material differences between the two groups remain, which we take into account in our analyses below.

Panels C and D of Table 2 provide additional summary statistics for the samples used in our regressions below. Panel C has statistics for the consumer-quarter panel used in our difference-in-differences tests. Panel D has statistics for our IV sample, which consists of one observation per consumer. We report both pooled and within-fixed-effects standard deviations of each variable, where the fixed effects are those used in our regressions below.

4. BNPL Adoption and Financial Health

We investigate the effects of BNPL on consumers' financial health proxied by *Overdraft*, *Interest*, and *Late_Fee* (all logged). Section 4.1 investigates BNPL users' financial health before/after adoption, compared to matched non-users, using a differences-in-differences (DID) approach. Section 4.2 uses an instrumental variable approach to further isolate exogenous BNPL adoption.

4.1 Difference-in-Differences (DID) Analysis

Our DID analyses examine the financial health of BNPL users and matched non-users in eight calendar quarters around BNPL adoption, excluding the adoption quarter itself. The sample includes 572,475 matched pairs, for a total of 9,159,600 consumer-quarters. Our tests use the following OLS model:

$$\begin{aligned} Health_{i,t} =\; & \beta_1 BNPL\_Adopter_i \times Post_{i,t-3} + \beta_2 BNPL\_Adopter_i \times Post_{i,t-2} \\ & + \beta_3 BNPL\_Adopter_i \times Post_{i,t-1} + \beta_4 BNPL\_Adopter_i \times Post_{i,t+1} \\ & + \beta_5 BNPL\_Adopter_i \times Post_{i,t+2} + \beta_6 BNPL\_Adopter_i \times Post_{i,t+3} \\ & + \beta_7 BNPL\_Adopter_i \times Post_{i,t+4} \\ & + \gamma_1 Post_{i,t-3} + \gamma_2 Post_{i,t-2} + \gamma_3 Post_{i,t-1} + \gamma_4 Post_{i,t+1} + \gamma_5 Post_{i,t+2} + \gamma_6 Post_{i,t+3} \\ & + X'_{i,t}\delta_0 + \eta_i + \mu_{s,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where i indexes a consumer, t indexes calendar year-quarter, and s indexes home state. $Health_{i,t}$ is one of our three measures of financial health. $BNPL\_Adopter_i$ is an indicator for BNPL users. $Post_{i,t+n}$ is an indicator for quarter n relative to BNPL adoption. We include indicators for each quarter so that the dynamic pre- and post-adoption trend is visible, and we omit quarter (t-4) as the baseline. Consumer fixed effects, η_i, control for fixed individual characteristics and substantially reduce variation in characteristics that are likely relatively constant over an eight-quarter window (e.g., a consumer's education and local demographics). Consumer fixed effects also absorb the $BNPL\_Adopter_i$ main effect. State-year-quarter fixed effects, $\mu_{s,t}$, control for common temporal trends.[18] Time-varying controls are represented by $X_{i,t}$. We cluster standard errors by both year-quarter and consumer to correct for cross-sectional and serial dependence. The DID coefficients, β_1-β_7, estimate the change in financial health for BNPL adopters, relative to matched non-adopters, in each pre- and post-adoption quarter.

Table 3 presents the regression results of Model (1), and Panels A through C of Figure 2 plot DID estimates. The quarters prior to BNPL adoption exhibit stable differences between adopters and non-adopters, which is expected given that we match on pre-adoption financial health, and boosts confidence in the parallel trends assumption for DID analysis. The difference between adopters and non-adopters widens immediately in the first quarter after BNPL adoption, suggesting that adopters' financial health deteriorates quickly. Observing a quick change upon BNPL adoption is consistent with BNPL's short repayment periods, and reduces concerns about alternative explanations due to coinciding events. Economically, and averaged over the post-adoption quarters, BNPL adopters have 4.0% higher *Overdraft*, 1.1% higher *Interest*, and 2.3% higher *Late_Fee* than their matches.

The DID evidence is consistent with consumers' financial health deteriorating in the year after BNPL adoption, relative to matched non-adopters. However, while pre-treatment trends in

[18] State-year-quarter fixed effects do not fully absorb *Post* because a given period can be both a pre- and post-adoption period, depending on the matched pair's adoption date. Our DID design has multiple treatment dates but no consumer transitions from being a control in one quarter to a treatment in another. Thus, our design is not susceptible to issues with heterogeneous effects in staggered DID models (e.g., de Chaisemartin & D'Haultfœuille 2020; Barrios 2021; Baker et al. 2022).

financial health appear similar between adopters and non-adopters, it is not clear whether the post-adoption declines in financial health are due to BNPL versus a coinciding negative shock to financial health.

4.2 Instrumental Variable (IV) Approach

This section uses an IV approach to better identify the causal effect of BNPL on financial health. The primary goal of our IV analysis is to abstract from a consumer's endogenous decision to adopt BNPL when she knows she is approaching financial difficulties.

4.2.1 Instrument Motivation and Development

Our instrument exploits differences in consumers' shopping habits and the gradual partner formation between BNPL providers and retailers. As discussed in Section 1, the intuition behind our instrument is that consumers are more likely to adopt BNPL when the retailers they frequently shop at partner with a BNPL provider.

To capture such exposure to BNPL, our instrument counts the number of transactions at BNPL partner retailers during the year before adoption. We illustrate the construction of our instrument using a hypothetical example in Panel A of Appendix B. Suppose there are two consumers shopping at three retailers, A, B, and C. As of the adoption quarter *t*, retailers A and B have partnered with a BNPL provider while retailer C has not. The BNPL adopter is a frequent shopper at A and B, with a total of 20 transactions during the last year. The non-adopter is a less frequent shopper at A and B and has 12 transactions over the same window. Our instrument, *BNPL_Exposure*, is the logged transactions that each consumer has at the BNPL retailers: *ln(1+20)* for the BNPL adopter and *ln(1+12*) for the non-adopter.

Panel B of Appendix B illustrates the intuition for how our instrument abstracts from the endogenous adoption of BNPL by consumers who experience a negative shock to financial health. In this example, two consumers shop at the same BNPL retail partners before adoption, so both have *BNPL_Exposure* of *ln(1+20)*. The first consumer experiences a negative shock to financial health that causes her to immediately adopt BNPL. Thus, a regression of future financial health on *BNPL_Adopter* would find that the first consumer's financial condition deteriorates, but the effect is due to the health shock (instead of BNPL). Because the two consumers have the same values of *BNPL_Exposure*, they would have the same values for *predicted* BNPL adoption from a first-stage IV regression. Therefore, a second-stage regression of future financial health on instrumented BNPL adoption would *not* find that our IV is associated with those future differences. Specifically, because both consumers have the same *BNPL_Exposure*, a regression of post-adoption financial health on our IV will produce a coefficient of zero.

Mathematically, our instrumental variable is calculated as follows:

$$BNPL\_Exposure_i = Ln(1 + \sum_{\tau \in [t_i - 4, t_i - 1\ ]\&\ t_i \geq t_p} \sum_p Spending_{i,p,\tau}) \tag{2}$$

where i indexes a consumer with an (actual or matched) adoption quarter t_i. p indexes a retailer that partners with BNPL providers through quarter t_p. For a consumer with adoption quarter t_i, we count her number of transactions during quarters [t_i-4, t_i-1] at retailers that offer BNPL as of t_i (partner formation quarter t_p<=t_i). We take the natural logarithm of one plus the value to mitigate skewness.

We identify retailers that partner with BNPL using information collected from BNPL providers' websites. BNPL providers tend to announce their partnerships with major new retailers, and we identify implementation dates based on the dates of those announcements. Panel C of Appendix B lists the retailers and implementation dates. The partnerships cover a wide range of retailers, from big box stores such as Walmart to high-end boutique stores such as Oscar de la Renta. Some partnerships are formed as early as 2014 but the majority are implemented in 2019 onwards. Our approach fails to identify the (plausibly numerous) retail partners that are not announced by the BNPL providers, in which case spending at those retailers is incorrectly excluded from our instrument, thereby weakening its ability to predict BNPL adoption.

4.2.2 First-Stage Results

Our first-stage regression is as follows:

$$BNPL\_Adopter_i = \beta_1 BNPL\_Exposure_i + \gamma_1 Health_i^{Pre} + \theta_1 Health_i^{Trend} + X_i'\delta_1 + \mu_{s,t} + \epsilon_i \quad (3)$$

The dependent variable is an indicator for BNPL adopters which equals one for adopters and zero for their matches, and the instrument is *BNPL_Exposure* as defined in Equation (2). Our control variables are the same as Model (1), with two exceptions. First, each consumer now has one observation in the sample, which precludes consumer fixed effects. Second, our second-stage tests control for pre-adoption financial health (discussed below), so we include the same controls in our first stage regression. Specifically, we control for the pre-adoption level and trend in financial health, $Health^{Pre}$ and $Health^{Trend}$, measured from t_i-4 to t_i-1.[19] Standard errors are clustered by year-quarter.

Columns (1) through (3) of Table 4 present the first-stage regression results for all three financial health proxies. *BNPL_Exposure* significantly predicts BNPL adoption in all models, indicating that our instrument satisfies the relevance condition, with *t*-statistic ranging from 19.5 to 22.1. According to the estimates in Columns (1) through (3), one within-fixed-effect standard deviation increase of *BNPL_Exposure* is associated with a 15% increase in the likelihood of

[19] Our second stage tests use three different proxies for financial health. Each second-stage test has a separate first-stage model with different $Health^{Pre}$ and $Health^{Trend}$ depending on which outcome measure is being examined. The structure of our IV analyses is similar to those in Bernstein (2015). Controlling for pre-adoption level and trend in health also further mitigates concerns that consumers with weak or deteriorating health tend to shop at the types of stores that offer BNPL, which we also further address in Section 4.2.4.

BNPL adoption, suggesting that our instrument is economically strong.[20] The strong statistical significance alleviates the concern of weak instruments (Roberts & Whited 2013), and the lower rows report Kleibergen-Papp Rank Wald F statistics that far exceed the threshold of 16.4 of Stock & Yogo (2005).

In untabulated tests, we find that the instrument coefficients are largely unchanged when controls are excluded, which indicates that *BNPL_Exposure* is largely uncorrelated with the controls (conditional on the fixed effects in all models). Minimal correlation between *BNPL_Exposure* and each of $Health^{Pre}$ and $Health^{Trend}$ mitigates concerns that users' pre-adoption shopping habits are affected by the level or change in their pre-adoption financial health.

4.2.3 Second-Stage Results

Our second-stage equation is as follows:

$$Health_i^{Post} = \beta_2 \widehat{BNPL\_Adopter_i} + \gamma_2 Health_i^{Pre} + \theta_2 Health_i^{Trend} + X_i'\delta_2 + \mu_{s,t} + \epsilon_i \tag{4}$$

where $Health_i^{Post}$ is the average value of the financial health proxy in the four post-adoption quarters (from t_i+1 to t_i+4, inclusive). $Health_i^{Pre}$ is the equivalent measure in the four quarters prior to the adoption (from t_i-4 to t_i-1), which controls for level differences between adopters and non-adopters. To further capture any differences in the trends of each health proxy between adopters and non-adopters, we also control for the change in financial health from t_i-4 to t_i-1 (variable $Health_i^{Trend}$).[21] The variable of interest, $\widehat{BNPL\_Adopter_i}$, is the predicted value from Model (3). All other specifications are the same as the first stage model. β_2 is the two-stage least

[20] We interpret the economic magnitudes using within-fixed-effect variation in the independent variable (Breuer & deHaan 2022; Mummalo & Petersen 2018). Per Panel D of Table 2, the within-fixed-effect standard deviation of *BNPL_Exposure* is 1.2. Thus, for *Overdraft*, the estimated effect is 1.2*0.061/0.5=15%.

[21] Figure 2 provides no evidence of pre-adoption differences in trends between adopters and non-adopters, but we include the trend variable here to be conservative. Untabulated analyses without the trend control produce virtually identical results, indicating that differences in trends do not correlate with our IV.

squares (2SLS) estimator, and estimates the effect of BNPL adoption on consumers' financial health.

Columns (4) through (6) of Table 4 report that β_2 is statistically positive in all three specifications, consistent with the inferences from DID analyses discussed in Section 4.1. Economically, instrumented BNPL adoption is associated with an 8.9% increase in overdraft charges, 2.5% increase in interest charges, and 8.4% increase in late fee charges in the one-year post-period.

In sum, the IV analyses are similar to the DID tests, and indicate that consumers' financial health deteriorates shortly after adopting BNPL. To the extent that our IV is valid, these results are consistent with BNPL causing consumers to spend beyond their means, leading to financial difficulties in the immediate future.

4.2.4 The exclusion condition

The exclusion condition for our IV is that spending at BNPL partners in the year before a consumer's BNPL adoption must not directly affect or predict changes in the consumer's financial health in the year after adoption, other than through BNPL itself.

A possible threat to our exclusion condition is that consumers who know they are approaching financial difficulty change their habits and start shopping at BNPL retailers in advance of adopting BNPL, in which case consumers' choices of retailers and BNPL adoption are both caused by approaching declines in financial health. This concern is mitigated by several factors. First, our first-stage IV regressions include both the level and trend in pre-adoption financial health, which should control for associations between financial health and the types of stores that offer BNPL. Second, because we measure spending over a one-year period before adoption, a consumer who switches to BNPL retailers a few months before adoption will have low values of our IV, and so will appear as low-likelihood adopters based on our first-stage models. Third, the list of BNPL partners in Panel C of Appendix B includes high-end retailers, which is inconsistent with BNPL being limited to stores where consumers shop when in distress. Fourth, Figure 2 reveals that changes in financial health happen quickly after BNPL adoption, which is inconsistent with a consumer beginning to experience distress in advance of BNPL adoption.

We further explore this possibility by lagging *BNPL_Exposure* by two quarters before adoption; i.e., $BNPL\_Exposure^{Lag}$ is measured over quarters (t-6, t-3). Our logic is that a consumer is unlikely to be able to predict a sharp change in financial health more than six months ahead, and therefore is unlikely to change her shopping habits more than six months before adopting BNPL. Untabulated analyses show that *BNPL_Exposure* in quarters (t-6, t-3) is highly predictive of *BNPL_Exposure* in quarters (t-2, t-1), which is inconsistent with consumers changing their spending habits in advance of BNPL adoption (specifically, the autoregressive coefficient is 0.92). Table 5 presents 2SLS results based on $BNPL\_Exposure^{Lag}$. While the results are somewhat weaker than those using *BNPL_Exposure*, which is expected due to using a less precise instrument, the inferences are qualitatively unchanged.

This alternative specification reduces concerns that our main findings are driven by violations of the exclusion condition. Of course, the exclusion condition is ultimately untestable, so it remains possible that our results are driven by an unforeseen confound.

4.3 Sensitivity Checks

We conduct sensitivity tests using our IV approach, given that it is likely better specified than our DID models. The following results are comparable to the specifications in Table 4 but we do not report the first stage regression results or control variable coefficients for brevity.

First, to more tightly link changes in financial health to BNPL, we narrow our measurement window to just one quarter before and after BNPL adoption. Consistent with the DID evidence which shows an almost immediate deterioration in financial health, the IV regressions in this narrow event window also find declining financial health for BNPL users, as reported in Panel A of Table 6.

Second, many BNPL adoptions were during the COVID pandemic, and could be confounded by COVID-related government cash payouts, credit relief programs, or distress. The directional effects of these confounds are difficult to predict, so we re-run our results excluding the pandemic. Specifically, we exclude all adopters and matches from Q1-2019 onwards, for which the post-adoption period overlaps with the pandemic (which started in 2020). Panel B of Table 6 shows that our results are qualitatively unchanged.

Third, instead of measuring our instrument *BNPL_Exposure* as the number of transactions at the BNPL partner retailers, we use the dollar amount as an alternative instrument. Panel C of Table 6 shows that our results hold.

Fourth, since overdraft and late fees are non-negative count variables, following the suggestions of Cohn et al. (2022), we conduct Poisson pseudo maximum likelihood regressions with unlogged dependent variables as a robustness check. Panel D of Table 6 tabulates the results, and yields similar inferences to our main analysis.

Fifth, one could be concerned that some non-adopters never shop at the types of retailers that offer BNPL, in which case they have zero *BNPL_Exposure* and it may affect our IV analyses in unpredictable ways. Panel E of Table 6 excludes non-adopters (plus matches) in our sample with zero values of *BNPL_Exposure*, and finds qualitatively unchanged results.

Sixth, in Panel F of Table 6, to further control for differences in demographics between

BNPL adopters and non-adopters, we include additional demographic characteristics listed in Table 2. All inferences are qualitatively similar.

Lastly, Panel G of Table 6 relaxes the main matching criteria and does not require BNPL adopters to share the same value of income tier, student loan, mortgage, or wage direct deposit with non-adopters. All other matching criteria remain unchanged. We get a larger matched sample, but the results are very similar.

4.4 Cross-sectional Tests of BNPL Usage Intensity

To the extent that BNPL adoption causes consumers to over-borrow and fall into financial difficulty, we expect the BNPL effects to be stronger for heavy BNPL users. We test this intuition by splitting BNPL adopters into groups based on the sample median (= 0.75) of BNPL providers each consumer uses each quarter in the post-adoption period. Controls and first-stage regression results are untabulated for brevity.

Panel A of Table 7 uses a DID approach and finds that both high and low BNPL users have declining financial health after adoption, but the effects are significantly larger for high-intensity users. Panel B of Table 7 finds similar results using our IV approach.

4.5 BNPL and Consumption

Our results are consistent with BNPL adoption causing deteriorating financial health, presumably because BNPL motivates consumers to spend beyond their means. Column (1) of Table 8 more directly investigates BNPL and consumer spending, using *Consumption* as the dependent variable. The DID results find evidence consistent with increased consumption after BNPL adoption. Observing an increase in consumption is another indicator that BNPL adopters do not experience a coinciding shock that causes declines in financial health (e.g., a layoff), in which case adopters would likely decrease consumption.[22] In Column (3), we find similar evidence with the IV approach.

We also investigate whether BNPL adopters substitute away from using credit cards, consistent with practitioners' assertions that BNPL is partially responsible for a decline in credit card spending (e.g., Nunez 2020). We investigate credit card consumption using *Card_Ratio*, which is the fraction of total consumption spent on credit cards. The DID results from Column (2) of Table 8 find significant declines in both variables, consistent with a substitution from credit cards to BNPL. Column (4) presents qualitatively similar findings with the instrumental variable approach.

5. Conclusion

We use bank and credit card transaction data of 10.6 million U.S. consumers to provide an initial investigation into the effects of BNPL on users' financial health. We find evidence that consumers experience increases in bank overdraft charges, credit card interest charges, and credit card late fees shortly after BNPL adoption, consistent with declines in leading indicators of financial health. IV analyses boost confidence that our observed associations are due to a causal effect of BNPL.

Our results indicate that regulators should take seriously the concern that BNPL negatively affects many users' financial health, and pave the way for future research on questions that we leave unanswered. As just a few examples, future research can: revisit our findings using alternative designs; extend our findings by examining longer-term changes in

[22] While it would also be interesting to examine the types of products that consumers buy on BNPL, we are unable to observe this in our data. BNPL payments are made to the BNPL provider, not to the retailer, so our transactions data do not identify which retailer's product was purchased in a BNPL transaction.

financial health (e.g., bankruptcies); evaluate whether BNPL has offsetting positive welfare effects; examine whether cross-sectional differences across BNPL loans, providers, or users affect outcomes; or examine whether regulatory interventions can improve outcomes for BNPL users. We view these and many other questions as promising avenues for future research.

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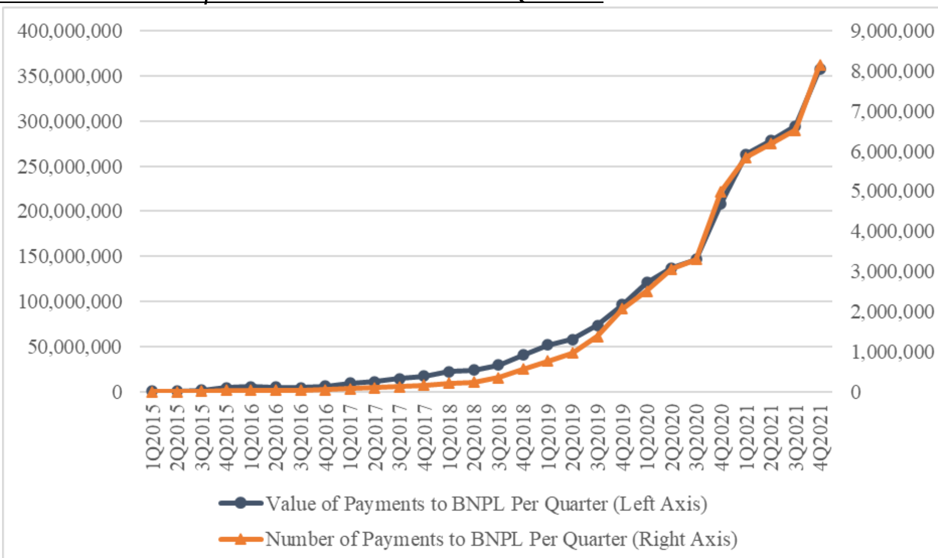
Figure 1. BNPL Usage over Time

This figure depicts the quarterly usage of BNPL from 2015 to 2021. In Panel A, the dark blue line (left axis) represents the total payments in dollar amount made to BNPL providers while the orange line (right axis) represents the number of BNPL payments. In Panel B, the dark blue line (left axis) plots the dollar amount of quarterly average BNPL payments per user and the orange line (right axis) plots the number of quarterly average BNPL payments per user.

Panel A. Value and Number of BNPL Transactions Per Quarter



Panel B. BNPL Use Intensity per Quarter (Intensive Margin)

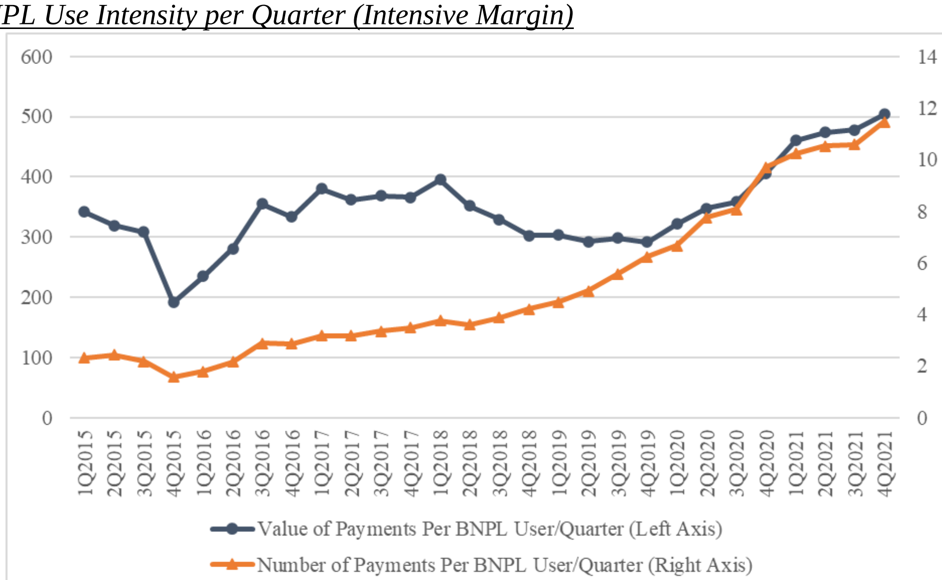
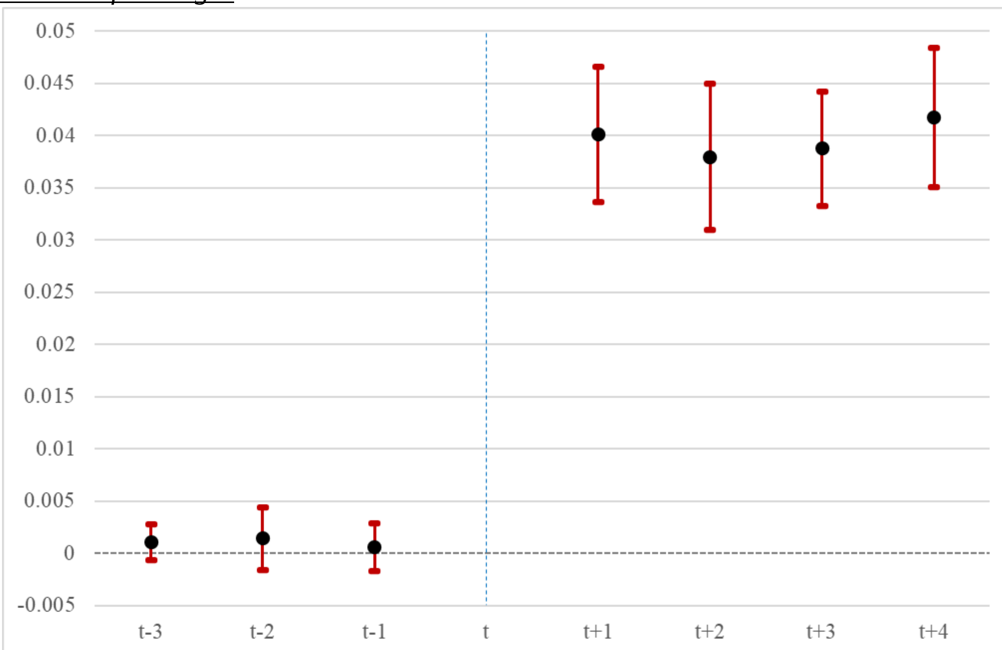


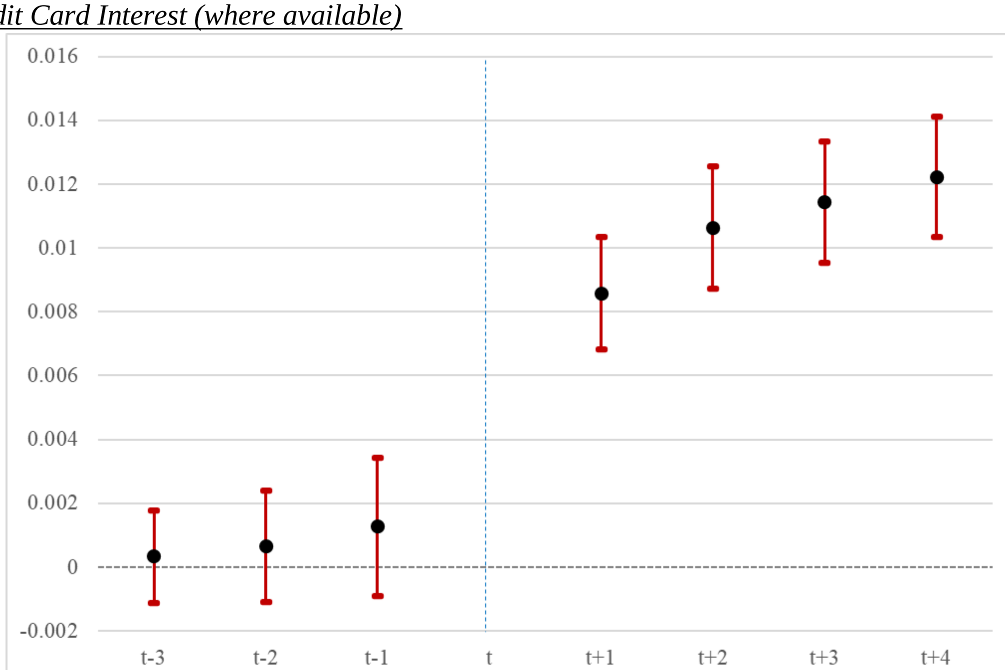
Figure 2. BNPL Adoption and Financial Health

This figure plots the β_1 through β_7 coefficients from Model (1). Quarter *t*-4 is the baseline period. Data for the adoption quarter *t* are omitted. Panels A, B, and C plot results for *Overdraft*, *Interest*, and *Late_Fee*, respectively. Confidence intervals are based on 1% statistical significance with standard errors clustered by consumer and time. Appendix A provides detailed variable definitions.

Panel A. Bank Overdraft Charges



Panel B. Credit Card Interest (where available)



Panel C. Credit Card Late Fee Charges (where available)

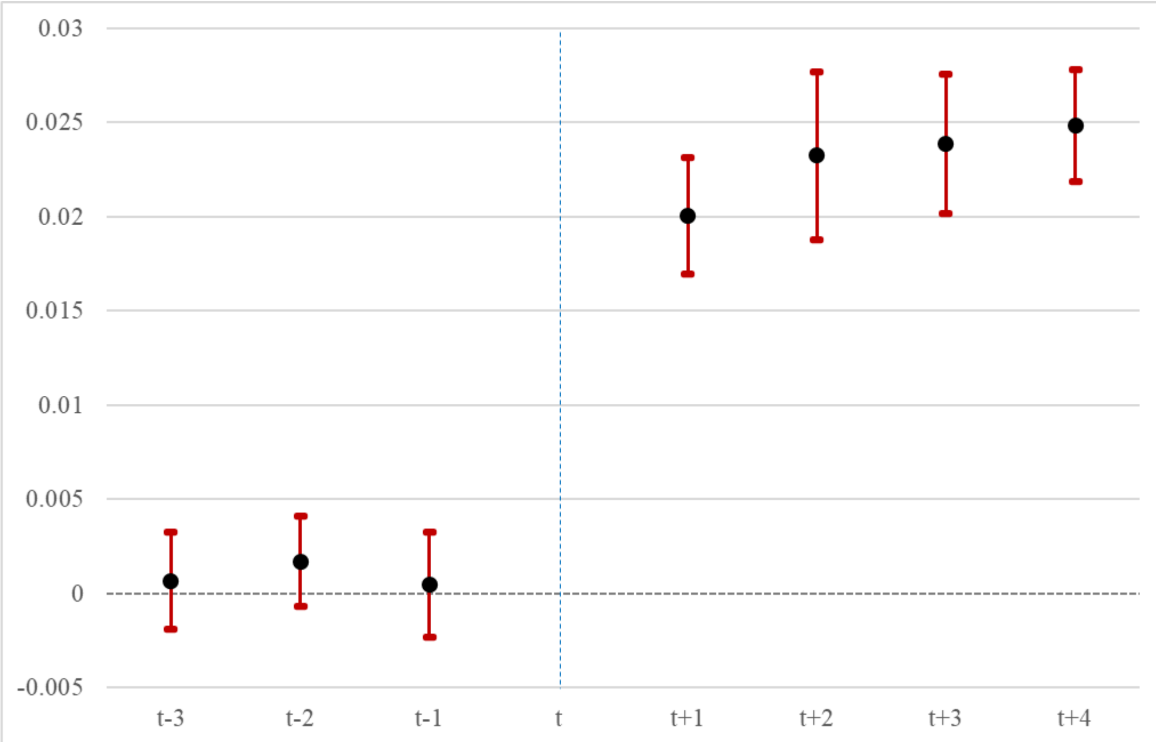


Table 1. Sample Selection

	BNPL Users	Non-Users	Total
Initial sample (consumers with basic data for at least one quarter during 2015-2021)	**1,374,901**	**9,192,111**	**10,567,012**
Matched Sample Restrictions			
Exclude consumers that do not exist in the next four quarters after BNPL adoption (largely adopters in 2021 and non-adopters who first appear in 2021).	(520,477)	(614,429)	(1,134,906)
Exclude consumers with missing matching variables (e.g., average consumption in the trailing four quarters)	(141,899)	(2,322,065)	(2,463,964)
Exclude unmatched consumers	(140,050)	(5,683,142)	(5,823,192)
Matched consumers	**572,475**	**572,475**	**1,144,950**

Table 2. Descriptive Statistics

Panel A reports the average characteristics of consumers who use BNPL at least once and consumers who never use BNPL throughout the sample period. Panel B reports the same variables but for our matched sample of BNPL users and non-users, measured in the matching quarter. The p-values of t-tests comparing BNPL users to non-users are reported in the last column. Panels C and D report the summary statistics for the observations used in the difference-in-differences and instrumental variable approaches, respectively. "Within standard deviation" is after residualizing each variable to the fixed effects used in the later tests (State-Year-Quarter & Consumer fixed effects for Panel C and State-Year-Quarter fixed effects for Panel D). Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, *, respectively. Please refer to Appendix A for detailed variable definitions.

Panel A. BNPL Users vs. Non-BNPL Users (average values per consumer over the sample)

	BNPL Users		**Non-BNPL Users**		**Difference:**		
	Consumers = 1,374,901		Consumers = 9,192,111		(Users – Non-Users)		
	N	Mean	N	Mean	Diff	%Diff	Sig.
Demographic Information							
Proportion of Senior Population	1,373,991	0.157	9,129,623	0.159	-0.002	-2%	***
Proportion with College Education	1,373,991	0.375	9,129,623	0.403	-0.027	-7%	***
Proportion of Population under Poverty	1,373,991	0.118	9,129,623	0.113	0.005	4%	***
Proportion of Households with Computer	1,373,991	0.929	9,129,623	0.934	-0.005	-1%	***
Bank Branches per 1,000 residents	1,373,991	0.321	9,129,575	0.333	-0.012	-4%	***
CFPB Complaints per 1,000 residents	1,373,991	0.580	9,129,575	0.488	0.092	19%	***
Minority	1,373,991	0.306	9,129,623	0.301	0.005	2%	***
Individuals' Financial Information							
Income Tier	1,374,901	3.609	9,192,111	3.678	-0.069	-2%	***
Student Loan Ind.	1,374,901	0.148	9,192,111	0.127	0.020	16%	***
Mortgage Ind.	1,374,901	0.208	9,192,111	0.227	-0.019	-8%	***
Wage DD Ind.	1,374,901	0.666	9,192,111	0.586	0.081	14%	***
Consumption	1,374,901	2.340	9,192,111	2.247	0.093	4%	***
Overdraft	1,374,901	0.223	9,192,111	0.150	0.073	49%	***
Overdraft (unlogged)	1,374,901	0.773	9,192,111	0.486	0.287	59%	***
Credit Card							
Interest	629,289	0.098	5,285,900	0.065	0.034	52%	***
Interest (unlogged)	629,289	0.120	5,285,900	0.079	0.041	53%	***
Late_Fee	629,289	0.145	5,285,900	0.098	0.046	47%	***
Late_Fee (unlogged)	629,289	0.257	5,285,900	0.169	0.088	52%	***

Panel B. BNPL Users vs. Matched Non-Users (measured in the match quarter)

	BNPL Users Consumers = 572,475		Non-BNPL Users Consumers = 572,475		Difference: (Users–Non-Users)		
	N	Mean	N	Mean	Diff	%Diff	Sig.
Demographic Information							
Proportion of Senior Population	565,736	0.156	552,262	0.159	-0.002	-2%	***
Proportion with College Education	565,736	0.372	552,262	0.382	-0.010	-3%	***
Proportion of Population under Poverty	565,736	0.118	552,262	0.114	0.003	3%	***
Proportion of Households with Computer	565,736	0.929	552,262	0.930	-0.001	0%	***
Bank Branches per 1,000 residents	565,730	0.313	552,254	0.323	-0.010	-3%	***
CFPB Complaints per 1,000 residents	565,730	0.633	552,254	0.592	0.041	7%	***
Minority	565,736	0.303	552,262	0.288	0.015	5%	***
Individuals' Financial Information							
Income Tier	572,475	3.794	572,475	3.794	0.000	0%	
Student Loan Ind.	572,475	0.146	572,475	0.146	0.000	0%	
Mortgage Ind.	572,475	0.221	572,475	0.221	0.000	0%	
Wage DD Ind.	572,475	0.739	572,475	0.739	0.000	0%	
Consumption (average *t*-4 – *t*-1)	572,475	2.417	572,475	2.417	0.000	0%	
Overdraft (average *t*-4 – *t*-1)	572,475	0.215	572,475	0.208	0.007	3%	***
Credit Card							
Interest (average *t*-4 – *t*-1)	184,019	0.111	184,019	0.113	-0.002	-2%	***
Late_Fee (average *t*-4 – *t*-1)	184,019	0.072	184,019	0.069	0.003	4%	***
BNPL_Exposure	572,475	2.365	572,475	2.021	0.344	17%	***

Panel C: DID sample descriptive statistics (consumer-quarter data)

Variables	N	Mean	Std. Dev.		P25	P50	P75
			Pooled	Within			
Overdraft	9,159,600	0.162	0.511	0.317	0.000	0.000	0.000
Interest	2,944,304	0.108	0.172	0.074	0.000	0.019	0.158
Late_Fee	2,944,304	0.067	0.246	0.186	0.000	0.000	0.000
Income Tier	9,159,600	3.768	2.008	0.694	2.000	3.000	6.000
Student Loan Ind.	9,159,600	0.148	0.355	0.192	0.000	0.000	0.000
Mortgage Ind.	9,159,600	0.224	0.417	0.183	0.000	0.000	0.000
Wage DD Ind.	9,159,600	0.719	0.449	0.228	0.000	1.000	1.000

Panel D. IV Sample descriptive statistics (one observation per consumer)

Variables	N	Mean	Std. Dev.		P25	P50	P75
			Pooled	Within			
$Overdraft^{Post}$	1,144,950	0.186	0.477	0.466	0.000	0.000	0.000
$Interest^{Post}$	368,038	0.107	0.164	0.162	0.000	0.028	0.154
$Late\_Fee^{Post}$	368,038	0.089	0.222	0.220	0.000	0.000	0.000
$Consumption^{Post}$	1,144,950	2.522	0.684	0.666	2.099	2.541	2.982
$Card\_Ratio^{Post}$	368,038	0.208	0.227	0.226	0.032	0.114	0.323
Income Tier	1,144,950	3.794	1.978	1.903	2.000	3.000	6.000
Student Loan Ind.	1,144,950	0.146	0.353	0.348	0.000	0.000	0.000
Mortgage Ind.	1,144,950	0.221	0.415	0.410	0.000	0.000	0.000
Wage DD Ind.	1,144,950	0.739	0.439	0.436	0.000	1.000	1.000
BNPL_Exposure	1,144,950	2.193	1.632	1.197	0.693	2.398	3.526
BNPL_Exposure(unlogged)	1,144,950	26.080	43.677	40.267	1.000	10.000	33.000

Table 3. DID Estimates of the Impact of BNPL on Financial Health

This table examines the impact of BNPL adoption on consumer financial health using a difference-in-differences model as specified in Model (1). The sample is a consumer-quarter panel of matched BNPL users and non-users during eight quarters centered around the initial BNPL adoption (quarter *t*-4 to *t*+4, excluding the adoption quarter *t*). The dependent variable is quarterly overdraft charges, credit card interest charges, and credit card late fees, as specified in the table header. The variable of interest is the interaction between *BNPL_Adopter* (equal to one for BNPL adopters) and a set of time indicator variables relative to the adoption quarter. T-statistics reported in the parentheses are clustered by both year-quarter and consumer. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, *, respectively.

	(1) *Overdraft*	(2) *Interest*	(3) *Late_Fee*
BNPL_Adopter × Post -3	0.001	0.000	0.001
	(1.470)	(0.530)	(0.628)
BNPL_Adopter × Post -2	0.001	0.001	0.002
	(1.091)	(0.889)	(1.668)
BNPL_Adopter × Post -1	0.001	0.001	0.000
	(0.579)	(1.359)	(0.383)
BNPL_Adopter × Post 1	0.040***	0.009***	0.020***
	(14.384)	(11.239)	(15.048)
BNPL_Adopter × Post 2	0.038***	0.011***	0.023***
	(12.577)	(13.007)	(12.175)
BNPL_Adopter × Post 3	0.039***	0.011***	0.024***
	(16.519)	(14.012)	(15.088)
BNPL_Adopter × Post 4	0.042***	0.012***	0.025***
	(14.504)	(15.108)	(19.592)
Post -3	0.001	0.001*	-0.001
	(0.751)	(1.925)	(-0.685)
Post -2	0.002	0.003***	-0.001
	(1.396)	(4.399)	(-0.802)
Post -1	0.007***	0.006***	0.000
	(4.985)	(6.036)	(0.456)
Post 1	-0.005**	0.004***	0.005***
	(-2.500)	(7.872)	(6.893)
Post 2	-0.003**	0.002***	0.004***
	(-2.081)	(6.551)	(5.222)
Post 3	-0.001	0.001***	0.003***
	(-1.259)	(4.487)	(6.405)
Income Tier	-0.004***	0.003***	-0.003***
	(-7.761)	(15.399)	(-11.052)
Student Loan Ind.	-0.004***	0.002***	-0.006***
	(-5.745)	(4.808)	(-5.900)
Mortgage Ind.	0.017***	0.009***	0.007***
	(18.860)	(16.576)	(7.772)
Wage DD Ind.	0.011***	0.002***	-0.002***
	(10.321)	(7.014)	(-3.365)
Observations	9,159,600	2,944,304	2,944,304
Adjusted R-squared	0.561	0.787	0.351
State-Year-Quarter & Consumer FE	YES	YES	YES

Table 4. Instrumental Variable Analysis

This table examines the impact of BNPL adoption on financial health using IV regressions. The unit of observation is one consumer. Columns (1)-(3) report the first stage results, as specified in Model (3). The dependent variable is an indicator for BNPL adopters (*BNPL_Adopter*). The instrument, *BNPL_Exposure*, is the log of one plus the number of transactions spent at BNPL partner vendors in the previous four quarters. Each health proxy requires its own first-stage regression, and is specified in the table header. Columns (4)-(6) report the second stage results, as specified in Model (4). The dependent variable is one of three proxies for financial health, as specified in the table header. All variables are defined in Appendix A. The last row reports the Kleibergen-Papp Rank Wald F statistic. The t-statistics reported in the parentheses are clustered by year-quarter. Statistical significance (two-sided) at the 1%, 5%, and 10% levels is denoted by ***, **, *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	First-stage Regressions			**Second-stage Regressions**		
DV=	*BNPL_Adopter*	*BNPL_Adopter*	*BNPL_Adopter*	*Overdraft*^{Post}	*Interest*^{Post}	*Late_Fee*^{Post}
Health proxy=	*Overdraft*	*Interest*	*Late_Fee*	*Overdraft*	*Interest*	*Late_Fee*
BNPL_Exposure	0.061***	0.055***	0.054***			
	(22.107)	(19.627)	(19.524)			
$\widehat{BNPL\_Adopter}$				0.089***	0.025***	0.084***
				(14.355)	(6.803)	(14.659)
Income_Tier	-0.002***	-0.002***	-0.003***	-0.001***	-0.000	-0.007***
	(-5.225)	(-5.557)	(-6.667)	(-2.983)	(-1.414)	(-28.917)
Student_Loan_Ind.	0.002**	-0.000	-0.002***	-0.010***	0.004***	0.000
	(2.610)	(-1.674)	(-4.172)	(-6.315)	(6.587)	(0.086)
Mortgage_Ind.	-0.004***	-0.006***	-0.006***	-0.013***	0.003***	0.002
	(-4.770)	(-5.629)	(-6.150)	(-9.428)	(6.996)	(1.422)
Wage_DD_Ind.	-0.012***	-0.007***	-0.007***	0.010***	-0.002***	0.005***
	(-8.177)	(-6.210)	(-6.482)	(13.885)	(-2.987)	(4.461)
Health^{Pre}	0.001*	-0.048***	0.000	0.642***	0.767***	0.489***
	(1.955)	(-9.996)	(0.029)	(24.145)	(47.738)	(37.133)
Health^{Trend}	0.001	0.033	0.001	0.100***	0.274***	0.075***
	(1.172)	(1.342)	(0.560)	(9.304)	(40.431)	(23.735)
Observations	1,144,950	368,038	368,038	1,144,950	368,038	368,038
Adjusted-R-squared	0.020	0.013	0.013	0.494	0.660	0.215
State-Year-Quarter-FE	YES	YES	YES	YES	YES	YES
Kleibergen-Papp-Wald-F-statistic	488.70	385.20	381.17			

Table 5. Investigating the Exclusion Restriction

This table repeats second stage IV regression results with an alternative instrument, $BNPL\_Exposure^{Lag}$. The alternative instrument is the same as the original instrument, except that BNPL transactions are measured over quarters [t-6,t-3] relative to BNPL adoption. All other model details are the same as in Table 4. First-stage results are untabulated for brevity. The dependent variable is one of three proxies for financial health, as specified in the table header. All variables are defined in Appendix A. The t-statistics reported in the parentheses are clustered by year-quarter. Statistical significance (two-sided) at the 1%, 5%, and 10% levels is denoted by ***, **, *, respectively.

	(1)	(2)	(3)
Health proxy =	$Overdraft^{Post}$	$Interest^{Post}$	$Late\_Fee^{Post}$
$BNPL\_\widehat{Adopter}^{Lag}$	0.028***	0.022***	0.074***
	(6.252)	(3.798)	(12.389)
Income Tier	-0.000	-0.000	-0.007***
	(-1.640)	(-0.947)	(-26.967)
Student Loan Ind.	-0.009***	0.004***	-0.001
	(-6.778)	(6.027)	(-0.637)
Mortgage Ind.	-0.011***	0.003***	0.002
	(-9.629)	(7.040)	(1.402)
Wage DD Ind.	0.009***	-0.002***	0.005***
	(11.806)	(-3.523)	(4.348)
$Health^{Pre}$	0.637***	0.765***	0.486***
	(23.395)	(47.508)	(36.714)
$Health^{Trend}$	0.097***	0.274***	0.076***
	(8.845)	(40.094)	(23.819)
Observations	1,048,090	338,996	338,996
Adjusted R-squared	0.497	0.663	0.223
State-Year-Quarter FE	YES	YES	YES
Kleibergen-Papp Wald F statistic	636.40	358.96	355.69

Table 6. Other Sensitivity Checks

This table reports the results of sensitivity checks for the IV regressions. Panel A examines the outcomes in the quarter immediately after BNPL adoption. Panel B excludes consumers who adopt BNPL during the pandemic and their matches. Panel C uses an alternative instrument, defined as the dollar value of transactions at BNPL retailers. Panel D estimates Poisson regressions with unlogged dependent variables. Panel E excludes consumers and their matches with zero spending at BNPL retailers. Panel F adds additional demographic controls. Panel G relaxes the main matching criteria and does not require BNPL users and non-users to share the same value of *Income_Tier*, *Student_Loan*, *Mortgage*, and *Wage_DD*. The dependent variable is one of three proxies for financial health, as specified in the table header. All variables are defined in Appendix A. The t-statistics reported in the parentheses are clustered by year-quarter. Statistical significance (two-sided) at the 1%, 5%, and 10% levels is denoted by ***, **, *, respectively.

Panel A. Narrower measurement window (i.e., one quarter pre- and post-adoption)

	(1) $Overdraft^{Post}$	(2) $Interest^{Post}$	(3) $Late\_Fee^{Post}$
$\widehat{BNPL\_Adopter}$	0.115***	0.021***	0.095***
	(4.839)	(5.165)	(10.289)
Observations	1,144,950	368,038	368,038
Adjusted R-squared	0.339	0.718	0.123
Controls & Fixed Effects	Yes	Yes	Yes

Panel B. Pre-pandemic period only (i.e., adoptions before Q1-2019)

	(1) $Overdraft^{Post}$	(2) $Interest^{Post}$	(3) $Late\_Fee^{Post}$
$\widehat{BNPL\_Adopter}$	0.076***	0.043***	0.050**
	(6.806)	(6.158)	(2.216)
Observations	247,378	103,904	103,904
Adjusted R-squared	0.533	0.657	0.229
Controls & Fixed Effects	Yes	Yes	Yes

Panel C. Alternative Instrumental Variable (Dollar Spending at Partner Retailers)

	(1) $Overdraft^{Post}$	(2) $Interest^{Post}$	(3) $Late\_Fee^{Post}$
$\widehat{BNPL\_Adopter}\$$	0.126***	0.040***	0.113***
	(17.128)	(6.555)	(18.974)
Observations	1,144,950	368,038	368,038
Adjusted R-squared	0.490	0.653	0.193
Controls & Fixed Effects	Yes	Yes	Yes

Panel D. Poisson regressions

	(1) $Overdraft(unlogged)^{Post}$	(2) $Interest(unlogged)^{Post}$	(3) $Late\_Fee(unlogged)^{Post}$
$\widehat{BNPL\_Adopter}$	1.323***	1.272***	1.867***
	(4.704)	(10.107)	(11.568)
Observations	831,738	256,250	256,250
Adjusted R-squared	0.486	0.628	0.083
Controls & Fixed Effects	Yes	Yes	Yes

Panel E. Excluding non-adopters (and matches) with zero BNPL_Exposure

	(1) $Overdraft^{Post}$	(2) $Interest^{Post}$	(3) $Late\_Fee^{Post}$
$\widehat{BNPL\_Adopter}$	0.136***	0.068***	0.193***
	(6.311)	(3.692)	(3.807)
Observations	831,738	256,250	256,250
Adjusted R-squared	0.486	0.628	0.083
Controls & Fixed Effects	Yes	Yes	Yes

Panel F. Additional Controls for Consumer Demographics

	(1) $Overdraft^{Post}$	(2) $Interest^{Post}$	(3) $Late\_Fee^{Post}$
$\widehat{BNPL\_Adopter}$	0.064***	0.015***	0.064***
	(13.131)	(3.654)	(11.138)
Additional Controls:			
Proportion of Senior Population	0.109***	-0.009	0.043***
	(7.870)	(-1.381)	(3.471)
Proportion with College Education	-0.041***	-0.019***	-0.036***
	(-13.564)	(-7.630)	(-8.341)
Proportion of Population under Poverty	-0.017	-0.011*	-0.028**
	(-1.232)	(-1.864)	(-2.465)
Proportion of Households with Computer	0.047**	-0.014	0.021
	(2.185)	(-1.085)	(0.848)
Proportion of Households with Internet	-0.073***	0.020	-0.005
	(-4.300)	(1.726)	(-0.244)
Bank Branches per 1,000 residents	0.000	0.000	0.004**
	(0.294)	(0.249)	(2.661)
CFPB Complaints per 1,000 residents	0.000	0.001*	0.000
	(0.215)	(2.088)	(0.356)
Minority	0.030***	-0.001	0.007
	(3.196)	(-0.499)	(1.179)
Observations	1,117,984	362,848	362,848
Adjusted R-squared	0.495	0.661	0.224
Controls & Fixed Effects	YES	YES	YES

Panel G. Alternative matching criteria

	(1) $Overdraft^{Post}$	(2) $Interest^{Post}$	(3) $Late\_Fee^{Post}$
$\widehat{BNPL\_Adopter}$	0.083***	0.025***	0.098***
	(12.461)	(6.982)	(13.959)
Observations	1,362,958	515,532	515,532
Adjusted R-squared	0.490	0.649	0.245
Controls & Fixed Effects	Yes	Yes	Yes

Table 7. Cross-Sectional Tests of BNPL Usage Intensity

This table reports difference-in-differences (Panel A) and instrumental regression (Panel B) results for the two subsamples split based on the sample median number of unique BNPL providers used. The dependent variable is one of the three financial health proxies, as specified in the table header. The last row reports differences in the regression coefficient estimate, and associated p-value in brackets. The t-statistics reported in the parentheses are clustered by consumer and year-quarter in Panel A and by year-quarter in Panel B. Statistical significance (two-sided) at the 1%, 5%, and 10% levels is denoted by ***, **, *, respectively.

Panel A. Difference-in-differences regressions

	$Overdraft^{Post}$		$Interest^{Post}$		$Late\_Fee^{Post}$	
	(1) High	(2) Low	(3) High	(4) Low	(5) High	(6) Low
$\widehat{BNPL\_Adopter}$	0.047***	0.032***	0.013***	0.008***	0.026***	0.020***
	(15.478)	(14.827)	(17.277)	(17.923)	(18.578)	(12.590)
Observations	4,255,712	4,903,888	1,263,072	1,681,232	1,263,072	1,681,232
Adjusted R-squared	0.561	0.560	0.789	0.784	0.357	0.346
Controls & Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Difference: High – Low	**0.015*** **		**0.005*** **		**0.006*** **	
P-value: (High – Low) > 0	[0.000]		[0.000]		[0.005]	

Panel B. Instrumental variable regressions

	$Overdraft^{Post}$		$Interest^{Post}$		$Late\_Fee^{Post}$	
	(1) High	(2) Low	(3) High	(4) Low	(5) High	(6) Low
$\widehat{BNPL\_Adopter}$	0.103***	0.073***	0.032***	0.019***	0.100***	0.071***
	(19.185)	(7.839)	(6.465)	(5.132)	(12.032)	(8.803)
Observations	531,964	612,986	157,884	210,154	157,884	210,154
Adjusted R-squared	0.493	0.496	0.663	0.655	0.215	0.214
Controls & Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Difference: High – Low	**0.030*** **		**0.013** **		**0.029** **	
P-value: (High – Low) > 0	[0.005]		[0.035]		[0.012]	

Table 8. BNPL and Consumption

This table examines the impact of BNPL adoption on consumption using the matched sample. Columns (1) and (2) report the difference-in-differences estimates. Columns (3) and (4) report instrumental variable estimates of second-stage regressions. The instrument, *BNPL_Exposure*, is the log of one plus the number of transactions spent at BNPL partner vendors in the previous four quarters. *Consumption* measures total spending, and *Card_Ratio* proxies for credit card usage, measured by spending on credit cards as a proportion of total spending. A superscript of "Post" means we take the average over the variable over four quarters in the post-adoption period. All variables are defined in Appendix A. The t-statistics reported in the parentheses are clustered by consumer and year-quarter in Columns (1) and (2) or by year-quarter in Columns (3) and (4). Statistical significance (two-sided) at the 1%, 5%, and 10% levels is denoted by ***, **, *, respectively.

	(1)	(2)	(3)	(4)
	DID Estimates		**IV 2SLS Estimates**	
	Consumption	*Card_Ratio*	$Consumption^{Post}$	$Card\_Ratio^{Post}$
$BNPL\_Adopter \times Post$	0.075***	-0.003***		
	(17.633)	(-5.553)		
$\widehat{BNPL\_Adopter}$			0.645***	-0.098***
			(14.934)	(-10.200)
Observations	9,159,600	2,944,304	1,144,950	368,038
Adjusted-R-squared	0.769	0.734	0.543	0.616
Controls & Fixed Effects	Yes	Yes	Yes	Yes

Appendix A. Variable Definitions

BNPL Variables	
BNPL_Adopter	An indicator for BNPL users who report non-zero BNPL payments at least once during the sample period.
Instrumental Variables	
BNPL_Exposure	The natural logarithm of one plus the number of transactions with BNPL partner vendors in the four quarters prior to BNPL adoption. For the control group, who do not use BNPL by construction, their "adoption quarter" is the adoption quarter of their matched treated individuals.
$BNPL\_Exposure^{Lag}$	The natural logarithm of one plus the number of BNPL transactions with partner vendors over quarters (t-6,t-3) relative to adoption.
Consequence Variables	
$\_\_\_\_\_\_^{Post}$	A superscript of "Post" means we take the average over the variable over four quarters in the post-adoption period.
Overdraft	The natural logarithm of one plus the number of overdraft charges on bank accounts, which are identified from transaction description using regular expression matching with keywords such as "insufficient funds," "overdraft," "OD CHG," and "OD FEE" (case insensitive).
Interest	The natural logarithm of one plus the dollar amount of interest charges on credit accounts (in $ thousands), which are identified from transaction description using regular expression matching with keywords "interest" excluding false positives due to "deferred interest payment plans" or merchants with "interest" in the name.
Late_Fee	The natural logarithm of one plus the number of late fee charges on credit accounts, which are identified from transaction description using regular expression matching with keywords such as "late fee" or "late charge" in the transaction category of "service charges/fees".
Consumption	The natural logarithm of one plus quarterly total consumption (in $ thousands), which is computed as the total dollar amount of debit transactions charged on bank accounts and credit accounts excluding the following categories: debt payments (credit card debt, mortgage, or consumer loans), tax payments, transfers (money transferred to another bank account), investments (contributions to retirement accounts or brokerage accounts), savings, and refunds/adjustments.
Card_Ratio	The proportion of consumption on credit cards out of total consumption (bank account plus credit cards).
Other Variables	
Income Tier	Income Tie, ranging from 1 to 7 as determined by the data provider based on prior salary, other income, and spending. The meaning of the variable value is as follows. 1: $0-$25K; 2: $25-45K; 3: $45-60K; 4: $60-75K; 5: $75-100K; 6: $100-150K; 7:$150K+.
Student Loan Ind.	An indicator for having student loans based on payments to major student loan servicers, including Department of Education, PHEAA, Granite, Great Lakes, Edfinancial Services, MOHELA, Navient, Nelnet, Fed Loans, American Education Services, ACS Education Services, Educational Computer Systems, ECSI, OSLA, UHEAA.
Mortgage Ind.	An indicator for having mortgage based on payments categorized as "Mortgage" by the data provider.
Wage DD Ind.	An indicator for receiving salary direct deposits which are identified from transaction descriptions.

Demographic Variables

Home State	Consumer’s home State is estimated by the data vendor based on the location of spending using a machine learning algorithm which weighs certain transaction categories (e.g., rent, mortgage, and utilities) higher.
*_______	All other demographic data are sourced from the 2020 American Community Survey (ACS) 5-year data, the FDIC annual summary of accounts data, or CFPB complaints data, as stated below. We approximate a consumer’s demographic information by obtaining the demographic information in the zip code of each of her transactions over the last year, where available, and then taking the average across transactions.
**Proportion of Senior Population*	Proportion of senior population (65 years and over). From the ACS data.
**Proportion with College Education*	Proportion of adult population (25 years and over) with bachelor’s degree or higher. From the ACS data.
**Proportion of Population under Poverty*	Percentage of families and people whose income in the past 12 months is below the poverty level. From the ACS data.
**Proportion of Households with Computer*	Percentage of households with a computer. From the ACS data.
**Bank Branches per 1,000 residents*	Number of bank branches. From the FDIC data.
**CFPB Complaints per 1,000 residents*	Annual number of complaints filed at CFPB. From CFPB complaints data.
**Minority*	Minority ratio. From the ACS data.

Appendix B. Instrument Examples and BNPL Partnership Dates

Panel A: Example instrument for a BNPL adopter and matched non-adopter

Actual BNPL Adopter

	BNPL Partner at t?	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
Retailer A	***Yes***	3	3	3	3					
Retailer B	***Yes***	2	2	2	2					
Retailer C	***No***	1	1	1	1					

Retailer Transactions (t-4 to t-1): **Pre-Adoption Period**; t: **Adoption**; t+1 to t+4: **Post-Adoption Period**

Instrument: *BNPL_Exposure* = log(1+20)

Matched BNPL Non-Adopter

	BNPL Partner at t?	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
Retailer A	***Yes***	1	1	1	1					
Retailer B	***Yes***	2	2	2	2					
Retailer C	***No***	3	3	3	3					

Retailer Transactions (t-4 to t-1): **Matched Pre-Adoption Period**; t: **Matched “Adoption”**; t+1 to t+4: **Matched Post-Adoption Period**

Instrument: *BNPL_Exposure* = log(1+12)

Panel B: Example for a consumer choosing to adopt BNPL upon a shock to financial health

Actual BNPL Adopter who experiences a financial wellbeing shock

	BNPL Partner at t?	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
Retailer A	***Yes***	3	3	3	3					
Retailer B	***Yes***	2	2	2	2	Financial Wellbeing Shock				
Retailer C	***No***	1	1	1	1					

Retailer Transactions (t-4 to t-1): **Pre-Adoption Period**; t: **Adoption**; t+1 to t+4: **Post-Adoption Period**

Instrument: *BNPL_Exposure* = log(1+20)

Matched BNPL Non-Adopter

	BNPL Partner at t?	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4
Retailer A	***Yes***	3	3	3	3					
Retailer B	***Yes***	2	2	2	2					
Retailer C	***No***	1	1	1	1	No Shock				

Retailer Transactions (t-4 to t-1): **Matched Pre-Adoption Period**; t: **Matched “Adoption”**; t+1 to t+4: **Matched Post-Adoption Period**

Instrument: *BNPL_Exposure* = log(1+20)

Panel C: List of retailers' partnership dates with each BNPL provider, as sourced from BNPL provider websites

Klarna	Partner Date	Affirm	Partner Date	Afterpay	Partner Date	Sezzle	Partner Date	Zip/Quadpay	Partner Date
Overstock	1-Sep-15	Casper	1-Jul-14	Trade Me	28-May-17	UNTUCKit	1-Oct-20	Gamestop	16-Sep-20
INDOCHINO	24-Oct-18	Peloton	1-Jul-15	Anthropologie	23-May-18	Ministry of Supply	9-Nov-20	Alternative Airlines	1-Oct-20
TOMS	1-Aug-19	Expedia	17-May-16	Free People	23-May-18	Wix.com	18-Nov-20		
ASOS	5-Aug-19	Eventbrite	17-May-16	Urban Outfitters	23-May-18	Gamestop	25-Nov-20		
Boohoo	5-Sep-19	Dyson	1-Jul-17	Kmart	14-Sep-18				
Abercrombie & Fitch	24-Oct-19	Walmart	27-Feb-19	Rebecca Minkoff	3-Oct-18				
H&M	14-Jan-20	StubHub	21-Jan-20	REVOLVE	23-Oct-18				
Sephora	7-May-20	Oscar de la Renta	18-May-20	Levi's	5-Jun-19				
ModCloth	11-May-20	Shopify	22-Jul-20	Ray-Ban	5-Jun-19				
Timberland	28-May-20	Herman Miller	27-Jul-20	O'Neill	5-Jun-19				
Adidas	6-Jul-20	UrbanStems	18-Aug-20	Tarte Cosmetics	5-Jun-19				
Beautycounter	20-Aug-20	Callaway Golf	27-Aug-20	MAC Cosmetics	18-Jul-19				
Missguided US	5-Oct-20	Bonobos	3-Sep-20	Ulta Beauty	26-Aug-19				
Macy's	6-Oct-20	Neiman Marcus	24-Nov-20	J.Crew	26-Aug-19				
Backcountry.com	19-Oct-20	HomeAdvisor	7-Dec-20	Madewell	26-Sep-19				
Etsy	20-Oct-20			Laura Mercier	26-Sep-19				
GameStop	26-Oct-20			Shiseido	26-Sep-19				
Saks OFF 5TH	24-Nov-20			Simon	6-Oct-20				
Express	25-Nov-20			GAP	11-Nov-20				
				Lilly Pulitzer	18-Nov-20				
				Aritzia	18-Nov-20				
				Fabletics	18-Nov-20				
				bareMinerals	18-Nov-20				
				Crocs	18-Nov-20				