The Economics of "Buy Now, Pay Later": A Merchant's Perspective

Tobias Berg, Valentin Burg, Jan Keil, Manju Puri*

This version: June 2023
First version: September 2022
First presentation: October 2022

"Buy Now, Pay Later" (BNPL) is a key innovation in consumer payments in recent years. Using a randomized experiment at an e-commerce company, we document that – when BNPL is available – sales increase by 20%, driven both by the intensive and extensive margin. When randomizing availability of PayPal as a payment method we do not find comparable effects. We find that payment defaults on BNPL inflict only moderate costs and the benefits of offering BNPL significantly outweigh the costs for the merchant. Our findings help to explain the surge in popularity of BNPL in e-commerce around the world.

JEL: D12 · G40 · G50
Keywords: BNPL · FinTech Lending · Payment · Consumer Credit

*Berg (berg@finance.uni-frankfurt.de) is affiliated with Goethe University Frankfurt, Burg (valentin.burg@gmail.com) and Keil (jan.keil@hu-berlin.de) are with Humboldt-Universität zu Berlin, School of Business and Economics, and Puri (mpuri@duke.edu) is with Duke University and NBER. Jan Keil is supported by grant number KE 2661/1-1 ("Geschäftszeichen") from the Deutsche Forschungsgemeinschaft. We thank seminar participants at Humboldt-Universität (in October 2022), SMU Lee Kong Chian (Mar 2023), and NTU NBS (Mar 2023) for their valuable comments and suggestions.

Buy-Now-Pay-Later (BNPL) schemes are estimated to amount to around USD 120 Billion globally in 2021, up from USD 33 Billion in 2019 and with further growth expected (Financial Times, 2022; Dikshit et al., 2021). This compares to just over USD 50 Billion in FinTech consumer lending worldwide in 2020 (Ziegler et al., 2021). While this dramatically expanding market has been largely dominated by dedicated BNPL service providers, actors from all sides are pouring in – including merchants, payment firms, FinTechs, big tech companies / TechFins, and traditional banks.

The largely unregulated nature of the BNPL market is increasingly catching the attention of lawmakers and regulators, who worry about excess consumption and payment default risks. Hearings and investigations in the US Congress, at the Consumer Financial Protection Bureau, and other agencies in the US and the UK have placed BNPL into the spotlight.[1]

We attempt to inform the debate on BNPL by taking a merchant's perspective of BNPL. In particular, we answer three basic questions: First, do sales increase when merchants offer payment via BNPL? Second, do other popular payment options have comparable effects on merchants' sales? Third, what are the economic costs and benefits for the merchant of offering BNPL as one of the payment options?

We access micro data from a German e-commerce company selling furniture. The unique feature of our setting is a randomized controlled trial conducted by the merchant in early 2022, where BNPL is made available for some randomly selected customers, but not for others. The BNPL payment option allows for a single payment delay by approximately one month, which resembles the popular "pay in 30" (days) BNPL product.[2] Furthermore, the merchant also randomized availability of PayPal in a separate experiment, allowing us to compare the effect of two major payment options on merchant sales in exactly the same setting.

We start with a descriptive analysis of BNPL usage. BNPL is used more frequently for larger purchases than for smaller purchases and it is used more frequently by fe-

[1] For example, the California Department of Business Oversight has taken on BNPL cases; the Financial Conduct Authority in the UK started working on regulatory action; the German BAFIN issued official warnings and started to provides information for consumers.

[2] BNPL is a form of short-term unsecured consumer finance usually offered by merchants at the point-of-sale, tied to a specific product, and with little to no background checks. Two popular schemes are a single 30-day payment delay and a loan with 4 installments over 6 or 8 weeks.

male customers compared to male customers. The effect of creditworthiness is non-linear: customers with a high and low creditworthiness are more likely to use BNPL, while customers in the middle of the credit spectrum are less likely to use BNPL.

We continue by addressig our three basic questions. In the first step, we analyze whether BNPL availability affects sales. We document that – when BNPL is available – sales increase by 20%. Effects at the extensive margin account for 60-70% of the total margin, the reminder is driven by the intensive margin. Offering BNPL to low-creditworthiness-customers has greater effects on sales than offers to any other group: purchases of low-creditworthiness-customers are twice to three times as responsive as purchases of high-creditworthiness-customers.

In the second step, we analyze an identical experiment where availability of PayPal was randomized. The PayPal expertiment was conducted at the same time, in the same setting, and with the same number of customers as the BNPL experiment, providing us with an ideal comparison. When randomizing availability of PayPal as a payment option, we do not find any effects on sales.

In the third step, we analyze the economic costs and benefits for the merchant of offering BNPL. Since BNPL is offered in our setting entirely in-house by the merchant, we observe both economic benefits and costs associated with this service. This allows for an economic assessment from the merchant's point of view. Interestingly, BNPL costs from payment defaults are substantially lower than costs of using other popular payment options. Taken together, additional gross profits generated outweigh costs by a factor of more than three, which help to explain the surge in popularity of BNPL in e-commerce around the world.

There are several related strands of the literature. First, several contemporaneous papers analyze BNPL from a consumer financial health perspective in the U.S. (deHaan et al., 2022; Di Maggio et al., 2022), the U.K. (Guttman-Kenney et al., 2022), Australia (Boshoff et al., 2022), and China (Bian et al., 2023). BNPL can alleviate financial constraints, but can also induce consumers to overspend. Both Guttman-Kenney et al. (2022) and deHaan et al. (2022) find negative effects of BNPL on consumer spending habits and consumer financial health. Di Maggio et al. (2022) document that BNPL increases spending levels – even for consumers without liquidity constraints – and attribute this to a liquidity flypaper effect where liquidity in one category drives additional same-category expenditure. Bian et al. (2023) document that BNPL boosts consumer spending in China, but does not lead to greater indebtedness. Bian et al. (2023) conclude that BNPL – instead of being a consumer credit with negative welfare implications as in developed countries – rather serves the role of digital cash in China. We complement this literature by analyzing the economics of BNPL from a merchant's perspective. Our findings help to rationalize the popularity of BNPL by merchants around the world.

Our paper is also related to the literature on access to finance and consumer behavior. Agarwal et al. (2018) analyze effects of card limits on spendings and daily balances. Adams et al. (2009) and Einav et al. (2012) investigate effects of subprime lending on car purchases. Karlan and Zinman (2010) analyze effects of a relaxed microcredit lending standards. Alan and Loranth (2013) examine how interest rate increases affect credit card balances for subprime borrowers. Turkyilmaz et al. (2015); Wells et al. (2011) analyze impulse shopping in the e-commerce space, however, without a BNPL angle, while Benton et al. (2007) and Heidhues and Kőszegi (2010) link self-control problems and over-borrowing to easy-to-use credit cards.

Since we analyze BNPL that is offered by an e-commerce company and that classifies as FinTech lending, work in this area is also related. Ghosh et al. (2021) document the informational synergies between cashless payments and lending in the FinTech space. Berg et al. (2020) show that the digital footprint a customer leaves behind on a website has similar explanatory power over default probabilities as traditional external credit scores. Parlour et al. (2021) develop a model where FinTech payment providers disrupt informational flows to traditional banks. Chen et al. (2019), De Roure et al. (2022), and Tang (2019) analyze competition between FinTech firms and traditional banks. In a review article, Berg et al. (2021) have highlighted the rise of BNPL firms within the FinTech space.

Research on effects of payment options in the retail sector is also related. Several studies have focused on payments as an example of two-sided markets, analyzed competition and pricing issues (see Baxter (1983), Rochet and Tirole (2002), Shy and Wang (2011)). Others have focussed on the adoption and use of cash vis-a-vis other payment

(Alvarez and Argente, 2022; Koulayev et al., 2016; Quinn and Roberds, 2008). Agarwal et al. (2019); Bounie and Camara (2020); Brown et al. (2022) analyze the use of contactless payment methods. Berg et al. (2022) focus on payment firms more broadly and on how digital currencies may represent chances and challenges.

We add to these literature strands by analyzing who uses BNPL provided via FinTech lending; how BNPL affects sales; how effects of BNPL availability are different from availability of other payment options; and by analyzing the economics of BNPL from a merchant/lender point of view.

On a broader level, our work is also relevant for financial intermediation in general. Parlour et al. (2021) model adverse effects on bank lending caused by a loss of information usually mediated through the observation of payments flows. Ghosh et al. (2021) show empirical evidence on informational synergies between cashless payments and lending. Mester et al. (2007); Norden and Weber (2010); Puri et al. (2017) show that payment flows are informative about borrower quality. The rise of BNPL redirects exactly such payment flows to other intermediaries and away from traditional lenders, with a potential to impact traditional intermediaries.

In the rest of the paper we describe the data and the institutional setting (Section 1), present the analysis and identification (2), analyze which customers are interested in using BNPL (3), discuss results on how BNPL affects sales (4), how this differs from availability of other payment methods (5), how costs and profits of merchants are affected (6), and conclude (7).

1. Data and Institutional Setting

A. Institutional setting

To understand the importance of BNPL, we analyze data from a German e-commerce company selling furniture through its own website. Customers browse the product pages of the website, add one or more items to their shopping cart, and proceed to a check-out site, where they view all available payment options. Prices do not depend on the payment option chosen. There are no discounts offered only for some but not for other payment options.

We observe a rich set of information – which payment options are available for the customer, whether a website visit is successfully converted into a purchase order ("conversion" in the following), what payment options are selected throughout a visit, and which option is actually used for a conversion. Furthermore, we also have access to detailed information on customer characteristics like internal credit scores or shipping addresses.

In Figure 1 we plot the fraction of all payment options used in the treatment group (when all payment options were available). BNPL is the most important payment option with 51%. It is followed by PayPal (39%), credit card (6%), prepayment (3%), and installment credit (1%).

For our analysis we utilize an AB-test or randomized controlled trial conducted by the e-commerce company, which we refer to as the "experiment" in the remainder of the paper.[3] BNPL was made either available or unavailable for customers on a random basis without regards to any customer or website visit characteristics (see the Appendix for technical detail). This yields two distinct experimental groups. In the first group (which we call treatment group) all payment options are shown to customers (74,128 distinct customers). In the other group (which we call control group) BNPL was hidden from customers (948 distinct customers). Once a customer is in one group, he or she will stay in it irrespectively of whether the customer returns another day after converting or after leaving the website without a conversion. Table 1 – to be discussed in more detail below – shows that treatment and control group are similar along observable dimensions. The Appendix discusses the technical details of the randomization.

B. BNPL in general and in our setting

BNPL is a form of short term unsecured consumer credit. It is mostly offered at the point-of-sale. This financial service is either designed and offered by a merchant directly or in cooperation with an external service provider. BNPL is most visible in the

[3]The randomized controlled trial was conducted for the period from February 23rd 2022 until March 3nd 2022. It was resumed on March 18th and up until March 23rd. Note that since the experiment was conducted by the company, we could not pre-register it. The rationale of the e-commerce company to contuct an RCT was to gain insights of the cost-benefit of offering BNPL.

e-commerce sector. It is usually offered at low or no fees and interest payments for the customer. Since BNPL is a relatively vaguely defined concept it covers differently structured products. These may differ between countries depending on the institutional background and on how payments have been organized in the past. Some BNPL providers offer different BNPL schemes in different markets or multiple alternatives in the same market. For example, Klarna offers an interest free "pay in 30 days" short-term loan with just one single final payment after 30 days in an invoice payment-like structure. It also provides "pay in 4" loans with four bi-weekly installments where the first payment is due at check-out and maturity is 6 weeks. These are examples for two broadly offered schemes. The former is more popular in continental Europe while the latter dominates the Anglo-American space.

The type of BNPL offered by the German e-commerce company in this analysis is similar to the "pay in 30 days" scheme and looks as follows: once customers receive the purchased items they are required to pay the bill 14 days upon delivery; shipping times are displayed before payment options are accessed by customers and amount to an average of 14 days in the period analyzed here, adding up to a total formal average loan duration of 28 days. If the customer does not pay on time, a reminder is sent via email on the day when payment is due. This reminder does not cause any fees for late payment for another 14 days. 14 days after the first reminder, there will be a second reminder via email and a penalty fee of 2 Euro. A final payment reminder is sent out via mail 14 days after that. If a customer does not pay 14 days after the last reminder, then the claim is forwarded to a debt collection agency and we define these claims as being in default. Slightly less than 2% of all BNPL transactions default. The average BNPL transaction volume of 300-400 Euro is in line with "pay in 4" BNPL loans offered in other markets (Dikshit et al., 2021).[4]

C. Key variables

A main explanatory variable of interest in our analysis is the conversion, coded as a dummy variable that is one if a check-out website visit converts into a purchase. Since it is fairly common for customers to interrupt and resume shopping sessions on the

[4]See Table 1 and Table A2.

website, we allow for a customer to complete a conversion not just immediately, but within a time period of one week. This dummy variable allows us to assess the extensive margin of BNPL availability on sales. Other dependent variables are the total revenue by customer during that same period (in Euros). We either use the unconditional amount as the measure of the total margin, or the amount conditional on a conversion occurring to capture effects at the intensive margin of sales. All these measures are net of cancellations.[5] As another dependent variable, we use a dummy that is equal to 1 if a customer arriving at the check-out site selects BNPL (and 0 if she or he selects another payment option).

The internal credit score we use in this study is computed in real time, designed to capture default risk, and ranges from 0 (highest risk) to 1 (lowest). The e-commerce company relies primarily on information from the digital footprint a customer leaves behind, such as the device used or the shopping cart balance.[6] Table A1 in the Appendix contains a list with a description of all variables used. Their summary statistics for the baseline estimation samples of this study are in Table A2. Shopping cart volumes and revenues are winsorized at 1% and 99%.

D. Remarks

BNPL is shown to every customer in the treatment group (for which all payment options are generally available). However, not every customers in the treatment group selecting BNPL will actually be allowed to use this payment method. The e-commerce company uses the credit score to decide whether to accept a BNPL application or not. Customers with a high default risk are filtered out and not approved for BNPL (around 13% of customers).[7]

If an application is approved, the customer can purchase items using BNPL. If it is rejected, he or she is directed back to the check-out website (with all items still included in the shopping cart) and allowed to select any other payment option instead

[5]This means that a conversion is any transaction where the ordered revenue is greater than 0 and the cancelled revenue (if any) is smaller than the ordered revenue. Revenue is the total amount purchased minus the value of items cancelled.

[6]See Berg et al. (2020) for details on credit scoring using digital footprints.

[7]Note that in Germany, the e-commerce company is not allowed to do credit checks unless a customer has selected a BNPL payment option. Since the e-commerce company could not prescreening for eligibility, it randomized the decision to display BNPL across all customers.

to complete the purchase. Thus, our setting is essentially an intention-to-treat design that enables us to estimate a local average treatment effect (LATE) for the subpopulation of customers with a sufficient creditworthiness. We believe this is a valuable feature of our setting, because eligible customers represent the vast majority that is also representative of customers using credit cards or mortgages. This increases external validity for consumer finance in general. In contrast, customers ineligible for BNPL represent only a small minority in our sample and a corner case at the low end of the market. Such customers are less to participate in the largest consumer finance markets.

Since the merchant offers BNPL entirely in-house, we observe all associated benefits and costs. This allows us to assess easily whether the business is sustainable in terms of its ability to generate a sufficient amount of value.[8]

2. Analysis and Identification

To understand effects on sales, we analyze the experiment using different approaches. First, we conduct a simple mean comparison based on treatment status W_i (1: BNPL is available; 0: BNPL is not available) of a customer i via

$$Y_i = \alpha + \beta W_i + \epsilon_i. \tag{1}$$

In our baseline estimations Y_i is a dummy variable indicating a conversion to capture the extensive margin of sales. In some estimations we alternatively analyze the intensive and total margins of sales using revenue per customer (either conditional or unconditional on a conversion taking place). We do not strictly need to include any covariates in order to estimate average treatment effects: our randomization was well-conducted without taking covariates into account (see Table 1 and the discussion below); we do not restrict the analysis to customers with non-missing variables or certain other values that might introduce a bias ex-post. With White robust standard errors (the error term is not independent of the treatment assignment) and our

[8]In other settings where BNPL may be provided in cooperation with an external BNPL service provider, there is an entire value chain. Observing just one link only would make it much harder to evaluate the full costs, benefits, and surplus generated by BNPL.

observation counts of several hundreds for the smallest of our groups, the estimator from Equation 1 will be unbiased (Athey and Imbens, 2017). However, to increase statistical power and obtain more precise estimates we also estimate regressions with covariates (again, we believe covariates are not required to address any other problem, since randomization was not compromised) via equation

$$Y_i = \alpha + \beta W_i + \delta X_i + \epsilon_i. \tag{2}$$

Covariates X_i include the internal credit score, the Euro amount of the cart value at the first check-out of the shopping visit, county level per capita GDP, county population density, and dummy variables for whether a customer purchased anything before, indicated to be a male, as well as dummies for the device type and for the operating system used. In yet another set of regressions we further add fixed effects for county (c), date (d), and time-of-day (t) via equation

$$Y_i = \alpha + \beta W_i + \delta X_i + \gamma_c + \theta_d + \sigma_t + \epsilon_i. \tag{3}$$

Equations (1)-(3) are reduced-form models. The coefficient β measures the impact of *showing* the BNPL option to a customer on a customer's purchase behavior (for simplicity we call this variable "BNPL Offered (1/0)" in all tables). Showing BNPL is not the same as using BNPL because some customers are not approved for BNPL (also when it is displayed to customers in the treatment group) and some customers choose not to use BNPL despite being offered to use it. Overall, showing BNPL increases the likelihood of using it by approximately 40-50% (that is, 0% of customers in the control group use BNPL, while 40-50% in the treatment group use BNPL). We can measure a LATE (effect on customers interested in BNPL who have a sufficient creditworthiness) by estimating an IV regression where the first stage estimates the effect of *showing* BNPL on actually selecting BNPL and being approved to use BNPL. We believe it is more natural to analyze the reduced-form model, as this directly informs us about the effect of showing BNPL on a merchants' sales volume. As a robustness check, we report IV regressions in Table A3 in the Appendix where we instrument selection and approval of BNPL using the randomized decision to show BNPL. First-stage regressions have F-stats in excess of 900 and second-stage results have similarly high statistical significance but naturally show higher coefficients (the IV is basically a scaled-up version of the reduced form model).

Table 1 compares selected descriptive statitics in the two groups of interest.[9] It indicates that customers are similar with respect to almost all characteristics.

3. Who Uses BNPL?

Which customers prefer using BNPL and how do they differ from customers using other payment methods? Any insights would allow us to understand which groups can be targeted in an effort to increase sales. To answer this, we focus on the period during which the experiment was conducted and on the treatment group in which all payment options were generally available. In Table 2 we compare personal and shopping visit related characteristics of customers that either freely choose BNPL to those that select any other payment option. Note that with regards to the selection of payment methods analyzed in this subsection we can only focus on choices for new (first-time) customers due to a technical limitation.[10]

There are two interesting insights. First, several indicators for personal income and default risk tend to correlate with BNPL such that interest in BNPL is associated with lower credit worthiness. Customers choosing BNPL have somewhat lower credit scores (low values correspond to high default probabilities), live in poorer and less densely populated areas, are slightly younger (unfortunately we have no age information for most customers), considerably less likely to use an expensive Apple device, and substantially more likely to be female. Second, some of these differences are only marginally different. Most importantly, credit scores of customers selecting BNPL are only 0.04 lower, which is just 5.6% lower the average score and the difference is not

[9] All variables and more descriptive statistics are in Table A2.

[10] In cases where customers with prior conversions return, the variable capturing which payment method they select can represent their past choice from the last transaction instead of the choice of the current website visit, not allowing for a clear interpretation. We can use both new and returning customers for all other analyses in the study. Note also that a customer selecting a payment method may not necessarily end up using it for a variety reasons, including rejections by the e-commerce company, external service providers, failure to provide identification information (with credit cards, for example) or change of mind.

highly significant statistically.

Next, we analyze more formally how different customer characteristics predict the intention to use BNPL.[11] For this, we regress a dummy variable that is equal to 1 if a first-time customer selects BNPL as the payment method of choice and 0 if he or she selects another payment method on a set of customer characteristics.[12] Results are in Table 3. Columns 1-6 in Table 3 confirm insights from Table 2. We also run a horse race regression in Column 7. In terms of economic magnitude the absolute value of the credit score coefficient in Column 7 in Table 3 is again rather moderate. It suggests moving from the "bad" 10th to the "good" 90th percentile of the credit score distribution is associated with a 1.9 percentage point or 3.6% increase in the likelihood of choosing BNPL (statistical significance is high). Column 8 shows standardized beta weights of Column 7 allowing to compare the economic magnitudes of coefficients between dependent variables with different units and distributions.[13] It shows that gender and mean county income lead absolute economic magnitudes.

Due to the surprisingly low correlation between credit scores and preference for BNPL, we explore this relationship more thoroughly. It could be that the relationship is non-linear, which might not be captured by statistics in Tables 2 and 3. We explore this possibility in Figure 2 by estimating the coefficient from Column 2, Table 3 separately for each credit score quintile. Interestingly, there is indeed a u-shaped relationship. Even though the lower observation count in each bin takes a toll on power, some coefficients are statistically significantly different from each other. Customers with either very or very high scores are more interested in using BNPL than customers in the middle. This may be due to financial constraints at the low and higher financial literacy at the high end. The analysis reveals that customers in the lowest credit score quintile with high default risk are those most interested in using BNPL – also more than those at the high end. Those at the lowest quintile are 3.3 percentage points or 6.3% more likely to select BNPL as a payment option than those with only moderately

[11] We exclude age because of the small amount of observations.

[12] We exclude cases where customers select both BNPL and another payment method during the same shopping visit or neither one of them.

[13] All variables are standardized to have a SD of one and the interpretation is that a one SD increase of one of the independent variables leads to an X (indicated by the corresponding coefficient) SD increase in the dependent variable. Significance levels are identical to those in Column 7.

low scores in the second lowest quintile.

4. How does BNPL Affect Sales?

A. Baseline Results

In this section, we explore how BNPL affects sales. At the extensive margin of sales we differentiate between a conversion (purchasing anything or nothing) as our baseline. At the intensive and total margins of sales we analyze revenue by customer conditional and unconditional on a conversion. Results for our main regressions are in Table 4. Column 1 represents the simple mean comparison (as in Equation 1). We add controls in Column 2 (Equation 2) and controls and fixed effects in Column 3 (Equation 3).

In Panel A, Table 4 we analyze the extensive margin of sales using the conversion dummy as the dependent variable. The regression coefficient in Column 1, Panel A suggest making BNPL generally available (conditional on the e-commerce company's lending function) increases the total number of conversions at the e-commerce company by 9 percentage points, a considerable economic magnitude.

To explore whether there is also an effect at the intensive margin of sales, we focus on customers that would have converted their website visits into a purchase also if BNPL was unavailable. Thus, we analyze the total revenue per customer conditional on a conversion taking place. When BNPL is not offered, the average converting customer purchases items for a value of around 314 Euro (Table A2). Offering BNPL increases the amount *converting customers* spend (conditional on the company's lending function) by around 16.3-24.5 Euro (Table 4, Panel B), or 5-8% of the average amount of 314 Euro. This means that the intensive margin increases the merchants' total sales by 5-8%.

The sum of the extensive and intensive margins of sales is the revenue per customer unconditional on a conversion taking place. Results in Table 4, Panel C suggest offering BNPL increases this average amount spent by 40.8-47.2 Euro (statistical significance is high). This corresponds to a 18-21% increase in total sales at the merchants' online shop.

So far, we have analyzed reduced-form results. These results provide the answer to a simple question: How much more revenues can the e-commerce company expect if it depicts a BNPL option to its customers? Showing a BNPL option is not the same as offering BNPL, as approximately 13% of customers are rejected. The local average treatment effect (LATE) of offering BNPL to all customers with a sufficient creditworthiness is therefore sligthly higher (by a factor of 100/(1-13%) = 1.15). IV-results are reported in Appendix Table A3.

B. Robustness

In robustness checks in Appendix Table A4 we show that results are similar when we define all dependent variables net of items eventually sent back. We are as conservative as possible in our baseline analysis, not counting subsequent conversions to the same address by another customer, but only analyzing the first customer within a unique address (see Appendix for more technical detail). We use a more liberal definition, where we count such visits by other customers from the same address towards conversions and revenues of the first customer visiting from a given address. Corresponding results in Appendix Table A5 are similar. Finally, we re-run our baseline estimation only for first-time customers in Appendix Table A6, showing that results at the extensive and total margins of sales are more robust than at the intensive margin.

C. Heterogeneity

An important question is if BNPL has a greater effect on sales to customers in the lower spectrum of the market with elevated payment default risk. From the perspective of the merchant this would mean that differential or targeted catering may drive sales even more. It also means that the general effect on sales observed in the prior subsection may contain some potential for risk relating to payment defaults. From a broader economic perspective a greater effect on sales to customers at the low end might mean that BNPL eases financial constraints in the short run. On the other hand it could also create a potential risk for households in shape of restricted or more costly access to finance in future.[14] On a larger scale this could even translate into risks for financial

[14] In our setting and in many other BNPL schemes, defaults have adverse impacts on credit scores, which in turn affect access to mortgages and other household credit.

stability of the economy as a whole.

In Table 6 we show that the credit score correlates as expected negatively with default rates and positively with mean county income. Higher scores are also associated higher population density and with higher age – both of which are indicators for income and wealth. The table further reveals that customers with high credit scores are more likely to convert. Consistent with our results discussed above and with the idea that a customer with financial constraints should be more interested in BNPL, the preference for using BNPL correlates negatively with our credit score.

The BNPL application approval rate associates positively and significantly with the credit score. This is a mechanical result of the company's lending function: the score is used such that customers with lower scores are more likely to be rejected. This has an important implication for interpreting estimation results. Assume for a moment that we define a treatment as showing BNPL *and* approving it if a customer selects BNPL (we do not know if a customer not selecting BNPL would be approved). In this case, the likelihood of receiving the treatment is not equal for two customers with different credit scores in the treatment group (or intention-to-treatment group). While BNPL will be shown to both customers in this group, the merchant is more likely to approve the BNPL application of the customer with a better credit score. This differential may generate a bias where customers with higher credit scores appear to be *more* responsive to our randomized BNPL availability only because they are more likely to receive treatment.

Searching for differential effects in our formal analysis we regress the conversion dummy against the internal score, the BNPL availability dummy, and their interaction term. Results are in Table 7, which is the main table in this subsection. Customers with high scores / low default probabilities are more likely to convert (as indicated by the credit score coefficient). Making BNPL available for customers with the *lowest* score / highest default probability has a positive and much more dramatic impact on the conversion likelihood (the coefficient from the BNPL × Credit Score interaction term is negative and significant). The economic magnitude is roughly twice the value from our baseline regressions, where we did not differentiate by credit score. Customers with the the highest score are much less affected by BNPL offers (adding the interacted coefficient to the coefficient of the BNPL availability dummy). High default risk customers with scores at the 10th percentile (a score value of 0.422, see A2) are twice to three times as responsive as low default risk customers with scores at the 90th percentile (a score value of 0.968).[15] In absolute terms this means that BNPL increases the conversion rate for customers at the 10th percentile by over 13 percentage points (conditional on rejections by the lending function). This is substantially more than the corresponding average 9 percentage point increase for the entire sample reported above. For customers at the 90th percentile, the effect is less than a 5 percentage point increase. In other words, the positive effect of BNPL on sales at the merchants' online shop is driven by BNPL offers to customers at the lower credit score spectrum.

Analyses in Tables 6 and 7 in this subsection do not reveal any possible non-linear relationships. We search for such in Figure 3 graphically. Panel A we plot average default rates for credit score quintile bins. This exercise reveals a convex function where default rates spike up especially at the very low end of the distribution. The mean is 5.5% in the worst quintile and 1% in the best. In Panel B, Figure 3 we plot coefficients for the interaction term between BNPL availability and credit score from regressions explaining conversions separately in every quintile. The heterogeneity appears quite linear, but the precision of estimations is quite low.[16]

It is important to recall that the differential effect of credit scores on conversions at the extensive margin of sales must be considered a lower bound, since customers with low credit scores are less likely to be approved to use BNPL. It is also important to note that our findings are not necessarily fully critical and may imply that BNPL eases financial constraints to at least some degree. However, correlations and regressions reveal a differential effect of credit scores implying that there is an increase in default risk. On a large scale this might potentially add up to increased costs for merchants and to deteriorations of external credit scores and access to finance for consumers.

[15] The calculation behind this statement is based on the coefficients from Column 1, Table 7 $(0.198 - 0.153 * 0.422)/(0.198 - 0.153 * 0.968) = 2.67$.

[16] The reduction of observation counts down to one fifth each takes a toll on statistical power that our regressions in Table 7 do not suffer from.

5. Do Other Payment Options have Similar Effects?

We framed results in subsection 4 as effects of financing characteristics of BNPL on consumer behavior. One might imagine that these effects could alternatively be explained rather by a higher level of convenience offered by this payment option. It could also be the result of a lack of trust in the online shop combined with the higher degree of safety offered by paying for a product after it is delivered. To explore these alternative explanations, we ideally would like to analyze random variation in the availability of another popular payment option with comparable convenience and safety features, but which is not predominantly used for financing. If results would lead to similar effects on shopping behavior as BNPL does, then this would suggest that the effects of BNPL uncovered in the previous subsection may have nothing to do with BNPL's financing character but with convenience or safety concerns.

To investigate this, we utilize an additional experiment conducted by the e-commerce company during the same period in which the BNPL experiment was conducted. This second experiment randomized the availability of PayPal, which is the most popular payment option right behind BNPL (at the e-commerce company) and a useful comparison for several reasons.

The PayPal and BNPL experiments were equivalent in their setup, sharing the same treatment group also used in the BNPL analysis in the previous subsection (74,128 distinct customers). However, analyzing PayPal relies on a new control group for which PayPal was not available (1,304 customers). With estimations equivalent to those in Table 4, we analyze the effects of adding PayPal on the total margin of sales (conversions) and on the intensive and extensive margins (revenue per customer conditional and unconditional on a conversion taking place). Results in Table 5 show that this alternative payment option does not have effects remotely equivalent to those of BNPL. All coefficients of PayPal availability are statistically insignificant, economic magnitudes are just a fraction of those from BNPL regressions, and coefficients even switch signs in some estimations. This suggests that BNPL is indeed different than other popular payment options and that this difference is likely to have something to do with financing, and not just with convenience and trust.

6. How Does BNPL Affect the Costs and Profits of Merchants?

In this section we explore the overall economics of BNPL from the merchant's point of view – including costs – and compare it to other payment options.

A. Economics of BNPL

In general, we can assess the economics of BNPL by determining the additional gross margin earned because BNPL is offered ($\Delta R \cdot m$) minus the costs of offering BNPL (c^{BNPL}):

$$\theta = \Delta R \cdot m - c^{BNPL} \tag{4}$$

where ΔR is the change in revenues from offering BNPL, m is the merchant's gross margin, and c^{BNPL} are the costs associated with offering BNPL. From the prior analysis, $\Delta R = EUR41$ or 20%, i.e., when BNPL is offered customers spend $EUR41$ more, which is equivalent to an increase in sales by 20%. The average gross profit margin m of the firm is equal to $m = 30\%$. Costs c^{BNPL} include write-downs due to defaults (1.87% in our sample) as well as operational costs of offering BNPL. These operational costs are extremely hard to measure precisely; however, discussions with the e-commerce firm suggests they are of second-order importance relative to the write-downs. Overall, the benefits clearly exceed the costs in our setting, with $\theta = 20\% \cdot 30\% - 1.87\% >> 0$.

Since BNPL is offered at no fee and most BNPL customers would otherwise use other payment options, one might expect a subsidy of these costs from customers not using BNPL, similar to other computations illustrating price increases required to subsidize credit card rewards (Schuh et al., 2010; Economist, 2022). A back-of-the-envelope computation that ignores the effect of BNPL on additional sales and ignores the costs of alternative payment options would look as follows. The 366 Euro in average losses from defaulting customers (amounting to a total of 207,522 Euro) would have to be borne by the converting customers (59,365), which would amount to 3.49 Euro per person. Given the 338.1 Euro in average transaction volume per converting customer (see Column 12, Table A2), this corresponds to a 1% increase in prices – assuming that this price increase has no adverse effect on sales. If the merchant could engage in price discrimination according to the payment method used – which is not legal in Germany but may be circumvented via discounts – then BNPL users would pay 6.85 Euro or 2% more.[17] This would not be a minuscule amount.

It is worth noting that costs are not symmetrically distributed across the credit score spectrum of BNPL users. We know from Figure 2 that BNPL is most popular among customers with low scores and from Figure 3 that such customers have the highest default risk, causing the highest costs for the merchant. There may thus be a moderate and progressive redistributive effect from high to low credit score income customers – depending on how stringently customers with low credit worthiness are rejected. This would be very different from the regressive redistribution of costs and benefits in the use of credit cards.[18]

B. Comparison to other Payment Options

All other payment options except prepayment involve transaction costs paid by the merchant to payment firms providing these services. Assessing the economics of BNPL thus requires comparing the costs of offering BNPL to the opportunity costs of offering PayPal, credit card, or installment credit.

Such costs are commonly expressed in percent of transaction revenue.[19] The reference here is thus the just mentioned loss due to BNPL defaults of 6.85 Euro per BNPL customer or 2% of BNPL sales.

Terms of the second most popular payment option PayPal requires the merchant to pay 2.49% on the transaction volume plus a fixed fee of 35 Cents added to every transaction, which sums up to 2.6% given the average transaction volume of PayPal converters.[20] Just in terms of pure and direct transaction costs, the merchant has substantial savings of almost 0.6% per transaction. Thus, if all BNPL converters would use PayPal, costs were to rise from 6.85 Euro per converting BNPL user by 2.11 Euro to 8.96 Euro.[21] In our alternative experiment we did not find any comparable positive impact of PayPal on sales. Adding this profit-reducing effect to the direct cost dif-

[17] BNPL users convert with a slightly higher balance of 345.68 Euro. The merchant could circumvent legal restrictions by offering different discounts by payment method.

[18] See Schuh et al. (2010) and Economist (2022) on this.

[19] For example, for credit card fees.

[20] The computation is based on PayPal users' slightly lower mean balance of 302.3 Euro.

[21] The computation is (2.49% * 345.68 Euro + 0.35 Euro) / 345.68 Euro.

ferential makes PayPal even less attractive relative to the type of "homemade" BNPL analyzed in our setting. This relative value of BNPL for e-commerce merchants shows how much of a threat it may be for the business of external payment service providers.

7. Conclusion

Offering BNPL drives sales on that platform. On the extensive margin of sales, BNPL causes some customers to actually finalize a purchase when they would otherwise not have purchased anything. To a somewhat lesser but still substantial extend, BNPL also raises sales on the intensive margin, inducing customers to spend more even if they would have purchased something anyways. In line with the idea that the impact of BNPL is related to its financing characteristic, we find that effects of PayPal are not comparable to effects of making BNPL available. This is important, since PayPal is similarly popular, convenient, and safe for customers to use – while not being predominantly used for payment deferral.

Our evidence suggests that e-commerce merchants can benefit vastly from BNPL vis-a-vis other popular payment options – not just in terms of BNPL's substantial ability to generate sales, but also with regards to cost advantages. Consistent with that, introducing BNPL dents considerably into the use of PayPal and represents a threat to certain payment service providers. We present some evidence suggesting that favorable economics are one driver behind the spectacular rise in BNPL.

In an attempt to search for possible future problems we find that especially those customers with high payment default probabilities are interested in using BNPL and become more likely to purchase consumer goods when it is offered. Thus, a future increase in household default risk appears possible. While BNPL may very well improve access to financing and ease financial constraints in the short run, it does also have the potential to deteriorate credit scores and accordingly reduce future access to other forms of household finance in the long run. These results suggest that there may indeed be some potential need for future regulation in the BNPL space. Findings call for additional research analyzing other BNPL schemes in other markets and alternative settings.

References

Adams, W., Einav, L., and Levin, J. (2009). Liquidity constraints and imperfect information in subprime lending. *American Economic Review*, 99(1):49–84.

Agarwal, S., Chomsisengphet, S., Mahoney, N., and Stroebel, J. (2018). Do banks pass through credit expansions to consumers who want to borrow? *The Quarterly Journal of Economics*, 133(1):129–190.

Agarwal, S., Qian, W., Yeung, B. Y., and Zou, X. (2019). Mobile wallet and entrepreneurial growth. In *AEA Papers and Proceedings*, volume 109, pages 48–53.

Alan, S. and Loranth, G. (2013). Subprime consumer credit demand: evidence from a lender's pricing experiment. *The Review of Financial Studies*, 26(9):2353–2374.

Alvarez, F. and Argente, D. (2022). On the Effects of the Availability of Means of Payments: The Case of Uber*. *The Quarterly Journal of Economics*. qjac008.

Athey, S. and Imbens, G. W. (2017). The econometrics of randomized experiments. In *Handbook of economic field experiments*, volume 1, pages 73–140. Elsevier.

Baxter, W. F. (1983). Bank interchange of transactional paper: Legal and economic perspectives. *The Journal of Law and Economics*, 26(3):541–588.

Benton, M., Meier, S., and Sprenger, C. (2007). Overborrowing and undersaving: lessons and policy implications from behavioral research. *Federal Reserve Bank of Boston Paper*, pages 07–04.

Berg, T., Burg, V., Gombović, A., and Puri, M. (2020). On the rise of fintechs: Credit scoring using digital footprints. *The Review of Financial Studies*, 33(7):2845–2897.

Berg, T., Burg, V., Keil, J., and Puri, M. (2022). On the rise of payment firms. *Working Paper*.

Berg, T., Fuster, A., and Puri, M. (2021). Fintech lending. *Annual Review of Financial Economics*, 14.

Bian, W., Cong, L. W., and Ji, Y. (2023). The rise of e-wallets and buy-now-pay-later: Payment competition, credit expansion, and consumer behavior. *Working Paper*.

Boshoff, E., Grafton, D., Grant, A. R., and Watkins, J. (2022). Buy now pay later: Multiple accounts and the credit system in Australia. *Working Paper*.

Bounie, D. and Camara, Y. (2020). Card-sales response to merchant contactless payment acceptance. *Journal of Banking & Finance*, 119:105938.

Brown, M., Hentschel, N., Mettler, H., and Stix, H. (2022). The convenience of electronic payments and consumer cash demand – causal evidence from the staggered introduction of contactless debit cards. *Journal of Monetary Economics*, 130:86–102.

Chen, M. A., Wu, Q., and Yang, B. (2019). How valuable is fintech innovation? *The Review of Financial Studies*, 32(5):2062–2106.

De Roure, C., Pelizzon, L., and Thakor, A. (2022). P2p lenders versus banks: Cream skimming or bottom fishing? *The Review of Corporate Finance Studies*, 11(2):213–262.

deHaan, E., Kim, J., Lourie, B., and Zhu, C. (2022). Buy now pay (pain?) later. *Working Paper*.

Di Maggio, M., Williams, E., and Katz, J. (2022). Buy now, pay later credit: User characteristics and effects on spending patterns. Technical report, National Bureau of Economic Research.

Dikshit, P., Goldshtein, D., Kaura, U., Tan, F., and Karwowski, B. (2021). Buy now, pay later: Five business models to compete. *McKinsey & Company*.

Economist (2022). Can the visa-mastercard duopoly be broken? *The Economist*.

Einav, L., Jenkins, M., and Levin, J. (2012). Contract pricing in consumer credit markets. *Econometrica*, 80(4):1387–1432.

Financial Times (2022). Rise and rise of buy now, pay later. *FT Tech*.

Ghosh, P., Vallee, B., and Zeng, Y. (2021). Fintech lending and cashless payments. In *Proceedings of Paris December 2021 Finance Meeting EUROFIDAI-ESSEC*.

Guttman-Kenney, B., Firth, C., and Gathergood, J. (2022). Buy now, pay later (bnpl)... on your credit card. *Working Paper*.

Heidhues, P. and Kőszegi, B. (2010). Exploiting naivete about self-control in the credit market. *American Economic Review*, 100(5):2279–2303.

Karlan, D. and Zinman, J. (2010). Expanding credit access: Using randomized supply decisions to estimate the impacts. *The Review of Financial Studies*, 23(1):433–464.

Koulayev, S., Rysman, M., Schuh, S., and Stavins, J. (2016). Explaining adoption and use of payment instruments by us consumers. *The RAND Journal of Economics*, 47(2):293–325.

Mester, L. J., Nakamura, L. I., and Renault, M. (2007). Transactions accounts and loan monitoring. *The Review of Financial Studies*, 20(3):529–556.

Norden, L. and Weber, M. (2010). Credit line usage, checking account activity, and default risk of bank borrowers. *The Review of Financial Studies*, 23(10):3665–3699.

Parlour, C. A., Rajan, U., and Zhu, H. (2021). When fintech competes for payment flows. *NBER Working Paper*.

Puri, M., Rocholl, J., and Steffen, S. (2017). What do a million observations have to say about loan defaults? opening the black box of relationships. *Journal of Financial Intermediation*, 31:1–15.

Quinn, S. and Roberds, W. (2008). The evolution of the check as a means of payment: A historical survey. *Economic Review*, 93.

Rochet, J.-C. and Tirole, J. (2002). Cooperation among competitors: Some economics of payment card associations. *Rand Journal of economics*, pages 549–570.

Rubin, D. B. (1978). Bayesian inference for causal effects: The role of randomization. *The Annals of statistics*, pages 34–58.

Schuh, S., Shy, O., and Stavins, J. (2010). Who gains and who loses from credit card payments? theory and calibrations. *Federal Reserve Bank of Boston Public Policy Discussion Papers*, 10–03.

Shy, O. and Wang, Z. (2011). Why do payment card networks charge proportional fees? *American Economic Review*, 101(4):1575–90.

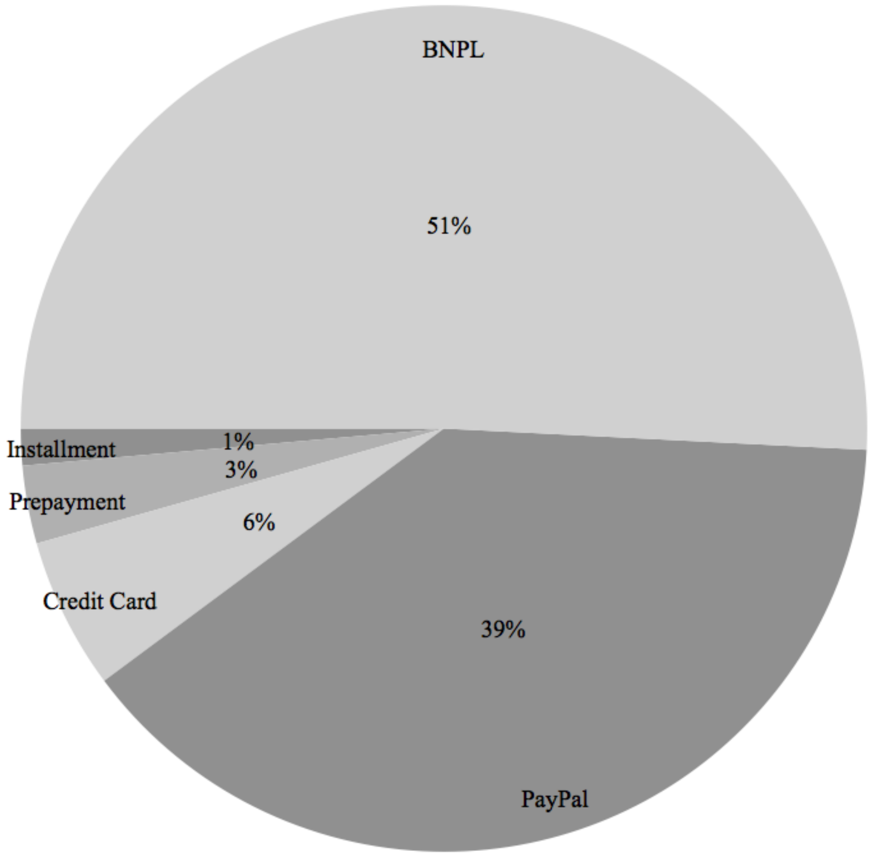
Tang, H. (2019). Peer-to-peer lenders versus banks: substitutes or complements? *The Review of Financial Studies*, 32(5):1900–1938.

Turkyilmaz, C. A., Erdem, S., and Uslu, A. (2015). The effects of personality traits and website quality on online impulse buying. *Procedia-Social and Behavioral Sciences*, 175:98–105.

Wells, J. D., Parboteeah, V., and Valacich, J. S. (2011). Online impulse buying: understanding the interplay between consumer impulsiveness and website quality. *Journal of the Association for Information Systems*, 12(1):3.

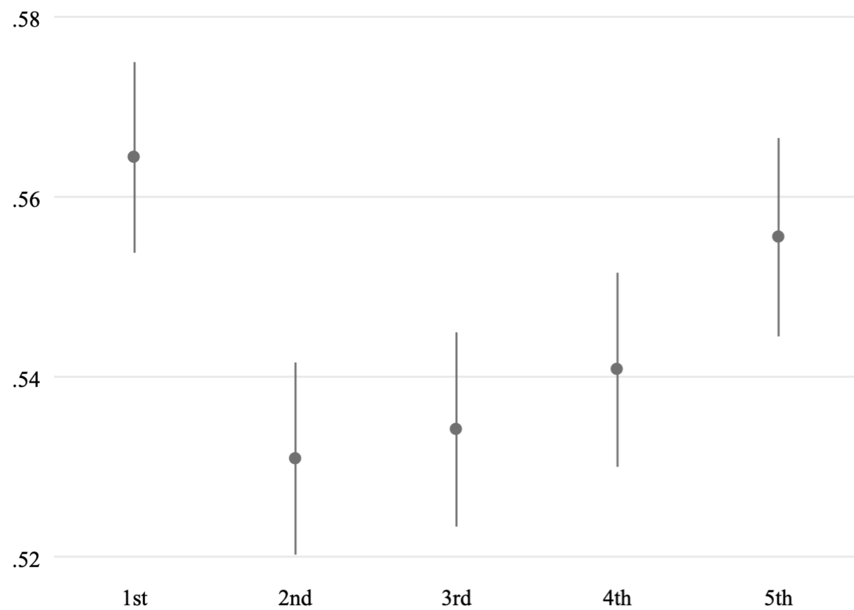
Ziegler, T., Shneor, R., Wenzlaff, K., Suresh, K., Paes, F. F. d. C., Mammadova, L., Wanga, C., Kekre, N., Mutinda, S., Wang, B., et al. (2021). The 2nd global alternative finance market benchmarking report. *Cambridge Centre for Alternative Finance*.

Figure 1: BNPL and other Payment Options



This figure plots the shares of Buy-Now-Pay-Later (BNPL) and all other payment options used at the e-commerce company. The sample is based on the treatment group (for which all payment options are available) in the experiment.

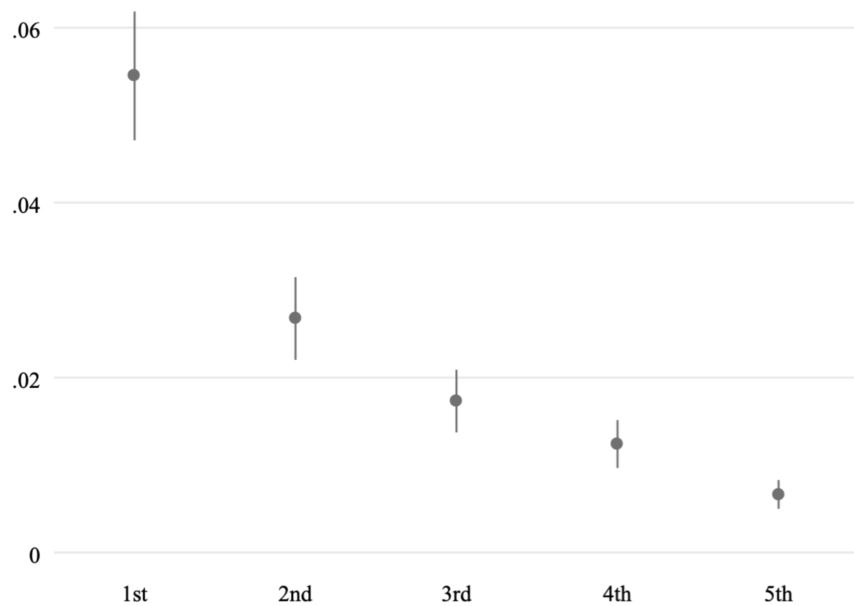
Figure 2: Heterogeneity in Selecting BNPL by Credit Score



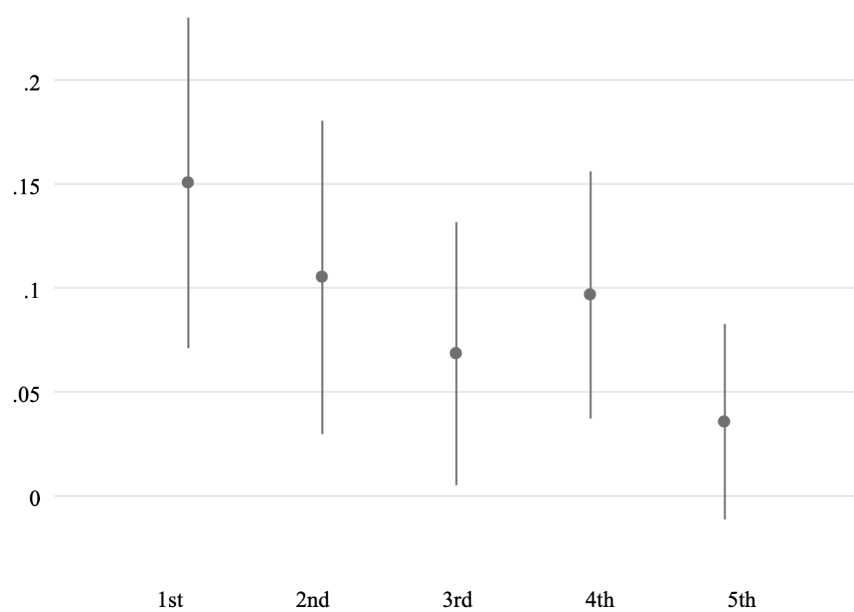
This figure plots the share (arithmetic mean) of customers selecting either BNPL (coded as a dummy variable value of 1) or some other payment option (coded as 0). We display it by quintile bins of the internal credit score (ranging from 0 to 1, where larger values correspond to lower default likelihoods). Whiskers correspond to 95% confidence intervals. The sample is based on the treatment group (for which all payment options are available) in the experiment. Note that the sample is based on first-time customers, as information on payment method selections for customers that visited the website before is unreliable.

Figure 3: Credit Score Heterogeneity

(a) Default Probabilities



(b) Differential Effects of BNPL Offers on Conversions



Panel A plots the probability of a payment default of customers using BNPL. We display it by quintile bins of the internal credit score (ranging from 0 to 1). The sample is based on the treatment group (for which all payment options are available) in the experiment. Panel B plots the coefficient of the interaction term Credit Score × BNPL Offered as in Table 7 from regressions explaining the likelihood that a customer's shopping visit at the e-commerce company's website is converted into a purchase. See Table 7 for details. Whiskers correspond to 95% confidence intervals.

Table 1: Assignment to Treatment and Control Groups

	Unavailable		Available		
	N	Mean	N	Mean	p-value
	(1)	(2)	(3)	(4)	(5)
Initial Cart Balance (€)	948	392.90	74,128	392.00	(0.953)
Credit Score (min. 0, max. 1)	907	0.735	70,159	0.746	(0.122)
Age (Years)	119	43.941	8,603	43.445	(0.634)
Male (1/0)	948	0.300	74,128	0.295	(0.759)
Returning Customer (1/0)	948	0.308	74,128	0.315	(0.663)
System: Apple (1/0)	948	0.423	74,128	0.447	(0.141)
County Mean Income (€)	937	22,034	73,441	22,199*	(0.067)
County Population Density	937	1,155	73,441	1,216	(0.168)

This table compares selected characteristics of customers randomly assigned to the group in which BNPL was either unavailable (Columns 1-2) or available (3-5). See Appendix Table A1 for details on the definition of variables and A2 for a comparison of all variables and more descriptive statistics. ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P-values are between parentheses.

Table 2: Customers Selecting BNPL and Other Customers

	Other Customers		**Selecting BNPL**		
	N (1)	Mean (2)	N (3)	Mean (4)	p-value (5)
Initial Cart Balance (€)	20,443	352.06	23,348	375.84***	(0.000)
Credit Score (min. 0, max. 1)	19,195	0.710	22,982	0.706*	(0.056)
Age (Years)	178	42.191	222	40.248*	(0.086)
Male (1/0)	20,443	0.346	23,348	0.232***	(0.000)
System: Apple (1/0)	20,443	0.436	23,348	0.405***	(0.000)
County Mean Income (€)	20,245	22,241	23,124	22,128***	(0.000)
County Population Density	20,245	1,312	23,124	1,042***	(0.000)

This table compares selected characteristics of customers reaching the check-out website and selecting either PayPal, credit card, pre-payment, or installments (Columns 1-2) or BNPL (3-5). The sample is based on the treatment group (for which all payment options are available) in the experiment. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10%. P- values are between parentheses. Note that the sample is based on first-time customers, as information on payment method selections for customers that visited the website before is unreliable.

Table 3: Selecting BNPL and Consumer Characteristics

	Dependent Variable: Selecting BNPL (1/0)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial Cart Balance (ln(€))	0.023***						0.026***	[0.053]
	(0.002)						(0.002)	
Credit Score (min. 0, max. 1)		-0.023*					-0.035***	[-0.014]
		(0.012)					(0.012)	
Male (1/0)			-0.140***				-0.152***	[-0.138]
			(0.005)				(0.005)	
System: Apple (1/0)				-0.032***			-0.024***	[-0.023]
				(0.005)			(0.005)	
County Mean Income (ln(€))					-0.078***		-0.081***	[-0.019]
					(0.020)		(0.020)	
County Population Density (ln)						-0.038***	-0.033***	[-0.086]
						(0.002)	(0.002)	
Adj. R^2	0.00	0.00	0.02	0.00	0.00	0.01	0.03	
Observations	43,791	42,177	43,791	43,791	43,369	43,369	41,759	

Regressions explain the likelihood that a customer selects BNPL during a shopping visit at the e-commerce company's website. Results are linear probability estimates. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors (between parentheses). In Column (8) we plot beta weights from Column (7), where all variables are standardized to have a SD of one and the interpretation is that a one SD increase of one of the independent variables leads to an X (indicated by the corresponding coefficient) SD increase in the dependent variable. Significance levels are identical to those in Column 7.

Table 4: Effects of BNPL Offers on Sales

	(1)	(2)	(3)
Panel A) Dependent Variable: Conversion (1/0)			
BNPL Offered (1/0)	0.091***	0.084***	0.085***
	(0.015)	(0.014)	(0.014)
Adj. R^2	0.00	0.11	0.12
Observations	75,076	70,393	70,389
Panel B) Dependent Variable: €-Revenue Conditional on a Conversion			
BNPL Offered (1/0)	24.538*	17.993***	16.257**
	(12.942)	(6.520)	(6.522)
Adj. R^2	0.00	0.84	0.84
Observations	60,038	57,302	57,301
Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion			
BNPL Offered (1/0)	47.158***	43.970***	40.779***
	(10.286)	(9.035)	(9.149)
Adj. R^2	0.00	0.40	0.41
Observations	75,076	70,393	70,389
Controls			
Customer		Yes	Yes
County		Yes	–
Fixed Effects			
County			Yes
Date			Yes
Time-of-Day			Yes

Regressions in Panel A explain the likelihood that a customer's shopping visit at the e-commerce company's website is converted into a purchase (the extensive margin). Results are linear probability estimates. In Panel B (C) the dependent variable is total realized revenue by customer conditional (unconditional) of a conversion taking place as a measure of the intensive (total) margin. The independent variable of interest is the treatment dummy equal to 1 (0) if BNPL was made available (unavailable) for a randomly selected customer. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors (between parentheses). "–" indicates that controls are absorbed by fixed effects.

Table 5: Effects of PayPal Availability on Sales

Panel A) Dependent Variable: Conversion (1/0)	(1)	(2)	(3)
PayPal Offered (1/0)	0.011	0.012	0.012
	(0.011)	(0.011)	(0.011)
Adj. R^2	-0.00	0.11	0.12
Observations	75,432	70,726	70,723
Panel B) Dependent Variable: €-Revenue Conditional on a Conversion			
PayPal Offered (1/0)	5.882	-0.040	-0.655
	(11.162)	(4.292)	(4.390)
Adj. R^2	-0.00	0.85	0.85
Observations	60,395	57,639	57,638
Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion			
PayPal Offered (1/0)	8.359	-3.457	-3.630
	(9.440)	(7.227)	(7.233)
Adj. R^2	-0.00	0.41	0.41
Observations	75,432	70,726	70,723
Controls			
Customer		Yes	Yes
County		Yes	–
Fixed Effects			
County			Yes
Date			Yes
Time-of-Day			Yes

Regressions in Panel A explain the likelihood that a customer's shopping visit at the e-commerce company's website is converted into a purchase (the extensive margin). Results are linear probability estimates. In Panel B (C) the dependent variable is total realized revenue by customer conditional (unconditional) of a conversion taking place as a measure of the intensive (total) margin. The independent variable of interest is the treatment dummy equal to 1 (0) if PayPal was made available (unavailable) for a randomly selected customer. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors (between parentheses). "–" indicates that controls are absorbed by fixed effects.

Table 6: Correlations of Variables with the Internal Credit Score

	Correlation	
	Coefficient (1)	p-value (2)
Payment Default (1/0)	-0.115***	(0.000)
Initial Cart Balance (€)	-0.079***	(0.000)
Age (Years)	0.089***	(0.000)
Male (1/0)	-0.009**	(0.016)
System: Apple (1/0)	0.000	(0.915)
County Mean Income (€)	0.075***	(0.000)
County Population Density	0.023***	(0.000)
Conversion (1/0)	0.265***	(0.000)
BNPL Selected (1/0)	-0.009*	(0.057)
BNPL Approved (1/0)	0.377***	(0.000)
BNPL Used (1/0)	0.023***	(0.000)
PayPal Used (1/0)	-0.015***	(0.000)
Credit Card Used (1/0)	0.034***	(0.000)
Installment Used (1/0)	-0.038***	(0.000)
Prepayment Used (1/0)	-0.047***	(0.000)

Column 1 contains correlation coefficients of the internal credit score with selected variables of interest. P-values are in Column 2. The score ranges from a minimum of 0 to a maximum of 1. Larger values correspond to a lower probability of a future payment default. Observations come from the treatment group (for which all payment options were available). For the BNPL selection and approval variables, the sample only consists of first-time customers due to technical reasons. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10%.

Table 7: Differential Effect of BNPL on the Extensive Margin by Credit Score

	Dependent Variable: Conversion (1/0)		
	(1)	(2)	(3)
Credit Score × BNPL Offered	-0.153**	-0.138**	-0.128*
	(0.072)	(0.069)	(0.069)
BNPL Offered (1/0)	0.198***	0.185***	0.179***
	(0.057)	(0.055)	(0.055)
Credit Score (min. 0, max. 1)	0.644***	0.621***	0.592***
	(0.071)	(0.069)	(0.069)
Adj. R^2	0.07	0.11	0.12
Observations	71,066	70,393	70,389
Controls			
Customer		Yes	Yes
County		Yes	–
Fixed Effects			
County			Yes
Date			Yes
Time-of-Day			Yes

Regressions explain the likelihood that a customer's shopping visit at the e-commerce company's website is converted into a purchase. Results are linear probability estimates. The independent variables of interest are the treatment dummy equal to 1 (0) if BNPL was made available (unavailable) for a randomly selected customer, the internal credit score (ranging from 0 to 1, where larger values correspond to lower default likelihoods), and their interaction term. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors (between parentheses). "–" indicates that controls are absorbed by fixed effects.

Appendix

A. Technical Detail on Experimental Randomization

The assignment decision into the different groups in the experiment was randomized and based on customer IDs. During the experiment and any other time, the e-commerce company assigns identifying numbers based on the sequential arrival of customers at the website. For the experiment it retained the second-last and the third-last digits of these IDs, resulting in numbers from 0 to 99 in this digit sequence. For customers with numbers from 50 to 54, BNPL was not offered (the control group). For customers with numbers from 60 to 64, PayPal was not offered (the alternative control group). The treatment group contained the remaining customers visiting check-out during that period. The experimentally unavailable payment option is still visible, but sorted to the bottom, is only shown in less visible gray, and cannot be selected.

B. Experimental Validity

The experiment was conducted by the e-commerce company without any knowledge by the customers. Thus, for our analysis there are is not a statistical problem regarding informed consent, where participants might self-select into an experiment. Due to the e-commerce company's fully randomized treatment assignment mechanism, there is also no problem related to sample selection by the researcher either (where treatment assignment may correlate with observable characteristics of individuals and potential outcomes). Given the large pool of customers, the heterogeneity regarding age and geographic locations, and the short duration of the experiment, we further believe it is realistic to assume that the potential outcome of customer i depends exclusively on the treatment received by customer i and not on the treatment received by another individual j in our sample. In other words, we assume the no-interference or stable unit treatment value assumption to hold (Athey and Imbens, 2017; Rubin, 1978).

Nevertheless, customers might attempt to circumvent the unavailability of BNPL and "try again" by either attempting a guest check-out, opening a new account, or using the account of a family member. In these cases a different customer ID will be applied and the customer has the chance to fall into a different group in the experiment where BNPL is available.

We analyze this by defining duplicates as those observations for which two or more distinct customer IDs match exactly the zip code, fuzzily the street name, and exactly the house number within the time of the experiment. However, we only find duplicates for 3% of all shipping addresses, with no significantly higher share in the control group for which BNPL was not available (we assume that customers which attempt to circumvent the experiment still use the same shipping address).

Nevertheless, we provide two answers. First, we exploit the idea that customers which have used BNPL at the shop before are likely still aware of the availability of this option when it is switched off. These returning customers are thus presumably more likely to attempt circumventing the experiment than first-time customers which have not used this payment option before. In alternative regressions in Table A6 in the Appendix we only analyze such new customers and find equivalent results.

Second, in our analysis in the main body of the paper we retain only the first observation of every address and discard all subsequent appearances. If a customer attempts to circumvent the experiment by using a guest check-out or another person's account, this will be coded as "no conversion", which is the most conservative way we can treat this phenomenon in our setting. This may be too conservative and create an error whenever a customer uses a quest account for any reason other that circumventing the experimental unavailability of BNPL. As a liberal alternative we again retain the very first customer ID for a unique shipping address, but count *any* subsequent conversion with the same address as a conversion of this customer during the respective shopping visit. Equivalent results in Table A4 reinforce our assumption that possible circumventing attempts are not driving our findings.

While we believe internal validity is of no concern in our experimental setting, another problem for randomized controlled trials can be their external validity. In our case it could be that the experiment period happened to be unusual in some way. We are not aware of any such problem. Available upon request are statistics comparing mean values of variables to other periods. It may also be that the e-commerce company is in a niche business and that the customers are somehow special and different from the general population. This is unlikely, since more than 5 Million customers or over

6% of the German population purchased something at the online shop during the 7 years leading up to the experiment (and this number does not include visitors not purchasing anything). This implies a quite popular use, suggesting that results are likely to be relevant for other businesses as well.

Table A1: Variable Definitions

Variable	Definition
Dependent Variables	
Conversion (1/0)	dummy equal to 1 if a check-out website visit converts into a purchase (up to 1 week thereafter)
Conditional Revenue (€)	Euro amount of revenue (net of cancellations) by customer; conditional on a conversion occurring
Unconditional Revenue (€)	Euro amount of revenue (net of cancellations) by customer; unconditional on a conversion occurring
Other Variables of Interest	
BNPL Used (1/0)	dummy equal to 1 if a conversion is paid with BNPL
PayPal Used (1/0)	dummy equal to 1 if a conversion is paid with PayPal
Credit Card Used (1/0)	dummy equal to 1 if a conversion is paid with credit card
Prepayment Used (1/0)	dummy equal to 1 if a conversion is paid with prepayment
Installment Used (1/0)	dummy equal to 1 if a conversion is paid with an installment credit scheme
BNPL Selected (1/0)	dummy equal to 1 if a new customer selects BNPL
PayPal Selected (1/0)	dummy equal to 1 if a new customer selects PayPal
Credit Card Selected (1/0)	dummy equal to 1 if a new customer selects credit card
Prepayment Selected (1/0)	dummy equal to 1 if a new customer selects prepayment
Installment Selected (1/0)	dummy equal to 1 if a new customer selects installment credit
BNPL Application Approved (1/0)	dummy equal to 1 if a customer selecting BNPL is allowed to use BNPL
BNPL Application Rejected (1/0)	dummy equal to 1 if a customer selecting BNPL is not allowed to use BNPL
Credit Score (min. 0, max. 1)	numeric internal score computed from the customer's digital footprint; ranging from 0 to 1; larger values indicate lower payment default probabilities
Payment Default (1/0)	dummy equal to 1 if a converting customer using BNPL defaults on a payment
Covariates	
Initial Cart Balance (€)	Euro value of the shopping cart at the first check-out during a website visit
Returning Customer (1/0)	dummy equal to 1 if the customer converted on the website previously
Age (Years)	age of customer in years (not used in regressions due to many missing values)
Male (1/0)	dummy equal to 1 if the customer selects Mr. as form of address
Device: Desktop (1/0)	dummy equal to 1 if the device used to access the website is a desktop
Device: Phone (1/0)	dummy equal to 1 if the device used to access the website is a phone
Device: Tablet (1/0)	dummy equal to 1 if the device used to access the website is a tablet
Device: Unknown (1/0)	dummy equal to 1 if the device used to access the website is unknown
System: Apple (1/0)	dummy equal to 1 if the operating system accessing the website is Mac OS or iOS
System: Windows (1/0)	dummy equal to 1 if the operating system accessing the website is Windows
System: Android (1/0)	dummy equal to 1 if the operating system accessing the website is Android
System: Other (1/0)	dummy equal to 1 if the operating system accessing the website is any other system
County Population Density	average number of inhabitants per square kilometer in a county in 2017
County Mean Income (€)	average per capital € income of inhabitants in a county in 2017
Time: Morning (1/0)	dummy equal to 1 if check-out time is after 6 am and before 12 pm
Time: Day (1/0)	dummy equal to 1 if check-out time is after 12 pm and before 6 pm
Time: Evening (1/0)	dummy equal to 1 if check-out time is after 6 pm and before 12 am
Time: Night (1/0)	dummy equal to 1 if check-out time is after 12 am and before 6 am

Table A2: Descriptive Statistics

	BNPL Not Available						BNPL Available						
	N (1)	p10 (2)	Median (3)	p90 (4)	SD (5)	Mean (6)	N (7)	p10 (8)	Median (9)	p90 (10)	SD (11)	Mean (12)	p-value (13)
Conversion (1/0)	948	0.000	1.000	1.000	0.454	0.710	74,128	0.000	1.000	1.000	0.399	0.801***	(0.000)
Conditional Revenue (€)	673	49.990	198.00	779.00	333.70	313.60	59,365	53.990	210.00	800.00	367.40	338.10*	(0.058)
Unconditional Revenue (€)	948	0.000	110.00	600.00	314.40	222.40	74,128	0.000	145.00	700.00	350.10	269.60***	(0.000)
BNPL Used (1/0)	673	0.000	0.000	0.000	0.039	0.001	59,365	0.000	1.000	1.000	0.500	0.510***	(0.000)
PayPal Used (1/0)	673	0.000	1.000	1.000	0.441	0.736	59,365	0.000	0.000	1.000	0.488	0.392***	(0.000)
Credit Card Used (1/0)	673	0.000	0.000	1.000	0.327	0.122	59,365	0.000	0.000	0.000	0.235	0.059***	(0.000)
Prepayment Used (1/0)	673	0.000	0.000	1.000	0.339	0.132	59,365	0.000	0.000	0.000	0.172	0.030***	(0.000)
Installment Used (1/0)	673	0.000	0.000	0.000	0.108	0.012	59,365	0.000	0.000	0.000	0.119	0.014	(0.550)
BNPL Selected (1/0)	656	0.000	0.000	0.000	0.154	0.024	50,807	0.000	1.000	1.000	0.500	0.517***	(0.000)
PayPal Selected (1/0)	656	0.000	1.000	1.000	0.491	0.595	50,807	0.000	0.000	1.000	0.475	0.343***	(0.000)
Credit Card Selected (1/0)	656	0.000	0.000	1.000	0.313	0.110	50,807	0.000	0.000	0.000	0.229	0.056***	(0.000)
Prepayment Selected (1/0)	656	0.000	0.000	1.000	0.317	0.113	50,807	0.000	0.000	0.000	0.179	0.033***	(0.000)
Installment Selected (1/0)	656	0.000	0.000	0.000	0.225	0.053	50,807	0.000	0.000	0.000	0.203	0.043	(0.239)
BNPL Approved (1/0)	16	0.000	1.000	1.000	0.447	0.750	26,243	0.000	1.000	1.000	0.339	0.868	(0.276)
Credit Score (min. 0, max. 1)	907	0.422	0.776	0.968	0.205	0.735	70,159	0.430	0.793	0.968	0.210	0.746	(0.122)
Payment Default (1/0)							30,255	0.000	0.000	0.000	0.136	0.019	
Initial Cart Balance (€)	948	55.980	230.00	980.00	448.80	392.90	74,128	57.980	235.00	935.30	441.80	392.00	(0.953)
Returning Customer (1/0)	948	0.000	0.000	1.000	0.462	0.308	74,128	0.000	0.000	1.000	0.464	0.315	(0.663)
Age (Years)	119	29.000	44.000	60.000	11.325	43.941	8,603	29.000	42.000	58.000	11.667	43.445	(0.634)
Male (1/0)	948	0.000	0.000	1.000	0.458	0.300	74,128	0.000	0.000	1.000	0.456	0.295	(0.759)
Device: Desktop (1/0)	948	0.000	0.000	1.000	0.488	0.389	74,128	0.000	0.000	1.000	0.490	0.402	(0.439)
Device: Phone (1/0)	948	0.000	1.000	1.000	0.493	0.584	74,128	0.000	1.000	1.000	0.496	0.563	(0.187)
Device: Tablet (1/0)	948	0.000	0.000	0.000	0.086	0.007	74,128	0.000	0.000	0.000	0.108	0.012	(0.123)
Device: Unknown (1/0)	948	0.000	0.000	0.000	0.137	0.019	74,128	0.000	0.000	0.000	0.152	0.024	(0.303)
System: Apple (1/0)	948	0.000	0.000	1.000	0.494	0.423	74,128	0.000	0.000	1.000	0.497	0.447	(0.141)
System: Windows (1/0)	948	0.000	0.000	1.000	0.440	0.262	74,128	0.000	0.000	1.000	0.436	0.255	(0.662)
System: Android (1/0)	948	0.000	0.000	1.000	0.447	0.275	74,128	0.000	0.000	1.000	0.436	0.256	(0.176)
System: Other (1/0)	948	0.000	0.000	0.000	0.196	0.040	74,128	0.000	0.000	0.000	0.201	0.042	(0.728)
County Population Density	937	107.30	501.80	4,055	1,339	1,155	73,441	106.70	515.00	4,055	1,352	1,216	(0.168)
County Mean Income (€)	937	18,924	21,796	25,251	2,739	22,034	73,441	19,174	21,942	25,135	2,752	22,199*	(0.067)
Time: Morning (1/0)	948	0.000	0.000	1.000	0.444	0.269	74,128	0.000	0.000	1.000	0.449	0.280	(0.447)
Time: Day (1/0)	948	0.000	0.000	1.000	0.481	0.363	74,128	0.000	0.000	1.000	0.481	0.363	(0.988)
Time: Evening (1/0)	948	0.000	0.000	1.000	0.473	0.338	74,128	0.000	0.000	1.000	0.469	0.327	(0.476)
Time: Night (1/0)	948	0.000	0.000	0.000	0.172	0.031	74,128	0.000	0.000	0.000	0.172	0.030	(0.966)

Observations come from the experiment. See Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors.

Table A3: Effects of BNPL Offers on Sales – IV Regressions

Panel A) Dependent Variable: Conversion (1/0)

	(1)	(2)	(3)
BNPL Selected & Approved (1/0)	0.309***	0.270***	0.275***
	(0.050)	(0.046)	(0.046)
Kleibergen-Paap Robust F-Statistic	5,406	1,417	1,284
Observations	75,076	70,393	70,389
Panel B) Dependent Variable: €-Revenue Conditional on a Conversion			
BNPL Selected & Approved (1/0)	71.530*	52.812***	48.083**
	(37.708)	(19.288)	(19.413)
Kleibergen-Paap Robust F-Statistic	5,522	1,041	944
Observations	60,038	57,302	57,301
Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion			
BNPL Selected & Approved (1/0)	160.062***	142.013***	132.489***
	(34.931)	(29.351)	(29.886)
Kleibergen-Paap Robust F-Statistic	5,406	1,417	1,284
Observations	75,076	70,393	70,389
Controls			
Customer		Yes	Yes
County		Yes	–
Fixed Effects			
County			Yes
Date			Yes
Time-of-Day			Yes

Regressions in Panel A explain the likelihood that a customer's shopping visit at the e-commerce company's website is converted into a purchase (the extensive margin). Results are linear probability estimates. In Panel B (C) the dependent variable is total realized revenue by customer conditional (unconditional) of a conversion taking place as a measure of the intensive (total) margin. The independent variable of interest is a dummy that is equal to 1 (0) if BNPL a customer selects BNPL and the e-commerce company approves this BNPL application. We instrument this variable via 2SLS from the dummy variable indicating if BNPL was made available (1) or unavailable (0) for a randomly selected customer (in Table 4 and elsewhere this latter variable is used as the independent variable of interest and called "BNPL Offered (1/0)"). See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors (between parentheses). "–" indicates that controls are absorbed by fixed effects.

Table A4: Effects of BNPL Offers on Sales – Net of Returns

	(1)	(2)	(3)
Panel A) Dependent Variable: Conversion (1/0)			
BNPL Offered (1/0)	0.085***	0.078***	0.072***
	(0.015)	(0.015)	(0.015)
Adj. R^2	0.00	0.09	0.09
Observations	75,076	70,393	70,389
Panel B) Dependent Variable: €-Revenue Conditional on a Conversion			
BNPL Offered (1/0)	26.016*	16.487**	13.806**
	(13.398)	(6.820)	(6.808)
Adj. R^2	0.00	0.84	0.84
Observations	56,860	54,268	54,267
Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion			
BNPL Offered (1/0)	45.758***	42.516***	37.345***
	(10.233)	(8.987)	(9.104)
Adj. R^2	0.00	0.41	0.41
Observations	75,076	70,393	70,389
Controls			
Customer		Yes	Yes
County		Yes	–
Fixed Effects			
County			Yes
Date			Yes
Time-of-Day			Yes

Regressions in Panel A explain the likelihood that a customer's shopping visit at the e-commerce company's website is converted into a purchase (the extensive margin). Results are linear probability estimates. In Panel B (C) the dependent variable is total realized revenue by customer conditional (unconditional) of a conversion taking place as a measure of the intensive (total) margin. All dependent variable are net of items sent back eventually. The independent variable of interest is the treatment dummy equal to 1 (0) if BNPL was made available (unavailable) for a randomly selected customer. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors (between parentheses). "–" indicates that controls are absorbed by fixed effects.

Table A5: Effects of BNPL Offers on Sales – Defining Conversions More Liberally

	(1)	(2)	(3)
Panel A) Dependent Variable: Conversion (1/0)			
BNPL Offered (1/0)	0.063***	0.056***	0.057***
	(0.014)	(0.013)	(0.013)
Adj. R^2	0.00	0.11	0.12
Observations	75,076	70,393	70,389
Panel B) Dependent Variable: €-Revenue Conditional on a Conversion			
BNPL Offered (1/0)	21.673*	15.790**	16.792**
	(12.847)	(6.621)	(6.652)
Adj. R^2	0.00	0.80	0.80
Observations	60,998	58,193	58,191
Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion			
BNPL Offered (1/0)	38.056***	35.254***	34.625***
	(10.673)	(9.201)	(9.313)
Adj. R^2	0.00	0.40	0.40
Observations	75,076	70,393	70,389
Controls			
Customer		Yes	Yes
County		Yes	–
Fixed Effects			
County			Yes
Date			Yes
Time-of-Day			Yes

Regressions in Panel A explain the likelihood that at least one shopping visit by persons from a unique address at the e-commerce company's website is converted into a purchase (the extensive margin). Results are linear probability estimates. In Panel B (C) the dependent variable is total realized revenue by address conditional (unconditional) of a conversion taking place as a measure of the intensive (total) margin. The independent variable of interest is the treatment dummy equal to 1 (0) if BNPL was made available (unavailable) for a randomly selected customer (using the first customer from every unique address appearing in the data). See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors (between parentheses). "–" indicates that controls are absorbed by fixed effects.

Table A6: Effects of BNPL Offers on Sales – 1st Time Customers

	(1)	(2)	(3)
Panel A) Dependent Variable: Conversion (1/0)			
BNPL Offered (1/0)	0.112***	0.106***	0.103***
	(0.018)	(0.017)	(0.017)
Adj. R^2	0.00	0.13	0.14
Observations	51,463	48,383	48,382
Panel B) Dependent Variable: €-Revenue Conditional on a Conversion			
BNPL Offered (1/0)	16.673	9.113*	7.965
	(16.430)	(4.927)	(5.010)
Adj. R^2	-0.00	0.91	0.91
Observations	40,772	39,097	39,097
Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion			
BNPL Offered (1/0)	48.829***	49.585***	43.995***
	(12.659)	(11.001)	(11.222)
Adj. R^2	0.00	0.42	0.42
Observations	51,463	48,383	48,382
Controls			
Customer		Yes	Yes
County		Yes	–
Fixed Effects			
County			Yes
Date			Yes
Time-of-Day			Yes

Regressions in Panel A explain the likelihood that a first-time customer's shopping visit at the e-commerce company's website is converted into a purchase (the extensive margin). Results are linear probability estimates. In Panel B (C) the dependent variable is total realized revenue by customer conditional (unconditional) of a conversion taking place as a measure of the intensive (total) margin. The independent variable of interest is the treatment dummy equal to 1 (0) if BNPL was made available (unavailable) for a randomly selected customer. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors (between parentheses). "–" indicates that controls are absorbed by fixed effects.