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The effects of buy now, pay later (BNPL) on customers' online purchase behavior

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A B S T R A C T

Recent innovations in financial technology (FinTech) have introduced short-term financing options for customer loans, allowing customers to make purchases and pay for them in future installments without incurring interest, a model commonly referred to as Buy Now, Pay Later (BNPL). Despite the increasing provision of BNPL by online retailers, there remains a limited understanding of its effects on customers' online purchase behavior. To address this gap, we utilize a synthetic difference-in-differences research design to estimate the impact of customers' BNPL adoption on their online purchase behavior, specifically measured by order size. Our empirical results indicate that customers who adopt BNPL provided by a focal retailer have a higher order size than those who use traditional payment services. Our empirical estimates indicate an increase of 6.42% in online spending by customers adopting BNPL. Additionally, we examine the moderating effects of various customer segments - including loyalty, category experience, and promotion sensitivity - as well as demographic factors such as age, income, household size, and product characteristics, particularly low-ticket items. The impact of BNPL adoption is found to be amplified among customers with high levels of category experience and promotion sensitivity. Conversely, the effect is attenuated among older and higher-income customers, indicating that younger and low-income customers are the primary drivers of this effect. Moreover, our analysis demonstrates that purchases of low-ticket items predominantly drive the observed effect. This study provides strategic insights for online retailers concerning the implementation and targeting of BNPL as an effective online payment option.

1. Introduction

Payment methods, along with interactive decision aids (Häubl & Trifts, 2000), delivery infrastructure (Lewis et al., 2006), and website design (Mallapragada et al., 2016), are key enablers of e-commerce. In 2023, over 50% of e-commerce transactions were completed using digital wallets, credit cards, and debit cards (FIS WorldPay, 2024). However, The Global Payments Report 2024 by FIS WorldPay (2024) indicates that the use of credit and debit cards is declining, consequently reducing pur-

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chases and sales. Concurrently, users are increasingly adopting a recent innovation in financial technology (FinTech[1]) — Buy Now, Pay Later (BNPL) — which accounted for over $316 billion or 5% of global e-commerce spending in 2023. BNPL differs from traditional cards in at least four key ways: first, unlike credit cards' revolving credit line, BNPL offers customers a fixed-duration installment option. Second, unlike surcharges typically passed onto customers using credit cards, surcharges are collected from merchants by BNPL providers (Worldpay, 2021). Third, BNPL integrates customer financing directly at the point of purchase, providing a customer-centric experience by reducing friction and enhancing convenience. Fourth, unlike credit cards, BNPL financing methods generally do not charge interest on the purchase amount. Thus, in an online shopping environment, BNPL streamlines the checkout process and boosts sales by increasing customer spending, as customers can cover transaction costs in installments without any surcharge within the installment period (Worldpay, 2021). As a result of BNPL's growing popularity among customers, online retailers have increasingly incorporated it as a payment option.

The rationale for online retailers to offer alternate payment options is multifaceted. The availability of a preferred payment option is a crucial consideration for 70% of consumers when selecting an online store, whose failure could result in an increased rate of cart abandonment (PYMNTS, 2024).[2] A significant portion of online customers (11%) abandon their online shopping carts due to the lack of multiple payment methods offered by retailers (Shopify, 2024). BNPL, an emerging online payment option, is perceived by customers as a distinct "way to pay" that differentiates itself from credit cards by mitigating the sense of debt, thereby enhancing the experiential aspect of online shopping (Cook et al., 2023). Consequently, BNPL is increasingly utilized by customers as a viable and sometimes preferred payment option, particularly in comparison to other forms of payment. This trend is especially pronounced during turbulent economic periods characterized by high inflation and interest rates (Cook et al., 2023). BNPL offers benefits beyond no-interest credit. Its presentation on shopping websites and platforms can significantly enhance user experience through features like social commerce integration, improved UX design, and one-click shopping and payment apps. These enhancements are often not achievable with traditional payment method like credit cards (Consumer Financial Protection Bureau, 2022). Unlike credit cards, BNPL represents a more equitable credit facility for customers as BNPL providers do not use credit scores to underwrite their purchases (Consumer Financial Protection Bureau, 2023). Therefore, its provision enables online retailers to access a broader customer base, including those who might not have made purchases otherwise. This expanded access often results in increased customer spending when BNPL is utilized (The Guardian, 2022).[3] Despite these macro and seller-level benefits of BNPL, our understanding of its impact on customers' actual purchase behavior is limited. The impact of customers' BNPL adoption on their purchase behavior and the drivers of such an impact are largely unexplored in academic literature. Understanding the impact of BNPL on customer purchase behavior is crucial for various stakeholders. These include online retailers, FinTech and other financial companies, credit card issuers, and also regulatory bodies such as the Consumer Financial Protection Bureau (CFPB) and Federal Reserve. BNPL has the potential to transform the retail experience by realigning the value proposition among customers, retailers, and credit providers. Insights derived from analyzing its impact can inform public policy decisions, particularly as regulators worldwide grapple with the questions of whether and how to regulate the BNPL sector (Soni, 2023).

In this study, we explore the impact of BNPL[4] on customers' online purchase behavior. To this end, we empirically estimate the effect of customers' BNPL adoption on their online order size at the individual level using their actual online purchase data spanning multiple years. We use order size, defined as the total spending per online order per customer, as our primary metric. This measure effectively captures the transactional aspect of the customer-retailer relationship.[5] We adopt a quasi-experimental research design (Goldfarb et al., 2022) using a synthetic difference-in-differences approach. Using observational data, we divide customers into two groups: a treatment group comprising customers who adopt BNPL and a control group consisting of customers who continue to use traditional payment methods when ordering from the focal retailer. In our research design, the treatment, i.e., BNPL adoption, is heterogeneous - BNPL adoption occurs in a staggered manner. Furthermore, treatment assignment may involve potential endogeneity issues. To address these challenges, we employ the synthetic difference-in-differences method introduced by Arkhangelsky et al. (2021) to estimate the effect of customers' BNPL adoption on their order size. The method does not rely on a strong parallel trend assumption, thus accounting for unobserved heterogeneity in BNPL adoption (Arkhangelsky & Hirshberg, 2023). Additionally, we examine the moderating effects of various factors, including customer segments, demographic characteristics, and product attributes.

[1] While the scope of FinTech is very wide, our focus is on consumer lending services where technology companies have started offering credits to customers for their purchases, which were provided by traditional financial institutions (Hendershott et al., 2021). This FinTech revolution in the customer credit market significantly affects customers' online purchase behavior (The Guardian, 2022).

[2] The report is based on a survey of US consumers in 2023 who identified credit cards, debit cards, PayPal, BNPL, and digital wallets (Apply Pay and Google Pay) as preferred payment options.

[3] A clothing retailer, Rue21, reported a 73% increase in the average purchase amount when it started using Klarna, a BNPL provider.

[4] According to Consumer Financial Protection Bureau (2021), "Buy Now, Pay Later (BNPL) is a type of installment loan that typically allows you to purchase something immediately with little or no initial payment and pay off the balance over four or fewer payments." However, unlike the market for traditional payment services (such as cards), the BNPL market is unregulated (Guttman-Kenney et al., 2023). In Appendix A, we describe the operational details of BNPL.

[5] We note that a BNPL transaction involves three agents: a customer, a retailer, and a BNPL provider. In our research setting, 'retailer' in 'customer-retailer relationship' refers to the focal retailer offering the BNPL payment option with the services of a BNPL provider.

Our empirical results demonstrate that BNPL adoption significantly impacts customers' online order size. Specifically, we observe a 6.42% increase in online spending among BNPL adopters compared to non-adopting customers at the focal retailer offering BNPL as an online payment option. Furthermore, our analysis reveals that this effect is predominantly driven by the purchase of low-ticket items, which are products priced at a lower cost. Demographic factors such as age and income significantly moderate this effect. The increases in online spending by customers who adopt BNPL are relatively young and have low incomes. Customer loyalty exhibits the weakest moderating effect on increasing online spending by customers who adopt BNPL.

We proceed as follows: first, we review the literature and develop our conceptual framework. Next, we present our research setting, which includes data description, institutional details, sample selection, and model-free evidence. Following this, we present our empirical strategy. We then discuss our empirical results and conduct robustness tests. Finally, we present a general discussion and conclude by outlining some limitations of the study.

2. Conceptual framework

We leverage theories from behavioral economics to examine the impact of BNPL on consumer behavior. Specifically, we apply the theory of hyperbolic discounting (Laibson, 1997), which posits that individuals have a stronger preference for immediate payoffs compared to later ones, even if later ones are larger. This theory contrasts the effects of immediate versus delayed costs or rewards on consumer decision-making. BNPL is characterized as a deferred payment plan. It allows customers to enjoy the purchase benefits of consumption in the *present* while shifting the purchase pain or cost across multiple payment installments into the *future*. For instance, when a customer makes a $100 purchase using BNPL, the immediate focus is on the current $25 installment rather than the total $100 expenditure. This psychological framing can influence the customer's perception of affordability and willingness to purchase. It is important to note that the customer is obliged to pay the remaining amount in three equal monthly installments of $25, typically without incurring interest charges. In such purchasing situations, customers prefer immediate gratification over long-term benefits, a behavior known as present bias[6] (Kuchler & Pagel, 2021). This cognitive bias leads individuals to overestimate immediate rewards relative to future ones. In marketing contexts, hyperbolic discounting or present bias is observed when customers face immediate costs with delayed benefits or immediate benefits with delayed cost (Ho et al., 2006). For instance, this bias may influence a customer's decision to purchase a gym membership, where the cost is immediate, but the health benefits are delayed in the future. BNPL exemplifies the application of behavioral economics principles in technology, exploiting bias in customers' preference for immediate rewards. BNPL offers borrowing capacity even to customers who may not qualify for traditional credit (D'Acunto et al., 2020) and features low transaction costs (Agarwal et al., 2020). These characteristics enhance the customer experience (Gomber et al., 2018) by embedding loan facilities at the point of purchase and reducing customer friction (Sieber & Guibaud, 2022). Thus, in an online shopping environment, BNPL, a FinTech-enabled payment solution, encourages customers to '*I want it, and I want it now*' behavior that captures intertemporal tradeoffs between present gain and future loss (Hardisty et al., 2013). Building on these theoretical foundations, our study aims to empirically quantify the impact of BNPL adoption on customers' online purchase behavior, an area that remains relatively unexplored in the existing literature (see Berg et al., 2021; Guttman-Kenney et al., 2023; Sng & Tan, 2021, for macro overviews). Furthermore, we extend our analysis by exploring the moderating effects of various factors, including customer segments, demographic characteristics, and product attributes, on the relationship between BNPL adoption and online purchase behavior.

2.1. Effect of BNPL adoption

Our primary research question examines the impact of BNPL adoption on customers' online purchase behavior. In an online shopping environment, the integration of BNPL as a payment option incorporates customer financing directly at the point of purchase. This integration effectively meets customers' financial needs at the moment of decision, creating a seamless purchase experience (Sieber & Guibaud, 2022). This integration enables customers to order products instantly, thereby facilitating immediate gratification, a key psychological factor in customers' decision-making. Furthermore, the interest-free installment-based payments offered by BNPL may influence customers' mental accounting processes. This could lead customers to prioritize the immediate pleasure of consumption over the delayed pain of payment, as described by Prelec and Loewenstein (1998). Customers often allocate a specific budget for online purchases over a given period, such as monthly. BNPL offers a mechanism that aligns with this budgeting approach, potentially allowing customers to make purchases while perceiving that they are staying within their allocated budget. In essence, BNPL aligns with customers' tendency to mentally allocate fixed spending limits for specific periods, both current and future, potentially influencing their perception of affordability and budget adherence. The structure of BNPL payments closely aligns with this mental accounting pattern, potentially increasing the likelihood of customer purchases. Consequently, the mental accounting processes facilitated by BNPL in an e-commerce environment could potentially encourage increased customer spending. Furthermore, the e-commerce environment incorporates various marketing technologies (e.g., 24-hour retailing, instant credit, website design, chatbots) that

[6] Present bias phenomenon is a special case of hyperbolic discounting (Heidhues & Strack, 2021).

have been shown to increase the likelihood of impulse buying among customers (Madhavaram & Laverie, 2004). BNPL messaging at checkouts often emphasizes certain elements, such as 'no fees,' making them more salient and drawing customers' attention (Financial Conduct Authority, 2017). Simultaneously, other important details may be less prominently displayed, potentially leading customers to not perceive BNPL as a form of credit (Soni, 2023). Drawing from these theoretical considerations and empirical observations, we posit that customers' adoption of BNPL will positively impact their online purchasing behavior, manifested through an increase in order size. In this study, we operationalize online purchasing behavior through order size[7], defined as the total spending per online order per customer. This metric reflects the transactional value of customers to retailers offering BNPL as a payment option.

2.2. Moderating effects

Having established our primary research question, we now turn our attention to examining the moderating effects of customer and product characteristics on the relationship between BNPL adoption and customers' online purchase behavior. In this study, customer characteristics encompass both segmentation variables and demographic features, allowing for a nuanced understanding of the moderating effects beneficial for online retailers with customer targeting strategies. As Ratchford et al. (2022) note, online retailers employ various segmentation strategies to target customers at various stages of their purchase journey, potentially influencing the impact of BNPL adoption. Consequently, we posit that the effectiveness of BNPL provision by online retailers may vary depending on the specific customer segments they aim to target. Retailers often operationalize segmentation metrics such as loyalty, category experience, and promotion sensitivity through loyalty card and scanner data. These metrics enable retailers to maximize profits by identifying and targeting their most valuable customers (Pauler & Dick, 2006). Moreover, the technological infrastructure of online retailing ensures continuous accessibility for customers, unlike traditional offline shopping. This constant availability may interact with customer segments in influencing the impact of BNPL adoption. Given this accessibility, it's plausible that online retailers may receive a higher proportion of visits from non-loyal customers compared to loyal ones, potentially influencing the effectiveness of BNPL offerings. It is reported that online retailers strategically employ BNPL as a mechanism to attract non-loyal customers and potentially encourage impulse purchases (Forbes, 2020). Hence, we hypothesize that the effect of BNPL adoption on customers' online purchase behavior is likely to be more pronounced for non-loyal customers compared to loyal ones. Furthermore, customers with high category experience and high promotion sensitivity may respond differently to BNPL adoption. When provided with unsecured credit access via BNPL (Di Maggio et al., 2022), these customers may exhibit higher spending compared to those with low category experience and low price sensitivity. Prior research has established that customers' demographic characteristics, including age, income, and household size, significantly moderate their online purchase behavior (Punj, 2011). We expect these factors to also influence the relationship between BNPL adoption and online purchase behavior. BNPL extends credit access to customers with low credit scores who would otherwise be unable to secure loans from traditional credit markets (Guttman-Kenney et al., 2023). Research suggests young and low-income customers typically have low credit scores compared to older and high-income individuals (Barr, 2004). Based on these observations, we hypothesize that the adoption of BNPL by young[8] and low-income[9] customers will have a higher impact on their online order size than old and high-income customers, respectively.

Loan limits typically constrain the scope of BNPL offerings. According to ChargeAfter (2023), loans granted by BNPL providers generally range from $50 to $1000. The average BNPL loan amount is $135 (Consumer Financial Protection Bureau, 2023). Given these loan amounts sanctioned by BNPL providers, we posit that BNPL offerings are inherently more oriented towards facilitating the purchase of low-ticket items (those with lower price points) rather than high-ticket items. Moreover, businesses report an interesting phenomenon called the 'lipstick effect,' wherein customers under financial strain tend to reduce spending on big-ticket items in favor of low-ticket items (The Guardian, 2008). This behavioral pattern may interact with BNPL adoption. We anticipate that the additional credit provision via BNPL may amplify this effect. Specifically, we hypothesize that BNPL adoption will result in higher spending on low-ticket items, driven by the convenience it offers (Berry et al., 2002) and its low hassle cost (Lambrecht & Tucker, 2012).

Based on the theoretical foundations and hypotheses discussed above, we present our conceptual framework in Fig. 1. In summary, our conceptual framework integrates several theoretical perspectives: hyperbolic discounting, present-bias phenomenon, mental accounting, convenience marketing, and hassle cost. These theories converge to explain the hypothesized positive impact of BNPL adoption on customers' online purchase behavior. Fundamentally, BNPL provides customers with *immediate* benefits while shifting costs incrementally into the *future*. Furthermore, our conceptual framework incorporates the potential moderating effects of customer segments, demographic characteristics, and product attributes. This comprehensive approach allows for a nuanced understanding of how BNPL adoption may differentially impact various customer groups and product categories in the context of online purchasing behavior.

[7] Order size is an appropriate metric for our study as online retailers embed BNPL at the point of purchase, and customers come across them at the final stages of checking out their online orders.

[8] The usage of BNPL gradually declines across generations: 37% Gen Z, 32% of millennials, 16% of Gen X, and 6% of baby boomers use BNPL (Morning Consult, 2023).

[9] According to Federal Reserve Bank of New York (2023), low-income customers have lacked access to low-cost, short-term, and smaller-size personal loans from banks and other traditional finance institutions, making them ideal target segment for FinTech firms.

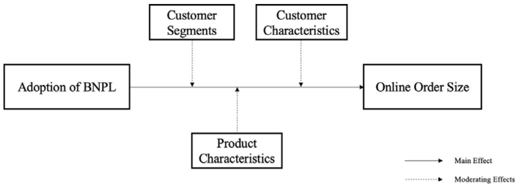

Fig. 1. Conceptual Framework. *Note*: The conceptual framework shows the main effect of BNPL adoption on customers' online order size. Customer segments, customer characteristics, and product characteristics moderate this main effect. BNPL stands for Buy Now, Pay Later.

3. Research setting

This section outlines the research setting for our empirical specification, detailing the data sources, institutional context, and methodological approach.

3.1. Data

Our data comes from an online retailer in the Nordic region[10], specializing in selling clothing, accessories, footwear, and equipment (e.g., game cameras, GPS tracking devices, guns, and skis, among others) for outdoor activities (such as hunting, sports, camping, and fishing). Our dataset spans from June 2012 to November 2014, encompassing detailed information on customers' online orders, including order timestamps, total spending, itemized purchases, product prices, promotional offers, shipping costs, and crucially, the payment methods used for each transaction.

The retailer's e-commerce platform offers customers three primary payment options: 1) card, 2) pay on delivery (POD), and 3) buy now, pay later (BNPL). For the purposes of this study, we classify card payments and POD as traditional payment services, in contrast to the more recently introduced BNPL option. Customers have the flexibility to select any of these payment methods when completing their online transactions. Before divulging further details on our dataset, it is crucial to elucidate the institutional context that informs our empirical strategy.

3.1.1. Institutional details

The online retailer was established in the region in early 1990. In the early period, it focused on offline retailing through physical stores. Gradually, it strategically shifted its focus primarily to its online channel. To facilitate BNPL transactions, the retailer has partnered with a reputable BNPL service provider with a leading market position in the Nordic region. In 2010, during the nascent stages of the BNPL sector, the BNPL provider initiated strong marketing campaigns in the region to obtain many online retailers as its clientele. The online retailer started providing this payment option in late 2011.[11] However, the adoption of BNPL by customers happened gradually over time. We emphasize that the primary objective of this study is to quantify the benefits accruing to the focal retailer from its customers' BNPL adoption, rather than examining the benefits to the BNPL service provider itself.

3.1.2. Sample selection

We start with the data of online orders containing details of each order at an individual customer level. We arrive at our final sample after cleaning the data using the following steps. First, we remove all incomplete orders. An order-status variable flags incomplete orders in the dataset with the following description: order canceled, payment waiting, and cart created. Canceled orders indicate that customers ordered items online; however, before the order is shipped, they cancel or return it. Payment waiting indicates that customers did not complete the payment for their online orders. Cart created suggests customers abandoned their carts without fulfilling their online orders. Second, we remove all those customers with multiple accounts. To that end, we use the customer number, a unique identifier assigned upon registration, and the email address provided for each online order (emails are used for updating order status, such as shipping updates and payment confirmation). Therefore, we exclude customers with multiple email addresses associated with a single customer number. We also exclude customers with identical email addresses associated with different customer numbers. The resulting filtered dataset comprises a unique set of customer number and email address combinations, ensuring each entry represents a distinct customer. This step ensures that in our empirical strategy, treatment assignment does not generate a contaminated sample (Horowitz & Manski, 1995) that creates problems in estimating treatment effects (Ding & Lehrer, 2010).

3.1.3. Variable operationalization and data description

Online purchase behavior, $OnPurBehavior_{ito} = \{(p_1, p_2 \ldots, p_{N_{ito}}), (q_1, q_2 \ldots, q_{N_{ito}})\}$ of customer i at time t for her online order o is a set of prices paid (p) and quantities ordered (q) for all the product items, where N_{ito} is the total num-

[10] In the Nordic region, BNPL has continued its growth as a preferred online payment, commanding 11.7%, 12.8%, 18.1%, and 25.2% of e-commerce shares in Denmark, Finland, Norway, and Sweden, respectively (Worldpay, 2021).

[11] We could not furnish the details of the online retailer and BNPL provider due to the non-disclosure agreement signed with them.

Table 1
Data Summary.

Variable	Value
Start Date	14-Jun-2012
End Date	27-Nov-2014
Total Customers	42,882
Total Orders	63,672
Order Size (€ /Customer/Order)	114.96 (98.18)
Shipping Cost (€ /Order)	9.05 (6.36)
Holiday (% of Orders)	3.68%
Hunting Season (% of Orders)	25.49%
Customer Age (in years)	43.14 (4.83)
Customer Income (€)	37,313.77 (7245.62)
Household Size	2.14 (0.30)

Note: Figures in brackets are standard deviations.

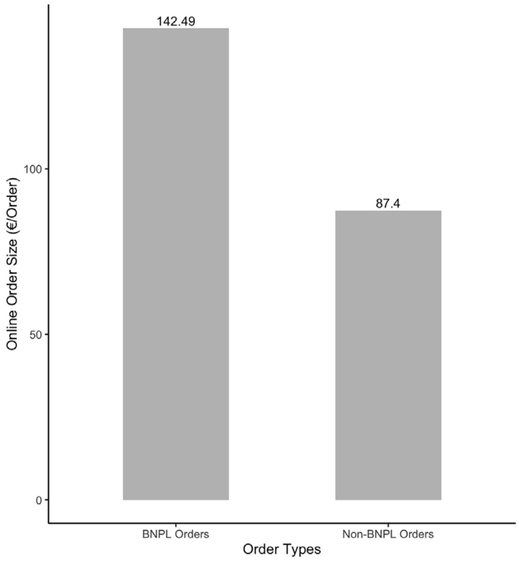

Fig. 2. Model Free Evidence. *Note*: The model-free evidence compares two types of online orders: BNPL orders and non-BNPL orders. BNPL orders refer to those online transactions in which BNPL was utilized as the payment method, while non-BNPL orders pertain to transactions completed using traditional payment methods.

ber of distinct product categories. We capture online purchase behavior using order size ($OrderSize_{ito}$), which is operationalized as $OrderSize_{ito} = \sum_{i=1}^{N_{ito}} (p_i \times q_i)$. This metric captures the transactional side of online customer-retailer interaction (Coviello et al., 2002). The main focus of the study is understanding the impact of BNPL adoption on order size. The sample selection resulted in 63,672 online orders from 42,882 customers. We provide the data summary in Table 1. The average order size per customer is € 114.96. The average shipping cost per order is € 9.05. Approximately 4% of online orders are placed during holidays[12], and 25% are placed during the hunting season[13] The average age of customers is 43 years, with an average annual income of € 37,314.

3.1.4. Model free evidence

Our model-free evidence (see Fig. 2) compares the average order sizes for two types of orders: BNPL orders and non-BNPL orders. BNPL orders refer to online orders paid for using BNPL. Non-BNPL orders refer to online orders paid using traditional payment methods (e.g., card and POD). During the study period, 14% of online orders are made via BNPL with an average order size ($OrderSize_{BNPL}$) of € 142.49. The average order size for non-BNPL orders ($OrderSize_{\overline{BNPL}}$) is € 87.40. The

[12] Holidays include New Year, Easter, Christmas, Independence Day, Midsummer, and May Day.
[13] The hunting season spans from Aug to Dec and includes the hunting of game animals (e.g., elk).

difference in these two order types ($\Delta_{Order} = OrderSize_{BNPL}$ - $OrderSize_{\overline{BNPL}} = 55.09$, $p \leq 0.01$) is statistically significant. Thus, BNPL orders tend to be 63% higher than non-BNPL orders. This model-free analysis provides prima facie evidence that BNPL usage is associated with an increased order size or online spending.

4. Empirical strategy

This section outlines the empirical strategy used to assess the impact of customers' BNPL adoption on their purchase behavior. In our research setting, customers adopt BNPL gradually. Thus, our empirical strategy is proposed in two stages to address identification challenges and derive managerial insights. Initially, our research design employs the first year of data to select customers and define key variables that reflect their behavioral characteristics. Subsequently, we outline our econometric modeling approach.

4.1. Research design

During the observational window, the retailer did not introduce BNPL. Furthermore, customers in our dataset adopt BNPL in a staggered manner. Given these characteristics in our dataset, accurately capturing the impact of BNPL on customers' purchase behavior requires a detailed empirical specification, which will be addressed subsequently. Moreover, examining its heterogeneous effects across various customer types necessitates a carefully designed research approach.

We utilize the first year of data to address these challenges related to initialization and operationalization. We select all those customers who did not adopt BNPL in the first year of the data period, from June 2012 to June 2013. Subsequently, data from the following 17 months, spanning from July 2013 to November 2014, is utilized for model estimation. Customers who do not adopt BNPL during the estimation period constitute the control group, while those who progressively adopt BNPL form the treatment group (Manchanda et al., 2015). Thus, BNPL adoption serves as the treatment in our research design.

We also utilize the initialization period to operationalize key customer segments, including customer loyalty, category experience, and promotion sensitivity. Customer loyalty is operationalized as the total number of successful online orders placed by each customer. To measure customers' category experience, we calculate the number of distinct product categories each customer ordered during the initialization period.[14] Promotion sensitivity for each customer is assessed by calculating the average discount received per online order during the initialization period. In addition to these customer segments, customer demographics (age, income, and household size) are also incorporated into our empirical model. In our model, customer segments and demographics are included as potential moderating variables.

During periods of financial pressure, such as inflation and rising interest rates, customers frequently reduce spending on big-ticket items (PYMNTS, 2023; Wall Street Journal, 2023). However, for low-ticket items, this pattern may not hold as during the downturn, rather than changing spending habits, customers switch to cheaper items, a phenomenon described as the lipstick effect (The Guardian, 2008). Most existing BNPL business models are built around financing low-ticket item purchases (McKinsey, 2021). Accordingly, we examine the impact of BNPL adoption on customers' spending behavior with respect to big-ticket versus low-ticket items, as a product characteristic. To classify products as either big-ticket or low-ticket, we perform a median split on the distribution of product prices during the initialization period.[15] Products priced above the median are categorized as big-ticket items, while those priced at or below the median are classified as low-ticket items. For each online order during the estimation, the model includes the proportion of low-ticket items in their basket.

After initialization, we arrived at 7104 treatment group customers and 32,355 control group customers with 9861 and 35,002 online orders, respectively. Customers in the treatment group adopt BNPL to make purchases from the focal retailer during the estimation period. Customers in the control group do not adopt BNPL to make purchases from the focal retailer during the estimation period. Fig. 3 shows the BNPL adoption dynamics of customers in the treatment group. We describe our sample characteristics in Table 2. The treatment group customers' order size is 11.65% larger than the control group customers. Furthermore, the treatment group also avails larger discounts on their orders, 34.85% more than the control group. Both treatment and control group customers have similar customer loyalty and category experience.

4.2. Econometric modeling

In our research design, we could not observe the customers who never adopted BNPL. Therefore, we estimate the effect of BNPL adoption as the average treatment effect on the treated (ATT) rather than the average treatment effect (ATE) as we can not systematically differentiate BNPL adopters from the non-adopters. However, the ATT estimator could still be valuable for retailers, given the increasing popularity of the BNPL payment system.

In our research design, we have a few identification challenges. First customers' decision to adopt BNPL could be endogenous, leading to a self-selection issue. For example, customers with financial hardships or low credit ratings or who default are more likely to adopt BNPL.[16] Second, an unbiased estimate of ATT requires a parallel trend assumption. If the

[14] In our dataset, we have 12 categories details of which are given in Appendix B.
[15] In retailing, a similar approach has been used to classify product category (e.g. Dhar et al., 2001).
[16] Di Maggio et al. (2022) report that lower-income and young users with high retail spending are more likely to adopt BNPL.

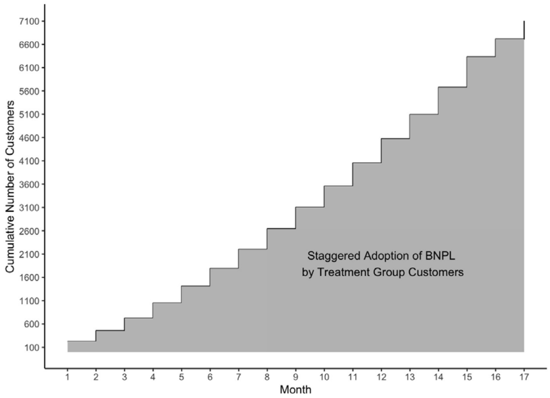

Fig. 3. Treatment Variation. *Note*: The figure illustrates the staggered adoption of BNPL among customers in the treatment group, depicting the cumulative number of customers who have adopted BNPL at the end of each month during the estimation period.

Table 2
Summary of Treatment and Control Groups.

Variable	Treatment	Control
Total Customers	7104	32,355
Total Orders	9861	35,002
Order Size	118.23	105.89
(€ /customer)	(67.96)	(97.86)
Customer Loyalty	1.56	1.38
(#/customer)	(0.56)	(0.87)
Category Experience	7.25	6.15
(#/customer)	(2.67)	(2.15)
Promotion Sensitivity	21.24	15.75
(€ /customer)	(8.34)	(6.89)

Note: The treatment group comprises customers who adopt BNPL, while the control group comprises customers who do not adopt BNPL. The figures in parentheses represent standard deviations.

order size of the control group customers is affected by the retailer's specific marketing strategies differentiated based on payment methods (e.g., discount or waiver of shipping cost if paid via BNPL), then the parallel trend is violated. Third, we note that the treatment is time variant as customers adopt BNPL in a staggered manner (see Fig. 3), requiring a model that can accommodate heterogeneous treatment effects.

To address the above challenges, we model using the Synthetic difference-in-differences (Synthetic DiD) introduced by Arkhangelsky et al. (2021). Synthetic DiD integrates difference-in-differences (DiD) and synthetic control (SCM) methods to enable an unbiased estimate of ATT where standard DiD assumptions (e.g., parallel trends, covariate balancing, and unobservables) may not hold. To account for the staggered adoption of BNPL by customers, we follow Berman and Israeli (2022). The estimation involves two steps. First, we construct a balanced panel for each cohort g.[17] Second, we arrive at cohort-specific treatment effects, β_g, by solving the following optimization problem,

$$(\hat{\beta}_g, \hat{\theta}) = \underset{\beta_g,\theta}{\arg\min} \Bigg\{ \sum_{i\in N_g} \sum_{t=\mu(g)}^{\nu(g)} \Bigg(OrderSize_{it} - \alpha_i - \tau_t - BNPL_{it} \times \left(\beta_1^g + \sum_{s=2}^{N_s+1} \beta_s^g CustSeg_{it} + \sum_{c=N_s+2}^{N_c+N_s+1} \beta_c^g CustDemo_{it} + \sum_{p=N_s+N_c+2}^{N_p+N_c+N_s+1} \beta_p^g ProdChar_{it} \right) + \sum_{s=1}^{N_s} \rho_s^g CustSeg_{it} + \sum_{c=1}^{N_c} \delta_c^g CustDemo_{it} + \sum_{p=1}^{N_p} \gamma_p^g ProdChar_{it} \Bigg) \hat{\omega}_i \hat{\lambda}_t \Bigg\}. \quad (1)$$

In Eq. (1), κ captures customer and time fixed effects, $\kappa = (\alpha_i, \tau_t)$. Cohort-specific treatment effects is captured using β_g, where $\beta_g = (\beta_1^g, \beta_2^g, \beta_3^g, \beta_4^g, \beta_5^g, \beta_6^g, \beta_7^g, \beta_8^g)$. β_1^g is the cohort-specific treatment effect of BNPL adoption, $\beta_2^g - \beta_4^g$, $\beta_5^g - \beta_7^g$, and

[17] Cohort is a group of customers from the treatment group who received treatment at the same time.

β_g^g capture the variation of treatment across customer segments[18], customer demographics[19], and product characteristics[20], respectively.[21] N_g is the total number of customers in cohort g. The treatment variable, $BNPL_{it}$, indicates whether customer i has adopted the BNPL at time t. We report the average treatment effects, β^{SDiD}, which is calculated as the average of the cohort-specific treatment effects across all cohorts, i.e.,

$$\beta^{SDiD} = \frac{1}{G}\sum_{g}\beta_g, \tag{2}$$

where G indicates the total number of cohorts. Pre- and post-adoption period for cohort g is indicated by $\mu(g)$ and $\nu(g)$, respectively. We consider four weeks before and after the BNPL adoption for each cohort. We define a time period at a weekly level.[22]. Synthetic DiD introduces two sets of weights: unit weights, $\hat{\omega}_i$, and time period weights, $\hat{\lambda}_t$. Unit weights are selected in such a manner to ensure treatment and control group customers have similar trends before the treatment or pre-adoption period of BNPL, i.e.,

$$\hat{\omega}_0 + \sum_{i\in N_g^{co}} \hat{\omega}_i OrderSize_{it} \approx \frac{\sum_{i\in N_g^{tr}} OrderSize_{it}}{|N_g^{tr}|}, \tag{3}$$

where N_g^{co} and N_g^{tr} are sets of customers for cohort g from the control and treatment groups, respectively. In Synthetic DiD, $\hat{\omega}_0$ is not constrained to zero to ensure similar but not identical outcomes for customers in treatment and control groups before treatment, satisfying parallel trends.[23] The time period weights $\hat{\lambda}_t$, are selected in such a manner that ensures the average post-treatment outcome for each of the control units to be the weighted average of the pre-treatment outcomes plus a constant ($\hat{\lambda}_0$), i.e.,

$$\hat{\lambda}_0 + \sum_{t=\mu(g)}^{g_t-1} \hat{\lambda}_i OrderSize_{it} \approx \frac{\sum_{t=g_t}^{\nu(g)} OrderSize_{it}}{\nu(g) - g_t + 1}, \tag{4}$$

where g_t is the adoption time for cohort g. The time weights improve the precision by eliminating those pre-adoption periods that differ from the post-adoption periods for control group customers. In the estimation, we include the logged value of $(OrderSize + 1)$ for an easy interpretation of the model parameters.

The proposed Synthetic DiD model addresses the identification issues and estimates the ATT consistently. First, it allows heterogeneous or time-variant treatment effects with cohort-based estimation. Second, it creates optimal synthetic control units thereby allowing relaxation of parallel trend assumption. Third, it provides a consistent estimate of ATT even if customers' BNPL adoption decision is correlated with customer-level time trend, as long as the combination of control group customers and pre-treatment period is sufficiently large (Arkhangelsky et al., 2021; Berman & Israeli, 2022).[24]

5. Results

In Table 3, we present the results from the Synthetic DiD model as specified in Eq. (1).

5.1. Main effect: BNPL adoption

The main effect of BNPL adoption (0.0622, $p \leq 0.01$) on customers' online order size is positive and significant, indicating that customers who adopt BNPL increase their online spending compared to those who do not. The ATT estimate of 0.0622 translates to a 6.42%[25] increase in online order size for customers who adopt BNPL compared to those who do not. This percentage increase translates to € 3.79 per week.

5.2. Moderating effects: customer segments

While customer loyalty (0.1123, $p \leq 0.05$) positively impacts online order size, its interaction with BNPL adoption (-0.0096, $p \leq 0.05$) is negative, resulting in a decrease of 0.96%. This suggests that non-loyal customers, or those who order less frequently, are more likely to increase their online spending compared to more loyal customers following BNPL adoption. Category experience (0.0034, $p \leq 0.05$) has a positive impact on online order size, and its interaction with BNPL

[18] $CustSeg = \{CustomerLoyalty, CategoryExperience, PromotionSensitivity\}$, thus, $N_s = 3$.
[19] $CustDemo = \{Age, Income, HouseholdSize\}$, thus, $N_c = 3$.
[20] $ProdChar = \{LowTicketItem\}$, thus, $N_p = 1$.
[21] We mean-center these covariates in the estimation to facilitate interpretation of interaction terms and reduce unessential multicollinearity (Pieters et al., 2022).
[22] For example, a cohort that adopts BNPL at $t = 8$, $\mu(g) = 6$, $\nu(g) = 9$.
[23] For further details on estimation please refer to Arkhangelsky et al. (2021).
[24] In Appendix C, we provide the number of customers in the treatment and control group for each cohort.
[25] $\exp(0.0622) - 1$.

Table 3
Results from Synthetic DiD Model.

Variable	Estimate
Main Effect: BNPL Adoption	
BNPL Adoption	0.0622*** (0.0095)
Moderating Effects: Customer Segments	
BNPL Adoption × Customer Loyalty	−0.0096** (0.0041)
BNPL Adoption × Category Experience	0.0582*** (0.0217)
BNPL Adoption × Promotion Sensitivity	0.0658*** (0.0221)
Customer Loyalty	0.1123** (0.0565)
Category Experience	0.0034** (0.0016)
Promotion Sensitivity	−0.0156***
Moderating Effects: Demographics	
BNPL Adoption × Age	−0.0745* (0.0389)
BNPL Adoption × Income	−0.1076*** (0.0176)
BNPL Adoption × Household Size	0.0021 (0.0217)
Age	0.1578*** (0.0487)
Income	0.1785** (0.0781)
Household Size	0.0037 (0.0038)
Moderating Effect: Product Characteristics	
BNPL Adoption × Low-ticket Items	0.1765*** (0.0589)
Low-ticket Items	0.2076*** (0.0167)

Notes: The table reports the parameter estimates of the Synthetic DiD model. Standard errors are in brackets. Significane level: $^{***}p \leq 0.01$, $^{**}p \leq 0.05$, $^{*}p \leq 0.10$

(0.0582, $p \leq 0.01$) is also positive, indicating an increase of 5.99%. Thus, customers who order across multiple categories are more likely to increase their online spending after adopting BNPL. Finally, while promotion sensitivity (−0.0156, $p \leq 0.01$) negatively impacts online order size, its interaction with BNPL adoption is positive (0.0658, $p \leq 0.01$), resulting in an increase of 6.80%. Thus, more promotion-sensitive customers tend to increase their online spending after adopting BNPL.

These results indicate that customer loyalty, category experience, and promotion sensitivity are the main driving factors behind the increase in customers' online orders following BNPL adoption. Promotion-sensitive customers are sale-prone and exhibit compulsive buying behavior (Kukar-Kinney et al., 2012). Since BNPL provides customers with unsecured credit access (Di Maggio et al., 2022), promotion-sensitive customers with compulsive purchase behavior may spend more. Furthermore, category experience impacts customers' shopping behavior, as familiarity with a category leads to the perception of lower expected prices, thereby increasing the utility of products (Tang et al., 2001). Therefore, customers with high-category experience who have access to credit facilities via BNPL could spend more. Finally, loyalty, in comparison to category experience and promotion sensitivity, does not significantly differentiate online spending patterns following BNPL adoption.

5.3. Moderating effects: demographics

We find that age and income have significant interaction effects with BNPL adoption. Older customers (0.1578, $p \leq 0.01$) have a higher online order size; however, the interaction of age with BNPL adoption (−0.0745, $p \leq 0.10$) is negative. Thus, younger customers are more likely to spend more online after adopting BNPL. Similarly, we find that higher-income customers (0.1785, $p \leq 0.05$) spend more online; however, the interaction of income with BNPL adoption (−0.1076, $p \leq 0.01$) is negative. Therefore, low-income customers who adopt BNPL tend to spend more online. Household size does not have a significant effect.

Young and low-income customers have lower spending power than older and high-income customers. BNPL adoption provides these customers with additional liquidity to increase their consumption. This phenomenon is similar to the "flypaper effect[26]" (Hines Jr & Thaler, 1995) in public finance, described as the "liquidity flypaper effect" in the context of customer consumption (Di Maggio et al., 2022). Thus, when young and low-income customers receive additional liquidity from BNPL, it leads to an increase in their online spending compared to older and high-income customers.

5.4. Moderating effects: product characteristics

As conceptualized in our framework, we expect low-ticket items to moderate the effects of BNPL adoption as most BNPL loans are smaller in amount. Our empirical results support the moderating effect of this product characteristic. We find that low-ticket items (0.2076, $p \leq 0.01$) spur online spending and their interaction with BNPL adoption (0.1756, $p \leq 0.01$) is positive, indicating an additional online spending increase of 19.30%. Thus, we conclude that sales of low-ticket items increase online spending when customers adopt BNPL. This result aligns with the BNPL providers' business models to finance customers' purchases for low-ticket items.

6. Robustness tests

We perform robustness tests using two specifications. First, we capture the effect of BNPL adoption on customers' online order size using alternative models. Second, we use an alternative outcome variable to ensure BNPL adoption has a similar effect on other metrics capturing customers' online purchase behavior.

6.1. Alternative model specifications

For alternative model specifications, we estimate two-way fixed effect difference-in-differences (TWFE) and staggered difference-in-differences (staggered DiD). We specify these models in parsimony to estimate only the ATT of BNPL adoption.

6.1.1. TWFE

We specify the TWFE model as follows:

$$\log(OrderSize_{it}) = \alpha_i^{TWFE} + \tau_t^{TWFE} + \beta^{TWFE} BNPL_{it} + \epsilon_{it}. \tag{5}$$

We estimate clustered standard errors by customers and time. β^{TWFE} measures the ATT of BNPL adoption, estimated using the least squares method.[27] Following Berman and Israeli (2022), we truncate our data before February 2014; thus, all customers who adopt BNPL after the truncation period are treated as controls.

Despite the easy implementation of the TWFE model in Eq. (5), there are a few identification challenges. First, the estimate of the treatment effect, β^{TWFE}, is time-invariant. Therefore, it does not account for a heterogeneous treatment effect[28] for customers adopting BNPL at different time periods. Second, the unbiased estimate of the treatment, i.e., β^{TWFE}, in the TWFE model requires the parallel trend assumption. If the order size of the control group customers is affected by the retailer's specific marketing strategies differentiated based on payment methods (e.g., discount or waiver of shipping cost if paid via BNPL), then the parallel trend is violated. Third, customers' decision to adopt BNPL could be endogenous, leading to a self-selection issue. For example, customers with financial hardships or low credit ratings or who default are more likely to adopt BNPL.[29] These factors may bias the TWFE estimate of Eq. (5). Some of these challenges are addressed using staggered DiD.

6.1.2. Staggered DiD

Following Berman and Israeli (2022) and Wooldridge (2021), we specify the staggered DiD model as follows:

$$\log(OrderSize_{it}) = \sum_{g=g_0}^{T} \eta_g C_{ig} + \zeta_t + \sum_{g=g_0}^{T} \theta_{gt} C_{ig} \mathbf{1}_{\{t \geq g\}} + \xi_{it}, \tag{6}$$

where C_{ig} indicates whether customer i first adopts BNPL at time g, and we define a cohort as a set of all the customers adopting BNPL at the same time. In Eq. (6), g_0 indicates the first cohort's adoption period of BNPL. η_g and ζ_t capture cohort and time fixed effects, respectively. Finally, $\mathbf{1}_{\{t \geq g\}}$ is an indicator function that takes value 1 when time t is greater than or equal to the cohort's adoption period g; otherwise, it is 0. Thus, θ_{gt} captures the treatment effect for cohort g at time t. The average treatment effect of BNPL adoption, θ^{StgDiD}, is obtained by aggregating θ_{gt} across cohorts and time periods. Thus,

$$\theta^{StgDiD} = \frac{\sum_{g=g_0}^{T} \sum_{t=g}^{T} \theta_{gt}}{(T - g_0 + 1)(T - g_0 + 2)/2}. \tag{7}$$

[26] The effect is summarized as "Money sticks where it hits." It refers to a significant increase in public spending due to exogenous grants-in-aid compared to an equivalent dollar of citizen income.
[27] Unbiased estimate of β^{TWFE} require assumptions of homogeneous treatment and parallel trend (De Chaisemartin and D'haultfœuille, 2023).
[28] Staggered adoption of BNPL.
[29] For example, Di Maggio et al. (2022) report that lower-income and young users with high retail spending are more likely to adopt BNPL.

Table 4
Robustness Tests.

	Alternate Methods	
	TWFE (β^{TWFE})	Staggered DiD (θ^{StgDiD})
ATT	0.0895***	0.0958***
	(0.0156)	(0.0278)
Customer FE	✓	NA
Cohort FE	NA	✓
Time FE	✓	✓

Notes: The table reports the average treatment effect (ATT) of adopting BNPL on customers' order size from TWFE and Staggered DiD models. Standard errors are in brackets. Significane level: $^{***}p\leq0.01$, $^{**}p\leq0.05$, $^{*}p\leq0.10$

Following Berman and Israeli (2022), the average treatment effect is calculated based on customers' order spending 4 weeks after adopting BNPL to ensure the online spending behavior of early BNPL adopters is not affected by other factors long after the adoption. We define the time period weekly. Thus, 4 weeks are 4 time periods. We calculate clustered standard error by customers and time.

Finally, we test the parallel trend assumption following Berman and Israeli (2022). In particular, we use data from the pre-adoption period to test the difference in online spending behavior of treatment and control customers before BNPL adoption. Thus, we run the following regression,

$$\log(OrderSize_{it}) = \sum_{g=g_0}^{T} \pi_g C_{ig} + \gamma_t + \sum_{k=1-T}^{-1} \mu_k C_{i(t-k)} + \zeta_{it}, \tag{8}$$

where, similar to Eq. (6), π_g and γ_t capture cohort and time fixed effects, respectively. In Eq. (8), $C_{i(t-k)}$ is an indicator that indicates whether customer i adopts BNPL at $|k|$ periods after time t. Thus, μ_k captures the difference in online orders between treatment and control group customers $|k|$ periods prior to adoption. If μ_k is insignificant in all four time periods, the parallel trend assumption is satisfied, i.e., the online spending behavior of customers in treatment and control groups does not differ prior to the BNPL adoption by the treatment group customers. Despite the attractiveness of modeling heterogeneous treatment using staggered DiD, the estimates could still be biased (Baker et al., 2022).

6.1.3. Results

In Table 4, we present ATT estimators from TWFE and Staggered DiD models. The two-way fixed effect estimator ($\beta^{TWFE}: 0.0895,\ p \leq 0.01$) is positive and significant. The staggered DiD estimate ($\beta^{StgDiD}: 0.0958,\ p \leq 0.01$) is also positive and significant.[30] These results are consistent with our main model, Synthetic DiD.

6.2. Alternative outcome variable specification

We use order volume as an alternative outcome variable. This alternative outcome variable will help establish the robust effects of customers' BNPL adoption on their online purchase behavior, measured using different metrics. We present the results of the synthetic DiD model in Appendix D (see Table D 1). We find the main effect of BNPL adoption (0.0058, $p \leq 0.01$) on customers' order volume is positive and significant, indicating an increase of 0.58% in quantity ordered after they adopt BNPL compared to the control group customers who do not adopt BNPL. The signs of the interaction effects of customer segments, demographics, and product characteristics are consistent with our main analysis using order size. Furthermore, we also estimate TWFE and staggered DiD models with order volume as an outcome variable (see Table D 2 in Appendix D). Both these estimates using order volume as an outcome variable, TWFE (0.0021, $p \leq 0.01$) and staggered DiD (0.0085, $p \leq 0.01$), are positive and significant, which are consistent with previous results using order size as an outcome variable.

7. Discussion

While the FinTech revolution has transformed many aspects of financial services, the impact of emerging payment options on customers' online shopping behavior remains an understudied area in academic literature. FinTech's provision of embedded finance enhances the customer experience by providing alternate funding sources at the point of purchase. This trend is evidenced by the increasing adoption of FinTech services in both advanced and emerging markets (Claessens et al., 2018). Buy Now, Pay Later (BNPL), a notable FinTech innovation, has disrupted the traditional consumer credit market. Merchants have rapidly integrated BNPL schemes at the point of purchase, and customers have swiftly

[30] Parallel trend assumption is validated as we find μ_k is insignificant in all 4 time periods in Eq. (8).

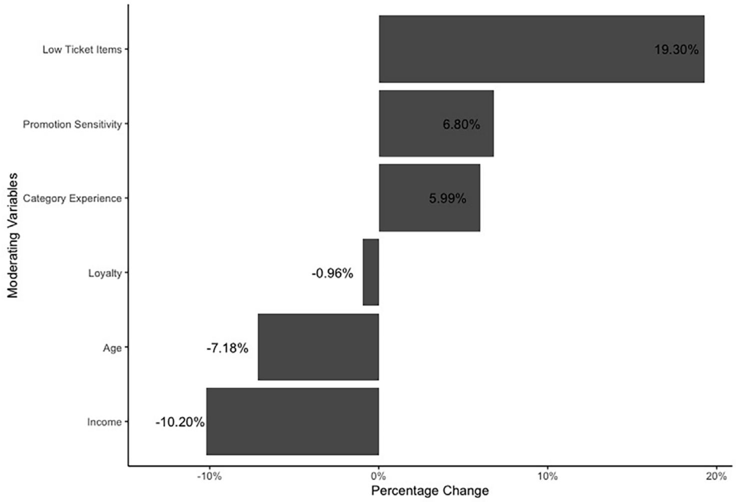

Fig. 4. Effects of Moderators on Online Order Size due to BNPL Adoption. *Note*: The figure shows the moderating effects of customer segments (loyalty, category experience, promotion sensitivity), demographics (age, income), and product characteristics (low ticket items) as a percentage increase or decrease of customers' online order size post their BNPL adoption.

adopted this alternative payment mode (Cornelli et al., 2023). In light of these developments, our study contributes to the literature by exploring the effects of BNPL adoption on customers' online purchase behavior, addressing a critical gap in our understanding of modern e-commerce dynamics with respect to payment services offered by online retailers.

Our empirical analysis reveals that customers' BNPL adoption leads to a significant 6.42% increase in their online spending, highlighting the substantial impact of payment innovation on customer behavior. These findings suggest that BNPL, as an alternative fintech-enabled payment method, functions as a potent e-commerce enabler, potentially reshaping the landscape of online retailing. The core feature of BNPL - interest-free installment payments for online purchases - appears to have a significant psychological impact on customers. Specifically, it leverages the principle that the perceived benefit of spending in the present outweighs the displeasure associated with future payments. This behavior aligns with theories of hyperbolic discounting (Laibson, 1997) and the present-bias phenomenon (Kuchler & Pagel, 2021). We posit that these effects may be particularly pronounced in an online shopping context, where the delay between purchase and product receipt due to shipping times might otherwise dampen the immediacy of gratification. Drawing from the convenience literature in marketing (Berry et al., 2002), we propose that the positive effect of BNPL adoption on customers' order size is largely attributable to the transactional convenience it provides. Specifically, BNPL offers a monetary benefit that effectively counterbalances customers' nonmonetary costs, thereby enhancing the overall value proposition of the transaction.

Our study extends beyond the main effect to examine the nuanced moderating effects of customer segments, demographic factors, and product characteristics, providing a more comprehensive understanding of BNPL's impact. Fig. 4 illustrates the relative magnitude of these moderating effects on online order size subsequent to BNPL adoption. Our analysis reveals that product characteristics, particularly the distinction between low-ticket and high-ticket items, emerge as the primary moderating factor in the relationship between BNPL adoption and order size. Notably, our findings suggest that BNPL adoption has a more pronounced effect on the purchase of low-ticket items, indicating that online retailers specializing in such products may derive particular benefit from offering BNPL options. While the sale of low-ticket items often presents margin challenges for online retailers, McWilliams and Gerstner (2006) argue that such sales can play a crucial role in customer acquisition, upselling opportunities, and retention strategies. Consequently, our findings suggest that the provision of BNPL could serve as a strategic tool for online retailers, potentially enhancing their overall sales performance through increased low-ticket item purchases.

Our analysis reveals that demographic factors, particularly income and age, play significant roles in moderating the effect of BNPL adoption on online purchase behavior. These findings suggest that the effectiveness of BNPL as a marketing strategy may be particularly pronounced for online retailers catering to a predominantly young and low-income customer base.[31] Moreover, our results indicate that BNPL adoption has a more substantial impact on customers with high category experience and high promotion sensitivity, suggesting potential avenues for targeted marketing strategies. Interestingly, our analysis reveals that customer loyalty exhibits the weakest moderating effect among the factors examined, suggesting that BNPL's impact is relatively consistent across different levels of customer loyalty.

[31] BNPL financing appears more attractive to low-income customers, with its wide prevalence among the income group $20,000 - $50,000 and least popular among the income group above $200,000 (Consumer Financial Protection Bureau, 2023). However, some recent reports (e.g., Federal Reserve Bank of New York, 2023; Morning Consult, 2023) suggest that BNPL users tend to have higher income. Therefore, our findings require further investigation across multiple categories for corroboration.

Recent economic observations have noted an unexpected trend: despite rising living costs, consumer spending has increased, a phenomenon colloquially termed 'YOLO' (You Only Live Once) spending(BBC, 2023). Although economists express reservations about the sustainability of this trend, there is a consensus that BNPL services are contributing significantly to this atypical spending behavior. The economic impact of BNPL is substantial in countries that have pioneered its adoption. For instance, in Australia, one of the pioneers of the BNPL sector[32], these services contributed $14.3 billion in gross domestic product (GDP) to the country's economy according to BIS Oxford Economics (2022). Juniper Research (2022) projects that global BNPL users will exceed 900 million by 2027, representing a 157% increase from 2022. This substantial growth is attributed to multiple factors: increasing e-commerce usage, economic pressures, the flexibility of payment options, and widespread merchant adoption. In light of BNPL's growing significance, our study makes a valuable contribution by empirically quantifying its effect on customers' online purchase behavior, addressing a critical gap in the existing literature. Our findings demonstrate a positive impact of BNPL adoption on customers' online spending. However, it is important to note that the decision to offer BNPL services remains a complex strategic consideration for online retailers, as highlighted by Desai and Jindal (2023). By quantifying the differential impacts of BNPL adoption across various customer segments and product characteristics, our study offers nuanced insights that can inform strategic decision-making in online retailing, particularly regarding the implementation and targeting of BNPL services.

8. Conclusion and limitations

The evolution of fintech-enabled payment services has emerged as a critical catalyst in the growth of e-commerce, profoundly shaping customers' online shopping behavior. A significant challenge in e-commerce is cart abandonment, with Baymard Institute (2022) reporting a global abandonment rate of 69.82%. Notably, 9% of online shoppers cite insufficient payment options as a reason for abandonment, contributing to an estimated annual revenue loss of $18 million for brands (PPRO, 2021). Based on our analysis, we conservatively estimate that brands could potentially recover $0.29 million annually in lost revenue by incorporating BNPL payment services, underscoring the economic importance of diverse payment options.[33]

The present study contributes to the literature by empirically investigating the impact of BNPL adoption on customers' online order size, addressing a critical gap in our understanding of modern e-commerce dynamics. Our empirical results demonstrate a significant positive effect of BNPL adoption, with customers who adopt this payment option spending 6.42% more on average compared to non-adopters. Extrapolating from our findings, we estimate that brands could potentially recover up to $0.32[34] million annually by implementing BNPL services, representing a significant opportunity for revenue enhancement. Our analysis reveals that the impact of BNPL on increasing online spending is most pronounced for low-ticket item purchases, suggesting a particular synergy between BNPL services and this product category. The findings suggest that BNPL services may be particularly effective for online retailers whose customer base includes a significant proportion of young and low-income demographics. Our results also indicate that the positive effects of BNPL are amplified for customers exhibiting higher price sensitivity and greater category experience, suggesting potential avenues for targeted implementation of BNPL services. Interestingly, our analysis reveals that customer loyalty is the least significant moderating factor in the relationship between BNPL adoption and increased online spending, suggesting that the benefits of BNPL may extend across various levels of customer loyalty. Despite the overall weak moderating effect of loyalty, our analysis indicates that non-loyal customers exhibit a greater increase in spending compared to loyal customers upon adopting BNPL, suggesting a potential strategy for customer acquisition and engagement. A recent study by Zulauf and Wagner (2022) suggests that in the aftermath of the COVID-19 crisis, many consumers have turned to online shopping as a coping mechanism to enhance their psychological well-being. In light of these findings and the post-pandemic shift in consumer behavior, our results suggest that providing BNPL could be an effective strategy for retailers to boost online sales, particularly among non-loyal customers.

There are some limitations to our study. A primary limitation of our study is the absence of data on customers' BNPL repayment behaviors, including specific installment plans and the incidence of late fees. This information could potentially influence subsequent online purchase behavior and provide a more comprehensive understanding of BNPL's long-term effects. Another limitation is the absence of data on customers' financial literacy levels. Prior studies by Bolton et al. (2011) and Gerrans et al. (2021) suggest that financial literacy can significantly influence the adoption and use of financial products such as BNPL services. The inclusion of this variable could provide additional insights into the drivers of BNPL adoption and its effects. Our study primarily examines BNPL usage at the point of purchase. However, it's important to note that customers may encounter BNPL options at various stages of their purchase journey. For instance, exposure to BNPL during the product exploration phase might influence perceptions of product affordability. Future research could benefit from a more comprehensive examination of BNPL's impact throughout the entire customer journey. It is worth noting that while a typical BNPL transaction involves three parties - the customer, the retailer, and the BNPL provider - our study primarily focuses on the

[32] Leading BNPL companies such as Afterpay, Zip, Openpay, and Latitude are from Australia.

[33] Our data shows around 18% (=7104/39459 $\times$100) of customers use the BNPL; we get a conservative estimate of $9 \times 0.18 = 1.62\%$ customers looking for the BNPL. Thus, we can safely assume $69.82 \times 0.0162 = 1.13\%$ carts are abandoned due to the lack of a BNPL payments option. Consequently, providing the BNPL payments option can help brands recover $18/69.82 \times 1.13 = 0.29$ million/year from lost revenue.

[34] $0.29 + 0.29 \times 6.42\% = 0.30$.

customer-retailer relationship. This narrow focus, while allowing for depth of analysis, may not capture the full complexity of BNPL transactions. Future research could extend our findings by investigating other critical relationships in the BNPL ecosystem, particularly those between customers and BNPL providers, and between retailers and BNPL providers. Such investigations could provide a more holistic understanding of the BNPL phenomenon. A significant limitation of our study is the lack of exploration into the long-term impact of BNPL on customers' financial well-being. While we examine immediate purchasing behavior, the potential consequences of BNPL usage on personal finance management and overall financial health remain unexplored in our analysis.[35] Given that BNPL essentially represents a form of consumer debt, it may have broader macroeconomic implications, as suggested by Garner et al. (1996). Furthermore, Ah Fook and McNeill (2020) emphasize the crucial nature of understanding BNPL's impact on customers' overall financial well-being, an aspect that warrants further investigation. The rapid growth of the BNPL sector has prompted regulatory attention, with authorities beginning to scrutinize both the potential risks[36] and benefits[37] associated with BNPL loans (The Guardian, 2022). This evolving regulatory landscape presents an important context for future research. The potential impact of aligning BNPL regulations with those of traditional credit markets on customer purchase behavior represents a critical and evolving area for future research. Such studies could provide valuable insights for policymakers and industry stakeholders alike. These identified limitations and emerging issues present compelling future research agendas, which could significantly enhance our understanding of the BNPL phenomenon and its broader economic and social implications.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jretai.2024.09.004

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