Should I Buy Now, Pay Later? An Empirical Study of Consumer Behavior in E-Commerce

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Abstract

The Buy Now, Pay Later (BNPL) payment service in FinTech has rapidly gained popularity as a new payment option for consumers. However, its effect on consumer behavior remains unclear. This study investigates the effect of BNPL adoption on consumer purchase behaviors using a proprietary dataset from a large e-commerce platform. We find that BNPL adoption increases monthly spending by 11.2%, leads to a shift in purchase channel usage towards the mobile channel, and has a cannibalization effect on cash, debit cards, and credit cards payment methods. Our further analyses shed light on the mechanisms behind these effects. We find that the increased consumer spending as a result of BNPL adoption is driven by increased credit accessibility, mobile device ubiquity, and induced consumption effects. Our findings contribute to the growing body of literature on BNPL in FinTech and provide various practical implications for e-commerce and FinTech service operators.

Keywords: BNPL, Consumer behavior, Fintech, E-commerce

Introduction

“Buy Now, Pay Later” (BNPL) is an emerging FinTech service that allows consumers to split a purchase into installments and pay back in the future. Due to its convenience and low cost, BNPL has been widely adopted by firms and consumers in recent years. The market size of BNPL in the U.S. has increased from US$3 billion in 2019 to US$43 billion in 2021 (Statista 2022) and over 17% of all U.S. adults have used BNPL for shopping in 2021 (MarketingCharts 2021). With the increasing market size and prevalence of BNPL, it has become significant for both consumers' daily lives and the economy. Therefore, understanding its effect on consumer purchase behavior has become an important question for both the industry and academia. However, research on the effect of this emerging FinTech is still lacking.

The aim of this study is to examine how BNPL influences consumer purchase behavior, particularly in the e-commerce context. Previous studies on credit cards have documented the consumption-stimulating effect of credit cards, but it is unclear whether this finding can be generalized to the BNPL context. Although BNPL shares some similarities with credit cards, BNPL is distinct from credit cards in three features. First, unlike credit cards offering a revolving credit line, BNPL is structured as installment loans and offers a fixed repayment plan. Second, BNPL is more accessible to consumers with no or low credits whereas credit cards require strict credit history verification. Third, BNPL requires lower costs to use than credit cards as it is often interest-free and without annual fees. Given these differences, BNPL can influence consumer purchase behavior in both directions. On the one hand, compared with credit cards, BNPL is a low-cost credit purchase option, thus consumers can replace credit cards or other spending with BNPL loans while maintaining their overall spending (Gomes et al. 2021). Such a phenomenon has been documented in prior studies (deHaan et al. 2022; Guttman-Kenney et al. 2023). On the other hand, similar to credit cards, BNPL stimulates consumer spending by reducing the pain of paying (Prelec and Loewenstein 1998; Raghubir and Srivastava 2008) and increasing their pleasure in purchasing (Banker et al. 2021). Thus, the overall effect of BNPL on consumer purchases is unclear and remains both a theoretical and empirical question.

Second, as multichannel retailing is becoming more prevalent, it is crucial to understand how the adoption of BNPL influences the use of purchase channels. Prior studies on user behaviors across PC and mobile channels have shown that consumers behave differently across PC and mobile channels in terms of information processing and social engagement (Ghose et al. 2013; Jung et al. 2019). As BNPL is an additional source of consumers' money that increases their disposable income, their consumption demand is likely to increase after the adoption of BNPL. It is unclear, however, through which purchase channel consumers would fulfill their increased consumption demand. On one hand, consumers may care more about product quality and product fit, thus utilizing the PC channel more to conduct thorough product research. On the other hand, it is possible that consumers rely more on mobile channels as they seek immediacy and convenience to fulfill their increased consumption demand. It is also possible that the adoption of BNPL does not bring any changes in the usage of the purchase channel. In addition, as BNPL can be used through both PC and mobile channels for conducting transactions, it is also an empirical puzzle to shed light on whether and how BNPL adoption would influence consumers' purchase channel usage. We aim to unravel this conundrum by studying the effect of BNPL on spending across PC and mobile channels.

Third, since BNPL is a new payment method, understanding whether and how BNPL influences existing payment methods is important for consumers, retailers, and payment companies. Although BNPL is mostly used online, it might affect physical payments, especially cash payments. Specifically, if consumers replace their cash payments with BNPL payments, then the usage of cash would decrease. Conversely, it is also possible that consumers retain their cash usage and thus, there is no spillover effect of BNPL on offline cash payments. Besides, BNPL might also have an effect on other digital payments, including debit cards and credit cards. For instance, while the credit cards have a monthly billing cycle that includes all transactions within a month, BNPL service is transaction-based and each purchase through BNPL is treated as a separate installment plan, which provides higher flexibility on the usage of money. Therefore, customers may replace their credit card spending with BNPL to enhance their control over the repayment schedule and their overall spending. However, customers may also treat BNPL as an additional source of consumers' money and use it for shopping while maintaining their credit card spending. Given the potential cannibalization or spillover of BNPL on existing payment methods, it is an important empirical question to understand the relationship between BNPL and existing payment methods. We aim to answer this question by exploring how the adoption of BNPL affects consumers' subsequent use of cash, debit cards, and credit cards.

To summarize, our paper aims to fill the prior gaps in the literature and answer the following questions:

RQ1: What is the effect of BNPL adoption on a consumer's purchase behavior?

RQ2: How does the effect of BNPL adoption vary across PC and mobile purchase channels?

RQ3: Does BNPL cannibalize or complement existing payment methods (cash, debit cards, credit cards)?

To answer these questions, we analyzed a data set obtained from a large e-commerce platform in China that introduced BNPL for its customers on the platform. Our results provide evidence of the consumption-stimulating effect of BNPL on consumers. First, we find that BNPL adoption increases consumers' monthly spending by 11.2%. Assuming that the consumers within our randomly chosen sample of active users are representative of the BNPL adopters within the platform's active customer base, our results suggest a US$87.8 million increase in annual sales revenue every year. Second, our findings show that BNPL adoption has varying effects on consumer behavior across purchase channels. While consumer spending via mobile channels increases by 9.0% after the adoption of BNPL, their spending via PCs remains unchanged after the adoption of BNPL. Third, our findings also suggest that after adopting BNPL, consumers reduce the usage of existing payment methods including cash, debit card, and credit card, thus indicating a cannibalization effect on existing payment methods.

After examining the effect of BNPL adoption on consumer purchase behavior, we then investigate the underlying mechanisms behind these findings. Our findings indicate that BNPL adoption has a stronger effect on consumers who lack credit card accessibility, including consumers without credit cards, young consumers, and those living in lower-tier cities, suggesting that increased credit accessibility drives consumer spending (Leth-Petersen 2010). Additionally, our results reveal that the effect of BNPL adoption is stronger for mobile-dominant users, indicating that mobile device ubiquity also drives consumer spending (Bang et al. 2013; Xu et al. 2017). We also find that the induced consumption effect also drives behavior subsequent to BNPL adoption (Arnold 2015; Feinberg 1986). Specifically, consumers engage in more hedonic browsing after the adoption of BNPL, leading to increased purchases of hedonic products and impulsive buying behaviors. Furthermore, we uncover that consumers prefer more expensive products and explore a wider range of products after the adoption of BNPL.

Our paper provides several theoretical contributions and practical implications. First, our study contributes to the literature on FinTech and BNPL as our paper is among the first empirical FinTech studies to examine the effect of BNPL on consumer behavior using individual consumer-level data (Balyuk 2022; deHaan et al. 2022; Di Maggio et al. 2022). The rare access to such empirical data related to BNPL adoption allows us to uncover the nuanced effects of BNPL on different consumer behavior dimensions. Second, our results provide insights into how BNPL interacts with different purchase channels of consumers and contribute to the literature on user behaviors across PC and mobile channels (Ghose et al. 2013; Jung et al. 2019). Third, our study also contributes to the literature on digital payments (Xu et al. 2023; Xue et al. 2011). BNPL is a new type of digital payment and has multiple characteristics that are different from other digital payments. We extend the literature on digital payments by unraveling the cannibalization effect of BNPL on cash, debit cards, and credit cards. Fourth, our paper sheds light on the underlying mechanisms of the effect of BNPL adoption on consumers. While BNPL is also a type of credit service, our paper uncovers novel mechanisms behind the effects of BNPL, i.e., in terms of increased credit accessibility, mobile device ubiquity, and induced consumption effects, thereby enhancing our understanding of the effects associated with BNPL.

Literature Review

Credit Cards and BNPL

Over the years, researchers have attempted to gain a deeper comprehension of how credit cards impact consumer behavior. A key outcome of credit card usage is the rise in consumer spending. Previous studies have identified two factors that contribute to this outcome. The mental accounting model proposes that paying for items with a credit card instead of cash can reduce the discomfort of payment, thereby increasing consumers' willingness to pay (Prelec and Loewenstein 1998; Raghubir and Srivastava 2008). Additionally, Banker et al. (2021) find that credit card usage can heighten the pleasure of purchasing, which may stimulate consumer spending. Due to these reasons, credit cards have been linked to various other behaviors, such as faster repayment of hedonic debt (Besharat et al. 2015) and nondurable goods debt (Quispe-Torreblanca et al. 2019), larger basket size (Hirschman 1979), stronger perceptions of ownership of the product (Kamleitner and Erki 2013), and reducing the use of cash (Snellman et al. 2001).

Despite these extensive findings and the increasing prevalence of BNPL among consumers, little is known about how consumers utilize BNPL and how it affects them. While BNPL shares some similarities with credit cards, it differs in three critical aspects. First, BNPL is structured as installment loans with a down payment due at the sale and a fixed repayment plan, whereas credit cards offer a revolving credit line. Second, BNPL is much more accessible than credit cards, as it does not require a rigorous credit check. Finally, the cost of using BNPL is considerably lower than that of credit cards, as there is no annual fee, and BNPL loans are typically interest-free (Forbes 2023; Guttman-Kenney et al. 2023).

Given these three fundamental differences from credit cards, it is uncertain how BNPL affects consumers. When it comes to overall spending, previous studies have suggested that consumers smooth out their consumption by using cash or low-cost credit (Baugh et al. 2021; Gomes et al. 2021). As BNPL provides consumers with easy access and low-cost loans, it is conceivable that consumers may simply substitute credit card spending with BNPL spending without altering the total spending amount (Gomes et al. 2021; Guttman-Kenney et al. 2023). On the other hand, another plausible scenario is that easier access to credit may lead to increased purchase intention and a consequent rise in overall spending (Feinberg 1986). Furthermore, previous studies on credit cards have demonstrated the cannibalization effect of credit cards on cash (Snellman et al. 2001), but debit cards have been neglected for an extended period. As BNPL is another type of short-term loan and differs from credit cards, we are unable to determine a priori how BNPL affects the usage of current payment methods, including cash, debit cards, and credit cards. Our research aims to address these research gaps by examining the effect of BNPL adoption on overall consumer spending and their subsequent use of existing payment methods.

User Behaviors Across PC and Mobile Channels

Given the proliferation of mobile devices and the development of mobile apps, companies have already been developing mobile channels to interact with their users (Bellman et al. 2011; Einav et al. 2014). Although PCs and mobile devices are both online channels, they differ in several aspects and lead to different user behaviors (Bang et al. 2013; Ghose et al. 2013). Previous research has emphasized two key features - usability and ubiquity - when distinguishing between PC and mobile channels (Bang et al. 2013). Mobile devices have limited functionalities and a small screen size compared to PCs, which results in higher search costs for users (Ghose et al. 2013). The lack of usability in comparison to PCs results in different user behaviors across PC and mobile channels. For instance, in mobile channels, consumers rely more on rankings (Park et al. 2020), numeric review ratings instead of review text (Kwark et al. 2021), and have smaller basket sizes (Huang et al. 2016). Despite lower usability in comparison to PCs, mobile channels have an advantage in ubiquity that enables users to overcome geographical restrictions and support immediate information searching and transactions anytime, anywhere (Bang et al. 2013). The ubiquity feature of mobile channels has also led to changes in user behaviors, such as an increase in social engagement (Jung et al. 2019), a decrease in PC channel usage (Xu et al. 2017), and an increase in content usage compared to content generation when traveling (Ghose and Han 2011).

Although this line of research has examined how users react differently in terms of information processing or social engagement, it remains unclear how users behave differently when using BNPL since it is a new payment method that does not provide any new information or require social engagement. Thus, we aim to contribute to the literature on user behaviors across PC and mobile channels by investigating the effect of BNPL adoption on consumer behaviors across PC and mobile channels.

Digital Payment

With the growing prevalence of digital devices and software applications, more consumers are using digital payment for their purchases. Prior literature on digital payment mainly focuses on Internet banking (Hitt and Frei 2002; Zhou et al. 2020), mobile money (Dong et al. 2018; Suri and Jack 2016), and mobile payment (Agarwal et al. 2020; Xu et al. 2023). Most of these studies show the benefits of adopting various digital payments. For instance, Xue et al. (2011) provide evidence of the increase in banking activities after the adoption of online banking, while Suri and Jack (2016) find access to mobile money leads to an increase in household consumption and savings, which also decreases poverty rates.

However, there has been limited research on the effect of digital payment on the use of existing payment methods, with only a few exceptions. Xue et al. (2011) study the impact of the adoption of Internet banking and found that it substitutes physical banking, with the substitution effect being stronger for high-service-demand customers. Xu et al. (2023) investigate how mobile payment adoption influences consumers' transaction activities and found that the adoption of mobile payment cannibalizes physical-card payment, whereas it complements PC payment. Agarwal et al. (2020) also study the consequences of mobile payment technology and find that it reduces the use of ATM cash withdrawals and increases credit card spending, indicating a substitution effect on cash and a complementary effect on credit cards.

BNPL is a new digital payment method, and previous studies on digital payment still lack an understanding of how BNPL influences consumer spending as well as the use of existing payment methods. Our study aims to contribute to the literature on digital payment by filling these gaps.

Research Context and Data Description

Data Description

We obtained access to a dataset of consumer-level purchase and browsing histories from a large Chinese e-commerce platform (hereinafter referred to as "the platform") with 50 million registered users. The products the platform offers are mainly men, women, and kids wear as well as furniture and appliance. The dataset we acquired is comprised of three parts. The first part records consumer demographic information, such as their account registration date, BNPL adoption date (if applicable), self-reported age and gender, opt-in status for promotional messages, and disclosure of their location, email, and phone number. The second part comprises the purchase history of each consumer from January 2013 to December 2017, which includes detailed information on the products purchased, the purchase channel (mobile or PC), and the payment method used (cash, debit cards, credit cards, or BNPL). This information allows us to measure the effect of BNPL adoption across purchase channels and payment methods. The third part collects consumers' browsing records from both PC and mobile channels from July 2017 to December 2017, including consumer ID, visit date and time, access channel, URL of each page, product ID, and time spent on each page.

To measure the effect of BNPL adoption on consumers, we follow Xu et al. (2017), we focus on active users who have registered accounts on the platform before the start date of the sampling and made at least one purchase before and after the introduction of BNPL. By focusing our analysis on active users, we can eliminate potential confounding factors that may influence consumer purchase behavior, such as consumers registering and purchasing due to the introduction of BNPL. This approach enables us to identify the causal effect of BNPL adoption on consumer purchase behavior. Our raw data set comprises 151,856 orders from a randomly selected group of 6,716 active users.

Quasi-Natural Experiment: Introduction of BNPL

In October 2015, the platform officially announced the introduction of BNPL as a new payment option for consumers. Consumers can get access to BNPL loans by simply providing their identity card number and their phone number. Although the BNPL purchase limit is different across different consumers, the limit is low and ranges from 1,000 RMB to 6,000 RMB (US$ 137 to US$ 823). Similar to other BNPL services, consumers are allowed to split the bills equally across 3 months, 6 months, or 12 months. This BNPL service is interest-free for consumers, however, when a consumer fails to repay within the contract period, they need to pay interest at a daily rate of 0.06% of the overdue amount.

The platform did not announce the launch of BNPL prior to October 2015. Thus, we deem the introduction of BNPL as an exogenous event in our natural experiment setting during the sampling window. By the end of 2017, more than 4.4 million consumers had adopted BNPL, accounting for 8% of the total customer base.

Although the introduction of BNPL is an exogenous shock for consumers, the difference in consumer purchase behavior should come from their actual adoption of BNPL. Therefore, in order to measure the effect of BNPL on consumers, we should compare the adopters of BNPL with the nonadopters. In our study, treated consumers are those who have adopted BNPL within our study period, from January 2013 to December 2017, and the control consumers are those who have never adopted BNPL within our study period. After this classification, we have 1,587 treated consumers and 5,129 control consumers.

Focal Variables and Measures

We evaluate consumer purchase behavior by their monthly spending amount. Specifically, we utilize a consumer's overall monthly spending amount (*Overall_Amt*) as the primary measure of purchase behavior. We further analyze consumer behavior across various purchase channels and payment methods, including monthly spending amounts via PC (*PC_Amt*) and mobile channels (*Mob_Amt*), cash payment (*Cash_Amt*), debit card payment (*Debit_Amt*), credit card payment (*Credit_Amt*), and their shares across channels and payment methods. We also control for consumer demographics attributes in our empirical model including gender (*Male, Female,* and *Gender_Unknown*), age, location, opt-in status for promotional messages (*OptIn*), and their tenure on the platform (*Tenure*). Specifically, we classify ages into groups: ages 18-30 (*Age∈[18,30]*), ages 31-40 (*Age∈[31,40]*), ages 41-60 (*Age∈[41,60]*), and those without age information

(*Age_Unknown*). We classify location into five groups based on the tier of the city that consumers live in[1], from first- to fifth-tier cities (*Tier1_City, Tier2_City, Tier3_City, Tier4_City, and Tier5_City*).

We provide a summary of the key variables in Table 1. Table 1 shows that consumers spend an average of US$161.987 per month, with the mobile channel having higher spending than the PC one. Consumers primarily use debit cards as their payment method, followed by credit cards and cash. At the consumer level, we find that the platform primarily attracts female consumers, with more than 82.4% of the customer base being female. We also find that consumers are mainly from second, third, and fourth-tier cities.

Variables	No. Obs.	Mean	SD	Min	Max
Order-Level Variables					
Overall_Amt	151,856	161.987	273.246	1.429	23894.860
PC_Amt	151,856	58.901	155.334	0	8343.429
Mob_Amt	151,856	103.087	238.737	0	23894.860
Cash_Amt	151,856	32.174	89.679	0	5252.143
Debit_Amt	151,856	78.546	189.758	0	23894.860
Credit_Amt	151,856	37.762	149.772	0	8343.429
Consumer-Level Variables					
Male	6,716	0.166	0.372	0	1
Female	6,716	0.824	0.381	0	1
Gender_Unknown	6,716	0.011	0.102	0	1
Age $\in$*[18,30]*	6,716	0.261	0.439	0	1
Age $\in$*[31,40]*	6,716	0.266	0.442	0	1
Age $\in$*[41, 60]*	6,716	0.148	0.355	0	1
Age_Unknown	6,716	0.324	0.468	0	1
Tier1_City	6,716	0.158	0.364	0	1
Tier2_City	6,716	0.287	0.452	0	1
Tier3_City	6,716	0.215	0.411	0	1
Tier4_City	6,716	0.201	0.401	0	1
Tier5_City	6,716	0.140	0.347	0	1
OptIn	6,716	0.137	0.344	0	1
Tenure	6,716	43.127	8.334	34	82

Table 1. Summary Statistics of Key Variables (Before Matching)

Model-Free Evidence of the Effect of BNPL

Before we use an econometric model to identify the effect of BNPL on consumer purchase behavior, we first provide model-free evidence of this effect of BNPL on consumer purchase behavior. We compare the monthly average spending between the control and the treated consumers. Figure 1 displays evidence of BNPL's effect on consumer purchase behavior. Prior to the introduction of BNPL, consumers in the control group spent an average of US$127.18 per month, and their monthly spending increased to US$180.23 after the introduction of BNPL. Treated consumers had a monthly spending increase from US$147.55 to US$225.50 after the introduction of BNPL. Although both groups increased their spending after the introduction of BNPL, treated consumers increased theirs more than those of the control ones ($t=8.34$, $p<0.001$). Thus, BNPL introduction led to an increase in consumer monthly spending. Correspondingly, Figure 1 shows that BNPL introduction led to a larger increase in spending via mobile channels ($t=20.18$, $p<0.001$), indicating a positive effect on the use of mobile channels. We also observe a larger decrease in spending via PC channels ($t=-12.33$, $p<0.001$) and spending via cash payment ($t=-14.66$, $p<0.001$), and a smaller increase in spending via debit cards ($t=-19.39$, $p<0.001$) and credit cards ($t=-3.62$, $p<0.001$) after the introduction of BNPL for treated consumers, suggesting a negative effect of BNPL introduction on the use of the PC channel, cash, debit cards, and credit cards.

[1] We classified the tier of cities based on the Chinese city-tier system, which accounts for GDP, population, commercial and educational resources, transportation, and so on.

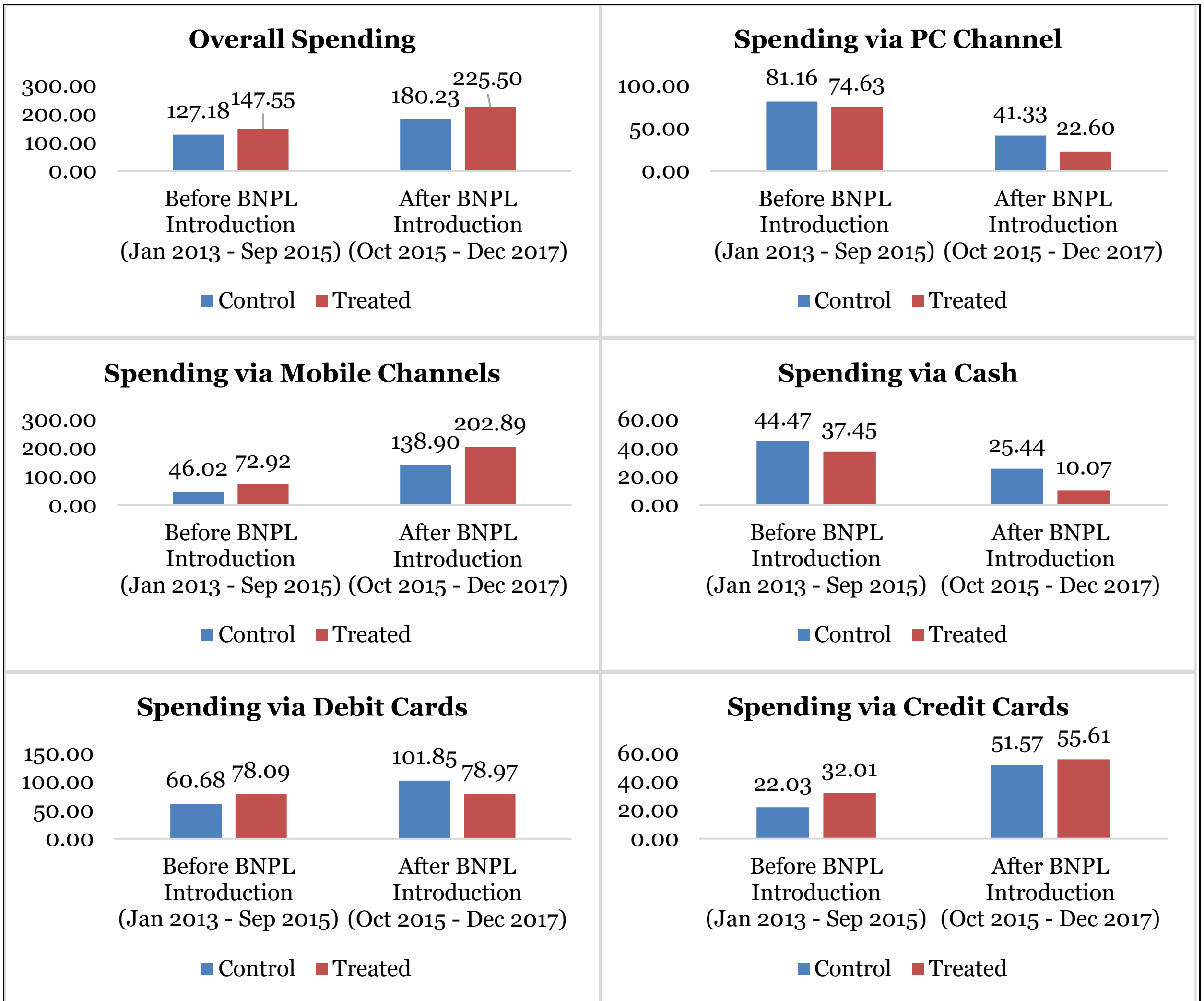

Figure 1. Model-Free Evidence of the Effect of BNPL on Consumer Purchase

Although we can observe significant differences in various aspects of consumer behavior between the control and the treatment group prior to the BNPL introduction, the effect of BNPL on consumer purchase behavior may be biased by other factors. Additionally, though using the launch of BNPL as the intervention can help to evaluate the change in consumer purchase behavior before and after this event, one concern is that we are unclear whether this effect comes from the launch of BNPL service or the actual adoption of BNPL by consumers. As the changes in consumer purchase behaviors are likely driven by the actual adoption of BNPL, we need to compare adopters with nonadopters based on their adoption dates. Thus, we employ difference-in-differences (DID) methods coupled with propensity score matching (PSM) techniques to compare adopters with nonadopters, which we will describe in detail in the following subsection.

Econometric Model and Identification Approach

Our data set includes all transactions before and after the adoption of BNPL, and the exact first adoption date of BNPL, allowing us to compare the differences between adopters and nonadopters pre- and post-BNPL adoption. However, as observed from Figure 1, there are significant differences in purchase behavior prior to the introduction of BNPL across the treatment and control groups which can lead to a biased result on the effect of BNPL. To address this issue, following Kumar et al. (2018), we use PSM to create a more valid control group for treated consumers so that they are comparable in terms of observable characteristics

(Heckman et al. 1998). We adopt a two-way fixed effects model to jointly account for consumer and time-related unobservable factors. We specify our main model as follows:

$$Y_{it} = \beta_0 + \beta_1 Treated_i \times After_{it} + X_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (1)$$

Here, Y_{it} represents a series of dependent variables used to measure consumer purchase behavior, including monthly overall spending, spending across purchase channels and payment methods, and their shares. We log-transform all consumer spending variables due to their skewed distribution and such that an elasticity interpretation of the effect of BNPL adoption can be derived. The variable $Treated_i$ equals 1 if a consumer has ever adopted BNPL within our study period and 0 if otherwise. The variable $After_{it}$ indicates the post-BNPL adoption period for each treated consumer and its matched counterpart. The coefficient of the interaction term between $Treated_i$ and $After_{it}$, β_1, represents the effect of BNPL adoption on consumer purchase behavior. X_{it} represents several time-varying control variables, including purchase amount in the last five months and product category fixed effects. We also control for consumer fixed effects (α_i) as well as time (month) fixed effects (θ_t) to capture consumer-time-invariant and time-varying unobserved factors. ε_{it} is the residual error clustered by consumers to account for potential correlation over time.

We use the PSM method to balance the observed factors between the control and treated consumers (Heckman et al. 1998). We first compute each consumer's propensity score which indicates the probability of adopting BNPL. We use several covariates to estimate the propensity score, including overall spending, spending across purchase channels and payment methods prior to the introduction of BNPL, and consumer demographic information such as gender, age, and location. In addition, we also include their opt-in status for promotional messages and their tenure on the platform. We rely on the one-to-one with replacement matching algorithm to derive the closest matched nonadopter. Under this procedure, all BNPL adopters have their matched counterparts. Table 2 shows the differences in covariate values for the treated and control consumers before and after PSM. We can observe that before matching, many of the matching covariates are significantly different but such differences become insignificant after the matching.

Variables	Unmatched			Matched		
	Treated	Control	T-test	Treated	Control	T-test
Log(Overall_Amt)	6.904	6.213	0.000	6.904	6.920	0.755
Log(PC_Amt)	5.716	5.368	0.000	5.716	5.755	0.638
Log(Mob_Amt)	5.118	3.574	0.000	5.118	5.098	0.834
Log(Cash_Amt)	3.792	3.659	0.114	3.792	3.717	0.489
Log(Debit_Amt)	5.786	4.785	0.000	5.786	5.797	0.880
Log(Credit_Amt)	3.318	2.305	0.000	3.318	3.337	0.866
Male	0.139	0.174	0.001	0.139	0.137	0.877
Female	0.851	0.815	0.001	0.851	0.855	0.764
Gender_Unknown	0.010	0.011	0.827	0.010	0.008	0.576
OptIn	0.187	0.122	0.000	0.187	0.193	0.651
Log_Tenure	3.757	3.744	0.010	3.757	3.752	0.420

Table 2. Covariates Balance Before and After PSM

Empirical Analysis and Results

Main Results

Effect of BNPL Adoption on Consumer Purchase

Table 3 and Table 4 present the regression results of Equation (1) for the one-to-one nearest matching with replacement matching method, which identifies the effects of BNPL adoption on consumer purchase behavior. Our findings show significant effects of BNPL adoption on consumer purchase behavior. Specifically, in Table 3, column (1), we observe an increase in the overall spending amount by 11.2% (i.e., $e^{0.106} - 1 = 11.2\%$) after the adoption of BNPL. Moreover, we find that the effects of BNPL adoption on consumer purchase behavior vary across different purchase channels. In columns (2) and (3) of Table 3, we observe that while spending via PC channel does not change significantly, spending via mobile channels increases by about 9.0% after the adoption of BNPL. These results show consumers increase their overall spending after the adoption of BNPL. However, they only increase their spending via the mobile channel while spending via the PC channel remains unchanged, indicating that the convenience and immediacy features of the mobile channel are likely key facilitating factors for consumers after the adoption of BNPL.

VARIABLES	(1) Overall Amt	(2) PC Amt	(3) Mob Amt	(4) Mob Amt Share
Treated × After	0.106***	-0.016	0.086**	0.002
	(0.013)	(0.052)	(0.044)	(0.010)
Constant	3.098***	3.732***	-0.876***	0.001
	(0.026)	(0.060)	(0.061)	(0.011)
Controls	Included	Included	Included	Included
Fixed effects	Included	Included	Included	Included
Observations	77,874	77,874	77,874	77,874
R-squared	0.491	0.382	0.488	0.457
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1				

Table 3. Effect of BNPL Adoption on Consumer Purchase Across Purchase Channels

We further show the effects of BNPL adoption on a consumer's subsequent usage of existing payment methods. Table 4 shows that after adopting BNPL, consumers decrease their extent and share of use of all existing payment methods, including cash, debit cards, and credit cards. Specifically, consumer spendings on cash, debit cards, and credit cards decreased by 19.2%, 72.0%, and 57.0% respectively. In terms of the changes in spending shares, we find that the shares of spending by cash, debit cards, and credit cards decreased by 3.1%, 31.4%, and 17.4% respectively after the adoption of BNPL. Therefore, BNPL cannibalizes all existing payment methods.

VARIABLES	(1) Cash Amt	(2) Cash Amt Share	(3) Debit Amt	(4) Debit Amt Share	(5) Credit Amt	(6) Credit Amt Share
Treated × After	-0.213***	-0.031***	-1.273***	-0.314***	-0.843***	-0.174***
	(0.046)	(0.009)	(0.062)	(0.013)	(0.062)	(0.011)
Constant	1.841***	0.487***	1.181***	0.457***	-0.175**	0.068***
	(0.065)	(0.014)	(0.076)	(0.016)	(0.076)	(0.013)
Controls	Included	Included	Included	Included	Included	Included
Fixed effects	Included	Included	Included	Included	Included	Included
Observations	77,874	77,874	77,874	77,874	77,874	77,874
R-squared	0.167	0.164	0.134	0.072	0.081	0.049
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1						

Table 4. Effect of BNPL Adoption on Existing Payment Methods

Robustness Checks

Parallel Trend Assumption Validity

As our main model utilizes the DID method, the parallel trend assumption for its identification has to be verified. We thus check the validity of this assumption by replicating our results in the main specification using a relative time DID model. Specifically, we model overall spending by Equation (2):

$$Overall\_Amt_{it} = \sum_j \beta_j \, Treated_i \times TimeInterval_t + X_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (2)$$

We partition time around the BNPL adoption date and denote it as $TimeInterval_t$. We estimate the model using the data from 12 months before and after BNPL adoption and plot the values of β_j along with their 95% confidence intervals. Figure 2 indicates that, all of pre-treatment dummies are insignificant. This suggests that there is no pre-treatment trend, and our DID model satisfies the parallel trend assumption needed for identification.

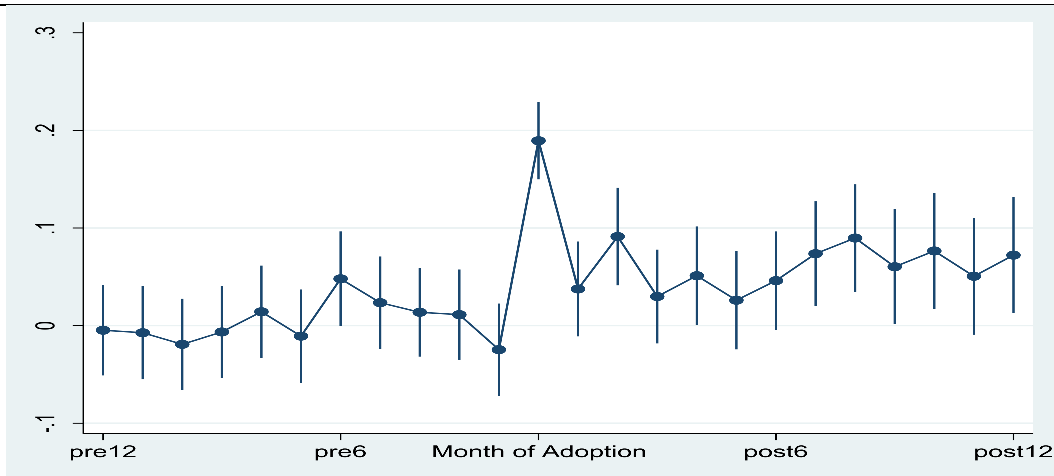

Figure 2. Visualization of Treatment Effects on Overall Spending from 18 Months Before and After the Adoption (Monthly Level)

Selection of BNPL Adoption by Consumers

Next, given that the decision to adopt BNPL is self-selected by consumers, our previous results might be biased. Although we rely on the PSM method in our main model, PSM can only balance the observable factors whereas unobservable factors are not taken into account. Therefore, we use two additional models to further address this self-selection issue. We first begin with a Heckman selection model. We first directly model consumers' decision to adopt BNPL by using a probit model estimation with exogenous covariates, and then reestimate our main model.

In the first-stage probit model, we include several exogenous variables such as gender, age, city tiers, tenure, and opt-in status for promotional messages. We believe a consumer's decision to adopt BNPL is related to their age, gender, and location due to the credit accessibility (Guttman-Kenney et al. 2023). We also expect a consumer's decision to adopt BNPL to be related to consumer loyalty, which is related to their tenure, the opt-in status of promotional messages, and their prior purchase behaviors (Oliver 1999). We measure consumers' prior purchase behaviors by their overall spending amount, spending amounts via PC and mobile channels, cash, debit card, and credit card payments prior to the introduction of BNPL. Therefore, the selection equation is modeled as Equation (3):

$$Treated_i^* = \gamma_1 Gender_i + \gamma_2 Age_i + \gamma_3 Tier\_City_i + \gamma_4 Tenure_i + \gamma_5 OptIn_i + PriorPurchase_i + \mu_i \qquad (3)$$

The indicator $Treated_i = 1$ if $Treated_i^* > 0$, and $Treated_i = 0$ otherwise. After taking the selection decision into account, we then jointly estimate Equation (1) and (3) and present our results in Table 5.

In addition to the Heckman selection model, we also use the look-ahead matching method to control for unobservable factors (Kumar et al. 2018; Narang and Shankar 2019). In the look-ahead matching method, the matching of the control group requires consumers to be nonadopters at the time of matching but to be adopters in a future period (Kumar et al. 2018). Given that late adopters are similar to the early adopters, late adopters might be a valid control group of the early treated consumers and thus account for unobserved characteristics for the treated and control consumers. We select consumers who adopted BNPL in the last 12 months of the study period (Jan 2017 – Dec 2017) to be matching candidates for treated consumers who adopted BNPL in the first 15 months (Oct 2015 – Dec 2016) of the treatment period. We utilize one-to-one with replacement matching algorithm with the same matching covariates as our main model to derive the new closest matched late adopters. We present the robustness check results via this method in Table 5.

As shown in Table 5, both results of the Heckman selection model and look-ahead matching method with PSM are largely consistent with the main results, suggesting that our results are robust after accounting for unobserved factors and selection bias.

VARIABLES	(1) Overall Amt	(2) PC Amt	(3) Mob Amt	(4) Cash Amt	(5) Debit Amt	(6) Credit Amt
Main model	0.106***	-0.016	0.086**	-0.213***	-1.273***	-0.843***
	(0.013)	(0.052)	(0.044)	(0.046)	(0.062)	(0.062)
Heckman selection model	0.061***	-0.057*	0.087***	-0.292***	-1.379***	-0.705***
	(0.015)	(0.034)	(0.031)	(0.031)	(0.044)	(0.045)
Look-ahead matching with PSM	0.122***	-0.015	0.125**	-0.281***	-1.122***	-1.084***
	(0.022)	(0.074)	(0.062)	(0.071)	(0.095)	(0.095)
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1						

Table 5. Effect of BNPL Adoption on Consumers: Addressing Selection Bias

Alternative Matching Methods and Dependent Variables

Next, since our main model relies on a one-to-one nearest neighbor matching algorithm with replacement, it is possible that our results are sensitive to the matching algorithm used. To further establish the robustness of our results, we also construct control groups by employing different matching algorithms. We thus use one-to-one nearest neighbor matching without replacement, the nearest three neighbors with replacement matching algorithms, and coarsened exact matching algorithm and report our results in Table 6. We find that all these estimated coefficients of the DID treatment effect are consistent with those from our main model, suggesting that our results are robust and not sensitive to the matching algorithms.

VARIABLES	(1) Overall Amt	(2) PC Amt	(3) Mob Amt	(4) Cash Amt	(5) Debit Amt	(6) Credit Amt
One-to-one without replacement	0.109***	-0.003	0.077**	-0.223***	-1.278***	-0.805***
	(0.012)	(0.043)	(0.038)	-0.041	-0.055	-0.054
Nearest three neighbors with replacement	0.114***	0.005	0.078**	-0.207***	-1.294***	-0.807***
	(0.012)	(0.045)	(0.039)	-0.042	-0.056	-0.056
Coarsened Exact Matching	0.117***	-0.100*	0.169***	-0.155***	-0.844***	-0.152**
	(0.014)	(0.057)	(0.052)	(0.053)	(0.067)	(0.062)
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1						

Table 6. Alternative Matching Methods

In addition, we use an alternative dependent variable to measure consumer purchase behavior. We use purchase frequency instead of dollar spending amount as there might be a concern that the increase in overall spending is driven by the increase in the average order value but not driven by the increase in the order frequency. Therefore, it is possible that purchase frequency remains the same or even decreases after the adoption of BNPL whereas the overall spending increases. Consistent with our main model, we measure consumer purchase behavior with overall monthly purchase frequency (*Overall_Freq*), monthly purchase frequency via the PC channel (*PC_Freq*), the mobile channel (*Mob_Freq*), cash payment (*Cash_Freq*), debit card payment (*Debit_Freq*), and credit card payment (*Credit_Freq*). Results in Table 7 show that the BNPL effects on purchase frequency are consistent with those for spending amounts in our main model.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Overall Freq	PC Freq	Mob Freq	Cash Freq	Debit Freq	Credit Freq
Treated × After	0.055***	0.009	0.031*	-0.040***	-0.314***	-0.201***
	(0.017)	(0.014)	(0.017)	(0.013)	(0.018)	(0.018)
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1						

Table 7. Alternative Dependent Variable: Purchase Frequency

Mechanism Evaluations

We conduct mechanism evaluations to shed light on the nature of the mechanisms for the above-reported effects of BNPL on consumers. Specifically, we focus on three main different mechanisms, i.e., credit accessibility, device ubiquity (for mobile), and induced consumption effects associated with BNPL.

Credit Accessibility Mechanism

Compared with credit cards, BNPL offers low-cost credits to consumers who have no or low credit ratings. Therefore, we expect that the effect of BNPL on consumers is not only driven by the reduced pain of paying but also driven by the credit accessibility on the consumer side. If credit accessibility on the consumer side is a key driving mechanism, the effect of BNPL on consumer spending should be larger for non- or low-credit users compared with high-credit users. To assess this, we run subsample and interaction effect analyses based on consumers' credit accessibility prior to the adoption of BNPL. Specifically, we classify consumers into two different groups: consumers who have ever used credit cards for spending prior to the introduction of BNPL are those with higher credit accessibility whereas consumers who have never used credit cards for spending prior to the introduction of BNPL are those who have no or low credit accessibility. Table 8 shows the results. We find that the effect of BNPL adoption on consumer spending is stronger (weaker) for consumers without (with) credit cards, supporting the credit accessibility mechanism.

	(1)	(2)	(3)
	Without Credit Cards	With Credit Cards	Interaction (Baseline: No credit card)
VARIABLES	Overall_Amt	Overall_Amt	Overall_Amt
Treated × After	0.121***	0.099***	0.128***
	(0.019)	(0.018)	(0.017)
Treated × After × Credit Card User			-0.035*
			(0.019)
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1			

Table 8. Effect of BNPL Adoption Across Credit Accessibility

We further conduct additional analyses to verify our credit accessibility mechanism. We examine whether the effect of BNPL adoption on consumers varies across their age and location. In terms of age, as young consumers may lack access to credit, the effect of BNPL is likely to be stronger for them based on the credit accessibility mechanism. Similarly, consumers in a less developed or low-tier (e.g., tier-5) city may have less access to credit compared to those in more developed or high-tier (e.g., tier-1) cities. Therefore, we also expect the effect of BNPL to be stronger for consumers in the less developed cities. To further verify this mechanism, we conduct interaction effects analyses based on consumer age groups and location. Specifically, we classify consumers into three different age groups: age 18-30, age 31-40, and age 41-60. We also classify consumers into two different location groups: consumers who live in tier-1/2/3 cities are those in the more developed cities while consumers who live in tier-4/5 cities are those in the less developed cities. In general, consumers in tier-1, 2, and 3 cities have been documented to have much higher credit accessibility than those in other cities (Sohu 2018). We report our analysis results in Table 9. Our results show that the effect of BNPL adoption on consumers is stronger for young consumers and for those who live in less developed cities, which further corroborates the credit accessibility mechanism.

	(1)	(2)
	Age Groups (Baseline: Age ∈ [18,30])	Location (Baseline: Less Developed City)
VARIABLES	Overall_Amt	Overall_Amt
Treated × After	0.168***	0.127***
	(0.020)	(0.018)
Treated × After × Age ∈[31,40]	-0.076***	
	(0.024)	
Treated × After × Age ∈[41,60]	-0.106***	
	(0.029)	
Treated × After × More Developed City		-0.034*
		(0.019)
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1		

Table 9. Effect of BNPL Adoption Across Age Groups and Locations

Device Ubiquity Mechanism

Next, we examine whether the effect of BNPL adoption is driven by device ubiquity of mobile devices. Since consumers increase their spending on mobile devices while decreasing spending on PCs after the adoption of BNPL, we want to further identify how device preference influences the effect of BNPL adoption on consumers. If device ubiquity drives consumers' overall spending after the adoption of BNPL, then the effect of BNPL adoption should be larger for mobile-dominant consumers than for PC-dominant consumers. We thus conduct subsample analyses based on consumers' device usage preferences. We measure device usage preferences based on consumers' purchase share from PCs prior to the introduction of BNPL. If a consumer's prior purchase share from PCs is larger than 0.5, we consider her a PC-dominant consumer. If the share is smaller than 0.5, she is considered a mobile-dominant consumer. We report our analysis results in Table 10. We find that the effect of BNPL adoption is stronger for mobile-dominant users than PC-dominant users, supporting the mobile device ubiquity mechanism.

	(1)	(2)
	Mobile-Dominant Users	PC-Dominant Users
VARIABLES	Overall_Amt	Overall_Amt
Treated × After	0.127***	0.089***
	(0.020)	(0.019)
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1		

Table 10. Effect of BNPL Adoption Across Device Preference

Induced Consumption Mechanism

Next, we evaluate the induced consumption mechanism of BNPL effects via several dimensions associated with search behavior, impulsive purchase, and product and price preferences for consumption. Induced consumption is a function of disposable income (Arnold 2015). Therefore, the change in disposable income will lead to a change in the consumption of goods and services. As BNPL offers additional future money for consumers, we expect to see an increase in consumer demand driven by this induced consumption mechanism. First, we examine how the adoption of BNPL influences consumers' search behavior. Although prior studies on credit cards show the consumption-stimulating effect of credit cards, they do not show how credit cards influence consumer search behavior, let alone the effect of BNPL on consumer search. While BNPL offers easy access to additional low-cost credit to consumers and increases overall spending, it is still unclear whether the adoption of BNPL drives targeted search or hedonic browsing behavior. On one hand, it is possible that consumers have certain goals but have limited purchase budget prior to the adoption of BNPL. With the adoption of BNPL, they can fulfill their consumption goals with this additional source of money or credit. Therefore, they can be more goal-oriented and are likely to engage in more targeted search behavior (Hong et al. 2004). On the other hand, consumers may not have any purchase goals before the adoption of BNPL. Therefore, they engage in more exploratory and hedonic browsing behavior to find products they favor. To evaluate the search behavior, we utilize the clickstream data and measure search intensity by the number of URLs browsed by each user in a month. We also measure the conversion rate by dividing the number of orders by the number of pages browsed in that month. We re-run the analysis using these alternative outcome variables and present the results in Table 11. Results show that after the adoption of BNPL, the number of pages browsed increased but the conversion rate decreases, indicating that consumers engage in more hedonic browsing behavior after the adoption of BNPL.

	(1)	(2)
VARIABLES	Number of Browsing Pages	Conversion Rate
Treated × After	0.223***	-0.002**
	(0.046)	(0.001)
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1		

Table 11. Effect of BNPL Adoption on Consumer Search

Second, we evaluate whether the adoption of BNPL increases consumers' impulsive buying behavior. Given that consumers engage in more hedonic browsing after the adoption of BNPL, we expect an increase in impulsive buying behavior after the adoption of BNPL (Moe 2003). Following Narang and Shankar (2019), we focus on product return behavior as it is one of the main consequences of impulsive buying behavior.

Table 12 shows that the product return rate increases by 1.4% after the adoption of BNPL. We also classify the product return reasons into three types: product fit issues, product quality issues, and other issues. We find that among these three product return reasons, consumers are sensitive to product fit issues after the adoption of BNPL, indicating that while consumers may purchase more abundantly under impulsivity with BNPL adoption or availability, they are less tolerant of product fit problems in their return decisions.

	(1)	(2)	(3)	(4)
VARIABLES	Overall Return Rate	Fit Return Rate	Quality Return Rate	Other Return Rate
Treated × After	0.014***	0.011**	0.002	0.002
	(0.005)	(0.005)	(0.002)	(0.001)
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1				

Table 12 Effect of BNPL on Product Return

Third, we examine whether the adoption of BNPL influences consumers' preferences for products. We first focus on hedonic and utilitarian products. Hedonic products are defined as products where consumption is mainly featured by an affective and sensory experience of aesthetic or sensual pleasure, fantasy, or fun, such as clothing, shoes, and cosmetics. However, utilitarian products are more cognitively driven, instrumental, goal-oriented, and accomplish a functional or practical task. Appliances and furniture are examples of utilitarian products (Dhar and Wertenbroch 2000; Hirschman and Holbrook 1982). Given that consumers engage in more hedonic browsing after the adoption of BNPL, we believe consumers are more likely to have a hedonic shopping motivation when browsing on the platform and thus may purchase more hedonic products. We re-estimate Equation (1) by using the outcome measures of the numbers of hedonic and utilitarian goods purchased in a month. The first two columns of Table 13 show that consumers do purchase more hedonic goods but the purchases of utilitarian products do not increase after the adoption of BNPL, which supports our assertion above.

Last, we also analyze how consumers' price preference changes after the adoption of BNPL. Given that consumers have additional disposable money for consumption after the adoption of BNPL, we assert that it would change their perception of the money they own and thus lead to an increase in expensive product purchases. In columns (3) to (6) of Table 13, we find that consumers purchase more expensive products after BNPL adoption, which supports our assertion above. Interestingly, we also find consumers decrease their purchases of cheap products after BNPL adoption, suggesting that consumers switch their purchases from cheap products to expensive products after the adoption of BNPL.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Number of Hedonic Products	Number of Utilitarian Products	Number of Expensive Products (Top 25%)	Number of Cheap Products (Bottom 25%)	Number of Expensive Products (Top 10%)	Number of Cheap Products (Bottom 10%)
Treated × After	0.018**	0.008	0.064***	-0.015	0.043***	-0.018**
	(0.009)	(0.008)	(0.011)	(0.010)	(0.009)	(0.009)
Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1						

Table 13. Effect of BNPL Adoption Across Product Types and Price

Discussion and Implications

BNPL is a rapidly growing FinTech that allows consumers to split their purchases into installments and pay them back in the future. It is changing the way consumers shop, purchase and pay on digital platforms. Thus, it is imperative to understand how BNPL influences consumer purchase behavior and the mechanisms behind this effect. Our study generates four theoretical contributions. First, our paper is one of the first studies that empirically quantify the effect of BNPL adoption on consumer purchase behavior via different behavioral dimensions. Despite the penetration of BNPL in many countries, previous research still lacks an in-depth and nuanced understanding of the effect of BNPL on consumers. Our findings extend the growing body of literature on FinTech and BNPL (deHaan et al. 2022; Guttman-Kenney et al. 2023). Second, previous studies on user behavior across PC and mobile channels have examined several behavioral differences between PC and mobile channels in terms of information processing (Ghose et al. 2013) and social engagement (Jung et al. 2019). However, how BNPL influences consumers differently across PC and mobile channels remains unclear as it does not provide new product information or social connections. Our paper fills this gap by showing increased spending via mobile channels and decreased spending via PCs after the adoption of BNPL, contributing to the literature on user behavior across PC and mobile channels. Third, our paper also contributes to the literature on digital payments. Although prior research on digital payments has examined the consequences of adopting Internet banking, mobile money, and mobile payment, and has documented some substitution and complementarity effects on existing payment (Xu et al. 2023; Xue et al. 2011), BNPL has been neglected in this stream of work. We extend the extant literature on digital payments by uncovering the cannibalization effect of BNPL on cash, debit cards, and credit cards. Fourth, we evaluate and unravel mechanisms driving the effect of BNPL on consumer behavior that have not been examined in the prior research on credit cards or BNPL. Based on the extant literature on credit cards, consumers increase their spending due to the reduced pain of paying (Prelec and Loewenstein 1998). Our paper further shows BNPL influences consumer spending by mechanisms associated with increased credit accessibility, mobile device ubiquity, and induced consumption effects which contributes to the literature on credit cards and BNPL (Di Maggio et al. 2022; Papich 2022; Prelec and Loewenstein 1998).

Our findings also provide a number of practical implications. First, our findings imply that e-commerce platforms can capitalize on this emerging FinTech service to boost sales revenue. Based on our results, we estimate a potential US$87.8 million increase in annual sales revenue every year for our focal platform. Second, we recommend to managers that before introducing BNPL to the platform, they should be aware of other potential consequences brought by the adoption of BNPL other than the increase in consumer spending. For example, as consumers increase mobile channel usage after the adoption of BNPL, platforms should better design their mobile app interface to reduce consumer search costs and provide them with better mobile shopping experience. Further, as BNPL adoption leads to an increased purchase of expensive products, platforms can provide reminders prior to the expensive item purchase for consumers to help them avoid overspending on expensive products. Based on our findings, managers can better fulfill BNPL adopters' consumption needs and help consumers better manage their BNPL loans. Third, as the shares of cash, debit card, and credit card payment decrease after the adoption of BNPL, it indicates that firms have more account receivables instead of cash, and lower credit card processing fees to pay. Therefore, firms may need to adjust their financial planning and budgeting. Fourth, our results also indicate that regulators should carefully assess the risks of BNPL adoption or usage on consumers' financial health, especially for those of younger age and who have no or low credit accessibility. As consumers who lack credit accessibility spend more than those who have access to credits, the platform and government should properly regulate this emerging FinTech, such as setting a lower credit limit for consumers who have no or low credit ratings, relating the BNPL payment history with the credit rating systems, and so on.

Conclusion

In this paper, we investigate the effect of BNPL adoption on consumer behavior and the underlying mechanisms driving this effect, providing valuable insights for both researchers and platform managers. Despite these contributions, our study has some limitations. First, our data only covers consumer spending data from online channels, limiting the generalizability of our findings to the offline context. Second, our data is from only one platform, and we cannot determine how BNPL influences the entire market or other competitors. Third, due to data limitations, we are not able to observe whether consumers have repaid their BNPL loans on time. However, according to the platform operator, the delinquency rate of BNPL in 2017 was 0.82%, which was lower than the credit card delinquency rates. Therefore, we believe payment delinquency is not a significant issue for our data set. Nonetheless, future studies can study how BNPL influences consumers' financial health such as their credit ratings and delinquency rates.

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