Buy now, pay later credit: User characteristics and effects on spending patterns*

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ABSTRACT

Firms offering "buy now, pay later" (BNPL) point-of-sale installment loans with minimal underwriting and low interest have captured a growing fraction of the market for short-term unsecured consumer credit. We provide a detailed look into the US BNPL market by constructing a large panel of BNPL users from transaction-level data. We document characteristics of users and usage patterns, and use BNPL roll-out to provide new insights into consumer responses to unsecured credit access. BNPL access increases both total spending levels and the retail share in total spending, with magnitudes too large for standard intertemporal and static substitution effects to explain. These findings hold for consumers with and without inferred liquidity constraints. Our findings are more consistent with a "liquidity flypaper effect" where additional retail liquidity through BNPL "sticks where it hits", than a standard lifecycle model with liquidity constraints.

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I. Introduction

Consumers have substantial demand for short-term, unsecured credit, evidenced by the nearly $1 trillion in outstanding unsecured consumer loans in the US. This borrowing has historically occurred through credit cards and other revolving lines of credit. But in recent years, fintech firms operating "buy now, pay later" (BNPL) platforms have grown by offering consumers alternative payment contracts through retailers at point of sale.

BNPL credit has three distinguishing features relative to standard credit cards. First, rather than offering a revolving line of credit, BNPL products are structured as installment loans with a down payment due at sale and a fixed repayment schedule. Second, BNPL loans are offered through retailers and are tied to the purchase of a particular product. Third, BNPL companies often offer easier lending terms, with no or limited credit checks, often zero interest, minimal fees, and no or limited negative reporting to credit bureaus. BNPL companies make money by charging merchants fees of around 5-8%, substantially higher than the 2-3% charged by credit card companies.

These features have proven popular with consumers. A March 2021 survey of 2,000 adults in the United States indicated that close to 60 percent of them had used BNPL – an increase of almost 50% year-on-year[1]. According to Worldpay, BNPL accounted for 2.1% – or roughly $97b – of global e-commerce transactions in 2020, and is expected to double to 4.2% by 2024.[2]. But since companies do not have to report to credit bureaus, there is limited information on individual-level BNPL use and little is known about how the product impacts financial outcomes.

In this paper, we provide a first look into the US BNPL market with two objectives. First, we overcome the data challenge by making use of transaction level data to construct a panel on BNPL use by a large set of consumers. This allows us to document characteristics of users and usage patterns. Since our data links user activity across bank, debit card, and credit card accounts, we can also connect BNPL use to broader user-level expenditure behavior. Second, we use BNPL introduction to provide new insights into consumer responses to unsecured credit access.

BNPL access can impact consumer outcomes in a number of ways. On the one hand, additional access to credit can facilitate high-frequency consumption smoothing in response to financial shocks for constrained borrowers[3]. On the other hand consumers may spend

[1]See results of the Survey conducted by The Ascent (Backman and Caporal, 2022) at https://www.fool.com/the-ascent/research/buy-now-pay-later-statistics/

[2]See Worldpay's Global Payments Report 2021

[3]See Gomes, Haliassos, and Ramadorai (2021) (https://www.aeaweb.org/articles?id=10.1257/jel.20201461) for a comprehensive up to date review of household financial decisions including how consumers use credit to smooth consumption.

too much relative to long-run preferences due to impatience, incomplete understanding of contract terms, or reference dependent preferences. BNPL offers an attractive laboratory to study these trade-offs. Little-to-no underwriting and interest payments limits selection into use based on ability to repay, and since BNPL can only be used to buy certain categories of products, heterogeneous impacts on spending across consumption categories sheds light on how access to short term credit can impact consumer consumption and savings decisions.

Consistent with BNPL alleviating credit constraints and facilitating consumption smoothing, we find that consumers use BNPL to (i) increase spending and (ii) decouple spending and income. However, a standard lifecycle consumption model cannot explain several features of our results. First, the consumption response to BNPL is too high, largely concentrated in retail spending, and also present for groups of consumers who appear to not face binding liquidity constraints. Second, BNPL increases the likelihood that consumers face negative outcomes resulting from low liquidity, such as overdraft or insufficient funds fees. These findings suggest that BNPL affects consumer spending through channels beyond intertemporal substitution. In particular, the results are consistent with BNPL reducing consumer price elasticity on covered items, increasing near-term spending at the possible expense of longer-run liquidity. We attribute the finding that BNPL significantly tilts expenditures towards retail to a "liquidity flypaper effect" (Hines and Thaler, 1995), where liquidity in one expenditure category drives additional same-category expenditure.

Our analysis proceeds in three steps. First, we use our transactions-level panel to provide the first evidence on granular patterns of BNPL use. We find that by 2021, BNPL spending was approximately 2% of total credit card spending, and the number of BNPL users was roughly one-fifth the amount of credit card users. Additionally by 2021, around 16% of all users had used BNPL at least once and around 30% of these users were persistent users. We also find that conditional on income and location of residence, BNPL users are less likely to use credit cards and be active savers, more likely to incur overdraft fees, and more likely to rent, than individuals who do not use BNPL. Higher-income users adopt BNPL earlier, and BNPL users spend a higher fraction of income on retail goods. Additionally we find that lower income users are more likely to use BNPL *relative* to credit cards, and higher income users are more likely to use BNPL for larger ticket items. These findings suggest that those who have less access to liquid resources are more likely to use BNPL.

Our second piece of analysis documents how BNPL access impacts spending levels across various expenditure categories. We find that BNPL use is associated with significant spending changes. Using a difference-in-differences design, we compare weekly spending after first time BNPL use to weekly spending over previous episodes. Total spending increases by around $130 at the time of first BNPL use and remains elevated over the 24 weeks following initial BNPL use. About $30 of this increase on impact is BNPL spend and the remaining is spending across other categories such as retail (non-BNPL), essential spending and other discretionary non-retail spending. Our findings show that the spending response to BNPL represents a significant shift of the expenditure basket towards retail spending. To build confidence in our findings, we instrument for BNPL use by exploiting heterogeneity in the timing of BNPL adoption by retailers in a consumer's past expenditure basket. We find that instrumented BNPL use causes a permanent increase in total spending of around $60 per week, again primarily concentrated in retail spending. BNPL use also results in increased likelihood of accessing savings and incurring overdraft, NSF and other late fees.

We would expect consumers with positive discount rates to increase spending in the short-term when offered low-cost credit. However, most BNPL products require repayment within 6 weeks of purchase; justifying levels of spending as high as we observe would require either (i) unrealistically high discount rates; or (ii) widespread and binding liquidity constraints. In heterogeneity analysis, we find evidence that consumers who engage in net savings or have liquidity buffers – for whom liquidity constraints are unlikely to bind – also increase their spending significantly. Additionally, binding liquidity constraints cannot explain the observed increase in retail expenditure. We observe an expenditure basket reallocation towards retail even for credit card users, who presumably have sufficient liquidity to obtain their desired intertemporal allocation over short horizons.

Our final piece of analysis assesses to what extent BNPL use is associated with consumption smoothing. We find that BNPL use is correlated with a significant reduction in spending sensitivity to income, especially for lower income users who are more likely to be liquidity constrained. We confirm these results using our instrument for BNPL use.

Collectively our results suggest that access to short term unsecured credit through BNPL alleviates credit constraints and facilitates consumption smoothing. Using a series of calibration exercises, we show that the large spending responses and static reallocation of user consumption baskets cannot be explained through substitution effects in a standard lifecycle consumption model. Our results are more consistent with BNPL reducing consumer price elasticity on items more likely to be in covered expenditure categories. This increases near-term total spending while possibly reducing longer-run aggregate liquidity. The final part of the paper outlines how this behavior could result from a "liquidity flypaper effect," where BNPL liquidity in retail leads to higher total spending driven by retail.

Our work makes three contributions. First, our findings add facts about consumer responses to new Fintech credit products to the existing literature studying consumer spending responses to income and liquidity. A number of recent papers document marginal propensities to consume out of transitory income that cannot be explained by reasonablyparameterized standard incomplete markets models without severe liquidity constraints. For example more recently, Baker and Yannelis (2017), Gelman, Kariv, Shapiro, Silverman, and Tadelis (2015), Ganong and Noel (2019), Olafsson and Pagel (2018), show that consumers do not smooth consumption in response to predictable positive and negative income shocks. Havranek and Sokolova (2020) provide a comprehensive review of this literature as a whole through a detailed meta-analysis of studies produced between 1982 and 2017 and argue that liquidity constraints better explain results than alternatives such as "rule-of-thumb" consumption.

Comparatively fewer papers study consumption responses to potential relaxation of liquidity constraints due to increased credit availability. Sodini, Vestman, and von Lilienfeld-Toal (2016) show that after a policy change that increased homeownership, consumption smoothing increased due to greater capacity for collateralized borrowing. Of more direct relevance for our work, Gross and Souleles (2002) and Aydin (2022) use observational and experimental variation in credit limits on existing credit cards and find marginal propensities to consume of around 10–15%.

The unique features of our setting allow us to make three contributions relative to the literature on the consumption response to expanded credit. First, because BNPL features minimal underwriting, we are able to study extensive margin responses for consumers who may have previously had almost no access to traditional unsecured credit. Perhaps for this reason, we find expenditure out of liquidity that are higher than found in the existing literature. Since each dollar in BNPL spending indicates additional current-period liquidity roughly equal to the number of payments in the specific BNPL contract, the \$140 total spending response out of \$30 in BNPL spending indicates a marginal propensity to spend out of BNPL liquidity of above 50%. Second, relative to work that studies collateralized borrowing, we are able to isolate a positive shock to credit access from a change in lifetime resources.

Third, since BNPL only covers certain types of purchases, we report evidence on how asymmetric liquidity impacts the composition of expenditure baskets. Our finding that BNPL significantly tilts expenditures towards retail suggests a "liquidity flypaper effect" where liquidity in one expenditure category drives additional same-category expenditure. Such behavior could be driven by mental accounting-style budgeting rules. While this has the effect of increasing borrowing, the underlying mechanism is different than standard intertemporal substitution motives. Such behavior would partly decouple expenditure patterns following additional liquidity from interest rates, helping to rationalize high MPCs for less constrained consumers or high levels of credit card borrowing.

Our second main contribution is to lend insight into digital platform business models. As previously noted, merchants pay very high fees to BNPL providers – much higher than credit card interchange fees. First, high fees provide revealed-preference evidence that offering BNPL must generate substantial value for merchants. This aligns with our findings that BNPL induces users to increase total expenditure, which would increase merchant profits under increasing user-level returns to scale (due to, for example, fixed user acquisition costs). Second, high fees suggest that BNPL providers have some scope to exert pricing power and extract surplus from merchants. Indeed, this aligns with theoretical results in literature on two-sided platforms. For example, in Armstrong (2006), platforms have incentives to form "competitive bottlenecks" to attract exclusive users on the more elastic side of the market and charge monopoly rents to the less elastic side of the market, while in Bedre-Defolie and Calvano (2013), platforms incentives purchases for consumers who can choose the payment medium for a given transaction and load markups on merchants who cannot. Applied to our setting, these results imply that BNPL platforms have incentives to aggressively compete to both (i) attract users and (ii) design their products in a way to increase purchase volumes as much as possible. These incentives explain our findings of low fees and a product design that significantly increases total spending.

Finally, our work has important implications for the on-going policy investigation into the rapid increase in short term unsecured consumer credit over the past few years via unregulated entities such as BNPL providers. Financial services regulators are concerned with the lack of specific rules for point-of-sale credit and potential risks to consumers. In November 2021, the House Financial Services Committee held a hearing investigating the state of the BNPL industry. In December, the Consumer Financial Protection Bureau followed up with a probe into five major BNPL providers over concerns about risks to consumers associated with accumulating debt, regulatory arbitrage, credit reporting, and data harvesting. Regulators are primarily interested in the extent to which BNPL users incur fees, consumer education and information access, the lack of evaluation of consumer creditworthiness, and cyber security and data harvesting.

In contemporaneous work, Guttman-Kenney, Firth, and Gathergood (2022) study BNPL using repeated cross-sections of UK credit card transactions data. The authors identify many BNPL transactions taking place on credit cards, identified as a potential financial mistake because credit card borrowing is often costly. Relative to this work, our data tracks expenditures across credit card, debit card, and bank accounts within the same user over time, enabling us to study broader effects of BNPL on expenditure patterns.

The paper is organized as follows. Section II contains institutional details about the BNPL market and providers present in our study, Section III describes our data and summarizes features of BNPL activity observed in our data. Section IV studies consumer spending responses to BNPL access, and Section V analyses how BNPL access impacts consumption smoothing. Section VI uses a series of calibration exercises to argue that standard models cannot explain observed responses, and details out "liquidity flypaper effect" interpretation of the results. Section VII concludes.

II. Institutional Background on BNPL

BNPL – a form of point of sale financing – is credit originated at the time of purchase that is repaid in installments over a short period of time. Globally, point of sale financing is growing faster than other unsecured borrowing such as via credit cards and personal loans. It is widely thought that the Covid crisis turbocharged the growth of e-commerce[4], which enabled BNPL providers to reach consumers more easily and in turn attract merchants.

In the U.S., there are five providers of point-of-sale financing who make up >95% of the market[5]: Afterpay, Affirm, Klarna, Quadpay and Sezzle.

The terms of the loan – specifically the payment schedule time-frame, interest rate, late fees, and whether or not a soft credit inquiry is required – can vary by provider. For example, as documented in Table I, Afterpay does not conduct a credit check and hence your credit score does not impact your ability to borrow. On the other hand Klarna, Affirm, Quadpay and Sezzle conduct a soft credit check. Afterpay offers only one product – a pay-in-4, zero interest loan, with a 25% down-payment required at the time of purchase and fees charged for late payments. On the other hand Affirm offers multiple products with interest rates that vary with the term of the loan and creditworthiness of the borrower: Interest rates are either 0% for the pay-in-4 product, or between 10 and 30% for loans between 3 and 12 months. Consumers are more likely to use Afterpay and Klarna for small ticket purchases, which are typically less than $250[6]. On the other hand, Affirm is primarily used for mid-size ticket items such as electronics, furniture and home goods with sticker prices anywhere between $250 and $3000[7].This is confirmed in Table II, which shows the average transaction size for Affirm is 3x as large as that for Afterpay.

Merchants are eager to team up with BNPL providers as point-of-sale financing can increase sales. For example, a survey released by Cardify – a data firm that tracks consumer spending – shows that nearly half of consumers said they spend anywhere from 10% to over 40% more when they use a BNPL plan versus when they use a credit card. Furthermore,

[4]To put this growth into context, A July 2021 McKinsey report on BNPL states that "10 years of e-commerce growth happened in just 90 days".

[5]by number of app downloads

[6]With an average ticket size of $100

[7]With an average ticket size of $800 and the average length of the loan term is 9 months

two-thirds of BNPL users said they are buying jewelry and other "want" items that they might not otherwise get. Similarly, RBC Capital Markets estimates these point-of-sale loans increase retail conversion rates 20% to 30%, and lift the average ticket size between 30% and 50%.

Survey evidence suggests that the vast majority of consumers who use these products already have a credit card with enough capacity to fund the purchase[8], but state that they use BNPL instead because of more affordable terms. This is also consistent with a survey distributed by Ascent via Pollfish to 1,862 U.S. consumers aged 18+ on July 7 2020 that finds 39.4% of respondents use BNPL in order to avoid credit card interest. Respondents also used BNPL to make purchases that otherwise wouldn't fit within their budget (38.4%), to borrow money without a credit check (24.7%), because they couldn't get approved for a credit card (14%) and because their credit cards were maxed out (14%).

III. Data

A. *Consumer transaction data*

We construct a data-set on BNPL activity using consumer transaction data from a large U.S. data aggregation and analytics provider. The platform uses advances in data analytics to clean and categorize transaction data, which is offered as a product to institutional investors and investment managers in aggregated and disaggregated form. Access to these data is provided pursuant to agreements between the platform and its partners – financial institutions and FinTech firms – rather than directly by consumers.

We obtain access to de-identified transaction data (bank and credit card transactions) and demographics data (income and geographical location) for an unbalanced panel of approximately 10 million active consumers on average from January 2010 to May 2021[9]. BNPL transactions are largely completed directly from bank accounts. However, we also include credit card transactions in constructing certain consumption measures, as described in Table A.I.

We identify BNPL transactions by making use of merchant classification provided by the data aggregator. Specifically, the data provider extracts information from transaction descriptions using proprietary analytics and machine learning models. One piece of information obtained is the merchant to whom the transaction is directed. For BNPL transactions, the transaction description does not contain information about the actual merchant from where

[8] We confirm this in Section III

[9] While some consumers enter and exit the panel at different points in time, we observe roughly 10.6 million distinct consumers on average in the panel on a monthly basis

the product was purchased, but instead contains information about the BNPL provider. Hence we identify BNPL transactions using the primary and secondary merchant classifications. We supplement these measures by manually searching the transaction descriptions for abbreviations of BNPL provider names.

We conduct our individual-level analysis using a data subsample that oversamples BNPL users. Specifically, we randomly sample 200,000 users out of the sample of consumers ever observed to use BNPL. We then select an additional 200,000 users out of the sample never observed to use BNPL, where each non-BNPL user is selected within the same city of residence × income class bin as a BNPL user. If users are not observed in the same city × income bin each period, we assign them to the bin where they are most frequently observed. This sample selection procedure results in a panel with 400,000 unique users and 39 million user-week observations.

We also obtain dates that BNPL is first detected on retailer websites using data from Builtwith.com – a website profiler tool. We manually match websites to retailer names in our data for around 20,000 retailers, containing all of the largest retailers in the U.S.

B. Summary statistics

In this section we summarize BNPL activity observed in our transactions level data and e-commerce data and document characteristics of BNPL users.

We first examine aggregate trends in BNPL use in the full transactions dataset. Figure 1 documents the rapid increase of merchant adoption of BNPL payment options using data obtained from `www.builtwith.com` and shows a substantial increase in adoption of BNPL merchant offerings beginning in 2020, consistent with the Covid pandemic-related paradigm shift towards the digital economy.[10].

Figure 2 documents consumer BNPL use – consistent with this merchant adoption – observed in our transactions data and shows a spike in usage starting in 2020. Specifically, Panel A shows total sales by month defined as the sum of all BNPL transactions in the bank panel where the merchant is identified as one of Afterpay, Affirm, Klarna, Sezzle or Quadpay. Panel B scales this total spending by total credit card spending observed in our data and Panel C shows BNPL users relative to credit card users. Figure 2 shows that by 2021, BNPL spending was approximately 2% of total credit card spending, and that the number of BNPL users is about one-fifth the amount of credit card users. Figure A.I breaks down Panel C Figure 2 by income bucket[11] and shows that within the \$25-\$45k income group, more individuals use BNPL on average. Figure A.I highlights that low-middle income individuals

[10]See for example Qureshi (2022).

[11]The data provider assigns users to one of the seven income buckets documented in Figure A.I

are more likely to use BNPL, and there is less observed usage in the lowest and highest income groups.

Using a balanced panel of active users,[12] Figure 3 shows that by 2021, around 16% of all users had used BNPL at least once, and round 30% of all BNPL users are persistent users[13]. Consistent with this Figure 4 shows that most BNPL users conduct on average a small number of BNPL transactions each year in absolute terms.

We next analyze BNPL use at the individual level using our sample of 400,000 users. Table III compares summary statistics for BNPL users and non-BNPL users by calendar year. Recall that our sample selection procedure matches on city of residence by income. This means summary means implicitly control for time invariant city of residence by income class differences across BNPL users and non-BNPL users. We take averages over a 1 month period, as of December in each year within our sample. We find that conditional on city of residence and income, BNPL users are less likely to use credit cards and less likely to save, are more likely to incur overdraft fees and spend a higher fraction of income on retail spending. Additionally, BNPL users are more likely to rent. These statistics collectively suggest that BNPL users are more likely to be liquidity constrained relative to non-users.

Finally, note that as of 2017-2019, BNPL users tend to earn more than non-BNPL users. Since we match on a persistent income measure – and so incomes in each group should be approximately equal by the end of the panel – this indicates that early BNPL adopters tend to have higher incomes than later BNPL adopters.

Tables I – III and Figures 1–4 demonstrate that BNPL usage is widespread and is particularly popular among consumers with less access to liquid resources. Additionally, consumers who spend more on non-essential consumption, and who are more likely to incur overdraft fees, are also more likely to use BNPL in any given month.

IV. BNPL use and spending

In a standard lifecycle model, access to zero-interest unsecured credit has two immediate effects. First, consumers will optimally increase current spending, both through standard intertemporal substitution effects if the interest rate is less than the marginal non-BNPL interest rate, and through a diminishing precautionary savings motive. Second, consumers with access to zero-interest unsecured credit will have have a greater capacity to smooth expenditure across liquidity shocks. This section investigates the spending level responses

[12] Specifically, we restrict the sample to people who have been active in the data from 2017 through 2021

[13] Affirm shows earlier persistence of use which is likely because Affirm contracts are longer term vs the Afterpay pay-in-four/once every two weeks model

to BNPL, while the next section studies scope for expenditure smoothing.

A. *Motivating Evidence*

We begin our analysis by documenting spending responses to first time BNPL use. We compare BNPL users to a random point in their past, provided that BNPL use occurs on the same payweek cycle as the comparison period. Specifically we run regressions of the following form at the calendar week level:

$$y_{it} = \alpha_{it} + \sum_{k=-12}^{24} \gamma_k \mathbb{1}\{First\_BNPL_i - t = k\} \times Tit + \varepsilon_{it} \tag{1}$$

where $Tit = 1$ for the $= 12$ to $+24$ weeks around first BNPL use, and $Tit = 0$ for a random $= 12$ to $+24$ period in the past, pre-BNPL use. In our most stringent specification, $\alpha_{i,t}$ contains person and time by income class by city of residence fixed effects, absorbing within-user expenditure calendar time trends that vary by income within each city.

The coefficients of interest are γ_k, which describe how within-user spending changes in the weeks following first time BNPL use relative to another 36 week period in the past. Figure 6 plots γ_k from equation (1), along with robust 95% confidence intervals from standard errors clustered at the person and calendar time level. Consistent with standard lifecycle model predictions, BNPL use is associated with an increase in spending, at the time of BNPL use and in the weeks following.

While some of the spending increase is mechanical, in the sense that BNPL purchases automatically trigger payments at 2, 4 and 6 weeks, Panel's B and D of Figure 6 indicate that there might be additional spending responses to BNPL use. For example, spending across all categories – including non-BNPL spending – increases at the time of BNPL purchase. Additionally these spending differences remain elevated in the weeks following BNPL purchase. While an increase in spending is consistent with standard lifecycle theory, the spending response is large – especially given the short tenor of most loans.[14]

For instance, at the time of use, total spending increases by around $130, which represents a 12% shift towards retail spending as a fraction of total spending, as highlighted in Panel A of 7. This increase in retail spending declines substantially but remains elevated at around +1.5% in the weeks following BNPL use.

We also find that BNPL use is associated with an increase in the likelihood of using savings, of reducing bank account balances and incurring overdraft or low balance fees. 8. Decreased savings and lower balances could be consistent with a diminished precautionary

[14]The "pay-in-4" loans offered by all providers are repaid fully within just six weeks

savings motive. However, it is not clear why greater access to BNPL credit would increase *intentional* overdraft and low balance fees, which are implicitly a form of high cost, short-term unsecured borrowing and hence should be substitutes for BNPL.

This within-user analysis is consistent with an increase in spending as a result of BNPL use. However, the timing of BNPL use might be correlated with unobserved time-varying user-specific expenditure trends. Ex-ante, these trends could cause us to over or underestimate the expenditure impacts of BNPL availability. First, positive expenditure demand shocks might induce BNPL use, leading us to overestimate expenditure impacts. For example, users might use BNPL during shopping periods, leading BNPL use to be associated with higher spending in general. Second, consumers might use BNPL due to negative liquidity shocks. If such liquidity shocks are mean-reverting, we will overestimate expenditure impacts of BNPL, since post-BNPL use liquidity – and hence spending – will tend to be higher. If liquidity shocks are persistent, we will underestimate expenditure impacts, since liquidity – and hence spending – post-BNPL use will remain low. To make progress and isolate causal effects, we construct an instrument for BNPL use.

B. *Instrumenting for BNPL use*

We instrument for BNPL use by exploiting heterogeneity in the timing of BNPL adoption by retailers in a consumer's past expenditure basket. More specifically, we make use of the fact that shopping habits or people's choice of retailer are relatively stable[15], and that retailer choice to offer BNPL is likely uncorrelated with consumer-specific expenditure trends.

We obtain individual previous year shopping baskets from transactions data, and BNPL integration dates for 20,000 of the largest retailers in the U.S. from `www.builtwith.com` to obtain a binary exposure variable that captures the timing of individual exposure to BNPL as a function of previous shopping habits.

More formally, we define exposure as:

$$E_{i,t} = \mathbb{1}\{i, r, T-1, t\} \tag{2}$$

where $\mathbb{1}\{i, r, T-1, t\}$ is an indicator variable taking a value of 1 if at least one retailer r in consumer i's year $T-1$ expenditure basket offers BNPL by week t[16]. Table A.III lists some of the major retailers identified as offering BNPL and the date BNPL was offered.

[15] cite

[16] Note, given our method of calculating exposure we will capture discontinuous jumps in week 1 of every year when the previous year shopping baskets change. We hence make adjustments to the exposure measure by subtracting the cumulative week 1 changes in retailer transaction count.

Our exclusion restriction for interpreting estimates as causal effects of BNPL use is that the pre-period shopping mix interacted with the national retailer BNPL adoption does not directly affect local spending variables outside of its effect on BNPL access.

By focusing on the extensive margin, our instrument enables us to capture changes in outcomes that result from BNPL exposure itself, rather than the intensity of BNPL exposure. We do so because the level of BNPL exposure might correlate with user-specific expenditure trends that are unrelated to BNPL use. For example, consumers who shop at fewer retailers likely have higher measured BNPL exposure conditional on being exposed, but also could be, for instance, younger, and hence expected to have higher expenditure growth. Focusing on the extensive margin limits such threats to identification.

Figure 5 Panel A and B respectively shows the number of consumers exposed to BNPL in our sample, and the average number of purchases per year at BNPL offering merchants. Figure 5 Panel C shows the average exposure, $E_{i,t}$, across all users.

C. *Causal Evidence*

Formally, we aim to estimate coefficients in the structural equation:

$$y_{it} = \alpha_{it} + \beta Post_{it} + \varepsilon_{it} \tag{3}$$

where $Post_{i,t}$ is an indicator variable equal to one after the first time a person uses BNPL. The coefficient of interest is β, which describes how average weekly spending changes after first time BNPL use, our proxy for BNPL availability. The identification challenge is that $Post_{i,t}$ may be correlated with the structural error term.

We hence instrument for $Post_{i,t}$ using $E_{i,t}$ described above, and we estimate the equation using two-stage least squares. We collect results in Table IV.

We start our analysis by estimating the following first stage:

$$Post_{it} = \gamma_{it} + \delta E_{i,t} + X_{i,t-1} + \mu_{it} \tag{4}$$

where $X_{i,t}$ are time varying individual level controls – specifically four lags of pay-week cycle, and $\gamma_{i,t}$ represent person, person by pay-week and calendar time effects by income class and city of residence. We report Cragg-Donald (CD) and Kleibergen-Paap (KP) statistics to evaluate the strength of the first stage. In our just-identified setting with one endogenous regressor, these are respectively equal to a homoskedastic F-stat and asymptotically equivalent to a robust F-stat. Table V shows a strong first stage.

We next report results for the reduced form and two-stage least squares estimates. The column labeled "Reduced form" reports estimates from the second-stage regression of y_{it} on instruments and excluded controls:

$$y_{it} = \tilde{\alpha}_{it} + \tilde{\beta} E_{i,t} + + \tilde{\varepsilon}_{it} \tag{5}$$

The column labeled "TSLS" reports IV estimates.

Consistent with the within-user difference-in-differences tests, we report in Table V, that post-BNPL availability, total spending increases by around $60 per week, and this increase is concentrated almost entirely in non-BNPL retail spending. As a result, the static consumption basket shifts towards retail spending and away from other discretionary type spending that is not categorized as retail. These results together confirm that BNPL use impacts users' static consumption basket, in addition to inducing intertemporal substitution.

If BNPL use increases spending, we would expect to see a combination of decreased liquidity, lower savings, or increased unsecured borrowing elsewhere down the line. Table VI shows evidence for these effects by studying impacts on savings, liquid bank account balances, and increased short-term unsecured borrowing in the form of incurring overdraft and low balance fees. Table VI shows that BNPL use increases the chance of incurring an overdraft fee by about 0.47 percentage points and increases the chance of incurring a low balance fee by .48 percentage points. Since the average chance of incurring an overdraft or low balance fee is 2.4% and 2.8%, respectively, BNPL use causes the probability of incurring overdraft fees or low balance fees to increase by 20% and 17%, respectively. Table VI also shows that credits to savings accounts decline, as do liquid bank account balances.

Since many merchants adopted BNPL around the start of Covid, there might be some concern that we are erroneously associating Covid-related expenditure trends with BNPL. We confirm this is not the case by estimating our specifications excluding individuals who initiated BNPL purchases in 2020 or later. Results are presented in Tables A.IV, A.V and A.VI.

D. Heterogeneity

In this section we study heterogeneous responses to BNPL access by separately analysing individuals with different liquidity characteristics. We define three characteristics related to availability of liquid resources. The first is whether or not the individual has any identifiable savings defined as any credits or debits to savings accounts: if so we label the user as a saver. The second is whether the individual is likely maintaining less than $400 in their bank accounts most of the time. We do this by summing total credits and subtracting total debits over an 8 week period, and identifying if the absolute value of this difference is less than $400 or not[17]. We then define a person as usually having less than $400 in available liquid resources if they have less than $400 liquidity more than 50% of the time. Finally, we define a credit card user as an individual who has observable credit card debits or credits at any point in their history.

We estimate equation (5) but for the six separate groups: saver/not a saver, usually less than $400/usually more than $400, credit card user/not a credit card user. Given that BNPL features minimal underwriting, we are able to study extensive margin responses for these consumers who may have previously had little access to traditional unsecured credit or other liquid resources.

Table VIII presents results of the two-stage least sqaures estimation by liquidity characteristics. First, across all liquidity characteristics, users with less liquid resources increase total spending and retail spending by more. This is consistent with classical consumption / savings models with liquidity constraints: additional access to credit increases spending for constrained individuals. The additional spending is not coming from differences in the amount of BNPL spending itself, since BNPL spending is fairly similar across groups. Thes results suggest that particularly liquidity constrained individuals are using BNPL liquidity to increase spending elsewhere.

Second, we also find effects on both (i) spending levels and (ii) the retail composition of total spending for individuals who likely don't face binding liquidity constraints. For example, those who have savings and available liquid buffers also use BNPL to increase spending. While BNPL might enable these consumers to maintain their buffer stock, we also find that individuals who have credit cards and hence likely have available liquidity, use BNPL to increase retail spending and reallocate their expenditure basket towards retail goods. The fact that BNPL significantly tilts expenditures towards retail goods, even for individuals with available liquid resources, provides insight into the mechanisms driving consumption responses to liquidity changes aside from typical intertemporal substitution motives.

These findings demonstrate the novel aspects of our setting. BNPL introduction is particularly useful to isolate the effects of a positive shock to credit access not only because of our ability to study the broader population, but also because this change in credit access is not related to changes in lifetime resources, given that BNPL does not require collateral.

[17]Note, we take an absolute value here, since if for example a person spends more than $400 than they have coming into the account, it is likely that they had more than $400 liquidity to start with.

V. BNPL use and the relationship of spending to income

For consumers facing credit constraints, BNPL access could help manage liquidity shocks by distributing expenditure for current consumption across multiple pay periods. Constrained consumers rely on income as their main source of liquidity; if BNPL has consumption smoothing benefits, then access should allow consumers to decouple spending from income. This section investigates whether BNPL availability weakens the correlation between spending and income. We broadly find that the correlation between spending and income declines following BNPL use, consistent with consumers using BNPL to smooth expenditure across liquidity shocks.

We make two sample restrictions unique to this section. First, we limit to consumers whom we observe using BNPL at least once during the sample period. Second, we exclude people who do not appear to rely on observed salary for consumption. In particular, we require that (i) we observe at least two quarters where salary income exceeds half-time at federal minimum wage; and (ii) pre-BNPL average weekly salary exceeds half-time at the federal minimum wage. For people not meeting these requirements, high-frequency variation in observed salary income is unlikely to indicate variation in liquidity.

A. Motivating evidence

We first examine the reduced-form relationship between spending and income before and after consumers first use BNPL. Figure 9, Panel A plots the raw relationship, pooling across consumers and time periods. The slope of the relationship post-BNPL is less steep than the pre-BNPL slope. Panel B reports the same relationship, demeaning observations at the person and week level. This measures the within-user association between spending and income, using heterogeneity in the timing of BNPL first use to difference out common calendar time variation. To ensure the estimated slope reflects the within-user, rather than cross-sectional, association between spending and income, Panel B demeans observations at the unit level. The broad pattern remains.

The previous analyses pool together responses for people with vastly different incomes. To put everyone on the same scale, Panel C normalizes weekly salary and weekly total spending by pre-BNPL average weekly salary, and again demeans observations by person and calendar time. This normalization makes the association between first BNPL use and expenditure smoothing much more stark. The relationship between spending and relative weekly salary is almost flat after first BNPL use, compared with a fairly steep relationship in the prior time period. The figure also reveals that the main post-BNPL change in expenditure occurs in periods when weekly salary is much lower than its pre-BNPL average. This is consistent with BNPL availability helping maintain relatively higher expenditure levels during times of significant financial hardship.

Three additional pieces of evidence suggest that the change in the relationship between spending and income represents a causal effect of BNPL availability.

First, BNPL use occurs mostly in periods where expenditure smoothing effects appear largest, and are of the right magnitude to free up liquidity for additional expenditure. Figure 10 keeps the horizontal axis from Figure 9, Panel C, but in each relative weekly salary bin plots weekly expenditure on BNPL down payments normalized by pre-BNPL average weekly salary. It is clear that BNPL spending increases substantially in periods when weekly salary drops substantially.[18]

Quantitatively, in periods when weekly salary is lowest, BNPL spending is about 3% of pre-BNPL average weekly salary. About 43.4% of BNPL purchases during this period are via Affirm, with the remainder through predominantly pay-in-four services like Afterpay. If we assume the average number of payments for Affirm users is 12, then the average number of payments for BNPL purchases in this category is around 7.5 in total. Therefore, the 3% of pre-BNPL average weekly salary in down payments made during low-salary weeks supports consumption equal to $6.5 \times 3\% \approx 19.5\%$ of pre-BNPL average salary. If following first BNPL use, consumers maintained their previous consumption level but changed payment method to BNPL by the observed amount, liquidity would increase by almost 20% of pre-BNPL average weekly salary. A marginal propensity to spend out of this liquidity of one – roughly in line with results in the previous section – would almost completely account for the change in spending post-BNPL during low-income periods observed in Figure 9, Panel D.

Second, if the change in the relationship between spending and income were driven by BNPL availability, then we would expect the relationship to be stronger for consumers who are the most credit constrained. Figure 9, Panel D tests this prediction, using average pre-BNPL salary quartile as a proxy for credit constraints on the hypothesis that lower income corresponds with lower liquidity, and hence less capacity to smooth expenditure over income fluctuations. As in Panel C, we normalize both spending and weekly salary by pre-BNPL average salary. As expected, post-BNPL expenditure smoothing is almost completely driven by changes for consumers in the lowest salary quartile, although the relationship between spending and income becomes flatter for consumers in each income category.

Third, if increased post-BNPL expenditure smoothing were causal, we would expect the

[18]BNPL use is also high during high income periods. This is probably because overall shopping on discretionary items is high when relative income is high, with BNPL used as the payment method

relationship between spending and income to change immediately around first BNPL use. To study this prediction, we run regressions of the following form at the calendar week level:

$$
\begin{aligned}
y_{it} = \alpha_{it} &+ \sum_{k=-5}^{7} \delta_k \mathbb{1}\{First\_BNPL_i - Qtr_t = k\} \times Payweek_{it} + \gamma Payweek_{it} \times Salary_{it} \\
&+ \sum_{k=-5}^{7} \gamma_k \mathbb{1}\{First\_BNPL_i - Qtr_t = k\} \times Payweek_{it} \times Salary_{it} + \varepsilon_{it}
\end{aligned} \tag{6}
$$

where total spending y_{it} and $Salary_{it}$ are both normalized by average pre-BNPL weekly salary; $First\_BNPL_i$ gives the calendar quarter of first BNPL use; Qtr_t gives the calendar quarter of calendar week t; $Payweek_{it}$ is an indicator for weeks with nonzero salary; and α_{it} represents the set of fixed effects used as additional controls. In our baseline specification, α_{it} includes person, person-by-payweek, and calendar time fixed effects. The coefficients of interest are γ_k, which describe how the within-user relationship between spending and the intensive margin of salary changes in the quarters immediately before and immediately after consumers begin to use BNPL, relative to the period more than 5 quarters before first BNPL use. Note that γ_7 pools all periods after 6 quarters post first BNPL use.

Figure 11 plots γ_k from Equation (6), along with robust 95% confidence intervals computed from standard errors clustered at the person and calendar time level. Consistent with a causal effect of BNPL availability on expenditure smoothing, salary becomes significantly less predictive of weekly expenditure starting in the first quarter relative to BNPL use. Appendix Figure A.II performs the same analysis, subsetting to calendar quarters before March 2020 to demonstrate that this is not an artifact of Covid-related upheaval, which could have simultaneously driven BNPL adoption and impacted how spending responds to income.

B. Causal evidence

Person-level trends in the correlation between spending and income correlated with the timing of first BNPL use could drive results from the previous section. For example, consumers might make large purchases financed by BNPL when they anticipate a near-term change in salary or economic circumstances. To isolate the causal effect of BNPL availability on expenditure smoothing, we instrument for BNPL use using the BNPL exposure instrument introduced in the previous section.

Formally, we seek to estimate coefficients in the structural equation:

$$\begin{aligned} y_{it} = \alpha_{it} + \beta_0 Post_{it} \gamma_0 Payweek_{it} \times Salary_{it} + \gamma_1 Payweek_{it} \times Salary_{it} \times Post_{it} \\ + \delta_0 Payweek_{it} + \delta_1 Payweek_{it} \times Post_{it} + \varepsilon_{it} \end{aligned} \tag{7}$$

where $Post_{it}$ is an indicator variable equal to one after the first time a person uses BNPL, and as before, y_{it} and $Salary_{it}$ are normalized by pre-BNPL average salary. The coefficient of interest is γ_1, describing how the relationship between expenditure and salary changes after first BNPL use, our proxy for BNPL availability. The identification challenge is that ε_{it} may correlate with $Payweek_{it} \times Salary_{it} \times Post_{it}$[19].

To address the identification challenge, we instrument for endogenous variables $Post_{it}$, $Payweek_{it} \times Post_{it}$ and $Payweek_{it} \times Salary_{it} \times Post_{it}$ using the extensive margin exposure instrument $Exposed_{it}$ and its interaction with $Payweek_{it}$ and $Payweek_{it} \times Salary_{it}$. We estimate the just-identified system using two-stage least squares.

Table IX reports baseline results, where specifications include person, person × payweek, and calendar time fixed effects. To understand effects for consumers whom we predict to face more or less binding constraints, we estimate coefficients in equation (7) separately for each pre-BNPL salary quartile. The column labeled "Fixed effects" reports OLS estimates of coefficients in equation (7). The column labeled "Reduced form" reports estimates from the second-stage regression of y_{it} on instruments and excluded controls:

$$\begin{aligned} y_{it} = \tilde{\alpha}_{it} + \tilde{\beta}_0 E_{it} + \tilde{\gamma}_0 Payweek_{it} \times salary_{it} + \tilde{\gamma}_1 Payweek_{it} \times Salary_{it} \times E_{it} \\ + \tilde{\delta}_0 Payweek_{it} + \tilde{\delta}_1 Payweek_{it} \times E_{it} + \tilde{\varepsilon}_{it} \end{aligned} \tag{8}$$

The column labeled "TSLS" reports IV estimates. We only report smoothing coefficients for brevity. We also report KP and CD statistics, which indicate strong first stages. [20]

The results broadly align with findings from the previous subsection. First, the pre-BNPL relationship between expenditure and salary ($\hat{\gamma}_0$) is stronger and economically meaningful for lower income quartiles, validating our proxy for individual constraints. Second, both our fixed effects and IV estimates for γ_1 are of opposite sign and approximately equal magnitude as corresponding γ_0 estimates. That is, BNPL availability appears to essentially eliminate the high-frequency correlation between expenditure and income. This suggests that BNPL availability indeed allows constrained consumers to decouple consumption from

[19]Technically, correlation with $Post_{it}$ could also produce inconsistent estimates

[20]Under homoskedasticity, a sufficiently high CD test statistic can reject the null that the TSLS bias due to weak instruments is large relative to the bias of OLS. While the KP statistic is the heteroskedasticity-robust version of the CD F-stat, there is no formal justification for its use with associated critical values in a weak IV test outside of the just-identified case with a single endogenous regressor.

high-frequency salary fluctuations.

It is noteworthy that estimated γ_0 and γ_1 are substantially higher in magnitude for IV specifications compared to fixed effects specifications. There are two factors that could explain the difference. First, recall that BNPL is often endogenously used in relatively low liquidity periods. If such low liquidity periods are persistent, then the associated strengthened relationship between spending and income may partly offset the expenditure smoothing impacts of BNPL. Second, even absent endogenous BNPL first use timing, the fixed effects and IV estimates may differ in the presence of treatment effect heterogeneity. Specifically, the fixed effects estimates would deliver an average treatment effect under conditional unconfoundedness, whereas the IV estimates deliver the average treatment effect for consumers induced to use BNPL by its availability. Expenditure may more closely track income for this group – and hence have more scope to be smoothed – if this group of compliers screens out higher wealth or relatively more sophisticated consumers.

Table X reports results from a specification that additionally includes calendar time $\times$ income class $\times$ geography fixed effects to absorb location-specific time trends separately by income. Estimates are very similar, suggesting that previous results are not driven by correlation between BNPL adoption timing and such heterogeneous time trends.

Finally, Table XI conducts heterogeneity analysis using the same proxies for low liquidity as in Section IV. We estimate coefficients in equation (7) using TSLS, using calendar time $\times$ income class $\times$ geography fixed effects on samples that restrict to consumers in each liquidity category – savers and nonsavers, consumers who do or do not typically have balances exceeding $400, and credit card users and nonusers. Results confirm our findings in results that split by salary – consumers with proxies that indicate low liquidity both (i) have a higher pre-BNPL correlation between spending and income, and (ii) see the correlation largely disappear after BNPL becomes available.

VI. Discussion

In line with our findings, standard incomplete-markets consumption models would predict that agents facing liquidity constraints would both (i) increase near-term expenditure and (ii) engage in expenditure smoothing in response to liquidity from BNPL availability. In this section, we argue that the magnitude and incidence of spending responses do not align with reasonable parameterizations of standard models. Our findings are more consistent with a "liquidity flypaper effect," where consumers use BNPL liquidity to increase current-period spending on retail goods.

We first present a set of simple calibration exercises that suggest that standard models would struggle to explain our results. We then discuss our alternative interpretation of the data.

A. Calibration

In Section IV, we document a sharp increase in total spending around the time of BNPL use in difference-in-differences specifications, and show that this increase is persistent in IV specifications. We further show that expenditure baskets reorient towards retail and away from other categories. However, standard models predict that constrained consumers with positive discount rates will increase their consumption in response to low-cost credit. Furthermore, if credit only applies to certain items – as is the case with BNPL – and consumers choose current consumption myopically due to for example severe liquidity constraints or impatience – then consumers should increase their expenditure share on BNPL covered items as a way to boost current consumption levels. In this subsection, we argue that effects we observe are too big for standard forces to explain.

We first consider the increase in total spending and conduct an exercise to roughly determine how high discount rates would have to be to justify the observed spending response based on pure intertemporal substitution. In a very simple model with no income uncertainty and liquidity constraints, the consumer solves:

$$\max_{\{c_t\}} \sum_{t=0}^{\infty} \delta^t u(c_t)$$
$$\text{s.t. } c_t \leq x_t \equiv R\left(x_{t-1} - e_{t-1}(c_{t-1}, \cdot)\right) + y_t \quad \forall t$$

where c_t represents consumption, x_t represents current-period liquidity, y_t is income, $R = 1$ is the interest rate on liquid savings, and $e_{t-1}(\cdot, \cdot)$ is a function mapping from consumption to expenditure. The e function allows for the possibility of buy now, pay later borrowing that lowers the expenditure impact of current consumption, where the second argument reflects possible dependence on earlier consumption and expenditure (to distinguish between periods with borrowing and periods with repayment).

Suppose that $y_t = y$, $x_0 = 0$, and $\delta < 1$. In the initial situation, the consumer is liquidity constrained and $c_t = y$. Now suppose the consumer is granted access to a pay-in-four BNPL product with no interest that allows one outstanding loan at a time. Assume that the consumer can use BNPL credit to finance as much of her consumption basket as she wants. If spending satisfies the Euler equation, then:

$$u'(c_0) = \delta u'(c_1) = \delta^2 u'(c_2) = \delta^3 u'(c_3)$$

Since the loan must be repaid by period $t = 3$, $c_3 = 4y - c_0 - c_1 - c_2$. Assuming CRRA utility with coefficient of relative risk aversion γ, marginal utility is $u'(c) = c^{-\gamma}$ and:

$$\frac{c_0}{y} = \frac{4}{1 + \delta^{1/\gamma} + \delta^{2/\gamma} + \delta^{3/\gamma}}$$

Note that in the model, $c_0 = y + \Delta c_0$. Estimates in Table IV indicate that $\Delta c_0 \approx 60$, and median salary by 2020 for BNPL users in Table III indicate that $y \approx 1,290/2 = 645$.[21] This indicates that $c_0/y \approx 1.093$. For $\gamma = 4$, these figures imply $\delta \approx 0.78$. Recall this is a *weekly* discount rate – therefore, implied annual discount rate is *much* lower.

Note that we stacked our empirical analysis in favor of finding a larger discount factor in several ways. For one, we used the long-term change in spending from TSLS estimates, which is probably a lower bound on the relevant initial-period change in spending. A higher spending response would predict an even lower discount factor. Second we considered pay-in-four products with zero interest rate. However, in our analysis we also include BNPL spending via products offered by Affirm, which often carry positive interest rates and should hence lead to a lower spending response on impact. Put differently, our spending estimates might be even higher if we only consider zero-interest products. Finally, sub-setting specifically to people who face binding liquidity constraints – as in Table VIII – gives a higher spending response which would in turn lower the calibrated discount factor. Intuitively, BNPL only provides liquidity over a short horizon and over such a short horizon we can only explain such large consumption responses if consumers discount the future at a counterfactually high rate.

It is important to note that this simplified exercise assumes no income uncertainty, and in a classical model with income uncertainty, BNPL could increase consumption by reducing a precautionary savings motive. However diminished precautionary savings is unlikely to explain our findings for three reasons. First, reducing the precautionary savings motive only implies higher consumption during periods of low liquidity. Therefore, consumers who typically enjoy ample liquidity will not change their behavior much. But in Table VIII, we show that both savers and consumers with bank account liquidity typically exceeding \$400 – for whom the precautionary motive would be small – still increase spending significantly when BNPL becomes available. Second, in Table VI, we show that BNPL availability increases overdraft and low balance fees. Paying such fees represents a high-interest form of short-term unsecured borrowing. If increased spending were due to a lower precautionary motive, we would not expect an increase in such borrowing. Third, even if a lower precautionary

[21] This table lists median salary conditional on nonzero salary. Since most people are paid biweekly, this roughly equals twice the average weekly salary.

motive could explain higher total spending levels, it cannot explain our finding that the retail share of total expenditure increases. We now analyze whether standard economic forces can explain this result.

It might seem natural that BNPL would lead to an increased budget share on retail due to standard static substitution effects. However, if demand is locally homothetic and BNPL does not have large effects on consumer net worth, we argue that such substitution forces are too small to explain our findings.

First, note that *non-BNPL retail* expenditure share increases in Table V. Assuming that BNPL-covered products are closer substitutes for general retail than non-retail goods, and assuming there are no large local non-homotheticities, standard substitution effects would predict that this share should *decline*, not increase, as the effective price of its closest substitute (BNPL retail spending) declines.

Second, substitution effects cannot quantitatively explain the observed increase in overall retail share of expenditure. To show this, we again consider a setup that is biased towards finding a large substitution effect. Suppose consumers are credit constrained pre-BNPL, and that discount rates are low enough that even after additional liquidity via BNPL becomes available, consumers will still want to exhaust all current period liquidity. Additionally suppose that consumers have CES preferences over retail and non-retail consumption x_1 and x_2 respectively:

$$u(x_1, x_2) = (x_1^r + x_2^r)^{1/r}$$

then the budget share in retail is:

$$\mu_1 \equiv \frac{p_1 x_1}{y} = \frac{p_1^{1-\sigma}}{\sum_k p_k^{1-\sigma}}, \quad \sigma \equiv \frac{1}{1-r}$$

where p_k give the price indices of retail and non-retail goods, respectively. If BNPL-covered and non-BNPL covered retail goods are perfect substitutes, then the effective retail price index falls by at most the fraction of BNPL spending in overall retail spending (taking the most conservative assumption that BNPL-covered products require no down payment).[22] Looking at Table III, the BNPL spending share in retail spending is around $4/68 = 5.8\%$.

[22] In this perfect-substitutes case, the only reason for non-BNPL retail spending would be if BNPL providers impose binding credit limits on the amount that consumers can borrow. For an alternative micro foundation for why the retail price index falls by at most the fraction of BNPL spending in overall retail spending without appealing to credit constraints, suppose that retail spending is chosen according to Leontief preferences so that $\sigma = 0$.

The change in retail budget share therefore is:

$$\frac{\mu_1'}{\mu_1} = \frac{(p_1'/p_1)^{1-\sigma}}{\left(\sum_k (p_k')^{1-\sigma}\right) / \left(\sum_k (p_k)^{1-\sigma}\right)} = \frac{(p_1'/p_1)^{1-\sigma}}{(p_1'/p_1)^{1-\sigma}\mu_1 + (1-\mu_1)}$$

With $p_1'/p_1 = 1 - 4/68$, $\mu_1 = 0.14$, and $\sigma = 4$,[23] we have $\mu_1'/\mu_1 = 1.17$ implying that the change in retail expenditure share should be $0.17 * 14 = 2.38$ percentage points. This upper bound is less than half of the 6.3pp increase we report in Table V.

B. *Alternative explanations*

In this subsection, we argue that our results are more consistent with a "liquidity flypaper effect" where consumers use additional liquidity from BNPL to increase purchases of similar goods. Such behavior would be consistent with mental accounting-style spending rules.

This effect could work as follows. Since providers partner with retail merchants, BNPL disproportionately provides liquidity for retail purchases. We hypothesize that the additional liquidity "sticks" in retail and leads to higher retail consumption. Ad-hoc budgeting rules or mental accounting combined with consumer myopia could produce this sort of behavior. First consider consumer purchasing behavior when merchants offer BNPL. Suppose that consumers budget a certain amount for, say, clothing expenditure in each period. If consumers can suddenly use BNPL to pay for some of these purchases – and they fail to fully recognize how future payments will impact future liquidity – then the original budget will go further, leading to more up front same-category behavior.

Now consider consumer behavior in periods when BNPL installment payments come due. For the argument to hang together, and lead to an increase in spending that persists beyond the repayment term, consumers must not code repayments in the same category as the initial purchase. Otherwise, increased initial spending in a BNPL category would lead to offsetting future decreases in that category. It is sensible that consumers may not associate BNPL repayments with a particular budgeting category, since (i) repayment decisions happen outside of actual shopping experiences and (ii) if a consumer makes multiple BNPL purchases over multiple periods, they may not remember which payments correspond to which item. Instead, BNPL repayments might be financed out of other sources of liquidity, such as savings or borrowing from other sources.

Such a "liquidity flypaper effect" makes a set of predictions that align with our results. First, we would expect an immediate increase in the retail share of total expenditure. This is because the additional liquidity "sticks" in retail and leads to higher retail consumption.

[23]This is a standard calibration that matches average developed economy markups in monopolistic competition models.

We would also expect an increase in non-BNPL retail spending due to the increased liquidity in the broader retail mental account. Additionally we would expect to find these increases in retail share among people who already have alternative forms of unsecured credit, such as credit cards, or for those who do not face more general liquidity constraints. The "liquidity flypaper effect" we describe here would also predict that these increases in retail share persist after the immediate liquidity "sticks". This would happen if individuals do not code repayments as part of the same mental account. In this case, we would also expect to see that this additional future retail spending would have to be financed with additional liquidity such as savings, lower checking account balances, and potentially other sources of high-cost credit like account overdrafts. We observe each of these effects in our empirical analysis.

Finally, note that nothing in this alternative mechanism is inconsistent with our result that BNPL facilitates expenditure smoothing. Recall that expenditure smoothing increases largely because spending increases in lean times. The observed drop in spending in low salary periods results from a tight budget constraint. Regardless of the theoretical mechanism driving increased spending after BNPL becomes available, BNPL availability does make budget constraints less likely to bind and enables higher spending in these periods. Put another way, our expenditure smoothing results mostly show that BNPL relaxes a credit constraint. But the credit constraint drove the correlation between income and spending in lean times through an accounting relationship, relaxing the constraint mechanically reduces the correlation. Since these mechanical forces apply regardless of the behavior driving increased spending, our expenditure smoothing results do not help distinguish between mechanisms.

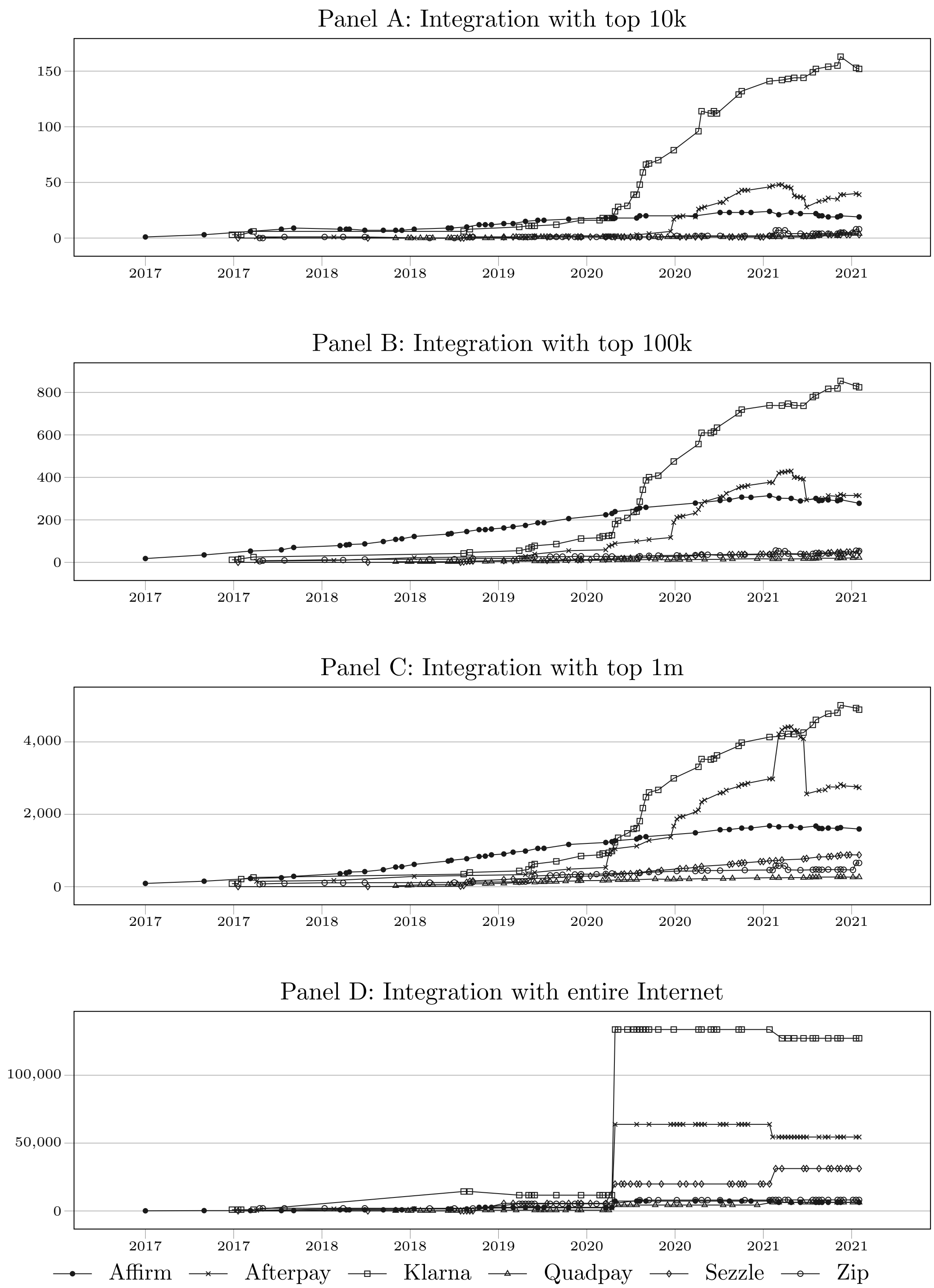
VII. Conclusion

We provide a detailed look into the US BNPL market by making use of transaction level bank account and credit card data to construct a panel on BNPL use by a large set of consumers.

We document characteristics of users and usage patterns and use BNPL introduction and show that BNPL use is widespread. We find that by 2021, BNPL spending was approximately 2% of total credit card spending, the number of BNPL users is about one-fifth the amount of credit card users and around 30% of all BNPL users are persistent users. Low-to-middle income individuals are more likely to use BNPL, and we observe that there is less observed usage in the lowest and highest income groups. BNPL users are also less likely to use credit cards and less likely to save, are more likely to incur overdraft fees and spend a higher fraction of income on retail spending. Additionally, BNPL users are more likely to rent.

We next use BNPL introduction to provide new insights into consumer responses to access to unsecured consumer credit. We find a large increase in spending with BNPL access that is inconsistent with traditional life cycle models with liquidity constraints. Put differently, given that BNPL only provides liquidity over a short horizon and over such a short horizon we can only explain such large consumption responses if consumers discount the future at a counterfactually high rate. We argue that our results are more consistent with a "liquidity flypaper effect" where consumers use additional liquidity from BNPL to increase purchases of similar goods. Such behavior would be consistent with mental accounting-style spending rules. This flypaper effect would predict an immediate increase in the retail share of total expenditure and also an increase in non-BNPL retail spending due to the increased liquidity in the broader retail mental account. We would expect to find these increases in retail share among people who already have alternative forms of unsecured credit, such as credit cards, or for those who do not face more general liquidity constraints. We observe these dynamics in the data, We also find that these increases in retail share persist after the immediate liquidity "sticks", which is consistent with individuals coding repayments as part of a different mental account. We also find an increased likelihood of overdraft and low balance fees, lower checking account balances and increased use of savings after BNPL access.

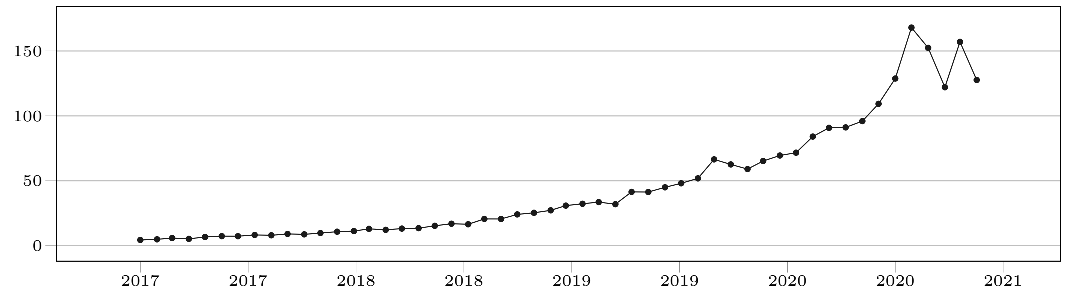
Figure 1. BNPL adoption by merchants



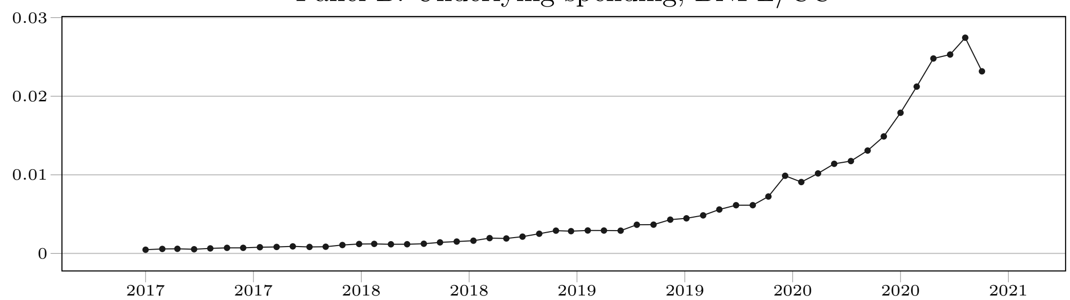
This figure plots merchant BNPL adoption by BNPL provider using data provided by builtwith.com. Plots correspond to the groups of websites ranked by traffic – for example "Top 10k" includes the most popular websites 10,000 websites.

Figure 2. Consumer BNPL usage by month-year

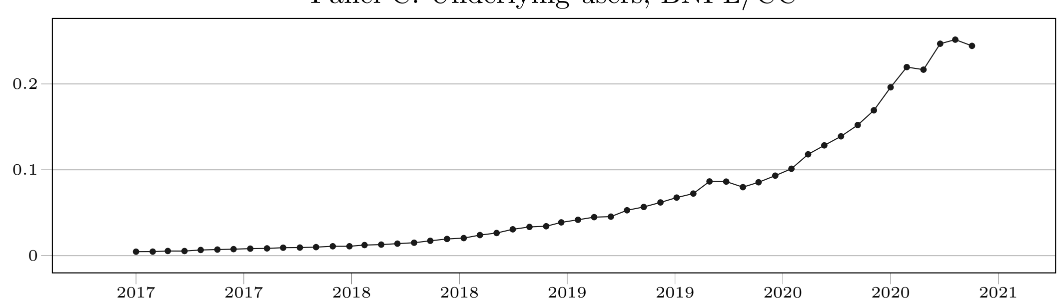
Panel A: Underlying sales, million ($)



Panel B: Underlying spending, BNPL/CC

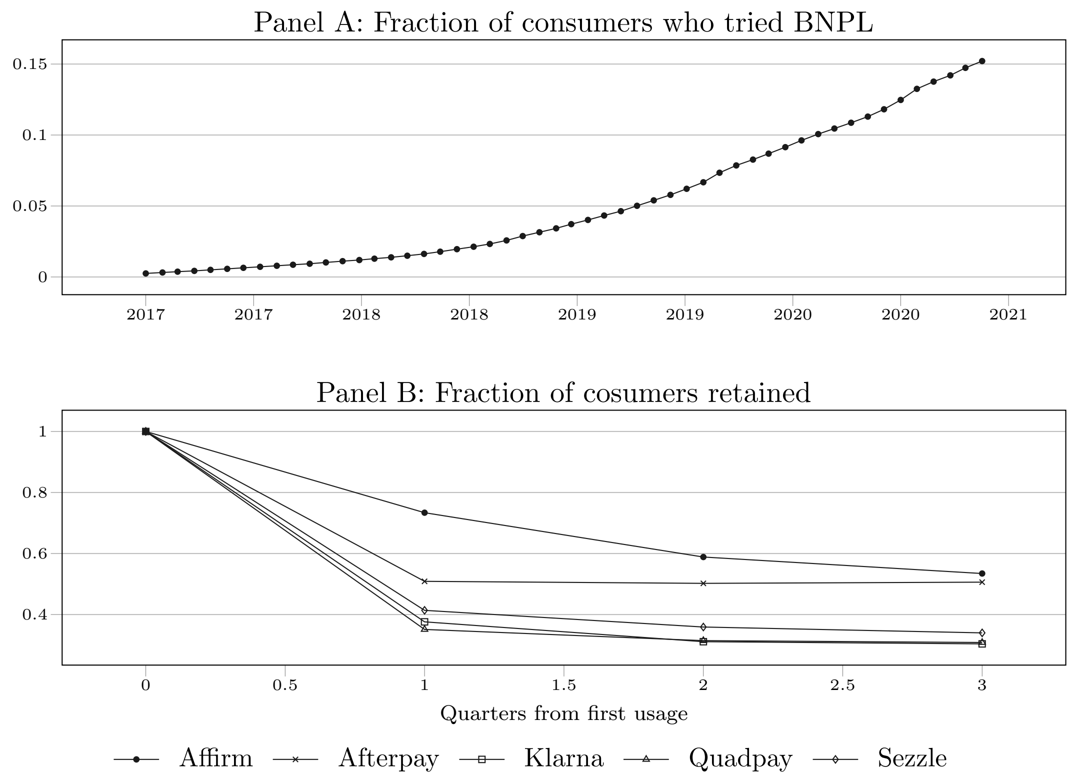


Panel C: Underlying users, BNPL/CC



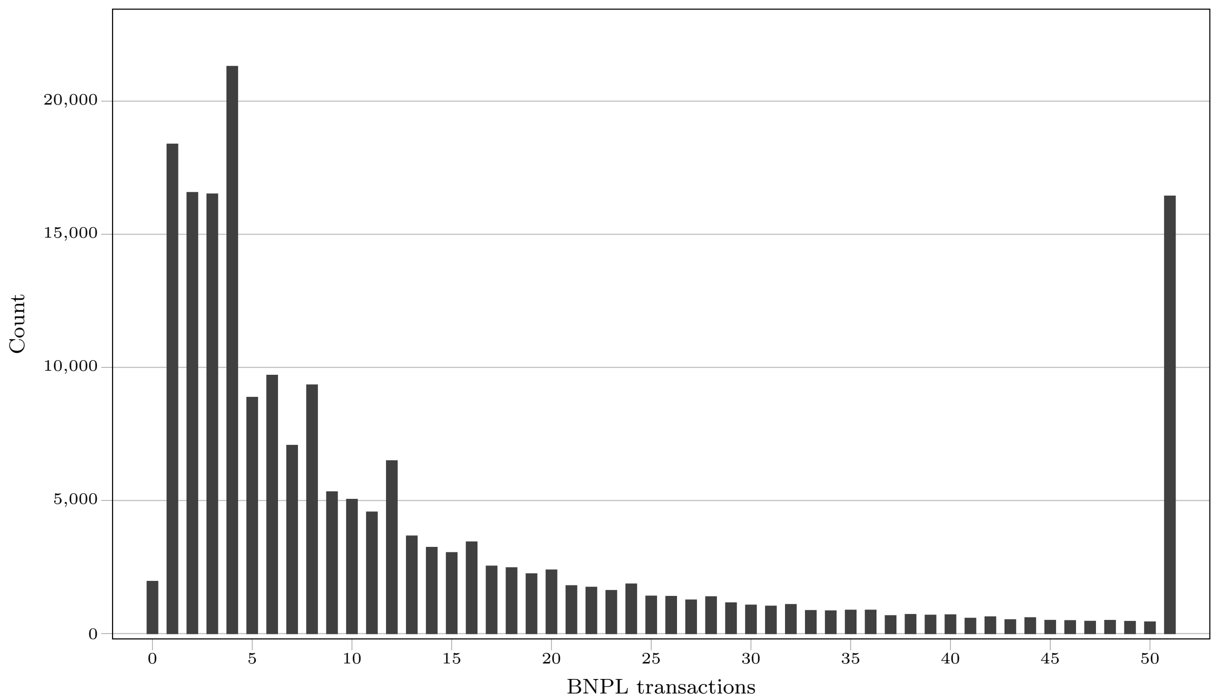
This figure plots BNPL usage by month/year. Panel A records total BNPL spending in $mn, Panel B plots total BNPL spending relative to total credit card spending, Panel C plots total BNPL users relative to total credit card users. BNPL transactions are transactions identified as either Affirm, Afterpay, Klarna, Quadpay or Sezzle as defined in A.I

Figure 3. Fraction of users who have tried BNPL at least once and Retention by provider



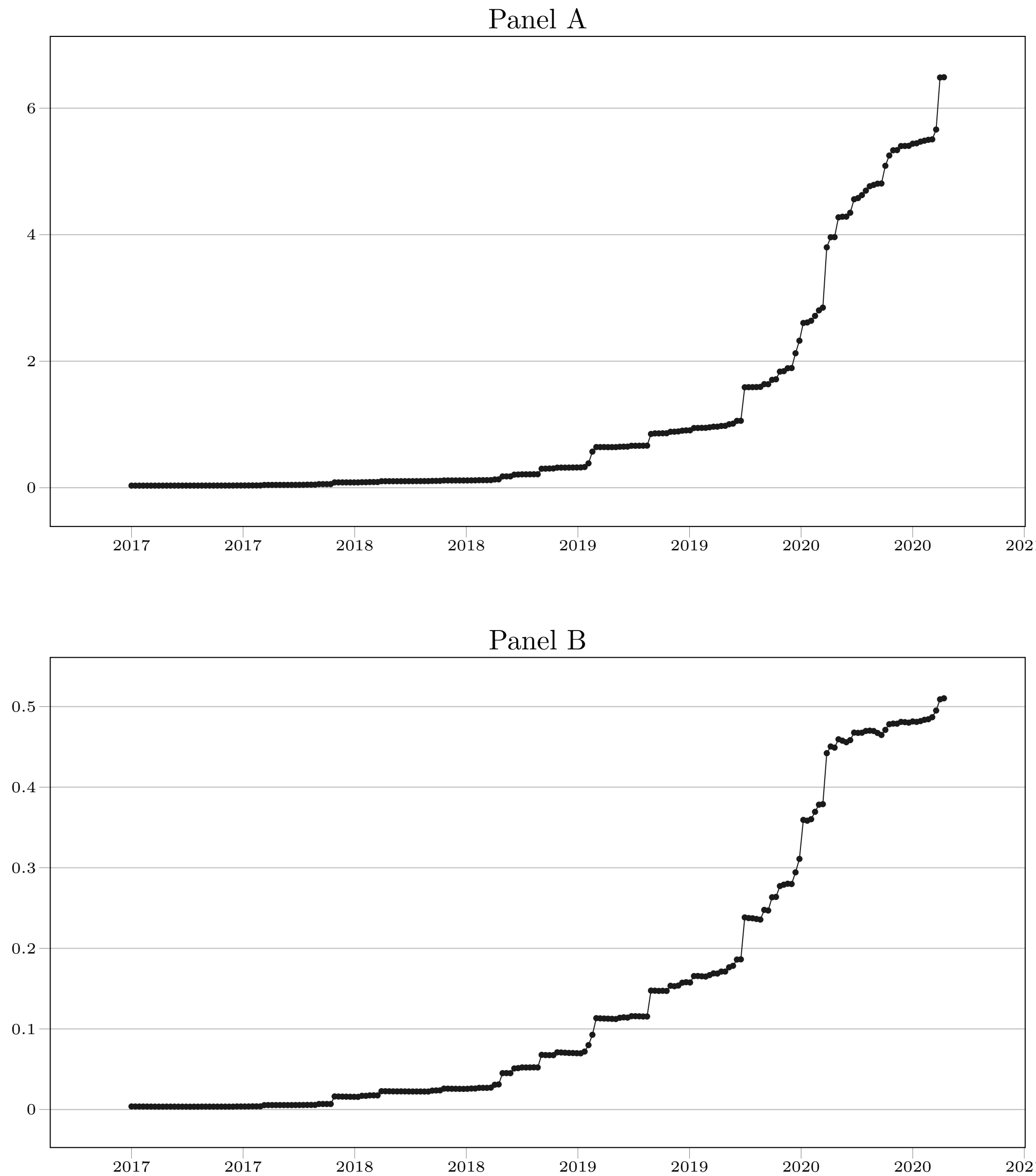
This figure plots BNPL usage statistics. Panel A plots the fraction of users in our sample who have used either Affirm, Afterpay, Klarna, Sezzle, or Quadpay, at least once. BNPL transactions are transactions identified as either Affirm, Afterpay, Klarna, Quadpay or Sezzle as defined in A.I. Panel B plots the fraction of users still using BNPL in each quarter after first BNPL use, by provider.

Figure 4. Distribution of BNPL transactions by user



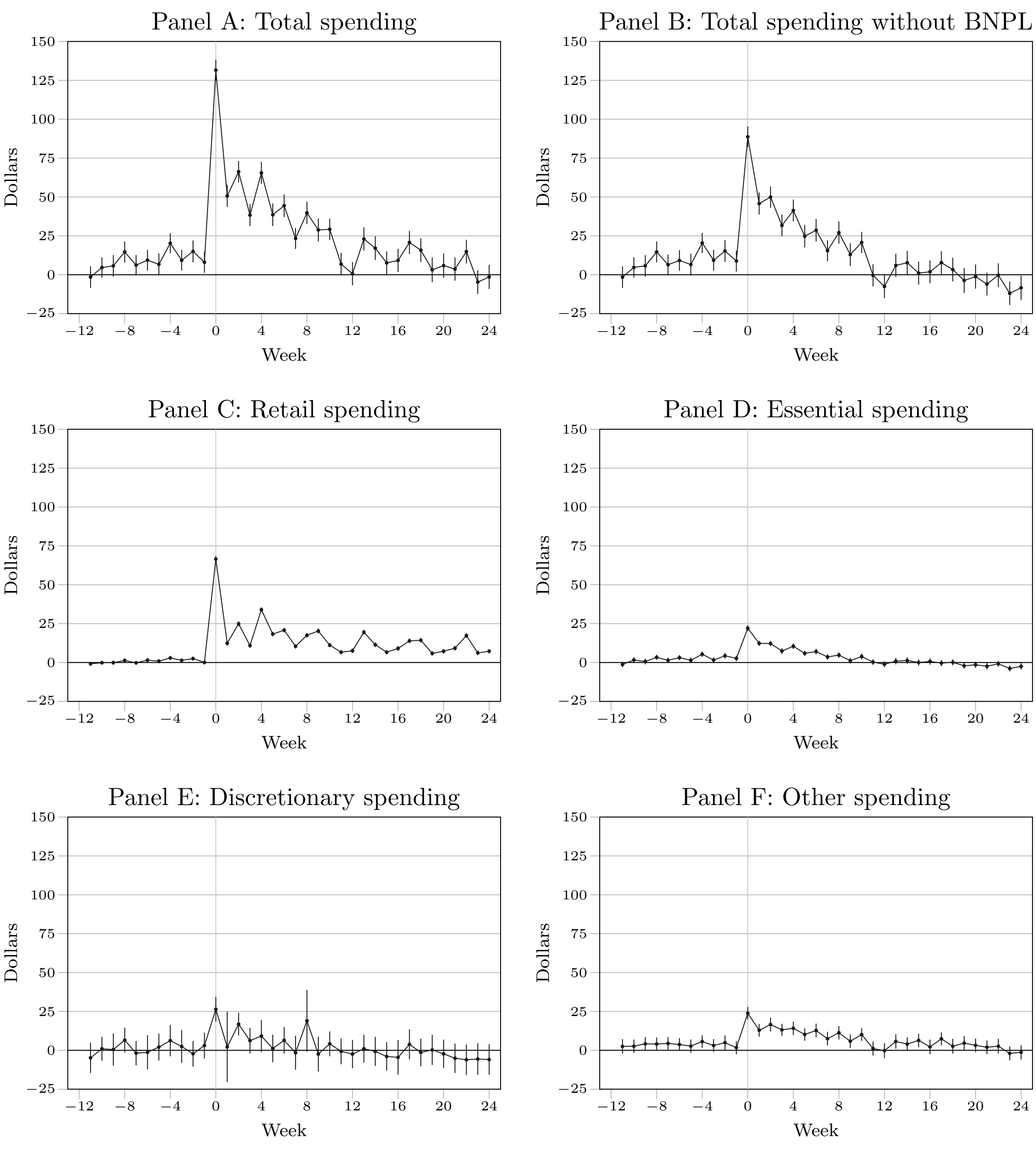
This figure plots a histogram of the number of BNPL transactions for all users. BNPL transactions are transactions identified as either Affirm, Afterpay, Klarna, Quadpay or Sezzle as defined in A.I

Figure 5. Retail Exposure Share Instrument: Average across users by week/year



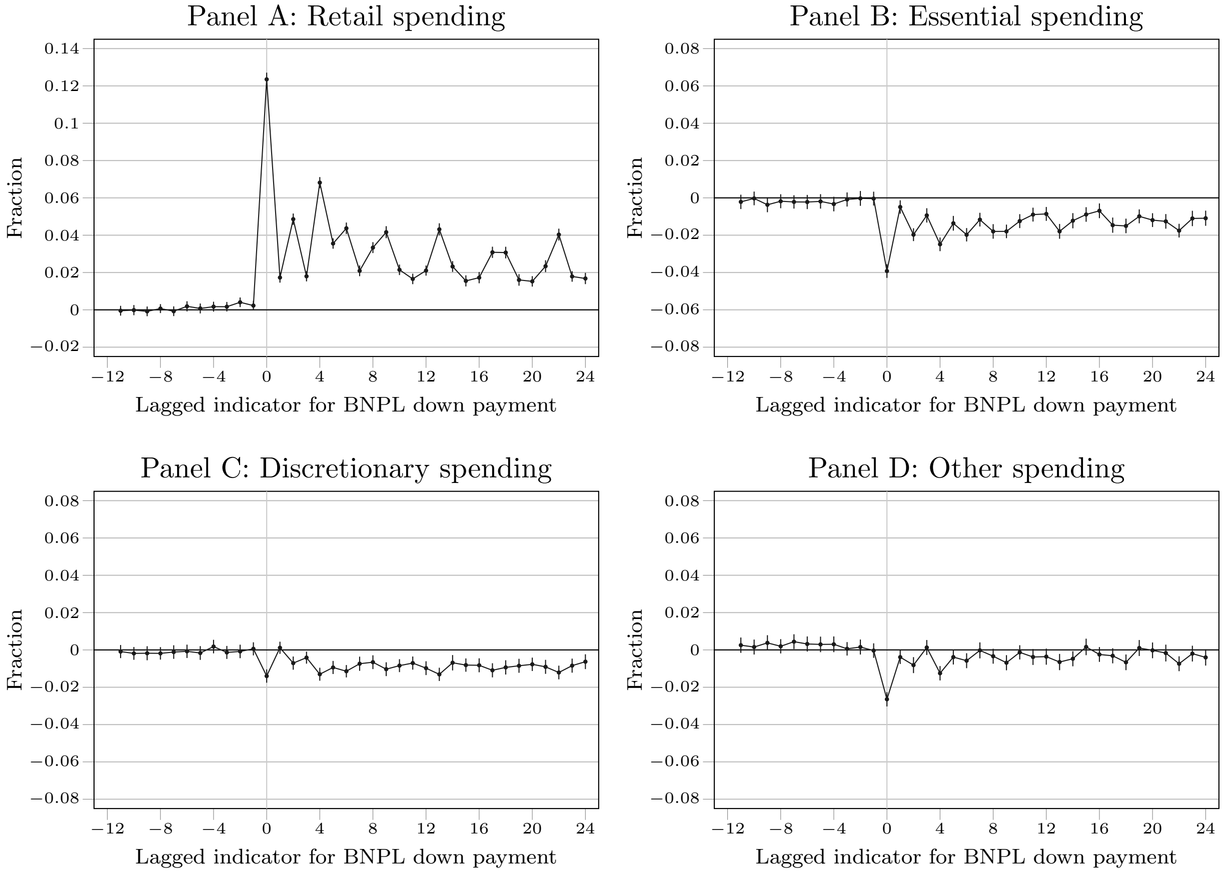
Panel A displays the average number of transactions by user at retailers that offer BNPL in each week/year. Panel B plots the fraction of users each week/year, who shopped at at least one retailer last year that currently offers BNPL as defined in 2. BNPL transactions are transactions identified as either Affirm, Afterpay, Klarna, Quadpay or Sezzle as defined in A.I.

Figure 6. Spending responses after first time BNPL use



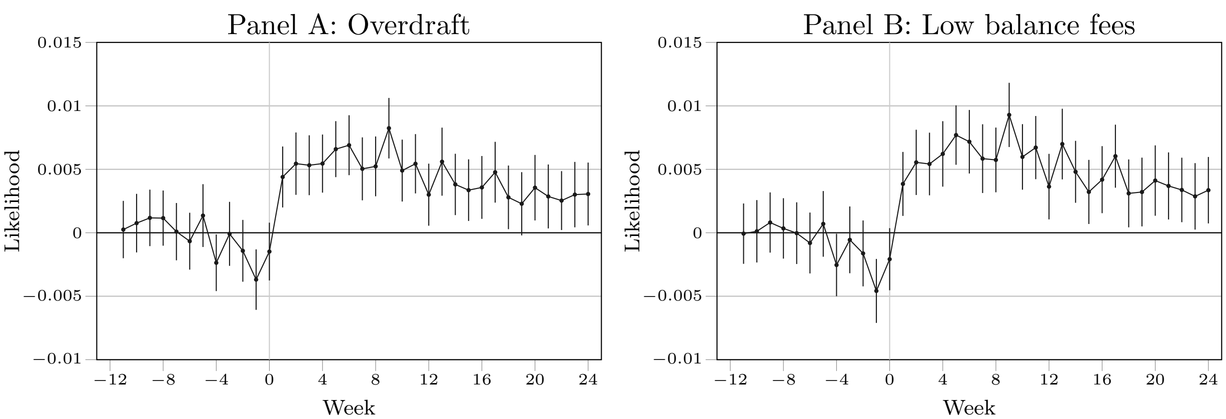
This figure displays the difference between spending pre vs post BNPL use. All figures plot γ_k from equation 1, for total spending, total spending without BNPL, retail spending, essential spending, discretionary non-retail spending and other spending – all defined in A.I

Figure 7. Spending reallocation responses after first time BNPL use: Within user difference in differences plots



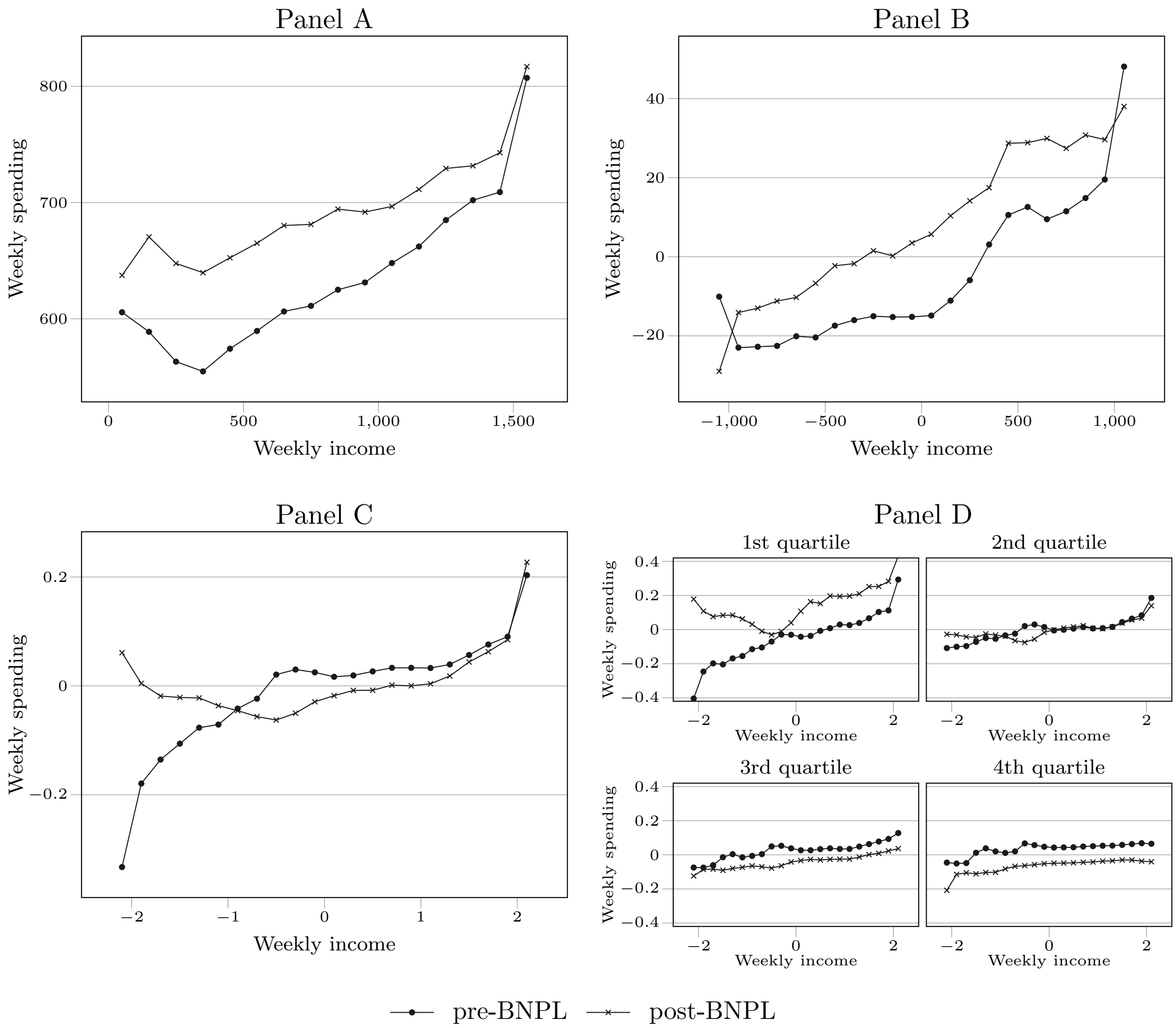
This figure displays the difference between spending pre vs post BNPL use. All figures plot γ_k from equation 1, for retail spending, essential spending, discretionary non-retail spending and other spending – all divided by total spending. All variables are defined in A.I

Figure 8. Liquidity responses after first time BNPL use: Within user difference in differences plots



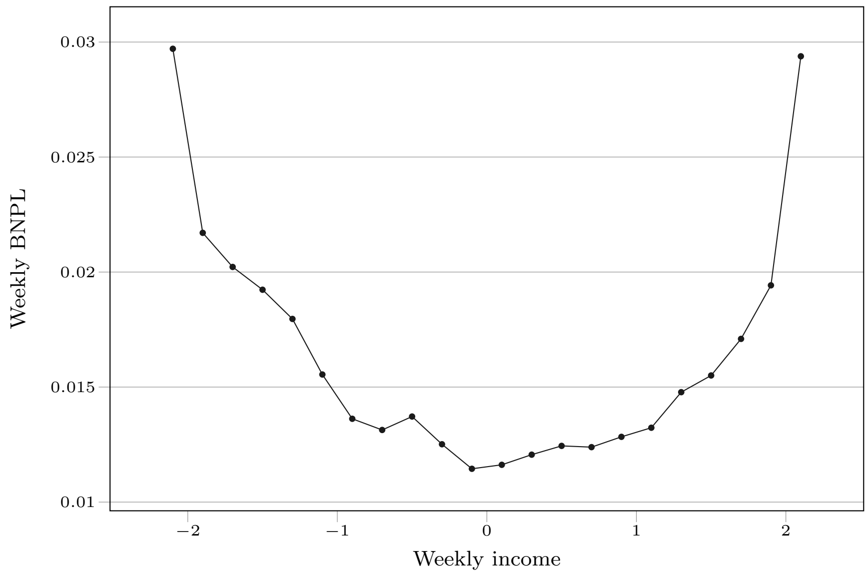
This figure displays the difference between spending pre vs post first time BNPL use. All figures plot γ_k from equation 1, for overdraft and low-balance fees, defined in A.I

Figure 9. Total spending vs income, before and after BNPL



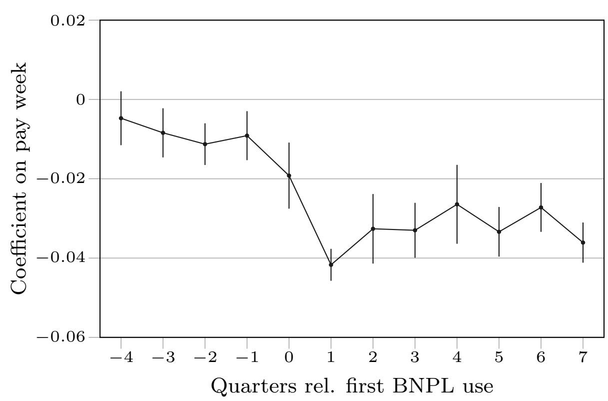
This figure displays the relationship between weekly salary income and weekly total spending. Panel A plots raw weekly total spending against raw weekly total income, pooling across consumers, before and after the first time that a consumer uses BNPL. Panel B plots the same relationship, but demeans weekly spending and weekly income at the person and calendar week level and displays average residuals. Panel C normalizes weekly spending and weekly income by average pre-BNPL weekly salary income, before demeaning at the person and calendar week level. Panel D displays the same relationship as Panel C, but splits the sample by pre-BNPL average weekly salary quartile.

Figure 10. BNPL spending vs weekly income



This figure calculates average weekly BNPL use normalized by average pre-BNPL weekly salary income, and plots averages within post-BNPL weekly income bins, where income has been demeaned at the person and calendar week level as in Figure 9, Panel C.

Figure 11. Total spending vs income, quarters relative to BNPL first use



This figure displays coefficients γ_k in the regression specification (6), representing the relationship between weekly spending and weekly income within event time quarters relative to BNPL first use. Coefficients are relative to the cross-sectional relationship in periods more than four calendar quarters relative to first BNPL use.

Table I. BNPL contract terms by provider

BNPL Provider	Credit Check	Pay-in-4 Option?	Late fees	Non Pay-in-4 Option?	Interest Rates	Negative Reporting	Positive Reporting
Affirm	Yes – Soft	Yes	None	Yes	0–30%	Yes	Yes
Afterpay	No	Yes	\$8/max 25%	No	NA	No	No
Klarna	Yes – Soft	Yes	max 25%	Yes	0–20%	Yes	No
Quadpay	Yes – Soft	Yes	\$7/max \$21	No	NA	Yes	No
Sezzle	Yes – Soft	Yes	\$10	No	NA	Yes	Yes

This table contains loan terms for BNPL providers – Affirm, Afterpat, Klarna, Quadpay and Sezzle as defined in A.I. Soft inquiries occur when a person or company checks your credit as part of a background check and do not affect credit scores. Negative reporting includes reports of unpaid debts, charge-offs, late payments, judgments, liens, foreclosures and bankruptcies. Negative information related to late and missed payments remains on the credit report for seven years from the original date of delinquency. Positive Credit Reporting, is the report of on time payments to credit bureaus and can positively impact credit scores.

Table II. BNPL Transactions characteristics by provider

BNPL Provider	# of trans. mn.	Consumers mn.	Spending mn.\$	Mean paym. \$	Med. paym. \$
Affirm	12.5	1.1	1,150	91.8	60.0
Afterpay	20.9	1.4	615	29.4	22.4
Klarna	10.0	0.8	385	38.4	24.7
Quadpay	2.7	0.2	106	40.0	23.1
Sezzle	1.6	0.2	38	23.3	16.3

This table contains company level statistics as of fiscal year end 2020 for BNPL providers – Affirm, Afterpat, Klarna, Quadpay and Sezzle as defined in A.I. Affirm is listed on the Nasdaq, Afterpay, Quadpay and Sezzle are listed on the Australian Securities Exchange. Klarna is a privately held company. Company level information is obtained from public filings and websites.

Table III. Summary statistics for panel members by BNPL use

	As of December							
	2017 BNPL user		2018 BNPL user		2019 BNPL user		2020 BNPL user	
	no	yes	no	yes	no	yes	no	yes
Mean, %								
Renter	8.1	10.3	9.9	13.2	10.3	14.1	6.3	10.4
Credit card use	39.7	33.7	38.9	32.1	39.4	30.2	34.9	26.3
Active saver	15.7	11.6	15.9	14.9	14.8	18.1	10.6	16.6
$400 buffer	81.0	79.4	84.2	84.6	84.2	84.4	85.2	86.5
Paid overdrafts	5.7	7.9	5.9	9.9	5.6	11.8	4.1	9.8
Median, $								
Salary	385	1,054	691	1,079	715	1,120	1,060	1,290
Essential spending	344	471	346	476	366	503	339	509
Discretionary spending	200	326	201	335	216	347	175	319
Bills	165	201	175	213	178	227	156	211
Retail spending	136	228	136	237	160	283	159	331
Credit transaction	4,222	4,179	4,459	4,335	4,655	4,604	4,867	5,050
Debit transactions	4,194	4,154	4,731	4,587	4,943	4,880	4,237	4,567
Sample size	80,723	85,166	81,089	97,366	75,939	107,127	64,043	107,817

This table contains week level summary statistics over the month of December for each of 2017, 2018, 2018, and 2020, for individuals in our main panel. The top panel contains means of binary variables. An individual is identified as a BNPL user if they have ever used Affirm, Afterpay, Klarna, Quadpay or Sezzle as defined in A.I. An individual is classified as a renter if they have transactions categorized as rent. An individual is classified as a credit card user if they have credit card credit or debit transactions. An individual is classified as a saver if they have transactions categorized as savings. An individual is classified as having above a $400 buffer if the absolute value of the sum of bank account credits minus the sum of bank account debits is greater than $400. An individual is classified as incurring an overdraft if an overdraft transaction, as defined in A.I, is identified. The bottom panel contains the median of weekly variables defined in A.I. Salary is the median value of non-zero transactions categorized as salary/regular income – and hence represents the median actual salary payment. All other variables are defined in A.I

Table IV. Effect of BNPL availability on expenditure levels by category

	Fixed Effects	Reduced Form	TSLS
		Total Spend	
Post	40.16***		60.47***
	(1.39)		(10.74)
Exposure		7.512***	
		(1.479)	
KP Wald F Stat			1,163
CD Wald F Sat			547,920
		Total Spend – Non BNPL	
Post	29.39***		49.81***
	(1.39)		(10.69)
Exposure		6.188***	
		(1.449)	
KP Wald F Stat			1,163
CD Wald F Sat			547,920
		Retail Spend	
Post	20.16***		53.58***
	(0.37)		(2.68)
Exposure		6.758***	
		(0.449)	
KP Wald F Stat			1,220
CD Wald F Sat			535,884
		Discretionary (Non-Retail) Spend	
Post	5.871***		−13.07***
	(0.484)		(4.34)
Exposure		−1.654***	
		(0.522)	
KP Wald F Stat			1,199
CD Wald F Sat			537,993
		Essential Spend	
Post	8.965***		17.42***
	(0.540)		(4.05)
Exposure		2.197***	
		(0.551)	
KP Wald F Stat			1,203
CD Wald F Sat			535,227
		Other Spend	
Post	10.58***		22.77***
	(0.66)		(4.37)
Exposure		2.829***	
		(0.576)	
KP Wald F Stat			1,168
CD Wald F Sat			517,975
N	36,038,812	36,038,812	36,038,812

This table reports estimates of β and $\tilde{\beta}$ coefficients in person/week regression specifications (3) and (5) that includes person, person $\times$ payweek, and calendar time $\times$ city of residence $\times$ income group fixed effects. LHS variables are defined in A.I. The first column reports OLS estimates of coefficients in (3). The second column reports OLS estimates of the IV reduced form coefficients in (5). The third column reports TSLS estimates of coefficients in (3) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses.

Table V. Effect of BNPL availability on expenditure allocation by category

	Fixed Effects	Reduced Form	TSLS
	Retail Spend/Total		
Post	0.0335***		0.0629***
	(0.0005)		(0.0035)
Exposure		0.00697***	
		(0.00045)	
KP Wald F Stat			1,165
CD Wald F Sat			364,150
	Retail Spend (Non-BNPL)/Total		
Post	−0.00157***		0.0412***
	(0.000311)		(0.00349)
Exposure		0.00457***	
		(0.000419)	
KP Wald F Stat			1,158
CD Wald F Sat			365,621
	Essential Spend/Total		
Post	−0.00945***		0.00547
	(0.00045)		(0.00385)
Exposure		0.000606	
		(0.000433)	
KP Wald F Stat			1,145
CD Wald F Sat			364,259
	Discretionary (Non-Retail) Spend/Total		
Post	−0.00625***		−0.0522***
	(0.00041)		(0.0046)
Exposure		−0.00581***	
		(0.00045)	
KP Wald F Stat			1,141
CD Wald F Sat			366,575
	Other Spend/Total		
Post	−0.00188***		0.0414***
	(0.00050)		(0.0044)
Exposure		0.00452***	
		(0.00047)	
KP Wald F Stat			1,113
CD Wald F Sat			355,235
N	30,439,967	30,439,967	30,439,967

This table reports estimates of β and $\tilde{\beta}$ coefficients in person/week regression specifications (3) and (5) that includes person, person $\times$ payweek, and calendar time $\times$ city of residence $\times$ income group fixed effects. LHS variables are spending defined in A.I and scaled by total spending. The first column reports OLS estimates of coefficients in (3). The second column reports OLS estimates of the IV reduced form coefficients in (5). The third column reports TSLS estimates of coefficients in (3) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses.

Table VI. Effect of BNPL availability on measures of individual liquidity

	Fixed Effects	Reduced Form	TSLS
		Overdraft Fee	
Post	0.00263***		0.00473***
	(0.00026)		(0.00161)
Exposure		0.000588***	
		(0.000203)	
KP Wald F Stat			1,163
CD Wald F Sat			547,920
		Low Balance Fee	
Post	0.00292***		0.00480***
	(0.00029)		(0.00174)
Exposure		0.000597***	
		(0.000220)	
KP Wald F Stat			1,163
CD Wald F Sat			547,920
		Savings	
Post	0.129***		0.209*
	(0.014)		(0.109)
Exposure		0.0260*	
		(0.0139)	
KP Wald F Stat			1,163
CD Wald F Sat			547,920
		Balance Estimate	
Post	−659.4***		−997.2**
	(63.9)		(408.7)
Exposure		−123.9**	
		(51.4)	
KP Wald F Stat			1,163
CD Wald F Sat			547,920
N	36,038,812	36,038,812	36,038,812

This table reports estimates of β and $\tilde{\beta}$ coefficients in person/week regression specifications (3) and (5) that includes person, person × payweek, and calendar time × city of residence × income group fixed effects. LHS variables are measures of liquidity defined in A.I. The first column reports OLS estimates of coefficients in (3). The second column reports OLS estimates of the IV reduced form coefficients in (5). The third column reports TSLS estimates of coefficients in (3) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses.

Table VII. Effect of BNPL availability on BNPL spending

	Full Sample			No Covid		
	BNPL Spending			BNPL Spending		
	Fixed Effects	Reduced Form	TSLS	Fixed Effects	Reduced Form	TSLS
Post	17.95***		20.99***	17.39***		20.87***
	(0.209)		(0.607)	(0.230)		(0.655)
Exposure		2.607***			3.176***	
		(0.121)			(0.136)	
KP Wald F Stat			1,163			1,123
CD Wald F Sat			547,920			617,153

This table reports estimates of β and $\tilde{\beta}$ coefficients in person/week regression specifications (3) and (5) that includes person, person × payweek, and calendar time × city of residence × income group fixed effects. LHS variables are total BNPL spending defined in A.I. The first column reports OLS estimates of coefficients in (3). The second column reports OLS estimates of the IV reduced form coefficients in (5). The third column reports TSLS estimates of coefficients in (3) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses.

Table VIII. Effect of BNPL availability on total spending levels by liquidity characteristic

	TSLS: Total Spend					
	Saver		Usually Below $400		Credit Card User	
	No	Yes	No	Yes	No	Yes
Post	66.10***	33.26*	50.92***	75.13***	68.26***	−1.844
	(11.04)	(17.83)	(12.08)	(11.74)	(10.57)	(16.68)
KP Wald F Stat	1,103	741.1	996.2	1,032	959.3	690.4
CD Wald F Sat	432,897	81,338	342,471	178,632	299,658	138,114
N	27,365,708	7,193,928	24,847,455	10,134,905	17,381,236	17,056,310

	TSLS: Retail Spend					
	Saver		Usually Below $400		Credit Card User	
	No	Yes	No	Yes	No	Yes
Post	54.54***	49.18***	61.83***	38.35***	57.08***	42.26***
	(2.736)	(4.151)	(3.325)	(2.259)	(2.650)	(4.132)
KP Wald F Stat	1,160	760.5	1,057	1,038	991	734
CD Wald F Sat	422,761	78,744	330,461	177,848	291,848	135,357
N	25,932,006	6,740,979	23,117,968	9,955,876	16,664,102	15,894,234

	TSLS: Retail Spend/Total					
	Saver		Usually Below $400		Credit Card User	
	No	Yes	No	Yes	No	Yes
Post	0.0660***	0.0500***	0.0632***	0.0646***	0.0720***	0.0447***
	(0.00395)	(0.00594)	(0.00401)	(0.00541)	(0.00430)	(0.00578)
KP Wald F Stat	1,087	672.1	1,016	863.1	892.7	680.1
CD Wald F Sat	281,352	59,093	245,807	100,963	183,455	101,568
N	22,895,824	6,170,099	21,301,702	8,221,557	14,481,182	14,483,776

	TSLS: BNPL Spending					
	Saver		Usually Below $400		Credit Card User	
	No	Yes	No	Yes	No	Yes
Post	20.40***	22.45***	23.69***	15.57***	22.01***	19.37***
	(0.651)	(1.137)	(0.715)	(0.697)	(0.757)	(0.925)
KP Wald F Stat	1,103	741.1	996.2	1,032	959.3	690.4
CD Wald F Sat	432,897	81,338	342,471	178,632	299,658	138,114
N	27,365,708	7,193,928	24,847,455	10,134,905	17,381,236	17,056,310

This table reports estimates of β and $\tilde{\beta}$ coefficients in person/week regression specifications (3) and (5) that includes person, person $\times$ payweek, and calendar time $\times$ city of residence $\times$ income group fixed effects. Results are presented by liquidity characteristic and the LHS variable is total spending, defined in A.I. The first column reports OLS estimates of coefficients in (3). The second column reports OLS estimates of the IV reduced form coefficients in (5). The third column reports TSLS estimates of coefficients in (3) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses.

Table IX. Effect of BNPL availability on expenditure smoothing – parsimonious fixed effects

	Fixed Effects	Reduced Form	TSLS
Quartile I			
Salary × Payweek	0.0357***	0.0118***	0.0674***
	(0.00146)	(0.00394)	(0.00568)
Salary × Payweek × Post	−0.0344***	–	−0.0672***
	(0.00177)	–	(0.00584)
Salary × Payweek × Exposure	–	−0.0111***	–
	–	(0.00399)	–
KP Wald F-stat	–	–	24.08
CD Wald F-stat	–	–	1,376
N	3,214,710	3,214,710	3,214,710
Quartile II			
Salary × Payweek	0.0296***	0.0213***	0.0388***
	(0.00132)	(0.00158)	(0.00346)
Salary × Payweek × Post	−0.0208***	–	−0.0343***
	(0.00189)	–	(0.00531)
Salary × Payweek × Exposure	–	−0.0128***	–
	–	(0.00280)	–
KP Wald F-stat	–	–	26.16
CD Wald F-stat	–	–	1,361
N	3,213,950	3,213,950	3,213,950
Quartile III			
Salary × Payweek	0.0150***	0.00927***	0.0116**
	(0.00100)	(0.00204)	(0.00584)
Salary × Payweek × Post	−0.00944***	–	−0.00430
	(0.00159)	–	(0.00779)
Salary × Payweek × Exposure	–	−0.00125	–
	–	(0.00200)	–
KP Wald F-stat	–	–	20.28
CD Wald F-stat	–	–	992.7
N	3,213,963	3,213,963	3,213,963
Quartile IV			
Salary × Payweek	0.00187***	0.00133***	0.00128
	(0.000295)	(0.000324)	(0.00106)
Salary × Payweek × Post	−0.000997**	–	−8.24
	(0.000404)	–	(0.00168)
Salary × Payweek × Exposure	–	−0.000206	–
	–	(0.000451)	–
KP Wald F-stat	–	–	22.83
CD Wald F-stat	–	–	1,115
N	3,213,778	3,213,778	3,213,778

This table reports estimates of γ and $\tilde{\gamma}$ coefficients in regression specifications (7) and (8) in a specification that includes person, person × payweek, and calendar time fixed effects. Coefficients are estimated separately for consumers in each pre-BNPL salary quartile. The first column reports OLS estimates of coefficients in (7). The second column reports OLS estimates of the IV reduced form coefficients in (8). The third column reports TSLS estimates of coefficients in (7) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses.

Table X. Effect of BNPL availability on expenditure smoothing – granular fixed effects

	Fixed Effects	Reduced Form	TSLS
Quartile I			
Salary × Payweek	0.0377***	0.0149**	0.0710***
	(0.00180)	(0.00659)	(0.00591)
Salary × Payweek × Post	−0.0365***	–	−0.0708***
	(0.00209)	–	(0.00607)
Salary × Payweek × Exposure	–	−0.0143**	–
	–	(0.00661)	–
KP Wald F-stat	–	–	15.22
CD Wald F-stat	–	–	811
N	2,289,049	2,289,049	2,289,049
Quartile II			
Salary × Payweek	0.0304***	0.0243***	0.0359***
	(0.00157)	(0.00164)	(0.00354)
Salary × Payweek × Post	−0.0174***	–	−0.0265***
	(0.00221)	–	(0.00572)
Salary × Payweek × Exposure	–	−0.0115***	–
	–	(0.00304)	–
KP Wald F-stat	–	–	17.62
CD Wald F-stat	–	–	908.7
N	2,233,163	2,233,163	2,233,163
Quartile III			
Salary × Payweek	0.0154***	0.0117***	0.0153***
	(0.00111)	(0.00183)	(0.00329)
Salary × Payweek × Post	−0.00801***	–	−0.00800
	(0.00157)	–	(0.00511)
Salary × Payweek × Exposure	–	−0.00280	–
	–	(0.00200)	–
KP Wald F-stat	–	–	13.14
CD Wald F-stat	–	–	643.2
N	2,211,961	2,211,961	2,211,961
Quartile IV			
Salary × Payweek	0.00150***	0.00125***	0.00148**
	(0.000288)	(0.000293)	(0.000649)
Salary × Payweek × Post	−0.000614	–	−0.000638
	(0.000376)	–	(0.00107)
Salary × Payweek × Exposure	–	−0.000351	–
	–	(0.000387)	–
KP Wald F-stat	–	–	17.05
CD Wald F-stat	–	–	854.6
N	2,503,032	2,503,032	2,503,032

This table reports estimates of γ and $\tilde{\gamma}$ coefficients in regression specifications (7) and (8) in a specification that includes person, person × payweek, and calendar time × income class × geography fixed effects. Coefficients are estimated separately for consumers in each pre-BNPL salary quartile. The first column reports OLS estimates of coefficients in (7). The second column reports OLS estimates of the IV reduced form coefficients in (8). The third column reports TSLS estimates of coefficients in (7) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses.

Table XI. Effect of BNPL availability on expenditure smoothing – heterogeneity

	Saver		Usually below \$400		Credit Card User	
Variables	Yes	No	Yes	No	Yes	No
Salary × Payweek	0.0229***	0.0365***	0.109***	0.00580	0.00810	0.0470***
	(0.00415)	(0.00356)	(0.00665)	(0.00806)	(0.0113)	(0.00312)
Salary × Payweek × Post	−0.0188***	−0.0357***	−0.109***	−0.000288	−0.00371	−0.0466***
	(0.00542)	(0.00422)	(0.00665)	(0.00904)	(0.0126)	(0.00332)
KP Wald F-stat	15.87	43.41	22.42	38.83	18.99	39.81
CD Wald F-stat	748.3	2,608	1,245	2,158	1,102	2,167
N	2,396,235	7,766,728	1,995,381	8,505,074	5,022,149	5,121,391

This table reports estimates of γ coefficients in regression specifications (7) in a specification that includes person, person × payweek, and calendar time × income class × geography fixed effects. Coefficients are estimated separately for consumers with and without the specified characteristic – see IV for description. The reported coefficients are TSLS estimates of coefficients in (7) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses.

REFERENCES

Armstrong, Mark, 2006, Competition in Two-Sided Markets, *The RAND Journal of Economics* 37, 668–691.

Aydin, Deniz, 2022, Consumption Response to Credit Expansions: Evidence from Experimental Assignment of 45,307 Credit Lines, *American Economic Review* 112, 1–40.

Backman, Maurie, and Jack Caporal, 2022, Study: Buy Now, Pay Later Services Grow in Popularity, The Ascent, https://www.fool.com/the-ascent/research/buy-now-pay-later-statistics/.

Baker, Scott, and Constantine Yannelis, 2017, Income Changes and Consumption: Evidence from the 2013 Federal Government Shutdown, *Review of Economic Dynamics* 23, 99–124.

Bedre-Defolie, Özlem, and Emilio Calvano, 2013, Pricing Payment Cards, *American Economic Journal: Microeconomics* 5, 206–31.

Ganong, Peter, and Pascal Noel, 2019, Consumer Spending during Unemployment: Positive and Normative Implications, *American Economic Review* 109, 2383–2424.

Gelman, Michael, Shachar Kariv, Matthew D. Shapiro, Dan Silverman, and Steven Tadelis, 2015, How Individuals Respond to a Liquidity Shock: Evidence from the 2013 Government Shutdown, Working Paper 21025, National Bureau of Economic Research, Cambridge, MA, USA.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai, 2021, Household finance, *Journal of Economic Literature* 59, 919–1000.

Gross, David B., and Nicholas S. Souleles, 2002, Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data, *The Quarterly Journal of Economics* 117, 149–85.

Guttman-Kenney, Benedict, Christopher Firth, and John Gathergood, 2022, Buy now, pay later (bnpl)...on your credit card.

Havranek, Tomas, and Anna Sokolova, 2020, Do consumers really follow a rule of thumb? Three thousand estimates from 144 studies say "probably not", *Review of Economic Dynamics* 35, 97–122.

Hines, James R., and Richard H. Thaler, 1995, The Flypaper Effect, *Journal of Economic Perspectives* 9, 217–226.

Olafsson, Arna, and Michaela Pagel, 2018, The Liquid Hand-to-Mouth: Evidence from Personal Finance Management Software, *The Review of Financial Studies* 31, 4398–4446.

Qureshi, Zia, 2022, How digital transformation is driving economic change, Brookings, http s://www.brookings.edu/blog/up-front/2022/01/18/how-digital-transformation-is-driving-economic-change/.

Sodini, Stijn, Paolo andVan Nieuwerburgh, Roine Vestman, and Ulf von Lilienfeld-Toal, 2016, Identifying the Benefits from Homeownership: A Swedish Experiment, Working Paper 22882, National Bureau of Economic Research, Cambridge, MA, USA.

Table A.I. Variable Definitions and Construction

Variable	Data Provider Transaction Classification & construction		
Essential Spending	automotive/fuel	restaurants	groceries
Retail Spending	general merchandise		
Discretionary Spending	charitable giving gifts pets/pet care entertainment and	recreation travel general merchandise home improvement	subscriptions/renewals personal/family
Bill Spending	cable/satellite/telecom utilities	healthcare/medical service charges/fees	
Housing Spending	mortgage	rent	
Other Spending	atm cash withdrawals expense reimbursement postage/shipping services/supplies	education other expenses check payments office expenses	refunds/adjustments rewards
Total Spending	Bill Spending Essential Spending	Discretionary Spending Housing Spending	Retail Spending Other Spending
Salary	salary/regular income		
Savings	savings		
Balance Estimate	$\sum$ bank account credits $-$ $\sum$ bank account debits		
Overdraft Fees	transaction descriptions contain:		
	overdraft & fee od fee	overdraft interest overdraft & charge	od itm fee od item fee
NSF Fees	transaction descriptions contain:		
	nsf returned & fee non-sufficient	non & sufficient ns & fee returned & check	insufficient returned & item
late fees	transaction descriptions contain:		
	late & fee late & amount late & charge	penalty & payment late & charge late & payment	penalty & fee missed & payment
BNPL Spending	primary or secondary merchants contain:		
	Affirm.com Afterpay Klarna	Klarna, Inc. Quadpay Sezzle Inc	Sezzle

This table contains definitions of variables frequently used in this study, Variables are defined by making use of primary/secondary merchant classification or by searching transaction descriptions for keywords. Variables are created by using the bank and credit card panel and hence are the sum of credit and debit transactions.

Table A.II. Summary stats

	Full Sample	BNPL User		Saver		Usually Below $400		Credit Card User	
		No	Yes	No	Yes	No	Yes	No	Yes
BNPL Spending	4	–	7	4	5	4	3	4	4
Total Spending	533	481	577	514	599	619	335	483	580
Retail Spending	68	55	79	66	76	80	42	61	75
Essential Spending	142	123	158	137	160	165	91	128	155
Discretionary (NR) Spending	93	78	106	89	108	110	57	81	106
Other Spending	188	183	191	181	212	223	109	172	203
Retail Spending/Total	14.0%	12.6%	15.1%	14.1%	13.8%	14.1%	13.9%	13.9%	14.1%
Retail Spending (non-BNPL)/Total	13.2%	12.4%	13.8%	13.3%	13.0%	13.3%	12.9%	13.0%	13.4%
Essential Spending/Total	31.1%	30.1%	31.8%	31.2%	30.7%	30.3%	33.2%	31.2%	31.0%
Discretionary (NR) Spending/Total	19.0%	17.8%	19.8%	18.9%	19.2%	19.0%	19.0%	18.4%	19.5%
Other Spending/Total	26.2%	28.1%	24.9%	26.0%	26.9%	27.8%	22.6%	26.4%	26.1%
Overdraft Fee (1/0)	2.4%	1.8%	2.9%	2.1%	3.5%	2.2%	3.0%	2.6%	2.2%
Low Balance Fee (1/0)	2.8%	2.1%	3.3%	2.4%	4.0%	2.6%	3.4%	2.7%	2.9%
Balance Estimate	7,994	10,491	5,927	7,418	9,944	10,873	1,290	6,204	9,652
Savings Credit	0.98	0.81	1.13	–	4.31	1.17	0.55	0.85	1.11
Use Savings (1/0)	5.3%	5.7%	5.0%	0.0%	23.2%	6.4%	2.8%	3.7%	6.8%
Total Bank Account Credits	2,426	2,654	2,238	2,286	2,900	3,200	624	1,990	2,830
Regular Income/Salary	643	634	650	618	725	838	189	543	735

This table contains summary statistics for users in our main panel.Variables are defined in A.I. The table reports weekly means across all weekly aggregate by user, including zeros. The first column reports weejly means for all users in the sample. The following columns report weekly means across subsamples for individuals who are or are not: BNPL users, savers, usually below $400, or credit card users. BNPL users are defined as individuals who have any transactions classified as BNPL spending, defined in A.I. Savers are individuals who have any transactions classified as savings credits or debits in their transaction history. Usually below $400 are individuals who have the absolute value of the difference between the sum of total credits and total debits over the previous 8 weeks, below $400, greater than 50% of the time. Credit card users are individuals who have any credit card panel debits or credits observed in their transaction history.

Table A.III. Largest retailers that offer BNPL

Retailer	Customers %	Revenue bn. $
Target	49.1	52.6
Bed Bath & Beyond	19.1	5.0
Michaels	18.8	2.7
Sam's Club	17.2	22.4
GameStop	12.7	2.6
IKEA	11.6	4.5
Nordstrom	11.5	15.0
Etsy	10.7	3.0
Forever 21	10.5	1.2
Sephora	9.2	2.5
Nike	8.4	3.4
Whataburger	7.3	1.0
Dillard's	6.8	3.2
Radio Shack	6.5	0.5
Foot Locker	6.0	1.2
Aeropostale	5.4	0.5
Charlotte Russe	5.2	0.4
Journeys	5.1	0.5
Finish Line	4.9	0.8
Adidas	4.5	0.9

This table contains a list of the largest retailers (by number of customers in our data) that we classified as offering BNPL payments as of April 2021. % of customers refers to the percentage of total customers in our data. Both variables are calculated over all available periods. For example, 49.1% for Target means that 1 out of 2 customers in our sample shopped at Target at least once.

Table A.IV. Effect of BNPL availability on expenditure levels by category: Excluding Covid

	Fixed Effects	Reduced Form	TSLS
		Total Spend	
Post	40.24***		60.29***
	(26.59)		(5.97)
Exposure		9.176***	
		(5.49)	
KP Wald F Stat			1,123
CD Wald F Sat			617,153
		Total Spend – Non BNPL	
Post	29.99***		49.17***
	(19.26)		(4.89)
Exposure		7.483***	
		(4.57)	
KP Wald F Stat			1,123
CD Wald F Sat			617,153
		Retail Spend	
Post	20.17***		49.00***
	(45.44)		(17.93)
Exposure		7.569***	
		(15.00)	
KP Wald F Stat			1,178
CD Wald F Sat			601,335
		Discretionary (Non-Retail) Spend	
Post	5.093***		−14.54***
	(10.13)		(−3.92)
Exposure		−2.253***	
		(−4.10)	
KP Wald F Stat			1,140
CD Wald F Sat			604,318
		Essential Spend	
Post	9.049***		13.10***
	(15.37)		(3.45)
Exposure		2.020***	
		(3.31)	
KP Wald F Stat			1,152
CD Wald F Sat			601,419
		Other Spend	
Post	11.60***		26.02***
	(14.75)		(6.11)
Exposure		3.976***	
		(5.80)	
KP Wald F Stat			1,127
CD Wald F Sat			585,063
N	25,626,478	25,626,478	25,626,478

This table reports estimates of β and $\tilde{\beta}$ coefficients in person/week regression specifications (3) and (5) that includes person, person $\times$ payweek, and calendar time $\times$ city of residence $\times$ income group fixed effects. LHS variables are defined in A.I. The first column reports OLS estimates of coefficients in (3). The second column reports OLS estimates of the IV reduced form coefficients in (5). The third column reports TSLS estimates of coefficients in (3) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses. Results are estimated for individuals who initiated BNPL transactions before 2020

Table A.V. Effect of BNPL availability on expenditure allocation by category: Excluding Covid

	Fixed Effects	Reduced Form	TSLS
		Retail Spend/Total	
Post	0.0317***		0.0666***
	(62.44)		(18.25)
Exposure		0.00928***	
		(16.31)	
KP Wald F Stat			1,108
CD Wald F Sat			422,062
		Retail Spend (Non-BNPL)/Total	
Post	0.000135		0.0368***
	(0.000494)		(0.00345)
Exposure		0.00514***	
		(0.000502)	
KP Wald F Stat			1,095
CD Wald F Sat			423,148
		Essential Spend/Total	
Post	−0.00786***		0.000270
	(−11.95)		(0.07)
Exposure		3.75	
		(0.07)	
KP Wald F Stat			1,080
CD Wald F Sat			422,749
		Discretionary (Non-Retail) Spend/Total	
Post	−0.00768***		−0.0470***
	(−15.60)		(−12.18)
Exposure		−0.00657***	
		(−13.05)	
KP Wald F Stat			1,070
CD Wald F Sat			425,103
		Other Spend/Total	
Post	0.00103		0.0362***
	(1.45)		(8.52)
Exposure		0.00499***	
		(8.61)	
KP Wald F Stat			1,058
CD Wald F Sat			413,751
N	21,365,386	21,365,386	21,365,386

This table reports estimates of β and $\tilde{\beta}$ coefficients in person/week regression specifications (3) and (5) that includes person, person $\times$ payweek, and calendar time $\times$ city of residence $\times$ income group fixed effects. LHS variables are spending defined in A.I and scaled by total spending. The first column reports OLS estimates of coefficients in (3). The second column reports OLS estimates of the IV reduced form coefficients in (5). The third column reports TSLS estimates of coefficients in (3) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses. Results are estimated for individuals who initiated BNPL transactions before 2020

Table A.VI. Effect of BNPL availability on measures of individual liquidity: Excluding Covid

	Fixed Effects	Reduced Form	TSLS
		Overdraft Fee	
Post	0.00250***		0.00391**
	(6.66)		(2.56)
Exposure		0.000595**	
		(2.53)	
KP Wald F Stat			1,123
CD Wald F Sat			617,153
		Low Balance Fee	
Post	0.00283***		0.00364**
	(6.80)		(2.17)
Exposure		0.000554**	
		(2.16)	
KP Wald F Stat			1,123
CD Wald F Sat			617,153
		Savings	
Post	0.178***		0.267**
	(9.29)		(2.52)
Exposure		0.0406**	
		(2.46)	
KP Wald F Stat			1,123
CD Wald F Sat			617,153
		Balance Estimate	
Post	−718.3***		−1.026**
	(−8.71)		(−2.32)
Exposure		−156.2**	
		(−2.31)	
KP Wald F Stat			1,123
CD Wald F Sat			617,153
N	25,626,478	25,626,478	25,626,478

This table reports estimates of β and $\tilde{\beta}$ coefficients in person/week regression specifications (3) and (5) that includes person, person $\times$ payweek, and calendar time $\times$ city of residence $\times$ income group fixed effects. LHS variables are total BNPL spending defined in A.I. The first column reports OLS estimates of coefficients in (3). The second column reports OLS estimates of the IV reduced form coefficients in (5). The third column reports TSLS estimates of coefficients in (3) using the exposure instrument. Robust standard errors clustered at the person and calendar time level are in parentheses. Results are estimated for individuals who initiated BNPL transactions before 2020

Figure A.I. Number of users by income class, $\frac{\text{BNPL}}{\text{CC}}$

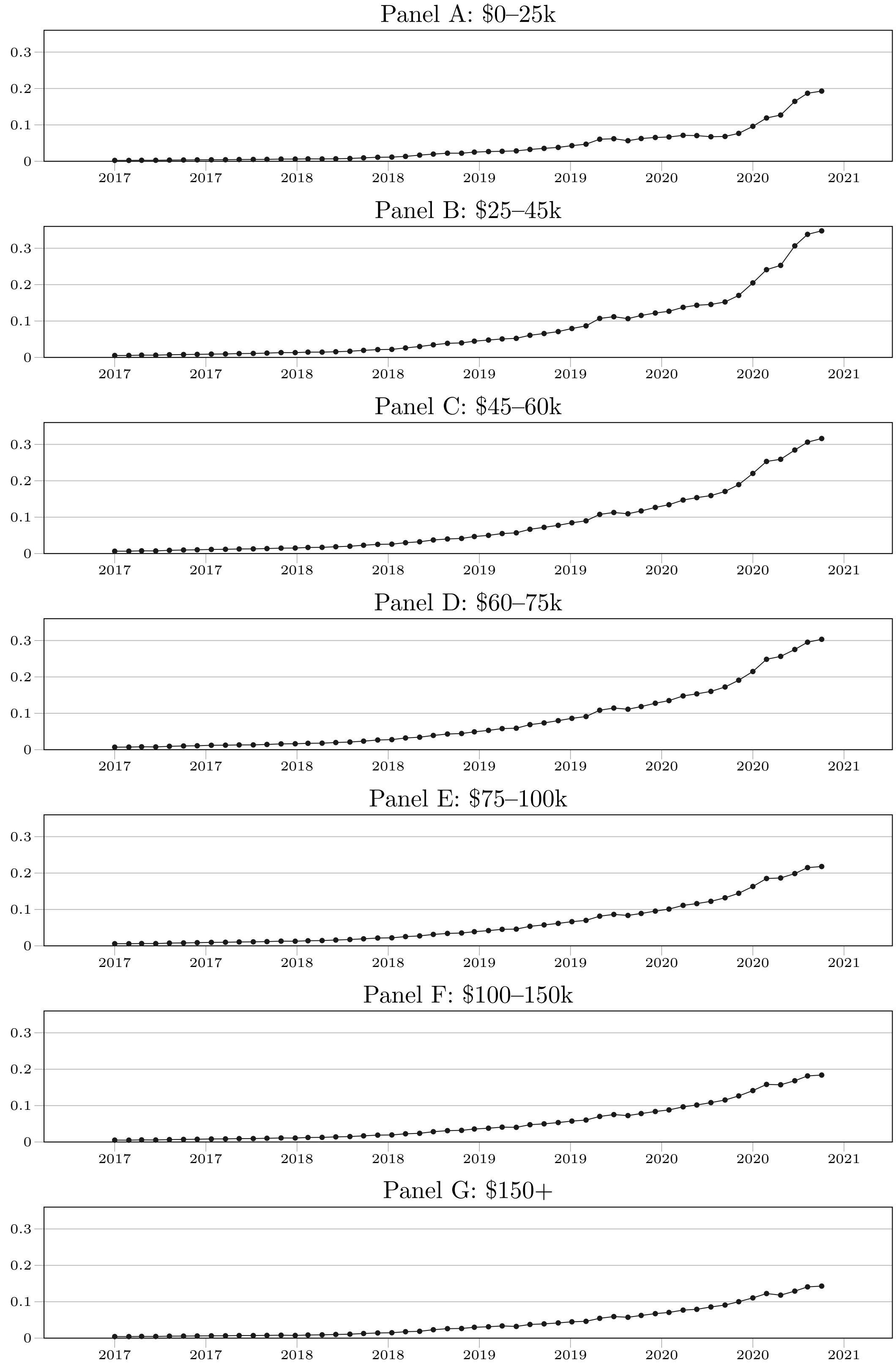
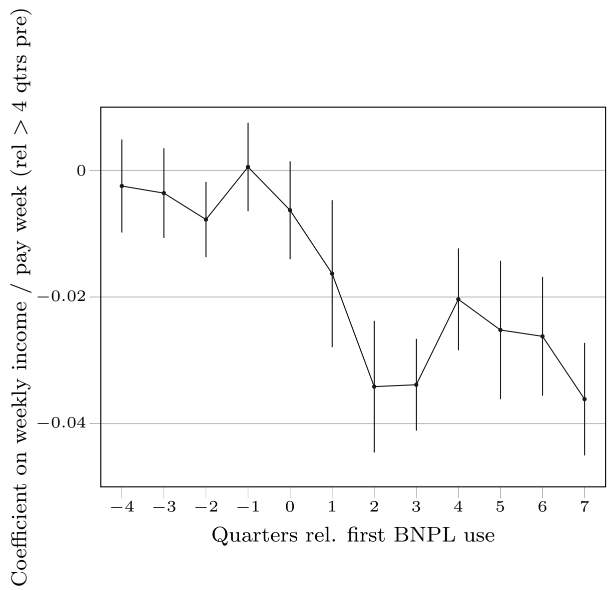


Figure A.II. Total spending vs income, quarters relative to BNPL first use – before March 1, 2020 (pre-Covid)



This figure displays coefficients γ_k in the regression specification (6), representing the relationship between weekly spending and weekly income within event time quarters relative to BNPL first use and restricting to observations before March 1, 2020 (pre-Covid). Coefficients are relative to the cross-sectional relationship in periods more than four calendar quarters relative to first BNPL use.