THE ECONOMICS OF "BUY NOW, PAY LATER":
A MERCHANT'S PERSPECTIVE

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<u>ABSTRACT</u>

"Buy Now, Pay Later" (BNPL) is a key innovation in consumer payments. It bundles the sale of a product with a subsidized loan, effectively offering lower prices to low-creditworthiness customers. BNPL thereby allows merchants to price-discriminate among customers with different willingness-to-pay. Consistent with a price-discrimination mechanism, we show that BNPL increases sales by 20%, driven by low-creditworthiness customers and products where market power is larger. We find that 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.

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Buy-Now-Pay-Later (BNPL) volumes have increased more than sixfold between 2019-2023, from USD 50 Billion globally in 2019, USD 210 Billion in 2021, to USD 370 Billion in 2023, with further growth expected (Financial Times, 2022; Dikshit et al., 2021; Cornelli et al., 2023). This compares to just over USD 50 Billion in FinTech consumer lending worldwide in 2020 (Ziegler et al. (2021), the latest global report available). Actors from all sides are pouring into this dramatically expanding market – including merchants, dedicated BNPL service providers, 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 by analyzing the economics of BNPL from a merchant's perspective. We develop a simple model to guide our empirical analysis. We argue that BNPL bundles the sale of a product with a subsidized loan, effectively offering lower prices to low-creditworthiness customers. BNPL thereby allows merchants to price-discriminate among customers with different willingness-to-pay. Price-discrimination via BNPL is feasible if the merchant has some market power and if there is positive correlation between creditworthiness and willingness-to-pay. Our model predicts that BNPL increases sales, particularly at the lower end of the creditworthiness spectrum; it predicts that BNPL is offered more when market power is high; and it predicts that BNPL is offered more in an e-commerce setting than in-store (due to both a screening channel as well as due to an operational cost channel).

We access micro data from a German e-commerce company selling furniture, using both a randomized control trial where BNPL is made available for some randomly selected customers, as well as observational data on the provision of BNPL by the merchant. The BNPL payment option allows for a single payment delay, which resembles

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[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.

the popular "pay in 30" (days) BNPL product.[2]

We provide several empirical findings in line with our interpretation of BNPL being a tool for price discrimination. First, we analyze whether BNPL availability affects sales. We confirm that making available BNPL increase sales by 20%. Effects at the extensive margin account for 60-70% of the total margin (the remainder 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 the merchant's lending function. In line with the model's predictions, we find that customers with high credit scores and customers interested in products with high profit margins are more likely to be approved. While the merchant offers BNPL on its online platform, it is not available in its physical stores due to technical difficulties and costs.

Finally, we provide a merchant profitability analysis of offering BNPL, taking into account increases in sales, losses from providing a zero-interest loan, and substitution effects from customers switching from cheaper payment options to 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. We find that BNPL significantly increases merchant profitability. Interestingly, the effect of BNPL on merchant profitability follows an inverse u-shape: offering BNPL is most profitable in the middle of the creditworthiness spectrum and less at the extreme ends: for high-creditworthiness customers, BNPL has little effect on sales, but is also cheap to offer because default rates are low. For low-creditworthiness customers, the merchant offers BNPL up to the point where marginal costs (driven mainly from defaults) are equal to marginal gains (driven by additional sales and the profit margin on the respective products).

Our empirical analysis is limited to data from a single e-commerce firm, raising questions about external validity. We expect our mechanism to be relevant when it is primarily the merchant and not the customer who pays for BNPL. The fact that

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[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.

the merchant subsidizes the zero-interest loan is pivotal for the price discrimination mechanism that we describe. We use this intuition to discuss two settings: First, our mechanism is not generally applicable to purchases made via credit card. While purchases made via credit card involve short-term financing as well, the interest on credit card balances is paid by customers according to their creditworthiness, and it is not subsidized by merchants. Second, our mechanism is generally applicable to external BNPL providers, such as Klarna and Affirm. Using data and quotes from annual reports, we verify that short-term loans provided by external BNPL providers are typically subsidized by merchants.

Our paper contributes to the burgeoning literature on BNPL. The literature so far has taken a consumer perspective, documenting that BNPL increases spending and showing that BNPL is used more by households with a lower creditworthiness. Di Maggio et al. (2022) and Bian et al. (2023) document that BNPL boosts consumer spending, while deHaan et al. (2024) document that the additional spending can facilitate overborrowing. Both Bian et al. (2023) and Guttman-Kenney et al. (2023) provide evidence that BNPL users are liquidity-constrained and have below-average creditworthiness, while Boshoff et al. (2022) document that BNPL users typically have to refinance BNPL debt using credit cards. We contribute by taking a merchant's perspective: BNPL facilitates price-discrimination, effectively offering lower prices to households with a lower creditworthiness. Our paper thereby connects the provision of BNPL to the literature on bundling in general (Stigler, 1963; Adams and Yellen, 1976; McAfee et al., 1989), as well as to studies describing vendor financing as a tool for price discrimination (Brennan et al., 1988; Bertola et al., 2005; Bouvard et al., 2022).

More generally, we contribute to the literature on economics of payments (Baxter (1983), Rochet and Tirole (2002), Shy and Wang (2011), Wang (2023)) and the use of payment methods (Alvarez and Argente, 2022; Koulayev et al., 2016; Quinn and Roberds, 2008; Agarwal et al., 2019; Bounie and Camara, 2020; Brown et al., 2022; Berg et al., 2024). We document that BNPL effectively provides lower prices to low-creditworthiness customers. This mechanisms explains both the appeal of BNPL to merchants (extraction of consumer surplus) as well as the appeal of BNPL to low-creditworthiness customers (benefit of zero-interest loan). Our mechanims also sheds

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light on the distributional consequences of BNPL, benefitting low-creditworthiness customers in particular, which are opposite to the pattern observed for credit cards (Schuh et al., 2010; Felt et al., 2020).

BNPL is a form of FinTech lending. FinTech lending has been associated with the use of alternative data (see, for example Berg et al., 2020; Agarwal et al., 2020) and with lower operational costs (see, for example Buchak et al., 2018; Fuster et al., 2019). Our simple model suggests that BNPL is facilitated by both channels and should be offered more in an e-commerce setting than in-store. This prediction is consistent with the fact that the merchant from our study offers BNPL on its online platform, but not in its physical stores.

More generally, our paper speaks to the competition between FinTech lenders and traditional banks (Chen et al., 2019; De Roure et al., 2022; Tang, 2019). Compared to consumer loans and credit cards, BNPL allows for price discrimination via subsidized lending. The availability of BNPL can be tailored to specific products, allowing the merchant to improve profits by extracting a larger share of the consumer surplus. Parlour et al. (2022) model adverse effects on bank lending caused by a loss of information that is derived from observing payments flows. Ghosh et al. (2021) reveal informational synergies between cashless payments and lending empirically. Mester et al. (2007), Norden and Weber (2010), and Puri et al. (2017) show that bank accounts and the associated inflows and outflows are informative of borrower quality. The rise of BNPL redirects the information from payment flows to new intermediaries and away from traditional lenders, with a potential to impact traditional intermediaries.

In the rest of the paper we discuss our conceptual motivation and present a theoretical model (Section 1), provide some background on BNPL and our setting (Section 2), analyze empirically how BNPL affects sales (Section 3), what drives BNPL application approval decisions (Section 4), how costs and overall economics of merchants are affected (Section 5), discuss external validity (Section 6), and conclude (Section 7).

1. CONCEPTUAL MOTIVATION

In this section, we argue that bundling a product together with a zero-interest loan effectively allows a merchant to price-discriminate among customers with different

willingness-to-pay (WTP). The basic idea behind bundling has been explored in seminal papers (Stigler (1963), Adams and Yellen (1976), and McAfee et al. (1989)): bundling can improve profits when merchants have market power, and when the WTP is negatively correlated across products. Assume two products P1 and P2, with a WTP of customer A of $1 (P1) and $2 (P2), and the opposite WTP by customer B ($2 for P1, $1 for P2). A merchant that bundles both products at a price of $3 can extract the entire consumer surplus, even if first-degree price discrimination is not possible. In the setting of BNPL, the two products are the actual product (e.g., a piece of furniture) and a loan. If customers that value a loan highly have a lower willingness-to-pay for the actual product, bundling can increase merchants' profits.

The key assumption is that creditworthiness is negatively correlated with WTP: customers with a poor creditworthiness are plausibly willing to pay less for the same product than customers with a good creditworthiness. Offering a zero-interest rate loan to all customers implies a larger subsidy for poor-creditworthiness customers and thus serves as a mechanism to effectively price-discriminate between high- and low-creditworthiness customers.

The fact that the merchant subsidizes the zero-interest rate loan sets BNPL apart from other consumer loan products such as credit cards. We also argue further below that this mechanism interacts with technology, explaining why it has gained traction over the last decade across the world.

A. Price-discrimination via BNPL: A simple example

We start with a simple example to highlight the mechanism at play: Assume there are two customers, a high-income customer with a high willingness-to-pay (WTP) of $w = 100$ and a low-income customer with a low WTP of $w = 95$. The merchant's marginal costs are $c = 92$. If the merchant is unable to price-discriminate, she can sell either at a price of $P = 100$ or at a price of $P = 95$, making a profit of

$$\pi(P = 100) = 1 \cdot (100 - 92) = 8 \tag{1}$$

$$\pi(P = 95) = 2 \cdot (95 - 92) = 6. \tag{2}$$

Thus, under these assumptions, the merchant will sell at a high price and only the customers with a high WTP will buy in equilibrium.

Now further assume the merchant can offer a bundle consisting of the product and a zero-interest rate loan ("BNPL"). We assume that the low-income customer values a zero-interest loan more than the high-income customer. To make this explicit, we assume the high-income customer has a low probability of default ($p = 0\%$) and the low-income customer has a high probability of default ($p = 5\%$), and customers' expected payment for a bundle of a product with a price P and a zero-interest loan is equal to $P \cdot (1 - p)$. In this case, the merchant can improve profitability by bundling the product at a price of $P = 100$ with a zero-interest loan. The effective price for the low-WTP customers is $P = 100 \cdot (1 - p) = 95$ which is exactly equal to her WTP. The effective price for the high-WTP customer is $P = 100$ (as she never defaults), which is also exactly equal to her WTP. The profit to the merchant from selling the bundle (product + BNPL) is equal to

$$\pi^{BNPL}(P = 100) = \underbrace{(100 \cdot (1 - 0\%) - 92)}_{\substack{\text{profit from} \\ \text{high-income customer}}} + \underbrace{(100 \cdot (1 - 5\%) - 92)}_{\substack{\text{profit from} \\ \text{low-income customer}}} = 8 + 3 = 11 \qquad (3)$$

The key point of our model is that the effective price (price of the product minus subsidy from the zero-interest rate loan) is lower for low-income customers. We provide a general model in Appendix A1. The model closely follows the trade credit model by Brennan et al. (1988) which shows that – even in the presence of a perfectly competitive banking industry – it can be optimal for firms with market power to engage in trade credit financing. Notes:

- Negative correlation between WTP and creditworthiness: Even if both customers choose BNPL, the bundle (product + BNPL) price-discriminates because the high-income customer has a lower probability of default than the low-income customer. The key assumption that allows price discrimination via BNPL is the existence of a negative correlation between income and WTP. Empirical research often finds a lower price-sensitivity for high-income customers, see Nevo (2001) for cereals, Nakamura and Zerom (2010) for coffee, Grieco et al. (2024) for auto-

mobiles and Sangani (2023) using a wide range of consumer products from the NielsonIQ Retail Scanner data set.

- Observability of creditworthiness: For BNPL to improve merchant profits, the merchant does not need to be able to observe creditworthiness. However, if the default probability of the low-income customer is too high (above $p = 8\%$ in the example above), BNPL no longer increases merchant profits. Thus, having access to an estimate of the probability of default is beneficial to the merchant as we discuss in Appendix A1. The existence of digital footprints significantly facilitates the prediction of default probabilities in the e-commerce sphere (Berg et al., 2020).

- Product margin and BNPL: The merchant needs to have market power to allow for price discrimination. In a fully competitive market, prices are equal to marginal costs and the merchant does not earn any surplus. Our model predicts that BNPL will be offered more when the merchant has market power, i.e., when the merchant can set prices above marginal costs.

- Cross-subsidization: When selling to the low-income customer, the merchant makes a profit on the product ($100 - 92 = 8$) and a loss on the zero-interest loan ($5 \cdot \%100 = 5$). Thus, even with a perfectly competitive consumer loan market, it is optimal for the merchant to provide a loan directly to the customer.

- Robin Hood effect: The low-income customer pays a lower effective price than the high-income customer (because she values the zero-interest rate loan more). This effect is the opposite to the Reverse Robin Hood effect observed for credit card payments (Schuh et al., 2010; Felt et al., 2020).

- Perfect price discrimination: In the example above, the merchant is able to perfectly price discriminate, charging the WTP to both the high-income customer ($P = 100$, zero value of the loan) and to the low-income customer ($P = 100$, benefit of 5 from the zero-interest rate loan). Thus, the merchant captures the entire consumer surplus. If the probability of default of the low-income customer is smaller than $p = 5\%$, the merchant is not able to capture the entire surplus from

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the high-income customer (because the merchant would need to charge a price below 100 to entice the low-income customer to buy); if the probability of default is higher than $p = 5\%$, the merchant cannot capture the entire surplus from the low-income customer.[3]

B. Price-discrimination via BNPL: Effect on sales

The example in Section 1.A and our model in Appendix A1 predicts that BNPL leads to an increase in sales volume. This prediction holds both in equilibrium (where BNPL increases prices and sales volumes) and off-equilibrium (randomization of BNPL while holding the price constant).

More specifically, the model allows for two theoretical limit cases: in the first case, the merchant – absent BNPL – finds it optimal to sell at a high price to high-income customers only (this is the case from our the example in Section 1.A). In this case, BNPL allows the firm to attract additional low-income customers by offering low-income customers a price subsidy via a zero-interest loan. In the other case, the merchant – absent BNPL – finds it optimal to sell at a low price to all customers. In this case, BNPL allows the merchant to effectively raise prices only for high-income customers. This is because the merchant bundles a higher price with a zero-interest rate loan that is worthless to high-income customers but valuable for low-income customers. Empirical observations are likely to be within these two theoretical limit cases, suggesting that BNPL increases both prices and sales in practice.

In Section 3, we empirically analyze the effect of BNPL on sales. In our empirical setting we randomize BNPL while holding prices constant. We expect an increase in sales, and the random experiment will inform us about the economic magnitude of the effect.

C. Price-discrimination via BNPL: When is BNPL offered?

The example in Section 1.A and our model in Appendix A1 predicts that BNPL provision varies across customers, across products, and across technologies. First, we predict that BNPL is offered more to high-creditworthiness customers. This prediction is

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[3]In the latter case, the merchant could charge an interest rate on the BNPL loan to fully capture the consumer surplus; in the first case, the merchant would not be able to perfectly price-discriminate.

intuitive: if default rates of customers are very high, the loss on the zero-interest rate loan is too high to compensate for the profit from selling the product. Second, we predict that BNPL is offered more when a product's profit margin is higher, i.e., when the merchant has more market power. Without market power, prices equal marginal costs and there is no room for any price discrimination across customers. A high market power enables merchants to price-discriminate: If the merchant makes a large profit from selling the product, the merchant can afford to make a large loss on the zero-interest rate loan, and the merchant will find it optimal to offer this bundle if it entices low-income customers to buy in the first place. Third, BNPL interacts with technology. We expect BNPL to be offered less in-store than in an e-commerce setting, both because of a screening channel (predicting defaults with digital footprints is easier in an e-commerce setting) as well as an operational costs channel (fully automated process).

We test the first two predictions (BNPL offered more for high-creditworthiness customers, BNPL offered more for high-margin products) using observational data in Section 4.A - 4.D. We provide anecdotal within-firm evidence for the third prediction in Section 4.E.

2. Background

A. BNPL in General

BNPL is a type 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 in-house or in cooperation with an external service provider (in which case the merchant usually pays for the service and is involved in the lending decision). BNPL is most visible in the 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. The former scheme is very popular in continental Europe while the latter dominates the Anglo-American space.

B. BNPL IN OUR 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.

The e-commerce company offers BNPL similar to the "pay in 30 days" scheme. It 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 are on average (value weighted) equal to 25.8 days, adding up to a total formal average loan duration of 40 days. If the customer does not pay on time, a reminder is sent via email two days after the payment is due (i.e. a 2 days grace period). 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. 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, the claim is forwarded to a debt collection agency and we define these claims as being in default. Around 2% of all BNPL transactions default, depending on the period. The average BNPL transaction volume is € 300-400 (see Table 1 and Table A2 – to be discussed in more detail below), in line with "pay in 4" BNPL loans offered in other markets (Dikshit et al., 2021).

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 and shopping cart characteristics (like the shipping address or the cart's gross profit margin). We use the internal credit score in our two empirical analyses (Sections 3 and 4). It 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.[4] Table A1 in the Appendix contains a list and description of all variables used. Summary statistics for the two main estimation samples of this study are in Tables A2 and A3. Continuous variables that are not in percent are winsorized at 1% and 99%.

In Figure 1 we plot shares of payment options used when all options are 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%).[5]

3. Does BNPL Affect Sales?

A. Setting

To analyze the effects of BNPL on sales, we utilize an AB-test or randomized controlled trial conducted by the e-commerce company in early 2022, which we refer to as the "experiment" in the remainder of the paper.[6] BNPL was made either available or unavailable for customers on a random basis without regards to any customer or shopping 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

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

[5]Note that customers can pay via card directly or indirectly via PayPal. We do not observe if a customer uses a credit card or a bank wire transfer when paying via PayPal. The category "credit card" includes all payment cards including credit and debit cards. We are not able to differentiate between these. For simplicity we call the entire category "credit card" in this paper and treat all payment cards as if they were credit cards throughout. Also note that PayPal is a very prominent payment option throughout Germany (not only limited to our e-commerce firm). 30% of e-commerce purchases are made via PayPal in this market (Handelsblatt, 2023), which is not far from our number. A reason why credit cards are not as popular in Germany is that they typically do not offer "point"-type benefits as in the U.S.

[6]The randomized controlled trial was conducted for the period from February 23rd 2022 until March 3rd 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 conduct an RCT was to gain insights of the cost-benefit of offering BNPL.

group (which we call control group) BNPL is not shown as a selectable option for customers (948 distinct customers). Once a customer is in one group, she will stay in it irrespectively of whether the customer returns another day after converting or after leaving the website without a conversion. In Table 1 we compare selected descriptive statistics in the two groups of interest. It shows that treatment and control group are similar along almost all observable characteristics, suggesting that randomization was not impeded.

In Table 2 we compare characteristics of customers that either choose BNPL to those that select any other payment option.[7] Customers choosing BNPL have somewhat lower credit scores (corresponding to higher 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. In Appendix Table A4, we confirm this with a more formal regression analysis.

In Panel A, Figure 2 we explore the relationship between credit scores and preference for BNPL in more detail. We find a u-shaped relationship, with both customers with very low credit scores and customers with very high credit scores being more likely to choose BNPL than customers in the middle of the creditworthiness spectrum. Possible explanations are financial constraints at the low and financial literacy at the high end (we come back to this in more detail later on in this section).

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 exploits 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; we analyze the lending function in the next section).[8]

If an application is approved, the customer can purchase items using BNPL. If it

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[7]We focus on choices for new, first-time, customers due to a technical limitation: in cases where customers with prior purchases 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.

[8]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.

is rejected, there will be a message reading that the payment method is not available (it cannot be selected again). 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 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 likely to participate in the largest consumer finance markets. The advantage is that we can analyze the introduction of a main-stream payment and financing scheme as a whole, which commonly excludes some extreme segment of the market. The Appendix discusses the technical details of the randomization.

A main explanatory variable of interest in our analysis of sales is the conversion, coded as a dummy variable that is one if a check-out website visit converts into a pur-chase. Since it is fairly common for customers to interrupt and resume shopping ses-sions on the website, we allow for a customer to complete a conversion not just imme-diately, 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 mea-sure the total revenue by customer during that same period (in €). 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.[9]

B. ANALYSIS

To understand effects on sales, we first analyze the experiment with a simple mean comparison based on treatment status W_i (1: BNPL is available; 0: BNPL is not avail-

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[9]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.

able) of a customer i via

$$Y_i = \alpha + \beta W_i + \epsilon_i. \tag{4}$$

In our baseline estimations Y_i is a dummy variable indicating a conversion to capture the extensive margin of sales. Analyzing the intensive and total margins of sales we use 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 above); 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 observation counts of several hundreds for the smallest of our groups, the estimator from Equation 4 will be unbiased (Athey and Imbens, 2017). However, to increase statistical power and obtain more precise estimates we also run regressions with covariates (again, we believe covariates are not required to address any other problem, since randomization was not compromised) via equation

$$Y_i = \alpha + \beta W_i + \delta X_i + \epsilon_i. \tag{5}$$

Covariates X_i include the internal credit score, amount of the cart value (in €) at the first check-out of the shopping visit, county level per capita GDP, county population density, and dummy variables for whether the 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

$$Y_i = \alpha + \beta W_i + \delta X_i + \gamma_c + \theta_d + \sigma_t + \epsilon_i. \tag{6}$$

Equations (4)-(6) 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 (or the effect of introducing a scheme as a whole). As a robustness check, we report IV regressions in Table A5 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).

C. Results

Exploring the effect of BNPL on sales we start analyzing the extensive margin as our baseline, explaining conversions (purchasing something or nothing). 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 3. Column 1 represents the simple mean comparison (as in Equation 4). We add controls in Column 2 (Equation 5) and controls and fixed effects in Column 3 (Equation 6).

In Panel A, Table 3 we analyze the extensive margin of sales using the conversion dummy as the dependent variable. The regression coefficient in Column 1, Panel A suggests 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 (or 13%) – which is 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 cus-

tomer purchases items worth € 314 (Table A2). Offering BNPL increases the amount *converting customers* spend (conditional on the company's lending function) by around € 13.7-24.5 (Table 3, Panel B), or 4-8%.

The sum of the extensive and intensive margins of sales is the revenue per customer unconditional on a conversion taking place (on average this is € 222). Results in Table 3, Panel C suggest offering BNPL increases this amount by € 40.8-47.2 or 18-21% (statistical significance is high). This is consistent with the implication from our model that BNPL increases sales. A smaller fraction of this effect is driven by the intensive margin. Since only 71% of customers convert, the coefficients in Panel B fall to € 9.7-17.4 or a 4-8% increase in unconditional revenue. The extensive margin boosts revenue by 13-14%, dominating the overall effect by a factor of 2-3.

It is important to note that 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 introduces a BNPL scheme to its customers? This is not the same as offering BNPL to every single possible customer, as approximately 13% are rejected. The local average treatment effect (LATE) of offering BNPL to all customers with a sufficient creditworthiness is therefore slightly higher (by a factor of 100/(1-13%) = 1.15).

Prior literature provides some context for the magnitude of a 20% sales increase in our analysis. Agarwal et al. (2018) find that a $1 increase in credit card limits raises spending by 58 cents at the low end of the credit score spectrum over a period of 12 months, while there is no significant effect on the higher end. Our estimate of 20% is thus well within this (large) range. For used subprime car dealerships, Adams et al. (2009) report that a $100 change in down payment requirements, equivalent to a $100 increase in the car loan, implies a 9% change in demand. Given an average used car price of $11.000 in their sample, a $100 increase in the car loan thus increases sales by more than $100, suggesting quite significant financial constraints.

Note that in our setting, in contrast to both Agarwal et al. (2018) and Adams et al. (2009), loans have an interest rate of 0%, implying both a credit access channel (BNPL provides credit access to financially constrained customers) as well as an interest savings channel (even if customers have access to credit, BNPL offers a subsidized credit

at a zero interest rate). On the other hand, BNPL loans are very short-term and can only be used for purchases at this e-commerce shop. Overall, the 20% increase in sales in our analysis does not seem implausibly high in light of results from the prior literature.

D. Robustness

Randomization of availability of PayPal:
There might be the concern that our results can be expected for *any* popular payment method. We address this with a placebo test, where we re-estimate our baseline regressions using another experiment where availability of PayPal was varied (PayPal did not yet have established BNPL services). Results in Appendix A4 show that there is no comparable effect on sales.

Prior knowledge on BNPL availability:
Another problem could occur if prior (differential) knowledge about BNPL generated a bias: if it was advertised upfront, more website traffic may be directed to check-out, average inclinations to convert may fall, and customers may respond strategically to self-control behavioral biases. This is of little concern in our setting, as customers view payment options upon reaching the check-out site for the very first time in a regular shopping journey and are unlikely to adjust their decision to proceed to check-out accordingly. Our randomized availability of BNPL is at check-out – not before when customers browse product pages. There is no variation in prior knowledge about payment option between our control and treatment groups. To ensure that our results are not driven by returning customers – who might have used BNPL before at the e-commerce firm and may remember this – we exclude all returning customers in Table A7 in the Appendix. Reassuringly, this exercise shows that baseline results are little affected (the extensive and total margins are more robust than at the intensive margin).

IV results and variable definitions:
We also include some robustness checks. IV-results are in Appendix Table A5. In Appendix Table A8 we show that results are similar when we define all dependent

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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 the Appendix for more technical detail). In Appendix Table A9 we use a more liberal definition, counting such visits by other customers from the same address towards conversions and revenue. Results are similar.

E. Heterogeneity

Our model predicts that BNPL has a greater effect on sales for customers with a lower creditworthiness (because the subsidy from the 0% loan is larger for these customers).

We regress the conversion dummy against the internal score, the BNPL availability dummy, and their interaction term. Results are in Table 4. Without BNPL being offered, customers with a higher score (that is, a better creditworthiness) are more likely to convert (as indicated by the positive coefficient on credit score). Making BNPL available for customers with a lower credit score (that is, a lower creditworthiness) has a significantly larger effect on the conversion likelihood than for customers with a high credit score (the coefficient from the BNPL × Credit Score interaction term is negative and significant). High default risk customers with scores at the 10th percentile are two to three times as responsive as low default risk customers with scores at the 90th percentile.[10] BNPL increases the conversion rate for customers at the 10th percentile by over 13 percentage points (conditional on rejections by the lending function). For customers at the 90th percentile, the effect is less than a 5 percentage point increase. The positive effect of BNPL on sales at the merchants' online shop is thus driven by BNPL offers to customers at the lower credit score spectrum.

The specification in Table 4 assumes that the credit score affects conversion rates from offering BNPL in a monotonic form. Panel B of Figure 2 plots the effect nonparametrically by plotting the coefficients for the interaction term between BNPL availability and credit score quintile. The results suggest that the effect of BNPL on the conversion likelihood indeed falls monotonically in the credit score quintile.

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[10]The calculation behind this statement is based on the coefficients from Column 1, Table 4 $(0.198 - 0.153 * 0.422)/(0.198 - 0.153 * 0.968) = 2.67$. See A2 for score values at the percentiles.

Contrasting this result with the U-shaped relationship in Panel A of Figure 2 provides an interesting finding: customers with high credit scores use BNPL frequently, but switch to other forms of payments when BNPL is not available. In contrast, low-credit-score customers use BNPL frequently, but do not switch to other forms of payment when BNPL is not available.

4. What Drives BNPL Approvals?

In this section, we analyze if BNPL is offered more to low-risk customers and if it is offered more when margins are high, i.e., when the merchant has higher market power.

A. Setting

The e-commerce company decides for each individual application whether to approve or reject it. While we have no direct access to the lending function's algorithm, we do observe the outcome (BNPL approved or rejected), the customers' credit scores, the products profit margins, as well as other customer and product item characteristics.

In the last section, we accessed a data set where BNPL was randomly made available in order to understand the effect of BNPL on sales. We now access a much larger sample preceding the experiment in order to understand *when* BNPL is made available by the e-commerce firm: the universe of all 594,859 BNPL applications in the year 2021. We also access additional variables containing information on BNPL loan approvals and shopping cart level gross profit margins. Note that the lending function is the same as in the control group in our analysis of sales: the merchant approves 87% of BNPL applications on average and rejects slightly less than 13% of BNPL applications. We provide variable definitions in Appendix Table A1 and summary statistics for this sample in Appendix Table A3.

B. Analysis

We explain the likelihood that the merchant approves a BNPL application by customer i at time t in a multivariate regression. The dependent variable is an approval dummy. The independent variables of interest are a customer's credit score – discussed in the prior section already – and the cart level gross profit margin. The cart level gross

profit margin is the difference between the cart value (before value added tax) and the purchase cost of the item, scaled by the cart value (before value added tax). It has a mean of 43.7% and varies both between different products as well as within product over time, with a p10-p90 range of [16.7%,64.3%], see Appendix Table A3.

We estimate equation

$$Approve_{i,t} = \alpha + \beta_1 Score_{i,t} + \beta_2 Gross\ Margin_{i,t} + \epsilon_{i,t}. \tag{7}$$

Greater tendencies to offer BNPL to low-risk customers and when margins are high hold unconditionally in our model. We therefore initially present results without further controls and fixed effects. To ensure robustness, we also report specifications where we add customer and county characteristics as well as customer and item category fixed effects. Item categories are 15 broad categories (such as "bath room"), where each product is assigned to exactly one item category. We cluster standard errors two-way by county and item category.

C. Results

Estimation results for versions of Equation 7 are in Table 5. As expected, the credit score is positively related to BNPL approvals. The merchant becomes 29-32 percentage points more likely to approve BNPL applications when a customers' credit score moves from the bottom to the top decile (see Appendix Table A3 for the distribution of the credit score). The substantial coefficient magnitude is stable across specifications (statistical significance is high). Note that item category plus customer fixed effects in Column 4 decrease the observation count substantially by more than half. For comparability and consistency with the preceding analysis of sales (especially Table 3) we do not enforce a harmonized estimation sample across all regressions of Table 5.

In the same table we also analyze if approvals depend on the gross profit margin of the shopping cart. We find that higher margins are associated with a higher approval rate. The coefficient in tightest specification, Column (4), suggests that when the gross profit margin of the shopping cart shifts from the bottom to the top decile (from 17 to 64%), the approval rate increases by 5%. Relative to the average approval rate in the bottom decile (which is 54%), this constitutes more than an 8% increase.

D. Robustness

Appendix Table A11 documents that coefficients hardly change when we analyze first time customers only. Likewise, results are equivalent when we swap the continuous credit score variable for a bottom credit score quintile dummy in Appendix Table A12.

One concern is that margins and credit score are correlated. For example, customers with higher default risk might happen to also be interested in higher margin products, making profit margins just another proxy for default risk. We test this with regressions in Panel A, Appendix Table A13, where the dependent variable is the product cart level profit margin. The independent variable is our credit score. Overall, the results suggest that credit score and margin have a low correlation. The coefficient is always statistically insignificant throughout and the economic magnitude is small – implying at most a 1.8 percentage point higher profit margin when a customer moves from the bottom to the top decile of the credit score.

Another concern is that customers with interest in BNPL are interested in higher margin products. We explore this by swapping the independent variable in Panel B, Table A13 for a dummy for a customer selecting BNPL. The coefficient is *negative* throughout and economically small – the profit margin of BNPL selectors is at 1-1.7 percentage points lower. This suggests that customers interested in BNPL are if anything slightly *less* interested in higher margin products. This makes intuitive sense: customers with a low creditworthiness are plausibly more interested in cheaper run-of-the-mill products, which tend to have lower margins.

E. BNPL in the Brick and Mortar Space?

We now provide some anecdotal evidence for the idea that BNPL is offered less in-store than in an e-commerce setting. Interestingly, the merchant also operates physical stores. While other payment options are available in this space, BNPL is not offered for any customer or product. Thus, holding the merchant fixed, we observe drastic differences in BNPL offering (87% are offered BNPL in the e-commerce setting, 0% in the in-store setting). As a caveat, this information is from only one single merchant.

To better understand the rationale, we have talked to company representatives. According to their information, the unavailability of BNPL in-store is due to technical

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complexities and associated costs, as well as more limited credit scoring abilities. This is exactly in line with our expectation that lower costs and more powerful technological capability enables merchants to offer BNPL more easily and economically online. On the merchant's website, BNPL is offered in a highly automated way. This includes not only the algorithmic approval via a lending function. It also extends to the entire processing and management of BNPL loans thereafter. If a customer does not pay in the required timeframe, payment reminders will be sent out automatically via email. In cases of defaults when customers fail to pay 2 weeks after the third reminder, recovery attempts are completely outsourced to a third party debt collection agency. Such steps are processed without employee involvement or significant other incremental organizational effort.

5. Merchant profitability analysis

In the two preceding sections we tested predictions from our model, documenting that BNPL increases sales and showing that it is offered more for customers with a better creditworthiness and for products where the merchant has more market power. In this section, we quantify both costs and benefits to the merchant, allowing us to assess the profitability of BNPL from a merchant's perspective. A feature of our setting is that the merchant offers BNPL entirely in-house. This means we observe both the benefits and costs for the merchant, allowing us to assess merchant profitability.

A. Costs of BNPL

Variable costs of BNPL:
The key variable costs stem from defaults on BNPL loans as well as from the cost of capital of financing BNPL loans. To assess these costs we again access data from 2021. In this section we work with a matched subsample of the data from the preceding analysis of loan approval decisions.

The default rate on BNPL loans was 2.46% in 2021 (see Appendix Table A3). Default is defined as non-payment 14 days after the third payment reminder, which is approximately 56 days after payment was initially due. At this point, the e-commerce firm transfers the claim to a debt collection agency. Ultimate losses are roughly half of

this value (1.17%), because the debt collection agency is able to collect payments from a considerable fraction of customers. We further show in Figure 3 that defaults increase dramatically at the low end. For the worst 5% of credit scores, 8.6% of revenue ends up in default. For this group the share of unrecovered in total default revenue increases to 67% (implying 5.8% of revenue is lost).

To assess capital costs we need (i) the maturity of the loans, (ii) an estimate of the cost of capital for the merchant. The value weighted average delivery time is over 26 days and customers pay on average 22 days upon delivery (also value weighted), adding up to 48 days of maturity. We assume a 7% p.a. cost of capital for the merchant, implying an 0.89% capital costs for the 48 days period of the BNPL loans. Since the lending process is highly automated in loan approval and management, we are not aware of any other significant variable unit costs of providing BNPL in our setting. Taken together, unrecovered defaults and capital costs add up to 2.1% variable costs (0.89%+1.17%) of providing BNPL.

Set up costs of BNPL:

In addition to variable costs, the merchant incurred set up costs as well. These costs can be split into two parts: operational costs (personnel costs and costs for building the IT infrastructure) and costs from training a credit scoring model, i.e., higher default rates before enough data for a proper model is collected. We focus on the latter part, mainly driven by data availability, but also because the e-commerce firm indicated they were their biggest concern.

Our analysis suggests that the e-commerce firm suffered a 7.16% default rate during the training period, which is 6.15 PP higher than the default rate after the model was trained (7.16% in the training period versus 1.01% after the model is used for screening). This loss is equal to approximately 0.1% of aggregate BNPL volume in the eight years since BNPL introduction. While not negligible, these numbers are still small compared to the benefits from offering BNPL. We discuss the set up costs in more detail in Section A5.

B. Costs of other Payment Options

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

According to information form the merchant, costs for using the second most popular option, PayPal, amount to 1%. This is lower than the standard terms described on the company's website, but it is common that larger online shops get better conditions.

For the third largest category, credit cards (used for 6.5% of total sales), fees are on average 1.33% (average in Germany, taken from data from Bundesbank, see Cabinakova et al., 2019). The two least popular payment options are installment payment and prepayment (which costs of 2.8% and 0%).

We summarize all variable operational costs in Column 1, Table 6. Taken together, the table shows that the value weighted cost of all alternatives to BNPL amounts to 0.9% on average, which is substantially less than the 2.1% costs of BNPL.

C. Substitution Effects and Displacement Costs

BNPL induces some customers to purchase who would have otherwise not purchased at all, but it also induces some customers to use BNPL who would have otherwise bought using cheaper payment methods. Table 6 compares the use of payment methods when BNPL is not available (in the control group of the RCT) to usage when it is available (in the treatment group). Results are in Columns 2 and 3, Table 6.[11]

The exercise reveals that that availability of BNPL decreases use of PayPal (-24PP), prepayment (-10.6PP), and credit card payments (-5.1PP). Combining the substitution effects with variable payment costs of all payment options reveals that the merchant pays on average 93 cents on €100 sales when BNPL is not available (Column 4, Table 6). Introducing BNPL (Column 5) raises variable transaction costs for these €100 that would have been spent anyways (also if BNPL was not offered) by 54 cents to €1.47 (or by 0.5% of sales to 1.5%).

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[11]As an alternative with similar implications we analyze selections (not actual use) of payment options in Appendix Table A15.

D. Merchant profitability analysis

We assess the economics of BNPL by focussing on the two most important factors. The first is the profit on additional sales generated by BNPL. It is the product of the additional revenue from offering BNPL, and the difference between the net margin and the costs of offering BNPL for these sales. The second are the additional costs for sales that would have occurred anyways, but are now paid with more expensive BNPL. More formally,

$$\Pi_{BNPL} = \Delta R \cdot (m - c_{BNPL}) - R_{displaced} \cdot (c_{BNPL} - c_{other}) \tag{8}$$

where ΔR is the change in revenues from offering BNPL, m is the merchant's margin, and c_{BNPL} are the costs associated with offering BNPL in % of BNPL revenue; $R_{displaced}$ is the revenue from customers with unaffected shopping decisions switching to BNPL; c_{other} are the costs associated with offering other payment options in % of revenue.

We illustrate the overall economics in a simplified, stylized example in Table 7 where we make the following assumptions:

- ΔR = 21% on average (see Section 3.C and Panel C of Table 3). We assume ΔR ranges from +14% (highest quintile by creditworthiness) to +30% (lowest quintile by creditworthiness; +35% for the worst 1%) using the results from Table 4, adopted to reflect both the intensive and extensive margin.

- m = 20% as an illustrative example for a product with a margin of 20%.

- c_{BNPL} = 2.1% on average (see Table 6), as the sum of cost of capital (0.89%) and costs of defaults (1.17%). We assume c_{BNPL} varies between 1.1% (highest quintile by creditworthiness) to 3.9% (lowest quintile by creditworthiness; 8.2% for the worst 1%), assuming a cost of capital of 0.89% and costs of defaults according to default rates by credit score quintile (using the sample from Appendix Table A3.

- $R_{displaced}$ = 39% based on Table 6.

- c_{other} = 0.9% based on Table 6.

We also provide estimates in Column (7) for the worst 1% by creditworthiness (conditional on being eligible for BNPL) in order to highlight the economics for the marginal customers that is allowed to use BNPL.

Table 7 highlights two countervailing effects: For customers with a low creditworthiness, BNPL only offers a large subsidy and therefore has a large effect on sales; at the same time, costs of providing BNPL is high for these customers, because default rates are high. For customers with a high creditworthiness, the increase in sales is smaller, but the costs of providing BNPL is small as well. In our example, these effects combined reveal an inverted u-shape: offering BNPL is most profitable in the middle of the creditworthiness spectrum and less at the extreme ends (see bottom row of Table 7).

This illustrative example is consistent with our theory which also predicts an inverse u-shape: BNPL has no effect on sales and costs for the customers with no default risk, and the merchant offers BNPL at the lower end of the credit spectrum up to the point where marginal costs equal marginal gains. Our model is obviously only an abstraction, assuming, for example, a zero percent risk-free interest rate. However, it is comforting to see that the shape of the cost/benefit example aligns well between our theory model and a realistic example in practice.

E. Does BNPL Survive a Business and Monetary Cycle?

One might imagine that the BNPL business model is just a temporary phenomenon. It might only be profitable when both interest rates and defaults are extremely low and unable to survive a monetary cycle or interest rate increases.

To explore this, we first recall our previous assumption that the merchant has capital costs of 7% p.a. This implied 0.89% capital for the average 48 day maturity period. Assuming a value of 14% that is twice as high would imply that costs rise by 0.85 percent of sales to 1.74%. This suggests that cost of capital effects can be significant for higher interest rates, albeit much smaller than the profits we derive in our example in Table 7.

Second, we analyze defaults as the second potential cost driver during a business cycle downturn empirically. For this we access all check-out visits for the four years

from 2016 until 2019. We aggregate data into a panel of 400 counties and 4 years. Since we do not have any "suited" crisis (social distancing in the COVID shock promoted e-commerce and government support prevented companies largely from laying off workers) we instead exploit heterogeneity in the cross-section of counties to find localized economic recessions. We regress the share of defaulting BNPL transactions against a dummy for counties where GDP growth is either negative (Panel A, Table 8) or less than −2% (Panel B). Default rates increase by 0.1-0.3 percentage points in these recession counties (albeit not always statistically significant). Assuming a rate at the higher end of the spectrum implies a modest increase in default rates from 1.17% to 1.47%. Again, this is smaller than the profits we derive in our example in Table 7.

As an extreme assumption, we can use increases in delinquency rates from U.S. credit card borrowers during the Global Financial Crisis. These spiked at 6.77% in Q2 2009, up by 3 percentage points from the years before the Global Financial Crisis (see https://fred.stlouisfed.org/series/DRCCLACBS). Based on our merchant profitability analysis in Table 7, this would, ceteris paribus, make BNPL unprofitable for the lowest end by creditworthiness, but not for the middle spectrum.

6. External Validity

We have analyzed one specific setting where BNPL was provided in-house by a German e-commerce firm. Our model helps to structure a discussion on external validity: The price discrimination mechanism is relevant when it is primarily the merchant and not the customer who pays for BNPL. The fact that the merchant subsidizes the zero-interest loan is therefore pivotal for the price discrimination mechanism that we have in mind. In contrast to credit cards, the merchant can subsidize a BNPL loan with both BNPL that is provided in-house and with BNPL that is provided through external service providers. We therefore believe our model is also generally applicable to external BNPL providers and we discuss this in more detail in the following.

Information from 2023 annual reports of external BNPL providers provides support for the key assumption that BNPL is subsidized by merchants: 78.7% of Klarna's primary revenue source (commission income) is paid by retailers (the rest by consumers). Interest income makes up just 15.7% of total revenue (they offer some prod-

ucts where customer pay interest or late fees). This shows that its BNPL schemes are overwhelmingly financed by merchants, not customers, just as in our in-house setting.

Affirm even explicitly describes that merchants or manufacturers subsidize BNPL finance as an alternative sales promotion tool that supports profit margins. Affirm writes in its 2023 annual report:

"Offering 0% APR financing to their customers is a compelling revenue accelerator for merchants, who are able to solve affordability for their customers without resorting to discounts. Merchants have the ability to subsidize and determine the range of interest rates to be paid by their customers."
and
"We have the ability to work with manufacturers on brand-specific promotional financing offers. These promotions are funded by suppliers and then made available through our merchants. The suppliers cover the costs of the lowered APR for their products... This gives our merchants a powerful alternative to markdowns as they can increase sales with no impact to their margins."

In addition to merchants paying for BNPL, there are schemes where the merchant and the service provider are both involved in the lending decision (applications require simultaneous approval of both). Note that this implies that our mechanism holds for the broader variety of different BNPL schemes offered by these BNPL companies (including "pay in 4") and is not just applicable for the "pay in 30" days scheme analyzed in our empirical setting.

Apart from the theoretical argument, we also provide some evidence that the data from our setting and our empirical estimates are is in line with what external BNPL service providers report. Regarding variable costs of providing BNPL we access data from Klarna's 2023 annual report. The company is the best comparison due to a similar geographical focus and comparable services. To derive average costs for merchants we divide transaction and service revenue by gross merchandise value. This implies costs of 2.02% – strikingly similar to the 2.1% we find in our in-house setting. 2023 consumer credit losses amount to just 0.4%, which is less than half of our setting.

However, losses were 0.55% for the 2021, which is more comparable to our number (that also comes from 2021). We impute capital costs as the product of total assets and an annual 7% interest rate, divided by gross merchandise value. The resulting 0.91% of BNPL financed revenue are again very close to the 0.89% from our setting.

An equivalent calculation for the report from the second leading BNPL service provider, Affirm, implies slightly higher total costs for merchants of 2.51% of gross merchandise value. A higher number is expected, as the company provides more pay in 4 and installment schemes, which have longer maturities and accrue more risk than pay in 30, where Klarna is more present.

Taken together, the key mechanism that we document – BNPL is a subsidized credit by the merchant – has external validity beyond our in-house setting. Overall costs of providing BNPL are also roughly in line in our in-house setting compared with published numbers from BNPL providers' annual reports.

7. Conclusion

In this paper, we argue that offering BNPL enables merchants to price discriminate between customers with different willingness-to-pay. We show this in a stylized model and find empirical evidence in support of it. We show that BNPL increases sales by 20%, driven by low-creditworthiness customers and products where market power is larger. BNPL thereby significantly increases merchant profitability.

Our results imply a "Robin Hood" effect: Low-income customer pays a lower effective price than the high-income customer, because she values the zero-interest rate loan more. This effect is the opposite to the Reverse Robin Hood effect observed for credit card payments. While our empirical results are limited to data from a single merchant, we expect our price-discrimination mechanism to be externally valid whenever it is primarily the merchant, and not the consumer, who pays for BNPL. This suggests that our mechanism is not generally applicable to credit cards (because consumers pay credit card interest rates accordingly to their creditworthiness), but applicable to external BNPL providers as well. Taken together, our findings help to explain the surge in popularity of BNPL in e-commerce around the world.

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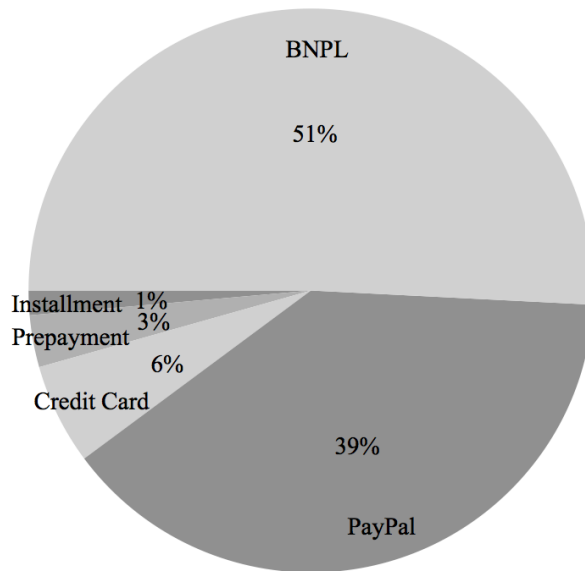
This figure plots the shares of Buy-Now-Pay-Later (BNPL) and all other payment options used at the e-commerce company. The sample is based on the treatment group (for which all payment options are available) in the experiment.

FIGURE 2: CREDIT SCORE HETEROGENEITY

(A) Share Selecting BNPL
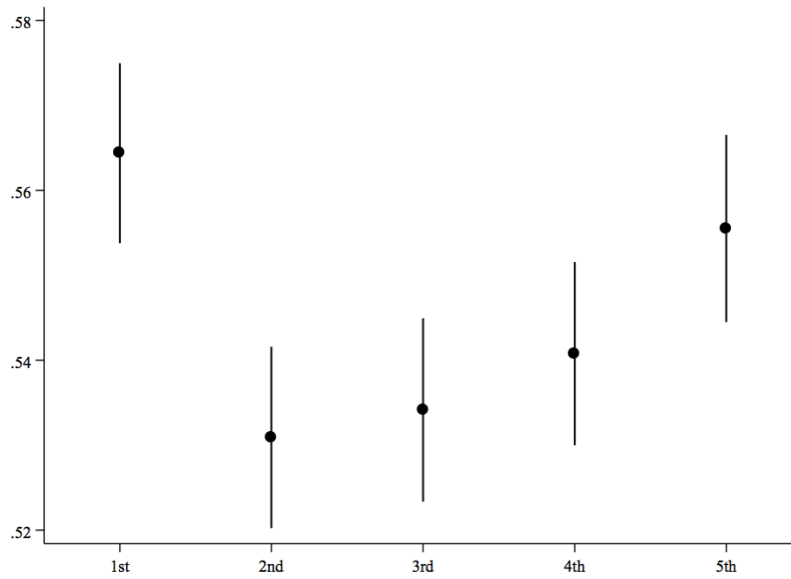
(B) Effect of BNPL Offers on Conversions
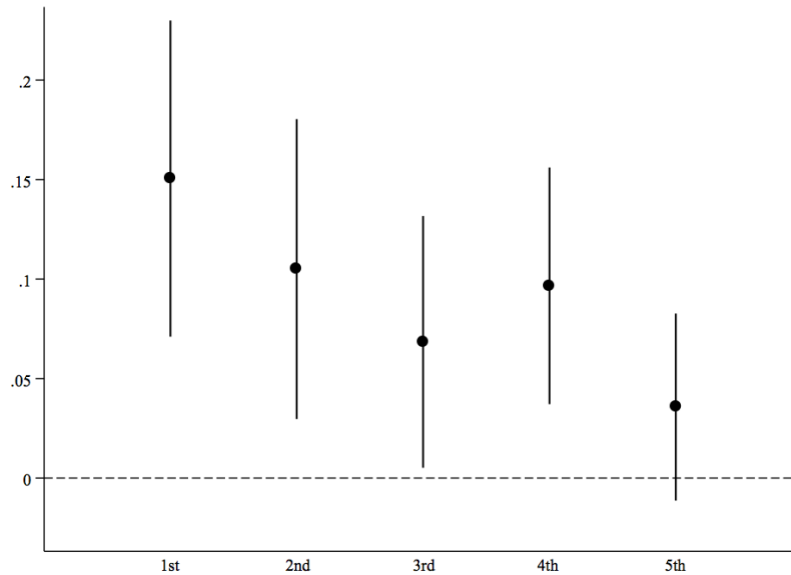
Panel A plots the share of customers selecting either BNPL (coded as a dummy variable value of 1) or some other payment option (coded as 0). We display it by quintile bins of the internal credit score (ranging from 0 to 1, where larger values correspond to lower default likelihoods). Whiskers correspond to 95% confidence intervals. The sample is based on first-time customers in 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 4 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 4 for details. Whiskers correspond to 95% confidence intervals.

FIGURE 3: PAYMENT DEFAULTS
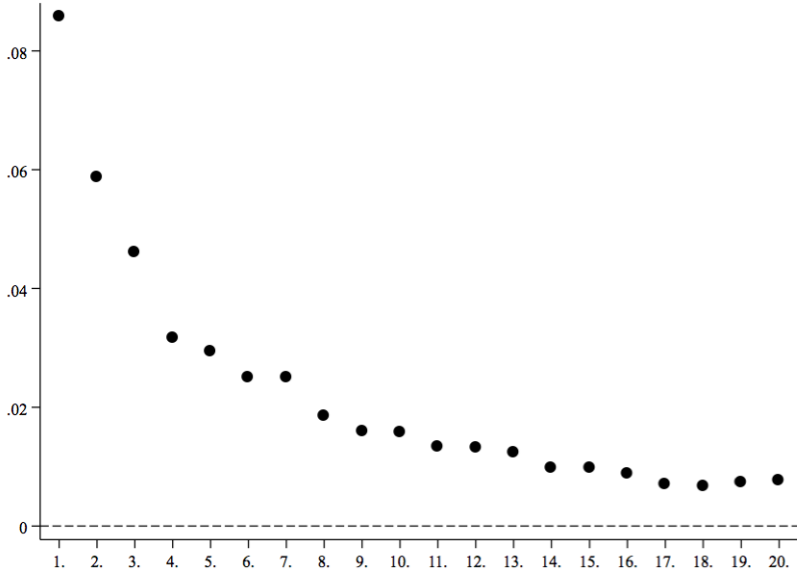
This figure plots the share of a BNPL financed revenue that ends up in payment default. We display it by 20 percentile bins of the internal credit score (ranging from a high default value 0 to a low default value of 1). The sample is based on all BNPL conversions in 2021.

	Unavailable		Available		
	N (1)	Mean (2)	N (3)	Mean (4)	p-value (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	Mean	N	Mean	p-value
	(1)	(2)	(3)	(4)	(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: Effects of BNPL Offers on Sales

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

	(1)	(2)	(3)
BNPL Offered (1/0)	0.091***	0.086***	0.086***
	(0.015)	(0.014)	(0.014)
Observations	75,072	75,072	75,072

Panel B) Dependent Variable: €-Revenue Conditional on a Conversion

	(1)	(2)	(3)
BNPL Offered (1/0)	24.530*	15.811**	13.720**
	(12.942)	(6.345)	(6.357)
Observations	60,036	60,036	60,036

Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion

	(1)	(2)	(3)
BNPL Offered (1/0)	47.156***	44.963***	40.806***
	(10.286)	(9.008)	(9.123)
Observations	75,072	75,072	75,072

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 4: DIFFERENTIAL EFFECT OF BNPL ON CONVERSIONS BY CREDIT SCORE

Dependent Variable: Conversion (1/0)

	(1)	(2)	(3)
BNPL Offered × Credit Score	-0.153**	-0.154**	-0.143**
	(0.072)	(0.069)	(0.069)
BNPL Offered (1/0)	0.198***	0.197***	0.190***
	(0.057)	(0.055)	(0.054)
Credit Score (min. 0, max. 1)	0.644***	0.643***	0.611***
	(0.071)	(0.069)	(0.069)
Observations	71,061	71,061	71,061
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.

TABLE 5: EFFECTS OF PROFIT MARGINS AND CREDIT SCORES ON BNPL APPROVALS

Dependent Variable: BNPL Application Approved (1/0)

	(1)	(2)	(3)	(4)
Score (min. 0, max. 1)	0.679***	0.630***	0.652***	0.658***
	(0.039)	(0.038)	(0.037)	(0.036)
Gross Margin (in %)	0.065***	0.083***	0.080***	0.093***
	(0.020)	(0.021)	(0.018)	(0.009)
Observations	590,994	590,994	590,994	224,570
Controls				
Customer		Yes	Yes	Yes
County		Yes	–	–
Fixed Effects				
County			Yes	Yes
Date			Yes	Yes
Time-of-Day			Yes	Yes
Cart Item Categories				Yes
Customer				Yes

Regressions explain the likelihood that the e-commerce company approves a customer's application for using BNPL. Results are linear probability estimates. The independent variables of interest are the customer's credit score (ranging from a high default risk value of 0 to a low default risk value of 1) and the gross profit margin (revenue − purchase costs) of customer i's shopping cart at time t The estimation sample includes all customers applying for BNPL in 2021. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for standard errors (between parentheses) that allow for clustering by product category and county. "–" indicates that controls are absorbed by fixed effects.

Table 6: Displacement Costs

Option	Costs in % (1)	Revenue per €100 unavailable (2)	Revenue per €100 available (3)	Costs × Revenue per €100 unavailable (4)	Costs × Revenue per €100 available (5)
BNPL					
New Revenue	2.1	0.0	21	0.00	0.44
Displaced Revenue	2.1	0.0	38.9	0.00	0.82
Other	0.9	100	61.3	0.93	0.65
PayPal	1.0	67.9	43.9	0.68	0.44
Credit Card	1.3	13.3	8.2	0.17	0.11
Installment	2.8	2.7	3.7	0.08	0.10
Prepayment	0.0	16.0	5.4	0.00	0.00
Sum (BNPL Displaced + Other)		100	100	0.93	1.47
Sum (BNPL All + Other)		100	121	0.93	1.91

Column (1) contains variable transaction costs, expressed in % of transaction volume. Information comes from both external sources and the merchant. BNPL costs include losses due to unrecovered defaults and capital costs. Payment option use when BNPL is either not shown or shown is in Columns (2) and (3), respectively and expressed per €100 of purchase volume. Column (4) is the product of Columns (1) and (2), representing total variable transaction costs per €100 purchase volume when BNPL is unavailable. Column (5) is the same number for when BNPL is available. BNPL - New Revenue in Column (3) is the estimate from the effect on the total margin in Table 3, scaled to €100. BNPL - Displace Revenue in Column (3) is the share of BNPL when this option is available, minus the new revenue generated by BNPL.

Table 7: Economics of BNPL

Per € 100	Mean (1)	Quintiles Q5 (2)	Q4 (3)	Q3 (4)	Q2 (5)	Q1 (6)	p1 (7)
ΔR	€ 21	€ 14	€ 17	€ 20	€ 24	€ 30	€ 35
m	20%	20%	20%	20%	20%	20%	20%
c_{BNPL}	2.1%	1.1%	1.1%	1.3%	1.7%	3.9%	8.2%
π on new R	€ 3.8	€ 2.6	€ 3.2	€ 3.7	€ 4.4	€ 4.8	€ 4.1
$R_{displaced}$	€ 39	€ 39	€ 39	€ 39	€ 39	€ 39	€ 39
c_{BNPL}	2.1%	1.1%	1.1%	1.3%	1.7%	3.9%	8.2%
c_{other}	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%
$\Delta\pi$ on old R	€ 0.5	€ 0.1	€ 0.1	€ 0.2	€ 0.3	€ 1.2	€ 2.9
Π_{BNPL}	€ 3.3	€ 2.6	€ 3.1	€ 3.6	€ 4.1	€ 3.7	€ 1.3

This table illustrates the overall economics of offering BNPL in a simplified and stylized way. Rows contain values for the variable in equation

$$\Pi_{BNPL} = \Delta R \cdot (m - c_{BNPL}) - R_{displaced} \cdot (c_{BNPL} - c_{other}).$$

$\Delta R \cdot (m - c_{BNPL})$ is the profit on new revenue generated by BNPL. $R_{displaced} \cdot (c_{BNPL} - c_{other})$ is the change in profit on revenue that would have occurred without BNPL, where customers chose to use the more expensive BNPL if available (without altering their shopping decisions). Columns 1 contains mean values for the entire sample. Means by bin for credit score quintiles are in Columns 2-6. Q5 is the highest quintile with the best credit scores. The worst 1% are in Column 7. All € -values are expressed on the basis of € 100 of shopping cart value at check out. For simplicity we assume constant margins, periods between order and payment, displacement revenue, costs of alternative payment methods. We instead focus on the dominating drivers behind the credit score heterogeneity: differential effects on revenue and differential losses due to payment default. The value in Column 1 for ΔR comes from Panel C, Table 3. For the other Columns it is based on calculations not included in any table or figure (available upon request). The value in Column 1 for c_{BNPL} comes from Table 6 (additional calculations for the other Columns; available upon request). We assume a value for *m* for a standard product. The value for $R_{displaced}$ comes from Table 6.
c_{other} it comes from Table 6. for *m*

Dependent Variable: BNPL Defaults (%)

Panel A) Counties with Negative GDP Growth

	(1)	(2)	(3)	(4)
Recession County (1/0)	0.003***	0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,588	1,588	1,588	1,588
Recession Counties	106	106	106	106

Panel B) Counties with GDP Growth $< -2\%$

	(1)	(2)	(3)	(4)
Recession County (1/0)	0.003*	0.002	0.003*	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,588	1,588	1,588	1,588
Recession Counties	28	28	28	28

Fixed Effects

Year Fixed Effects		Yes		Yes
County Fixed Effects			Yes	Yes

Regressions in this table are estimated from a county-year panel with 400 counties between 2016 and 2019. The independent dummy variable identifies recession counties. It equals 1 if annual GDP growth is negative. The dependent variable in Panel A) is the share of BNPL financed conversions that end up in default. In Panel B) it is the share of customers selecting BNPL (in % of all customers selecting some payment option). ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors (between parentheses). "−" indicates that controls are absorbed by fixed effects.

A1. Model

This appendix generalizes the example from Section 1. The model closely follows the trade credit model by Brennan et al. (1988) which shows that – even in the presence of a perfectly competitive banking industry – it can be optimal for firms with market power to engage in trade credit financing. We differ in two crucial aspects from Brennan et al. (1988). First, Brennan et al. (1988) model trade credit as non-recourse: a trade credit lender only has access to the product sold in case of bankruptcy. This makes bankruptcy endogenous to the profits generated from the piece of equipment bought via trade credit. This setting seems implausible for BNPL as products are typically bought for consumption, and not to generate profits. We therefore model the probability of default of a customer as an exogenous variable. Second, we extend the model by Brennan et al. (1988) by assuming fixed per-transaction costs of offering BNPL. For larger trade credit products, e.g. a tractor, transaction costs might be negligible. BNPL is offered for smaller amounts, making fixed per-transaction costs important to understand. The transaction cost assumption also helps to understand the effect of technology on BNPL as we discuss in detail below.

A. No BNPL

Assume there are two types customers: high-income customers with a high willingness-to-pay (WTP) which – without loss of generality – we set equal to $w^{high} = 1$, and low-income customers with a low WTP of $w^{low} = 1 - \Delta$ ($\Delta \geq 0$). The merchant's marginal cost of the product is $c = 1 - \Delta - m$ ($m \geq 0$). The parameter m has the interpretation of the margin of the product if the product is sold at the willingness-to-pay of the low-income-customer. The fraction of high-income and low-income customers is assumed to be both equal to 1/2. The merchant is not able to price-discriminate directly and therefore needs to set a uniform price to both types of customers. The inability to price-discriminate can either be because willingness-to-pay is unobservable to the merchant, or because of technological and organizational costs.

The merchant's profit $\pi(P)$ depends on the price she sets. A profit-maximizing firm

will set the price either equal to $w^{high} = 1$ or $w^{low} = 1 - \Delta$, with profits in each case given by

$$\pi(1-\Delta) \quad = (1-\Delta) - (1-\Delta-m) \quad = m \tag{9}$$

$$\pi(1) \quad = \tfrac{1}{2}(1 - (1-\Delta-m)) \quad = \frac{1}{2}(\Delta + m) \tag{10}$$

The merchant will therefore set an equilibrium price

$$P^* = \begin{cases} 1-\Delta & \text{if } m \geq \Delta \\ 1 & \text{if } m < \Delta. \end{cases} \tag{11}$$

This makes intuitive sense: Ceteris paribus, if the high-income customer's WTP is much higher than the low-income customer's WTP (that is, Δ is high), the merchant will offer the product at a high price ($P^* = 1$) and only sell to the high-income customer. If, on the other hand, the margin of selling to the low-income customers at her WTP is high (that is, m is high), the merchant will offer the product at a lower price ($P^* = 1-\Delta$) and sell to both customers. The merchant makes a profit of

$$\pi(P^*) = \begin{cases} m & \text{if } m \geq \Delta \\ \frac{1}{2}(\Delta + m) & \text{if } m < \Delta. \end{cases} \tag{12}$$

B. BNPL

Assume the merchant offers a bundle consisting of the product and a zero-interest rate loan ("BNPL"). The probability of default of the high-income customer is assumed to be 0%, the probability of default of the low-income customer is p. We assume that p is known to the merchant. To avoid unnecessary complexity, we assume that $p \geq \Delta$. In addition to losses from default, the merchant incurs a fixed per-transaction cost γ for offering BNPL which can be interpreted as operational costs for providing the loan. If the price P is set in such a way that both customers are willing to buy the bundle at the price P, profits for the merchant are equal to the price minus marginal cost minus

default costs:

$$\pi^{BNPL}(P) = \frac{1}{2}\left[P(1-0\%)-(1-\Delta-m)-\gamma\right] + \frac{1}{2}\left[P(1-p)-(1-\Delta-m)-\gamma\right] \qquad (13)$$

The maximization problem for the merchant is:

$$\max_P \pi^{BNPL}(P) \qquad (14)$$

$$s.t. \qquad P \leq 1 \qquad \text{(Part. constraint of high-income customer)} \qquad (15)$$

$$P(1-p) \leq 1-\Delta \quad \text{(Part. constraint of low-income customer)} \qquad (16)$$

Given our assumption $p \geq \Delta$, the participation constraint of the high-income customer (15) is binding. The merchant therefore sets a price equal to $P^* = 1$ and makes equilibrium profits of

$$\pi^{BNPL}(P^* = 1) = \frac{1}{2}\left[1-(1-\Delta-m)-\gamma\right] + \frac{1}{2}\left[1-p-(1-\Delta-m)-\gamma\right] \qquad (17)$$

$$= \underbrace{\frac{1}{2}(\Delta+m)}_{\text{profit from high-income customers}} + \underbrace{\frac{1}{2}(\Delta+m-p)}_{\text{profit from low-income customers}} \qquad (18)$$

$$= \Delta+m-\frac{1}{2}p-\gamma \qquad (19)$$

The merchant's profits are equal to the surplus of the high-income customer $(\Delta+m)$, minus the loss from the $\frac{1}{2}$ mass of customers that defaults with probability p, minus the fixed per-transaction cost for offering BNPL γ. If $p > 2(\Delta+m-\gamma)$, the merchant makes a loss when offering the bundle (product + zero-interest rate loan) to all customers.

C. ENDOGENOUS CHOICE TO OFFER BNPL

The choice to offer BNPL will be determined by whether the merchant makes more profits by offering BNPL or not, e.g., by comparing (19) to (12). For $m \geq \Delta$, BNPL increases profits iff $\Delta+m-\frac{1}{2}p-\gamma \geq m \Leftrightarrow p \leq 2\Delta-2\gamma$. For $m < \Delta$, BNPL increases profits iff $\Delta+m-\frac{1}{2}p-\gamma \geq \frac{1}{2}(\Delta+m) \Leftrightarrow p \leq \Delta+m-2\gamma$. Taken together, there are three potential outcomes

- Case 1 (BNPL): If $p \leq \max(\Delta+m-2\gamma, 2\Delta-2\gamma)$, the merchant maximizes profits

A·3

by offering a bundle of the product with a zero-interest rate loan ("BNPL").

- Case 2 (No BNPL): If $p > \max(\Delta + m - 2\gamma, 2\Delta - 2\gamma)$ the merchant maximizes profits by not offering BNPL.

    - Case 2a (No BNPL, high price): If $m < \Delta$, the merchant sells at a high price ($P^* = 1$) and only sells to the high-income customers.

    - Case 2b (No BNPL, low price): If $m \geq \Delta$, the merchants sells at a low price ($P^* = 1 - \Delta$) and sells to both high-income and low-income customers.

Figure A1 illustrates the resulting equilibrium without fixed per-transaction costs of offering BNPL ($\gamma = 0$). BNPL is offered more when default probabilities (p) are low and when margins (m) are high. Higher margins (m) in particular expand BNPL when probabilities of default are high. A model without fixed per-transaction costs can be interpreted as an e-commerce model, where BNPL provision is fully automated and all the information necessary for scoring and lending (name, address, digital footprint) are available to the merchant in any case. In contrast, in-store provision of credit is plausibly subject to higher fixed per-transaction costs. Figure A2 illustrates the resulting equilibrium with fixed per-transaction costs of offering BNPL ($\gamma > 0$), documenting that BNPL is provided less when fixed per-transaction costs are higher.

A2. 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.

A3. 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 A7 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 obser-

vation 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 A8 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.

A4. Do Other Payment Options have Similar Effects?

We framed results in this section 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 3, 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 A6 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.

A5. Cost for setting up BNPL

In addition to the marginal cost of running a BNPL scheme, firms occur costs from setting up a BNPL payment option from scratch. These costs can be split into two parts: operational costs (personnel costs and costs for building the IT infrastructure) and costs from training a credit scoring model, i.e., higher default rates before enough data for a proper model is collected (see also Berg et al. (2020) for how the use of digital footprint scoring models decreases default rates). We focus on the latter part, mainly driven by data availability, but also because the e-commerce firm indicated they were their biggest concern.

The e-commerce firm set up a BNPL payment option in 2015. In the first 4.5 months, the e-commerce firm extended BNPL generously to train its scoring model. In the subsequent months, the e-commerce firm used its model to provide BNPL to customers of sufficient creditworthiness. As more data came in, the e-commerce firm continuously refined its credit scoring model. In Table A14, we provide default rates for the 4.5 months training period, the subsequent 2.5 months of model refinement, as well as for the subsequent 9 months. Our analysis suggests that the e-commerce firm suffered a 7.16% default rate during the training period, a 1.49% default rate during the subsequent 2.5 months, and default rate between 0.94%-1.07% (average: 1.01%) during the subsequent 9 months.[12]

These numbers allow to assess the *additional* costs of BNPL during the training period: the default rate during the training period was 6.15 PP higher than the default rate after the model was trained (7.16% versus 1.01%). In absolute terms, the e-commerce firm suffered excess losses of €1.91 mn during the initial 2.5 months when it provided BNPL broadly in order to collect data that allowed for training the model. This loss is equal to approximately 0.1% of aggregate BNPL volume in the eight years since BNPL introduction. While not negligible, these numbers are small compared to the benefits from offering BNPL that we document in the rest of the paper.

Note that the training period was chosen in an ad-hoc manner by the e-commerce firm, without a clear model in mind that would trade-off costs and benefits from a longer or shorter training period, or from a more or less generous provision of BNPL during the training period. This suggests that the costs estimated above are an upper bound of the costs that are needed to collect the necessary data to properly train a scoring model.

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[12]The default rates in our main sample is 1.9%, see Table A2, and therefore somewhat higher than in 2015/2016. This is plausibly due to an expansion of the eligibility criteria as a response to the success of the BNPL offering.

This figure illustrates the equilibrium provision of BNPL as a function of m (margin) and p (probability of default for low-income customers) assuming no fixed per-transaction costs of providing BNPL ($\gamma = 0$).

p
(prob. of default)

2Δ

No BNPL
P*=1
Q=1/2

No BNPL
P*=1-Δ
Q=1

BNPL
P*=1
Q=1

Δ

Δ

m
(margin)
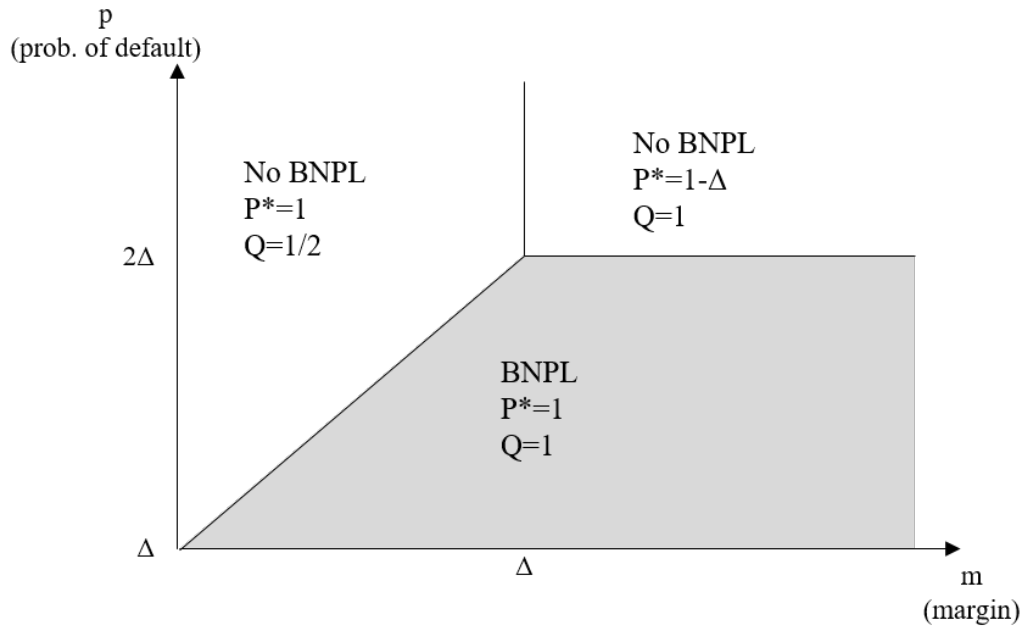
Figure A2: Equilibrium provision of BNPL ($\gamma > 0$)

This figure illustrates the equilibrium provision of BNPL as a function of m (margin) and p (probability of default for low-income customers) assuming fixed per-transaction costs of providing BNPL ($\gamma > 0$).

p
(prob. of default)

2Δ

No BNPL
P*=1-Δ
Q=1

2γ

No BNPL
P*=1
Q=1/2

BNPL
P*=1
Q=1

Δ

Δ

m
(margin)
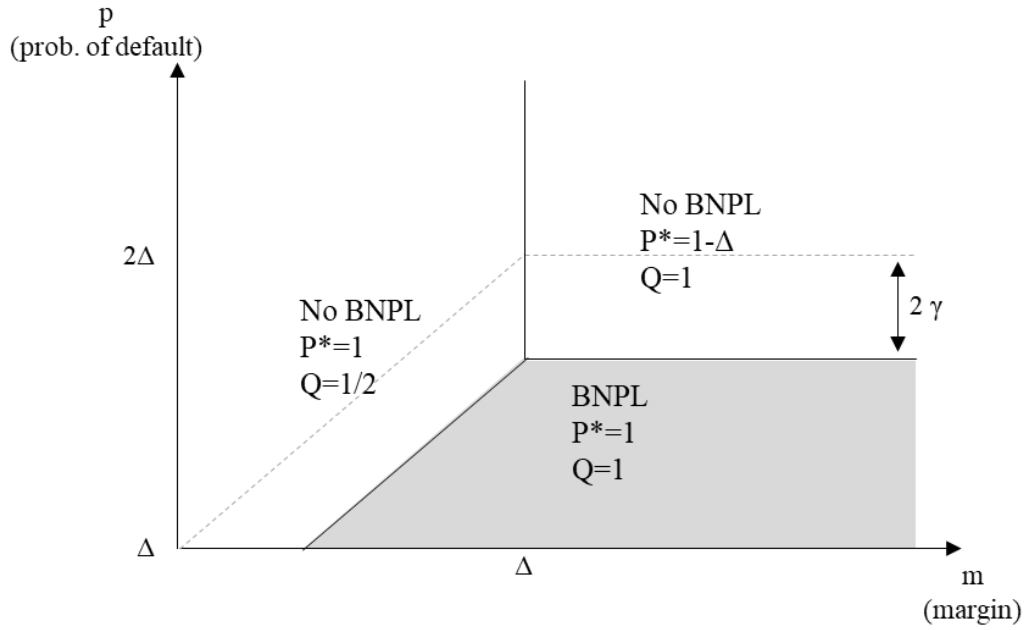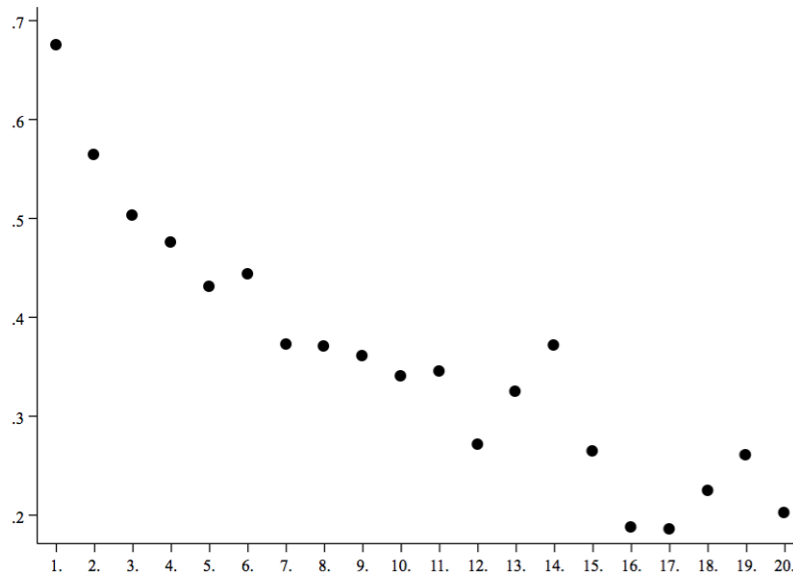
This figure plots lost BNPL financed revenue (that defaults and is never recovered) as a share of all defaulting BNPL financed revenue up in payment default. We display it by 20 percentile bins of the internal credit score (ranging from a high default value 0 to a low default value of 1). The sample is based on all BNPL conversions in 2021.

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 at check-out; 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
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
Unrecovered Loss / Default (%)	share of defaulted BNPL revenue lost after failed recovery attempts
Unrecovered Loss / Sales (%)	share of BNPL revenue lost after failed recovery attempts
Gross Profit Margin (%)	(cart value net of VAT - purchase costs) / cart value net of VAT
Net Profit Margin (%)	(cart value net of VAT - purchase costs - shipping costs) / cart value net of VAT
Net Profit Margin 2 (%)	(cart value net of VAT - purchase costs - shipping costs - predicted return costs) / cart value net of VAT
Recession County (1/0)	dummy equal to 1 if a county had GDP growth that was negative or smaller than -2 (depending on the analysis)
Miscellaneous & (Other) 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 – SALES ANALYSIS

	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.

	N (1)	p10 (2)	Median (3)	p90 (4)	SD (5)	Mean (6)
BNPL Approved (1/0)	594,859	0.000	1.000	1.000	0.327	0.878
Low Credit Score (1/0)	592,849	0.000	0.000	1.000	0.400	0.200
Credit Score (min. 0, max. 1)	594,859	0.492	0.796	0.958	0.182	0.757
Gross Profit Margin (%)	594,859	0.167	0.465	0.643	0.178	0.437
Net Profit Margin (%)	594,859	0.167	0.340	0.550	0.178	0.347
Net Profit Margin 2 (%)	594,859	0.128	0.304	0.529	0.219	0.298
Payment Default (1/0)	352,313	0	0	0	0.155	0.025
Unrecovered Loss / Default (%)	7,934	0	0.042	1	0.481	0.453
Unrecovered Loss / Sales (%)	352,313	0	0	0	0.105	0.012
Initial Cart Balance (€)	594,859	66.990	280.00	1,000	454.90	432.00
Age (Years)	238,816	0.000	0.000	0.000	0.000	0.000
Male (1/0)	594,859	0.000	0.000	1.000	0.452	0.286
Device: Desktop (1/0)	594,859	0.000	0.000	1.000	0.489	0.397
Device: Phone (1/0)	594,859	0.000	1.000	1.000	0.495	0.568
Device: Tablet (1/0)	594,859	0.000	0.000	0.000	0.152	0.024
Device: Unknown (1/0)	594,859	0.000	0.000	0.000	0.104	0.011
System: Apple (1/0)	594,859	0.000	0.000	1.000	0.491	0.407
System: Windows (1/0)	594,859	0.000	0.000	1.000	0.442	0.266
System: Android (1/0)	594,859	0.000	0.000	1.000	0.452	0.286
System: Other (1/0)	594,859	0.000	0.000	0.000	0.196	0.040
County Population Density	591,944	102.10	441.80	3,007	1,263	1,073
County Mean Income (€)	591,944	18,990	21,845	25,135	2,679	22,095
Time: Morning (1/0)	594,859	0.000	0.000	1.000	0.441	0.265
Time: Day (1/0)	594,859	0.000	0.000	1.000	0.484	0.373
Time: Evening (1/0)	594,859	0.000	0.000	1.000	0.471	0.331
Time: Night (1/0)	594,859	0.000	0.000	0.000	0.172	0.030
>1 Item in Cart (1/0)	594,859	0.000	0.000	1.000	0.479	0.356
Item: Dining Room (1/0)	594,859	0.000	0.000	1.000	0.342	0.135
Item: Bedroom (1/0)	594,859	0.000	0.000	1.000	0.392	0.190
Item: Other (1/0)	594,859	0.000	0.000	1.000	0.322	0.118
Item: Auxiliary Rooms (1/0)	594,859	0.000	0.000	1.000	0.364	0.157
Item: Lighting (1/0)	594,859	0.000	0.000	1.000	0.352	0.145
Item: Couches, Cushions (1/0)	594,859	0.000	0.000	1.000	0.430	0.245
Item: Living Room (1/0)	594,859	0.000	0.000	1.000	0.370	0.163

Observations come from the analysis of profit margins. See Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for robust White standard errors. Note that descriptive statistics for payment defaults, and unrecovered losses are weighted by cart value.

TABLE A4: SELECTING BNPL AND CONSUMER CHARACTERISTICS

Dependent Variable: BNPL Selected (1/0)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial Cart Balance (ln(€))	0.023***						0.032***	
	(0.002)						(0.002)	
Credit Score (min. 0, max. 1)		-0.023*					-0.036***	
		(0.012)					(0.012)	
Male (1/0)			-0.140***				-0.146***	
			(0.005)				(0.005)	
System: Apple (1/0)				-0.032***			-0.033***	
				(0.005)			(0.005)	
County Mean Income (ln(€))					-0.079***		-0.056***	
					(0.020)		(0.020)	
County Population Density (ln)						-0.038***	-0.031***	
						(0.002)	(0.002)	
Observations	43,791	43,791	43,791	43,791	43,791	43,791	43,791	

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.

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

	(1)	(2)	(3)
BNPL Selected & Approved (1/0)	0.309***	0.288***	0.291***
	(0.050)	(0.046)	(0.047)
Kleibergen-Paap Robust F-Statistic			
Observations	75,072	75,072	75,072

Panel B) Dependent Variable: €-Revenue Conditional on a Conversion

	(1)	(2)	(3)
BNPL Selected & Approved (1/0)	71.501*	47.254**	41.300**
	(37.706)	(19.068)	(19.217)
Kleibergen-Paap Robust F-Statistic			
Observations	60,036	60,036	60,036

Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion

	(1)	(2)	(3)
BNPL Selected & Approved (1/0)	160.047***	150.823***	137.780***
	(34.929)	(30.376)	(30.944)
Kleibergen-Paap Robust F-Statistic			
Observations	75,072	75,072	75,072

	(1)	(2)	(3)
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 3 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 A6: Effects of PayPal Availability on Sales

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

	(1)	(2)	(3)
PayPal Offered (1/0)	0.011	0.013	0.013
	(0.011)	(0.011)	(0.011)
Observations	75,429	75,429	75,429

Panel B) Dependent Variable: €-Revenue Conditional on a Conversion

	(1)	(2)	(3)
PayPal Offered (1/0)	6.365	1.204	0.588
	(11.162)	(4.492)	(4.588)
Observations	60,392	60,392	60,392

Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion

	(1)	(2)	(3)
PayPal Offered (1/0)	8.354	-3.404	-3.882
	(9.440)	(7.120)	(7.108)
Observations	75,429	75,429	75,429

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 A7: Effects of BNPL Offers on Sales – 1st Time Customers

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

	(1)	(2)	(3)
BNPL Offered (1/0)	0.112***	0.106***	0.103***
	(0.018)	(0.017)	(0.017)
Observations	51,461	51,461	51,461

Panel B) Dependent Variable: €-Revenue Conditional on a Conversion

BNPL Offered (1/0)	16.677	8.535*	7.161
	(16.430)	(4.951)	(5.034)
Observations	40,771	40,771	40,771

Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion

BNPL Offered (1/0)	48.836***	52.664***	46.586***
	(12.659)	(11.193)	(11.417)
Observations	51,461	51,461	51,461

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.

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

	(1)	(2)	(3)
BNPL Offered (1/0)	0.085***	0.081***	0.074***
	(0.015)	(0.014)	(0.014)
Observations	75,072	75,072	75,072

Panel B) Dependent Variable: €-Revenue Conditional on a Conversion

	(1)	(2)	(3)
BNPL Offered (1/0)	26.007*	14.897**	11.909*
	(13.398)	(6.631)	(6.635)
Observations	56,858	56,858	56,858

Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion

	(1)	(2)	(3)
BNPL Offered (1/0)	45.755***	43.678***	37.634***
	(10.233)	(8.948)	(9.068)
Observations	75,072	75,072	75,072

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.

Panel A) Dependent Variable: Conversion (1/0)			
	(1)	(2)	(3)
BNPL Offered (1/0)	0.063***	0.058***	0.059***
	(0.014)	(0.013)	(0.013)
Observations	75,072	75,072	75,072

Panel B) Dependent Variable: €-Revenue Conditional on a Conversion			
BNPL Offered (1/0)	21.663*	11.981*	12.593*
	(12.847)	(6.688)	(6.733)
Observations	60,995	60,995	60,995

Panel C) Dependent Variable: €-Revenue Unconditional on a Conversion			
BNPL Offered (1/0)	38.055***	35.635***	33.933***
	(10.673)	(9.307)	(9.420)
Observations	75,072	75,072	75,072

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 A10: 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 A11: Effects of Profit Margins and Credit Scores on BNPL Approvals –
Analyzing 1st Time Customers**

Dependent Variable: BNPL Application Approved (1/0)

	(1)	(2)	(3)	(4)
Score (min. 0, max. 1)	0.762***	0.668***	0.684***	0.655***
	(0.043)	(0.043)	(0.042)	(0.046)
Gross Margin (in %)	0.063***	0.087***	0.086***	0.079***
	(0.022)	(0.024)	(0.023)	(0.017)
Observations	386,172	386,172	386,172	386,172
Controls				
Customer		Yes	Yes	Yes
County		Yes	–	–
Fixed Effects				
County			Yes	Yes
Date			Yes	Yes
Time-of-Day			Yes	Yes
Cart Item Categories				Yes
Customer				

Regressions explain the likelihood that the e-commerce company approves a first time customer's application for using BNPL. Results are linear probability estimates. The independent variables of interest are the customer's credit score (ranging from a high default risk value of 0 to a low default risk value of 1) and the gross profit margin (revenue – purchase costs) of customer i's shopping cart at time t The estimation sample includes all customers applying for BNPL in 2021. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for standard errors (between parentheses) that allow for clustering by product category and county. "–" indicates that controls are absorbed by fixed effects.

TABLE A12: EFFECTS OF PROFIT MARGINS AND CREDIT SCORES ON BNPL APPROVALS – USING A LOW CREDIT SCORE DUMMY

Dependent Variable: BNPL Application Approved (1/0)				
	(1)	(2)	(3)	(4)
Low Score (1/0)	-0.275***	-0.246***	-0.253***	-0.219***
	(0.015)	(0.014)	(0.013)	(0.009)
Gross Margin (in %)	0.072***	0.089***	0.084***	0.093***
	(0.023)	(0.024)	(0.021)	(0.010)
Observations	589,005	589,005	589,005	223,334
Controls				
Customer		Yes	Yes	Yes
County		Yes	–	–
Fixed Effects				
County			Yes	Yes
Date			Yes	Yes
Time-of-Day			Yes	Yes
Cart Item Categories				Yes
Customer				Yes

Regressions explain the likelihood that the e-commerce company approves a customer's application for using BNPL. Results are linear probability estimates. The independent variables of interest are a dummy that is 1 if the customer's credit score is in the bottom quintile ("low") and the gross profit margin (revenue – purchase costs) of customer i's shopping cart at time t The estimation sample includes all customers applying for BNPL in 2021. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for standard errors (between parentheses) that allow for clustering by product category and county. "–" indicates that controls are absorbed by fixed effects.

Dependent Variable: Gross Margin (in %)			
(1)	(2)	(3)	(4)
Panel A) Are Low Credit Score Customers More Interested?			
Score (min. 0, max. 1)	0.026	0.039	0.030	0.004
	(0.023)	(0.025)	(0.023)	(0.009)
Observations	594,859	594,859	594,859	228,582
Panel B) Are BNPL Customers More Interested?			
BNPL Selected (1/0)	-0.010*	-0.017***	-0.015***	-0.015***
	(0.006)	(0.006)	(0.003)	(0.003)
Observations	1,049,291	1,049,291	1,049,291	436,013
Controls				
Customer		Yes	Yes	Yes
County		Yes	–	–
Fixed Effects				
County			Yes	Yes
Date			Yes	Yes
Time-of-Day			Yes	Yes
Cart Item Categories				Yes
Customer				Yes

Regressions explain the gross profit margin (revenue − purchase costs) of customer i's shopping cart at time t. The independent variable of interest in Panel A is the customer's credit score (ranging from a high default risk value of 0 to a low default risk value of 1). In Panel B it is an indicator for a customer selecting BNPL (1) or another payment method (0) when first visiting check-out. The estimation sample includes all customers applying for BNPL in 2021. See Appendix Table A1 for details on the definition of variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% for standard errors (between parentheses) that allow for clustering by product category and county. "−" indicates that controls are absorbed by fixed effects.

TABLE A14: Default rates during the training phase

Sample Period	Date	Default Rate	Δ to Post2-Post4	BNPL volume (€mn)	Excess defaults (€mn)
Training (4.5 months)	Jun - Oct 2015	7.16%	6.15%	31.06	1.91
Post 1 (2.5 months)	Oct - Dec 2015	1.49%	0.48%	18.69	0.09
Post 2 (3 months)	Jan - Mar 2016	0.94%	-0.07%	21.76	-0.01
Post 3 (3 months)	Apr - Jun 2016	1.01%	0.00%	18.17	0.00
Post 4 (3 months)	Jul - Sep 2016	1.07%	0.06%	21.04	0.01

This table provides BNPL volumes and default rates during the training period (generous provision of BNPL without a proper scoring model) as well as during the subsequent periods.

TABLE A15: NET EFFECT ON VARIABLE COSTS – USING SELECTIONS

	Costs in %	Selections per €100		Costs × Selections per €100	
Option	(1)	unavailable (2)	available (3)	unavailable (4)	available (5)
BNPL	2.1	0.0	56.1	0.00	1.18
Other	1.2	100.0	43.9	1.16	0.55
PayPal	1.0	58.8	28.9	0.59	0.29
Credit Card	1.3	13.9	5.2	0.18	0.07
Installment	2.8	14.1	6.7	0.39	0.19
Prepayment	0.0	13.3	3.1	0.00	0.00
Sum		100	100	1.16	1.73

Column (1) contains variable transaction costs, expressed in % of transaction volume. Information comes from both external sources and the merchant. BNPL costs include losses due to unrecovered defaults and capital costs. Payment option selections by first time customers for which BNPL is either not shown or shown are in Columns (2) and (3), respectively and expressed per €100 of shopping cart volume at check out. Note that selecting a payment option does neither imply a conversion, nor a use of this payment option conditional on a conversion. Check outs may be aborted. Transactions might be declined by the merchant or external payment service providers. Customers may not provide credentials required for using PayPal or a credit card. Column (4) is the product of Columns (1) and (2), representing total variable transaction costs when BNPL is unavailable and the €100 cart volume in is actually spend. Column (5) is the same number for when BNPL is available.