Unboxing Privacy: How Discreet Packaging Shapes Consumer Purchases?

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Abstract

With the heightened emphasis on customer privacy, there is much interest in assessing the tradeoffs associated with novel solutions for ensuring privacy. By doing so, firms can make more informed decisions regarding the strategy that is appropriate for their customers. In this context, we investigate the impact of discreet packaging, which conceals the contents of shipped items, on consumer behavior and, by extension, firm revenues. We collaborate with an online pharmacy platform, having both first- and third-party stores, to examine the causal impact of introducing a discreet packaging feature for purchases in its first-party stores. Using a difference-in-differences model, we find that the introduction of this feature boosts the overall purchases of adopters by roughly 20%. Moreover, we find supportive evidence that the positive effect is stronger among rural consumers as well as household consumers and is weaker among cherry pickers. The decomposition of the impact across store types indicates that first-party purchases increase by 34% while third-party orders experience a temporary decline that averages 23%. Despite the positive net impact of discreet packaging on demand, it is important to exercise caution as there is also a notable increase in first-party shipping costs due to purchase fragmentation.

Keywords: discreet packaging, privacy, healthcare, spillover effect

1. Introduction

There is a broad consensus that e-commerce has transformed the retail landscape by offering consumers access to a wide range of products with minimal effort (Grewal et al. 2004, Narang and Shankar 2019, Wu et al. 2004). Concurrently, there is also agreement that this convenience has come at the cost of diminished customer privacy (Martin and Murphy 2017, Martin et al. 2017). A common example is the use of cookies (e.g., Wernerfelt et al. 2025), which enable personalized experiences but raise significant privacy concerns as well. Please see Quach et al. (2022) for a comprehensive discussion. Firms, in turn, have begun offering privacy enhancing features (e.g., Google allows consumers to disable the collection of their search data) and highlighting customer privacy as a means of differentiation (e.g., Apple highlights customer privacy in their advertisements). From a demand perspective, there is much interest in assessing the impact of offering privacy enhancing features on customer demand and whether the benefits of doing so differ across customer segments (Lin 2022, Jones et al. 2018). From a cost perspective, there is extant work, largely theoretical in nature, showing that privacy enhancing features can lead to an increase in operational costs (e.g., Hu et al. 2022). Thus, firms should carefully assess the benefits and costs of any privacy-enhancing strategy they wish to pursue.

For e-commerce companies, product packaging serves an important role as the interface between customers' purchase decisions in the digital channel and the delivery of products. A well-designed outer packaging can enhance brand awareness and increase customer engagement (e.g., see Moreau 2020). Packaging is also intimately linked with customer privacy. For instance, the salience of a package can unintentionally expose consumers' purchase of sensitive items, such as politically expressive items or medications associated with stigmatized conditions, leading to discomfort or even social stigma (Jones et al. 2018, Krishna et al. 2019). This concern with the infringement of privacy has led firms across many industries (e.g., pharmacies such as Dr Fox, and DNA testing providers like My Forever DNA) to offer discreet packaging, which refers to non-descriptive packaging that conceals the nature of the products contained within and removes any retailer (or platform) identifiers. While there is discussion in popular press of discreet packaging as a privacy enhancing measure, there is relatively little rigorous analysis that documents its effects on consumer purchasing behavior.[1] In this paper, we evaluate the impact of introducing privacy-enhancing product packaging on customer demand.

A priori, there are good reasons to believe that offering discreet packaging as a form of privacy protection can serve as a competitive advantage, rather than merely a compliance measure. Martin (2015) suggests that strong privacy policies enhance brand trust, leading to long-term consumer loyalty. Similarly, Rust et al. (2002) show that offering even basic privacy protections benefits firms, as failing to do so can erode consumer engagement. Beyond these findings, Casadesus-Masanell and Hervas-Drane (2015) offer a more nuanced argument in that firms can compete on privacy *only* if consumer preferences for privacy are heterogeneous enough to create meaningful market segmentation. Although the literature on privacy protection is extensive, it predominantly relies on surveys (stated preferences) and analytical models, with limited empirical research based on actual consumer-level transactions (revealed preferences).

Beyond the overall impact of discreet packaging on demand, platforms may also want to assess how this effect varies across different types of consumers. We identify three sources of heterogeneity that are relevant for our context. The first pertains to consumers' geographic location, specifically whether they reside in urban or rural areas. The perceived value of discreet packaging may be greater for urban consumers, who often live in apartments or densely populated neighborhoods where packages are easily observed by neighbors. Conversely, the effect of discreet packaging may be stronger for rural consumers. Despite greater spatial distance between households, rural communities tend to be socially cohesive, with frequent interpersonal interactions and social monitoring that can intensify privacy concerns (Goffman 1963). Moreover, their greater reliance on online pharmacies for healthcare products, owing to limited local access, may further reinforce the potential value of discreet packaging. As a result, whether discreet packaging exerts a stronger influence among urban or rural consumers remains an empirical question.

The second dimension of heterogeneity concerns the consumption unit, i.e., individual consumers

[1] https://www.shopify.com/blog/discreet-packaging

versus households. Specifically, the impact of discreet packaging may differ between individual consumers, who primarily purchase for personal use, and household consumers, who often buy on behalf of multiple members. As Lancaster (1975) notes, household consumption often involves joint decision-making and aggregation effects that distinguish it from individual consumption. Consistent with classic marketing research conceptualizing the family as a central decision-making unit (Davis and Rigaux 1974, Davis 1976), household purchases are more likely to include privacy-sensitive items due to the broader range of needs and conditions represented among members. Moreover, in shared household environments, one member's use of sensitive or stigmatized products may reflect on others, intensifying the social cost of such purchases (Struening et al. 2001, Wahl and Harman 1989). Collectively, these mechanisms suggest that household consumers may place greater value on discreet packaging than individual consumers.

The third source of heterogeneity relates to consumers' value orientation, as reflected in their tendency to make purchases using coupons. Coupon-prone consumers are primarily motivated by financial incentives and the prospect of savings (Lichtenstein et al. 1990, Bawa and Shoemaker 1987, Mittal 1994). They derive psychological satisfaction from the comparative evaluation process inherent in bargain hunting, with studies showing that they are significantly more likely to purchase products with visible discounts (Andrews et al. 2014, Bawa et al. 1997). Consequently, such consumers may be less responsive to non-economic features such as discreet packaging, which offer privacy benefits but do not yield direct financial savings.

Having discussed how discreet packaging influences demand and how its effect may vary across consumers, it is also important to consider its potential implications for platform operations. While discreet packaging may reduce friction and ease privacy concerns, it can also have unintended consequences on operational efficiency. Prior research on other friction-reduction strategies, such as removing minimum free shipping thresholds (Guo and Liu 2023) and elimination of return fees (Iyengar et al. 2022), shows that purchase fragmentation can occur, i.e., customers place orders more frequently but reduce their basket size per transaction. Thus, while consumers may spend more, friction reduction strategies are accompanied by an increase in the operational costs for retailers (Fisher et al. 2019, Turkensteen et al. 2011). Some past work, albeit largely theoretical in nature, provides support for such an increase in costs specifically for privacy enhancing features. For instance, Hu et al. (2022) use a queuing model to explore how service providers can strategically manage privacy by allowing customers control over their personal information. Their results show that while this strategy does empower customers, it can lead to inefficiencies such as longer wait times. There is, however, less empirical documentation of such tradeoffs.

In sum, several questions regarding the impact of discreet packaging on customer purchase patterns are important to address:

1) Does the introduction of discreet packaging affect consumer purchases?

2) If so, how does the impact vary across consumers with different characteristics?

3) What, if any, are the operational implications of this feature for retailers?

We answer these questions using demand data from a major online pharmacy platform in Asia. This platform hosts both first-party (FP) and third-party (TP) sellers, each operating with independent logistics. In March 2018, the platform introduced a free, optional discreet packaging feature for all its FP products. When selected at checkout, this packaging conceals product details and omits the platform's logo, effectively anonymizing both the contents and the source.

Our setting is eminently suitable for addressing our research questions. First, online pharmacies are an increasingly popular mode of healthcare access and, from a policy perspective, it is important to assess the impact of privacy enhancing features for such platforms.[2] Second, given the broad appeal of the platform, there is considerable variation in customer demographics. The variation across customers should facilitate the identification of heterogeneous treatment effects of discreet packaging on purchases. Third, the presence of both FP and TP sellers on the platform, and *only* the former offering discreet packaging, allows for a more nuanced exposition of how discreet packaging may impact customer preferences, and its cost implications.

We estimate the impact of introducing discreet packaging on customer demand within a difference-in-differences (DiD) framework. There are three key findings. First, the introduction of discreet packaging

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[2] https://www.fda.gov/consumers/consumer-updates/how-buy-medicines-safely-online-pharmacy

leads to a 20% net increase in consumer purchases, boosting FP orders by 34% while resulting in a temporary decline in TP purchases that averages 23% within our observation window. Further analysis shows that this demand growth is primarily driven by high-sensitivity products, indicating that the increase is likely due to reduced privacy concerns. Second, there is significant heterogeneity across consumers in the treatment effect of discreet packaging on demand. For instance, the effects for rural (as opposed to urban) and households (as compared to individual) consumers are more positive. Conversely, the effects are less positive for coupon-prone consumers (cherry pickers who use coupons and look for good deals). Third, the analysis of basket size and shipping costs shows that while discreet packaging increases purchase frequency and overall spend, it reduces the basket size for each purchase, thereby elevating fulfillment costs for the platform.

We conduct several robustness checks to validate our main findings including, but not limited to, (i) testing the parallel trend assumption in the pre-treatment period, (ii) assessing the sensitivity of our results to potential violations of this assumption in the post-treatment period using the HonestDiD framework (Rambachan and Roth 2023), (iii) addressing concerns about selection on unobservables with two complementary sensitivity analyses namely, Rosenbaum bounds (Rosenbaum 2002) and Oster's method (Oster 2019), and (iv) using a doubly robust estimator (Sant'Anna and Zhao 2020) that is robust to model misspecification. Across these checks and others reported later, our key results are robust.

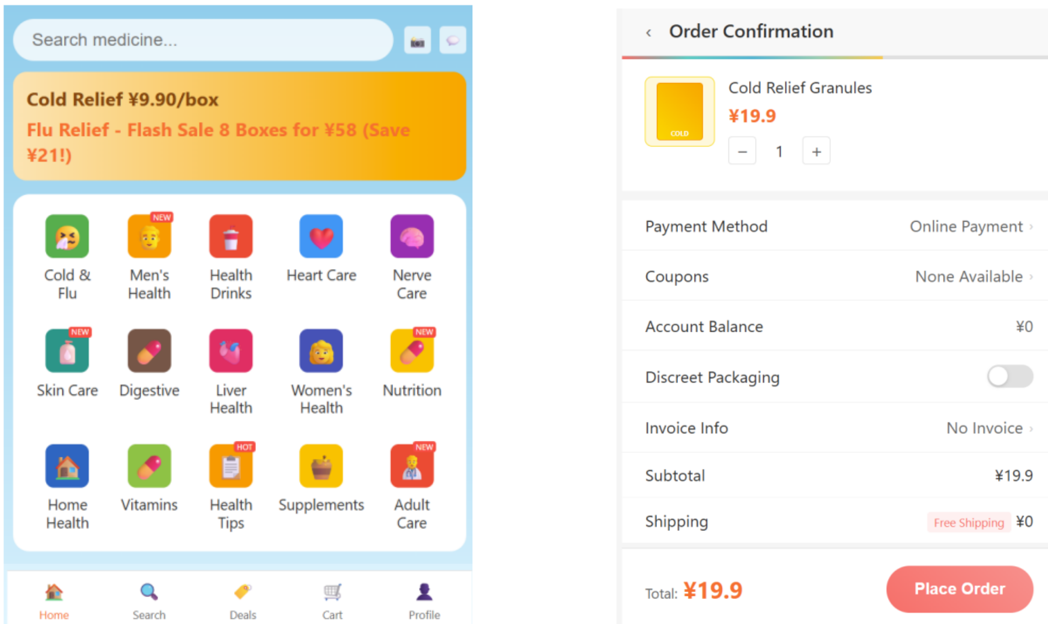
Our findings are relevant to a few different streams of literature. One stream of extant work has employed either stylized models or small-scale surveys to explore tradeoffs in strategically managing customer privacy (Hu et al. 2022, Lee et al 2011). There is also work that has explored the role of customer privacy for moderating competition across firms. Casadesus-Masanell and Hervas-Drane (2015) develop a theoretical model showing that privacy strategies can reduce competition intensity by enabling differentiation. Culnan and Armstrong (1999), based on survey evidence, find that firms with fair privacy practices gain better access to user data, securing a competitive advantage. Meanwhile, in a related conceptual review, Goldfarb and Tucker (2013) argue that strong privacy policies enhance brand trust, fostering consumer loyalty. More broadly, Dubé et al. (2025) provide a comprehensive perspective on the economic implications of privacy regulation, highlighting that privacy protections often involve tradeoffs that can reshape competition and consumer welfare. As a complement to the above work, we offer a large-scale empirical analysis to document the impact of a new consumer privacy strategy on demand. In addition, we demonstrate that there is considerable heterogeneity in the sensitivity to privacy across consumers and products (Lwin et al. 2007). Another stream of work has documented the tension between the impact of marketing actions (e.g., promotions) on customer demand and the increase in cost to serve customers. For instance, Shehu et al. (2020) find that free shipping promotions boost demand but lead to higher returns, reducing profitability due to added costs and lost shipping revenue. Similarly, Guo and Liu (2023) show that subscription-based shipping fragments orders, raising fulfillment costs, while Bandi et al. (2018) demonstrate that dynamic pricing, though substantially increasing profits, also leads to higher return rates due to customers' opportunistic behavior. We add to this literature by showcasing the implications of offering privacy enhancing features for both consumer demand and operational costs.

The remainder of the paper is organized as follows. Section 2 describes the research context and key variables. Section 3 presents our empirical approach including model-free evidence and the identification strategy. Section 4 presents the key results and summarizes the robustness checks. Section 5 concludes.

2. Data

2.1. Research Context

Our study focuses on a leading online pharmacy platform in Asia, which serves over 2 million active users and collaborates with brick-and-mortar pharmacies to offer a wide range of healthcare related products (e.g., over-the-counter drugs and prescription drugs) through its online portal and mobile application. It operates under a hybrid model that integrates first-party (FP) and third-party (TP) sellers. FP sellers are owned and managed directly by the platform, while TP sellers are independent merchants who set their own prices and handle logistics. Products sold by FP sellers are labeled "Self-Operated" before the product name, while those from TP sellers are labeled "Merchant." The FP sellers account for approximately 75% of total sales. As shown in Figure 1, the user interface and navigation process of the platform's mobile application are largely similar to Amazon's. Users can discover products through keyword searches, category browsing, and personalized recommendations. The recommendation algorithm primarily relies on browsing volume and applies the same criteria to both FP and TP offerings.



(a) Home Page (b) Checkout Page

Figure 1. Illustrative Interface of Platform Mobile App

The platform introduced the discreet packaging feature for all FP products on March 29, 2018, as a demand-driven response to the high share of socially sensitive products sold on the platform. The exterior of discreet packaging does not display any information related to the products or the platform. As shown in Figure 1(b), consumers could request discreet packaging free of charge at checkout by toggling a switch, which is turned off by default. Importantly, the platform does not allow users to filter products based on the availability of discreet packaging, and this option is not visible in the search results. This feature is not available for TP products, as their shipping is managed by TP sellers and thus falls outside the control of the platform.[3]

Our data observation window spans six months before and after the introduction of discreet packaging

[3] FP sellers typically ship orders on the same day or the following day, whereas TP sellers generally ship within two business days, though their delivery speed is less standardized and more variable.

from the platform. The dataset contains demographic information and purchase activities of consumers. Our sample focuses on 327,370 consumers with at least one purchase activity both prior to and following the feature introduction. We removed 42 (0.01%) outlier consumers who placed more than 500 orders or spent over 500,000 RMB (approximately 70,000 USD) within the observation window, as their behavior is unlikely to reflect typical consumer patterns. Our final sample includes 327,328 consumers, with 24,732 feature adopters comprising the treatment group and the remaining serving as the control group.

2.2. Matching

We employ propensity score matching (PSM) to obtain comparable treatment and control consumers (Rosenbaum and Rubin 1983). Specifically, we match adopters and non-adopters of the discreet packaging feature (using a 1:3 ratio) based on their demographic and behavioral characteristics prior to the introduction of discreet packaging. The resulting dataset includes 24,732 treated consumers and 74,196 control consumers. We compute the standardized mean difference (SMD) before and after matching to evaluate the matching quality (Rubin 2001, Stuart 2010). Appendix A1 contains the results and shows that the SMD is less than 0.1 for all covariates in the matched sample, suggesting the matched sample is balanced across all covariates.

2.3. Variables

Dependent Variables. Our main dependent variable is the total number of orders that a consumer (*i*) places in a month *t* (i.e., $Orders_{it}$). To investigate the differing impact of the privacy feature on FP and TP products, we further disaggregate this measure into FP orders (i.e., FP_Orders_{it}) and TP orders (i.e., TP_Orders_{it}).[4] In addition to these consumer demand measures, we construct a set of dependent variables that captures basket size. $Basket\_Size_{it}$ denotes the average number of items per order for consumer *i* in month *t*. To differentiate between product types, we further split this into $FP\_Basket\_Size_{it}$, the average number of FP items per order, and $TP\_Basket\_Size_{it}$, the average number of TP items per order. These basket size variables are conditional on purchase being made in a month.

[4] If an order contains both FP and TP products, we increase the counts for both FP_Orders_{it} and TP_Orders_{it} by 1. Note this simplification introduces minimal bias, as mixed orders are extremely rare (0.8% of all transactions).

Focal variables. A time-invariant binary variable $Treatment_i$ indicates if consumer *i* has ever adopted the feature during our observation window. In addition, a time-varying dummy variable $After_t$ denotes if the feature has already been introduced to the platform by month *t*. Since the feature launched on March 29, 2018, and only 256 consumers adopted it that month, we set $After_t$ to one starting in April 2018.

Table 1. Definitions and Descriptive Statistics of Variables

Variable	Variable definition	Observations	Mean	SD	Min	Max
Dependent variable						
$Orders_{it}$	The monthly orders of a consumer	1,227,423	0.53	1.03	0	66
FP_Orders_{it}	The monthly first-party orders of a consumer	1,227,423	0.41	0.80	0	66
TP_Orders_{it}	The monthly third-party orders of a consumer	1,227,423	0.12	0.57	0	53
$Basket\_Size_{it}$	Average number of items per order for a consumer in a given month	438,902	5.61	9.03	1	1,250
$FP\_Basket\_Size_{it}$	Average number of first-party items per order for a consumer in a given month	378,743	5.53	9.28	1	1,250
$TP\_Basket\_Size_{it}$	Average number of third-party items per order for a consumer in a given month	102,883	5.94	8.60	1	460
Focal variable						
$Treatment_i$	A dummy variable that equals 1 if a consumer adopted the discreet packaging feature during our observation window	1,227,423	0.25	0.43	0	1
$After_t$	A dummy variable that equals 1 if the discreet packaging feature was already available in a given month	1,227,423	0.48	0.50	0	1
Moderator						
Is_Rural_i	A dummy variable that equals 1 if a consumer resides in a rural area	1,227,423	0.24	0.43	0	1
$Household_i$	The platform's estimated probability of whether a consumer is a household consumer	1,227,423	0.68	0.46	0	1
$Coupon\_Ratio_i$	The percentage of orders utilizing coupons prior to the feature introduction for a consumer	1,227,423	0.11	0.25	0	1

Notes: We excluded 0.93% of orders without shipping information before matching. The reported statistics are based on the matched sample. Summary statistics for the raw sample are provided in Appendix A2.

Moderators. We investigate the moderating effects of the three consumer-level characteristics discussed earlier. The first moderator, Is_Rural_i, is a binary variable indicating whether consumer *i* resides in a rural area (= 1) or an urban area (= 0). The second moderator $Household_i$, ranging from 0 to 1, represents the platform's estimated probability that consumer *i* is a household consumer. Note that 99% of users have a value of either 0 or 1 for this variable.[5] The third moderator, *Coupon_Ratio*$_i$, is another continuous variable ranging from 0 to 1, defined as the ratio of a consumer's orders that involve coupon usage prior to the launch of the discreet packaging feature. A higher value indicates that the consumer has greater coupon proneness. Table 1 contains the definitions and descriptive statistics for all the variables.

3. Empirical Strategy

3.1. Model-Free Evidence

Figure 2 shows the average monthly orders for treatment and control groups over time, with the dashed vertical line indicating the introduction of discreet packaging on this platform.[6]

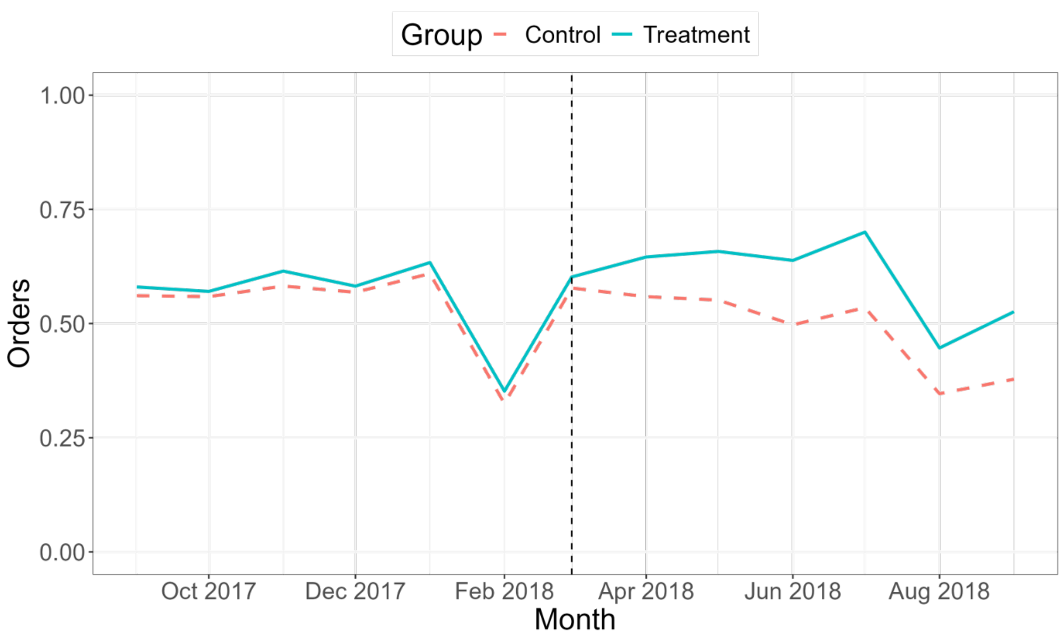


Figure 2. Purchase Trend for Treatment and Control Groups

[5] The variable *Household* is inferred by the platform through a proprietary algorithm that considers several factors, including manual labels assigned by pharmacists during consultations, purchases of items typically consumed by infants or the elderly, and whether the recipient's phone number matches the phone number used to register the account. Although the details of the algorithm cannot be disclosed, the binary classification of 99% users as individual (0) or household (1) consumers aligns with our conceptualization of individual versus household consumption (i.e., purchasing for oneself versus for the entire family). For the remaining 1% of users with inferred values between 0 and 1 for this variable, the underlying computation logic is somewhat opaque and not straightforward to interpret. Nonetheless, excluding these users does not affect the robustness of our results.

[6] The dip in February 2018 for both groups was caused by the suspension of certain courier services during the Lunar New Year holiday. Similar seasonal dips can be observed on the platform during other calendar years.

Prior to the introduction, the purchase patterns of the two groups are markedly similar, with divergence emerging only afterwards. This visual evidence suggests that the two groups followed parallel trends in the pre-treatment period and that the introduction of discreet packaging had a positive impact on the purchasing behavior of adopters. Patterns for FP and TP orders are reported in Appendix A3. In addition, as shown in Appendix A4, there were no notable price changes around the feature's introduction for either sensitive or regular products, indicating that the observed divergence in sales is unlikely to be driven by price adjustments.

3.2. Difference-in-Differences (DiD) Model

Prior to the description of our modeling framework, it is worth highlighting a key institutional detail of the context regarding the timing of the discreet packaging feature. The platform introduced the feature without any prior announcement. Thus, it is reasonable to assume that the launch of the feature is exogenous for all customers. Additionally, there is no reason for any anticipatory behavior from consumers, ensuring that before the launch of the feature, there is no adjustment in their purchasing decisions. Given this background, and following extant studies that investigate the impact of new platform features (e.g., Manchanda et al. 2015, Narang and Shankar 2019, Xu et al. 2024), we employ a classical DiD design, using the exogenous launch date to define pre- and post-treatment periods.[7] Our objective is to examine how the introduction of discreet packaging influences the purchasing behavior of users who ultimately adopt the feature. While adoption is self-selected, these users represent precisely the segment of interest to the platform. From a practical standpoint, it is crucial for the platform to assess how the introduction of this new feature affects the behavior of would-be adopters.

Let y_{it} represent the number of orders placed by consumer *i* in month *t*, our main DiD model can be specified as follows:

$$y_{it} = \beta_1 \times Treatment_i \times After_t + \delta_i + \theta_t + \epsilon_{it}. \tag{1}$$

[7] As a robustness check, we re-estimate our model using the actual adoption time for each consumer as the intervention point (see Appendices B5 and B6 for details). The results remain highly consistent.

In the model, the indicator variable $Treatment_i$ takes a value of 1 if consumer i adopted the discreet packaging feature during our observation window and is 0 otherwise. The variable $After_t$ is an indicator variable that takes a value of 1 if the feature has already been launched by month t and is 0 otherwise. The parameters δ_i and θ_t represent consumer- and month-level fixed effects, respectively. We cluster the error term (ϵ_{it}) at the consumer level to account for the serial correlation in errors within each consumer over time.

To investigate how treatment effects vary across consumers, we further interact the treatment dummy $Treatment_i$ with various consumer-level attributes, including Is_Rural_i, $Household_i$, and $Coupon\_Ratio_i$. The full model with all interaction effects is presented in Equation (2).

$$y_{it} = \beta_1 \times Treatment_i \times After_t + \beta_2 \times Treatment_i \times After_t \times Is\_Rural_i +$$
$$\beta_3 \times Treatment_i \times After_t \times Household_i + \beta_4 \times Treatment_i \times After_t \times Coupon\_Ratio_i +$$
$$\delta_i + \theta_t + \epsilon_{it}. \tag{2}$$

3.3. Parallel Trend Test

A key assumption for the DiD model is the parallel trend assumption (Abadie 2005), which requires the outcome trajectories of the treatment and control groups would have followed similar trends in the absence of the treatment. Following the prior literature, we test this assumption by interacting the treatment group dummy with the month dummies in the following model:

$$y_{it} = \sum_{k=-7}^{-2} \eta_k \times Treatment_i \times Month_{T+k} + \sum_{k=0}^{5} \eta_k \times Treatment_i \times Month_{T+k} + \delta_i$$
$$+\theta_t + \epsilon_{it}. \tag{3}$$

Here, y_{it} denotes the total number of orders placed by consumer *i* in month *t*, and T represent the month when discreet packaging became available on the platform (i.e., April 2018 as explained in Section 2.3). η_k indicates the difference between the treatment and control groups in month $T + k$. The last pre-treatment month ($k = -1$) is set as the baseline. Figure 3 illustrates how η_k varies with k, with error bars representing 95% confidence intervals. All the coefficients prior to the introducing of discreet packaging are very close to zero and nearly all of them are statistically insignificant, confirming the presence of parallel trends in the pre-treatment period.[8]

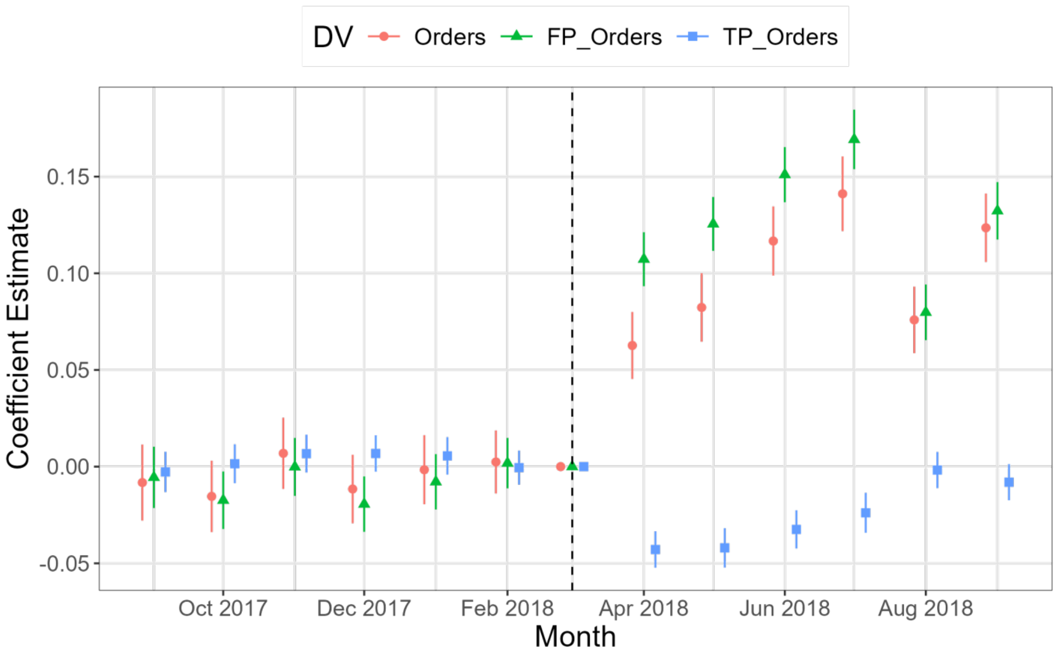


Figure 3. Parallel Trend Test

4. Results

4.1. Main Results

Table 2 presents the results with different model specifications, where the dependent variable is the monthly orders placed by a consumer: total orders in Columns 1–2, FP orders in Columns 3–4, and TP orders in Columns 5–6. Columns 1, 3, and 5 present estimates from the baseline models, in which the interaction term *Treatment* × *After* captures the average treatment effect of the discreet packaging feature's introduction on eventual adopters. Columns 2, 4, and 6 extend these models with three-way interaction terms to assess heterogeneity in the treatment effects.

The coefficient of *Treatment* × *After* in Column 1 is positive and statistically significant, indicating that the feature introduction increases adopters' overall purchase frequency on the platform. With an

[8] The dip in August 2018 resulted from a one-off platform-wide disruption, likely caused by flooding at the site of the company's primary warehouse during this period.

average monthly order volume of 0.509 in the control group, the coefficient of 0.104 implies a 20.4% increase in overall purchases.[9] Turning to FP orders, Column 3 shows an even stronger positive coefficient, indicating that the availability of discreet packaging makes consumers more inclined to purchase from FP sellers. Since the average monthly FP orders in the control group is 0.389, the coefficient of 0.134 translates into a 34.4% increase in FP purchases. In contrast, Column 5 reports a negative and statistically significant coefficient for TP orders, suggesting that consumers reduce their purchase from TP sellers that do not offer discreet packaging. Given that the average monthly TP orders in the control group is 0.124, the coefficient of –0.028 corresponds to a 22.6% decrease in TP purchases.

Table 2. Impact of Discreet Packaging on Consumer Purchases

	Dependent variable:					
	Orders		FP_Orders		TP_Orders	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.104***	0.101***	0.134***	0.130***	-0.028***	-0.026***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)
Treatment × After × Is_Rural		0.012		0.018**		-0.006
		(0.011)		(0.008)		(0.007)
Treatment × After × Household		0.037***		0.028***		0.009**
		(0.008)		(0.006)		(0.004)
Treatment × After × Coupon_Ratio		-0.061***		-0.080***		0.016***
		(0.016)		(0.015)		(0.005)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423
Within R^2	0.0007	0.0009	0.0019	0.0022	0.0002	0.0004
Overall R^2	0.368	0.368	0.314	0.314	0.398	0.398

Notes: The subgroup-specific time trends, captured by *After* × *Is_Rural*, *After* × *Household*, and *After* × *Coupon_Ratio* are controlled for but not shown. Robust standard errors clustered by consumers are reported in parentheses. *Household* and *Coupon_Ratio* are both mean-centered. Results are consistent when moderators are added separately instead of jointly. As shown in Appendices B1 and B8, the results remain similar when the dependent variables are log-transformed and when expenditure is used as the dependent variable. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Moderating Effect of Location. The coefficient of *Treatment* × *After* × *Is_Rural* is significantly positive

[9] The estimated treatment effects could be overstated if the introduction of discreet packaging adversely affected the purchasing behavior of non-adopters. However, there is little reason to expect such a negative influence, as the feature is benign and offered at no cost to users. Users may remain non-adopters for several reasons: (1) they exclusively purchase from TP sellers and are thus not exposed to the feature; (2) they did not notice the feature at the checkout stage; or (3) they were aware of the feature but did not regard it as necessary. None of these scenarios would plausibly reduce their purchasing activities on the platform.

for FP orders (Column 4), but negative and insignificant for TP orders (Column 6). Although the magnitude of the moderating effect for FP orders exceeds that for TP orders, the overall effect on total orders (Column 2) remains statistically insignificant due to large standard errors. These results suggest that the perceived value of this privacy-preserving feature is greater among rural consumers, who tend to reside in socially cohesive communities with stronger interpersonal visibility, compared to urban consumers, who experience higher social anonymity despite closer physical proximity.

Moderating Effect of Consumption Unit. The interaction term *Treatment* × *After* × *Household* is positive and significant across Columns 2, 4, and 6, though the interpretation differs by order type. For FP orders (Column 4), the positive coefficient indicates a stronger increase in FP purchases among household consumers, consistent with their elevated privacy requirements due to varied conditions of family members. In contrast, for TP orders (Column 6), the positive coefficient suggests that household consumers exhibit a smaller reduction in TP purchases, likely because diverse intra-household needs make it less feasible to shift entirely away from TP sellers.

Moderating Effect of Coupon Proneness. The coefficient of *Treatment* × *After* × *Coupon_Ratio* is negative and significant for overall and FP orders (Columns 2 and 4), but positive and significant for TP orders (Column 6). Despite the opposite signs for FP and TP orders, the interpretation is consistent: in both cases, the moderating effect offsets and attenuates the main treatment effect, indicating that the impact of discreet packaging is weaker among coupon-prone consumers. This result aligns with the notion that deal-oriented consumers are less responsive to features that do not provide direct economic benefits.

4.2. Impact on Preferences for Products

We explore how discreet packaging impacts the purchase of products with different levels of sensitivity. To do so, we employ a large language model (GPT-4o) to classify product categories into four sensitivity levels, ranging from low to high.[10] Based on this classification, we separately count the numbers of FP and

[10] We provide the details about the prompt and illustrative examples of product categories at each sensitivity level in Appendix A5.

TP orders for products within each sensitivity level and use them as dependent variables. Table 3 presents the results, with Columns 1–4 corresponding to FP orders and Columns 5–8 to TP orders.

Columns 1–4 show that the impact of discreet packaging on purchases from FP sellers remains relatively small for low- and moderately low-sensitivity products but becomes noticeably stronger for moderately high- and high-sensitivity products. This pattern suggests that the feature is particularly effective for products that evoke heightened privacy concerns, supporting the interpretation that discreet packaging reduces privacy-related friction in purchase decisions. In contrast, Columns 5–8 reveal increasingly larger declines in TP orders as sensitivity rises, indicating that the FP gains are accompanied by sharper reductions among sellers that do not offer the feature. Together, these results are consistent with a substitution mechanism: as privacy risk becomes more salient, consumers shift demand toward FP channels that provide privacy protection through discreet packaging.

Table 3. Impact of Discreet Packaging on Purchases of Products with Various Sensitivity

	Dependent variable:							
	FP_Orders				TP_Orders			
	Low	Moderately Low	Moderately High	High	Low	Moderately Low	Moderately High	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × After	0.015***	0.012***	0.045***	0.096***	-0.003***	-0.003***	-0.011***	-0.018***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.0005)	(0.001)	(0.001)	(0.002)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423
Within R^2	0.0002	0.0002	0.0005	0.0017	0.0000	0.0000	0.0001	0.0001
Overall R^2	0.197	0.181	0.291	0.310	0.150	0.154	0.285	0.366

Notes: Robust standard errors clustered by consumers are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

We further decompose orders by distinguishing between those consisting exclusively of "known" products and those that also include "new" products. A "new" product is defined as one that the user had not purchased before the current month, whereas a "known" product refers to an item previously purchased. As shown in Table 4, FP purchases increase for both types of orders, while TP purchases decline in both categories. This indicates that the demand shift induced by discreet packaging is not confined to repeat purchases of familiar products but also extends to exploratory purchases of unfamiliar ones. Therefore, the introduction of discreet packaging not only induces substitution from TP to FP products but also stimulates product exploration among consumers.

Table 4. Impact of Discreet Packaging on Orders with New vs Known Products

	Dependent variable:								
	Orders			FP_Orders			TP_Orders		
	Total	Known	New	Total	Known	New	Total	Known	New
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment × After	0.104^{***}	0.042^{***}	0.062^{***}	0.134^{***}	0.047^{***}	0.087^{***}	-0.028^{***}	-0.005^{***}	-0.023^{***}
	(0.004)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423
Within R^2	0.0007	0.0004	0.0004	0.0019	0.0006	0.0012	0.0002	0.0000	0.0002
Overall R^2	0.368	0.333	0.292	0.314	0.327	0.209	0.398	0.277	0.345

Notes: Robust standard errors clustered by consumers are reported in parentheses. Columns 2, 5, and 8 report results for orders containing only known products, while Columns 3, 6, and 9 report results for orders that include at least one new product. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

4.3. Impact on Basket Sizes and Shipping Costs

While prior analyses have showcased the demand-side effects of discreet packaging, extant research also suggests that demand-stimulating polices can have significant implications for operational efficiency (e.g., Guo and Liu 2023, Shehu et al. 2020). Given this background, we examine whether discreet packaging leads to purchase fragmentation, as reflected by changes in average basket size (i.e., the average number of items per order) and to changes in the shipping costs for the platform.

4.3.1. Impact on Basket Sizes

We compute the average monthly basket size for each consumer at the platform level, as well as separately for FP and TP sellers. This measure is conditional on a purchase occurring and provides insights into how consumers structure their transactions when they choose to buy.

The results, reported in Table 5, indicate that the introduction of discreet packaging leads to an average reduction in basket size by 0.169 items, reflecting a shift toward more disaggregated purchasing behavior. This effect is primarily driven by FP purchases, where basket size declines by 0.172 items. In contrast, TP purchases, which are not eligible for discreet packaging, show minimal change. This asymmetry reinforces the interpretation that the observed behavioral shift is attributable to the discreet packaging feature rather than to broader platform trends or external shocks. These results reveal an important operational implication: while discreet packaging increases demand, it also contributes to purchase fragmentation, potentially increasing shipping and fulfillment costs for the platform.

Table 5. Impact of Discreet Packaging on Basket Sizes

	Dependent variable:		
	Basket_Size	FP_Basket_Size	TP_Basket_Size
	(1)	(2)	(3)
Treatment × After	-0.169***	-0.172***	-0.076
	(0.043)	(0.050)	(0.134)
Consumer FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	438,902	378,743	102,883
Within R^2	0.0000	0.0000	0.0000
Overall R^2	0.662	0.692	0.678

Notes: Robust standard errors clustered by consumers are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

To assess whether privacy concerns underlie the observed purchase fragmentation, we categorize orders into three groups: (i) those containing only high-sensitivity items, (ii) those containing only regular items, and (iii) mixed orders. As shown in Table 6, the most pronounced decline in basket size occurs in orders containing only high-sensitivity products, suggesting that the change in purchasing behavior is indeed driven by privacy-related considerations.

Table 6. Impact of Discreet Packaging on FP Basket Size by Order Composition

	Dependent variable: Basket_Size		
	Sensitive Orders	Regular Orders	Mixed Orders
Treatment:After	-0.336***	0.234	-0.303
	(0.053)	(0.145)	(0.228)
Consumer FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	199,603	150,723	68,512
Within R^2	0.0003	0.0001	0.0001
Overall R^2	0.681	0.787	0.687

Notes: Robust standard errors clustered by consumers are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

4.3.2. Impact on Shipping Costs

To better understand the operational implications of discreet packaging, we examine its impact on shipping costs. Recall that the platform sells both FP and TP products. As TP sellers manage the logistics on their own, their shipping cost data is not accessible to the platform. However, according to our analysis in Table 5, basket sizes for TP orders remain largely unaffected by the introduction of discreet packaging. Therefore, our analysis of shipping costs focuses exclusively on FP orders, where the impact is most relevant and observable.[11] Given that most FP orders (86%) meet the platform's free-shipping threshold, the associated shipping costs are predominantly incurred by the platform. It is therefore important to evaluate the extent to which the availability of discreet packaging affects these costs.

Table 7. Impact of Discreet Packaging on Shipping Costs

	Dependent variable:
	Avg_Unit_Cost
	(1)
Treatment × After	0.026^{***}
	(0.009)
Consumer FE	Yes
Time FE	Yes
Observations	378,743
Within R^2	0.0000
Overall R^2	0.633

Notes: Robust standard errors clustered by consumers are reported in parentheses. $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01.

We measure the average shipping cost per FP item within a consumer-month (denoted *Avg_Unit_Cost*), expressed in RMB and conditional on at least one FP order being placed. This measure captures per-unit fulfillment efficiency and mirrors our approach to analyzing basket size in Section 4.3.1. As shown in Table 7, the average shipping cost per item increased by 0.026 RMB, which corresponds to a 1.5% increase relative to the control group mean of 1.7 RMB. This result indicates a higher per-unit fulfillment cost driven

[11] Due to data access limitations, we cannot observe the actual shipping costs incurred by FP warehouses. Instead, we estimate shipping costs using the platform's prevailing logistics rules during the study period. According to platform partners, 94% of orders are charged at the base rate for shipments under 1kg. Since item-level weight data is unavailable, we conservatively assume all orders fall within this tier. As a result, our estimates likely reflect a lower bound of the true shipping costs. In our setting, the shipping cost refers specifically to the shipping fee paid to third-party logistics providers. It does not include warehousing, internal handling, or other fulfillment-related costs such as packaging or mid-mile logistics.

by smaller basket sizes. Our findings thus highlight a critical, yet often overlooked, tension between consumer-oriented innovations and backend operations. While privacy-enhancing features like discreet packaging may improve customer experience and stimulate demand, they can inadvertently strain fulfillment systems. We note that the 1.5% increase in shipping costs is a conservative estimate, and the total operational burden that includes warehousing, handling, and inventory management is likely higher.

4.4. Robustness Checks

We conduct a series of additional analyses to assess the validity and robustness of our main findings. Table 8 summarizes these analyses. Across all checks, we find consistent results supporting the positive effect of discreet packaging on consumer demand. We describe each robustness check in Appendix B.

Table 8. Summary of Robustness Checks

Analysis	Objective	Location
Results using log-transformed dependent variables	Robustness of results to log transformation.	Appendix B1
Sensitivity to violation of parallel trend assumption	Robustness to violations of parallel trend assumption	Appendix B2
Sensitivity to selection on unobservables	Robustness to selection on unobservables	Appendix B3
Within-Customer DiD analysis	Robustness to within-customer setup	Appendix B4
Stacked DiD analysis	Robustness to Stacked DiD setup	Appendix B5
Cohort by cohort Analysis	Robustness of findings across treatment cohorts	Appendix B6
Doubly robust estimator	A model robust to misspecification in outcome or treatment selection model	Appendix B7
Alternative measure of consumer demand	Robustness to measure of consumer demand	Appendix B8

5. Conclusions

Discreet packaging has emerged as a popular strategy to safeguard consumer privacy and reduce the potential stigma associated with the purchase of sensitive items on e-commerce platforms. However, there is little rigorous analysis of how offering this privacy measure will impact consumer behavior. Leveraging data from an online pharmacy that offers both first-party (FP) and third-party (TP) products, our research reveals that the introduction of discreet packaging for FP products significantly boosts FP purchases, while leading to a temporal decline in demand for TP products. There is heterogeneity in the treatment effect across consumers with rural and household consumers placing higher value on privacy, but less so among coupon-prone consumers who prioritize deals. Further analysis reveals that purchase increases are more pronounced for highly sensitive products, highlighting the crucial role of discreet packaging in enhancing privacy and reducing perceived stigma. Despite these benefits, we also find that discreet packaging increases FP shipping costs due to purchase fragmentation, suggesting a tradeoff between privacy enhancement and operational efficiency.

Our study offers important implications for e-commerce platforms that sell products potentially associated with social stigma. First, our study highlights the significant role of discreet packaging in addressing consumer concerns about privacy, particularly for products related to sensitive health conditions. These conditions often carry a stigma that discourages individuals from seeking necessary products, ultimately hindering access to care. By implementing discreet packaging, e-commerce platforms can enhance consumer comfort, reduce perceived stigma, and encourage engagement, thereby facilitating better access to essential products and services in a private and supportive manner.

Second, our study emphasizes the importance of privacy-focused innovations, like discreet packaging, in meeting the needs of distinct consumer segments within e-commerce. Rural and household consumers, who often face greater challenges related to privacy or social stigma when purchasing sensitive products, benefit significantly from these measures. Discreet packaging enables these consumers to shop with greater ease and confidence. In contrast, its impact is less noticeable among coupon-prone consumers, who tend to prioritize financial savings over privacy. These findings suggest that e-commerce platforms could adopt a targeted promotion strategy to increase awareness and usage of discreet packaging among users most likely to benefit from it. For instance, platforms could highlight the availability of discreet packaging in marketing communications or order confirmation pages for users in rural areas or those with household purchasing patterns. Similarly, for sensitive product categories such as reproductive health or personal hygiene, platforms could make the discreet packaging option more salient on product pages. These design choices would help reduce perceived stigma, improve user experience, and ultimately facilitate transactions.

Third, our study contributes to a deeper understanding of how first-party innovations shape competitive dynamics within digital marketplaces. While the introduction of discreet packaging for FP products generates a sustained increase in FP purchases, it also leads to a notable temporary decline in the demand for TP sellers. This pattern suggests that similar features offered exclusively to first-party products, such as fast delivery options on platforms like Amazon, may inadvertently cannibalize third-party sales and place pressure on marketplace diversity. Nevertheless, this result should be interpreted with caution, as the negative spillover we observe is short-lived and small in absolute magnitude. The relatively large average percentage decline in TP purchases likely reflects both the limited duration of our observation window and the small baseline sales of TP sellers.

Lastly, our analysis of basket sizes and shipping costs documents an important trade-off associated with the introduction of discreet packaging. While the feature boosts consumer demand, it also leads to smaller and more frequent orders, which raise per-unit fulfillment and delivery costs. Although common pricing strategies such as free shipping thresholds can partially offset this effect by incentivizing larger baskets, they also introduce transaction frictions that may discourage purchases. Moreover, purchase fragmentation places operational strain on logistics infrastructure and scaling capacity, creating risks of service delays or inefficiencies even when the platform absorbs the financial costs. From a managerial perspective, these findings suggest that platforms should carefully evaluate their logistics readiness before promoting such consumer-oriented innovations at scale.

We acknowledge several limitations of this study. First, our data is from an e-commerce platform that primarily focuses on pharmaceutical products, which may limit the generalizability of our findings to other e-commerce settings. However, given that issues of sensitivity and stigma are particularly salient in the context of online pharmacies, this setting serves as a highly relevant and illustrative context for examining privacy-related consumer behavior. We believe the insights generated from our analysis can inform related industries where privacy concerns are similarly salient. Second, due to data limitations, our study focuses on users' actual purchasing behavior and does not capture underlying psychological factors, such as perceived privacy risk and feelings of stigma. While these factors are not directly measurable, our findings show that the positive effect of discreet packaging increases with product sensitivity, suggesting its role in alleviating privacy concerns. Future research could build on our findings by exploring the psychological mechanisms that drive consumer responses to privacy innovations. Finally, in addition to the trade-off we document between enhanced consumer demand and higher fulfillment costs, another potential cost of discreet packaging lies in the loss of passive brand exposure. Unlike standard branded packaging, which can serve as a form of advertising when visible to neighbors or others in the delivery process, discreet packaging eliminates this channel of visibility. Future research could investigate whether the removal of branded packaging diminishes brand awareness or advertising spillovers.

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Online Appendices

Appendix A. Data-Related Details

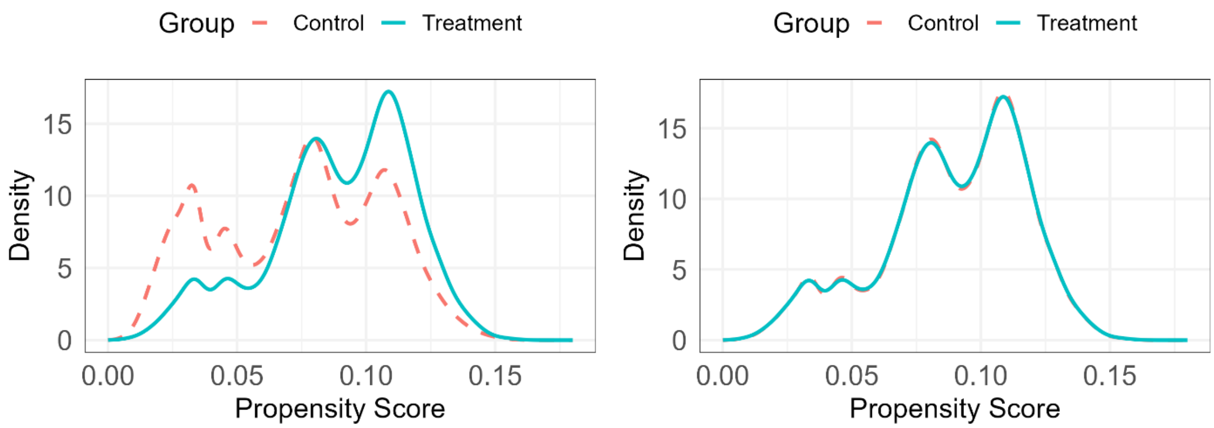
A1. Post-Matching Balance Check

Table A1 provides an overview of the variables used for propensity score matching and the balance check statistics post-matching. The results demonstrate that the treatment and control groups achieve comparable characteristics following the matching process.

Table A1. Balance Check for the Matched Sample

Variable	Variable definition	Mean of Treatment Group	Mean of Control Group	Standardized Mean Difference
Log_Orders_Before	The number of orders the consumer placed on the platform prior to the introduction of discreet packaging (log-transformed)	1.2925	1.2767	0.0268
Log_FP_Orders_Before	The number of FP orders the consumer placed on the platform prior to the introduction of discreet packaging (log-transformed)	1.1078	1.0945	0.0219
Log_TP_Orders_Before	The number of TP orders the consumer placed on the platform prior to the introduction of discreet packaging (log-transformed)	0.3454	0.3367	0.0149
Log_Expenditure_Before	The amount the consumer spent on the platform prior to the introduction of discreet packaging (log-transformed)	6.0446	6.0144	0.0252
Log_FP_Expenditure_Before	The amount the consumer spent on FP products on the platform prior to the introduction of discreet packaging (log-transformed)	5.4663	5.4353	0.0156
Log_TP_Expenditure_Before	The amount the consumer spent on TP products on the platform prior to the introduction of discreet packaging (log-transformed)	1.7770	1.7274	0.0187
Is_Rural	A dummy variable that equals 1 if a consumer resides in a rural area	0.2409	0.2381	0.0065
Household	The platform’s estimated probability of whether a consumer is a household consumer	0.6713	0.6719	-0.0012
Coupon_Ratio	The percentage of orders utilizing coupons prior to the feature introduction for a consumer	0.1105	0.1074	0.0122
Log_Tenure	The number of months a consumer had been registered on the platform prior to the introduction of discreet packaging (log-transformed)	2.7012	2.6847	0.0179

Figure A1 presents the density of propensity scores for both the treatment and control groups, before and after the PSM. After matching, the distributions of the treated and control groups are nearly indistinguishable.



(a) Before Matching

(b) After Matching

Figure A1. Density of Propensity Scores Across Treated and Control Groups

A2. Full Sample Statistics

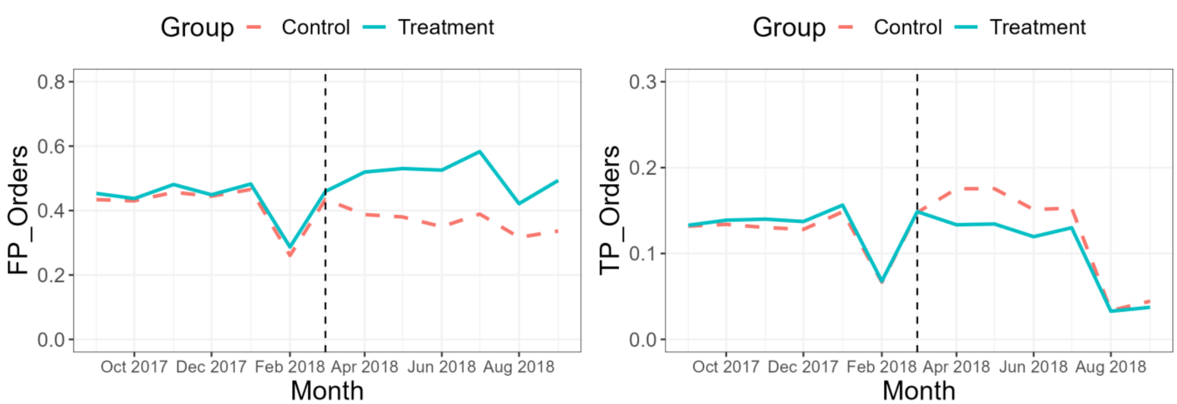
Table A2. Definitions and Descriptive Statistics of Variables on Full Sample

Variable	Variable definition	Observations	Mean	SD	Min	Max
Dependent variable						
$Orders_{it}$	The monthly orders of a consumer	4,026,558	0.53	1.08	0	203
FP_Orders_{it}	The monthly first-party orders of a consumer	4,026,558	0.33	0.71	0	66
TP_Orders_{it}	The monthly third-party orders of a consumer	4,026,558	0.20	0.77	0	203
$Basket\_Size_{it}$	Average number of items per order for a consumer in a given month	1,403,879	5.92	9.42	1	1,999
FP_Basket_Size	Average number of first-party items per order for a consumer in a given month	1,038,084	5.52	8.27	1	1,260
TP_Basket_Size	Average number of third-party items per order for a consumer in a given month	516,065	6.69	11.29	1	1,999
Focal variable						
$Treatment_i$	A dummy variable that equals 1 if a consumer adopted the discreet packaging feature during our observation window	4,026,558	0.08	0.27	0	1
$After_t$	A dummy variable that equals 1 if the discreet packaging feature was already available in a given month	4,026,558	0.49	0.50	0	1
Moderator						
Is_Rural_i	A dummy variable that equals 1 if a consumer resides in a rural area	4,026,558	0.26	0.44	0	1
$Household_i$	The platform's estimated probability of whether a consumer is a household consumer	4,026,558	0.60	0.49	0	1
$Coupon\_Ratio_i$	The percentage of orders utilizing coupons prior to the feature introduction for a consumer	4,026,558	0.08	0.21	0	1

Note: We removed 0.93% of orders without shipping information.

A3. Purchase Trends for FP and TP Products

Figure A3 displays the monthly average orders of FP and TP Products for consumers in the treatment and control groups. For both types of products, the purchase trends were largely parallel before the introduction of discreet packaging. However, after its introduction, the purchase of FP products in the treatment group notably exceeded that of the control group, while TP products in the treatment group experienced a temporary decline compared to the control group. This finding suggests that discreet packaging significantly increased consumers' demand for FP products with short-lived impact on the demand for TP products.



(a) FP_Orders (b) TP_Orders

Figure A3. Purchase Trends for FP and TP Products

A4. Price Changes Around Feature Launch

To rule out the possibility that our results are driven by price changes, Figure A4 plots average prices of products by sensitivity level. The figure shows no sudden adjustments around the launch of discreet packaging. At the product level, about 52% of items had no price changes within the one-month window before and after the launch, and roughly 80% showed changes of less than 5% (Table A4). These findings indicate that price variation is unlikely to be a driver of our results.

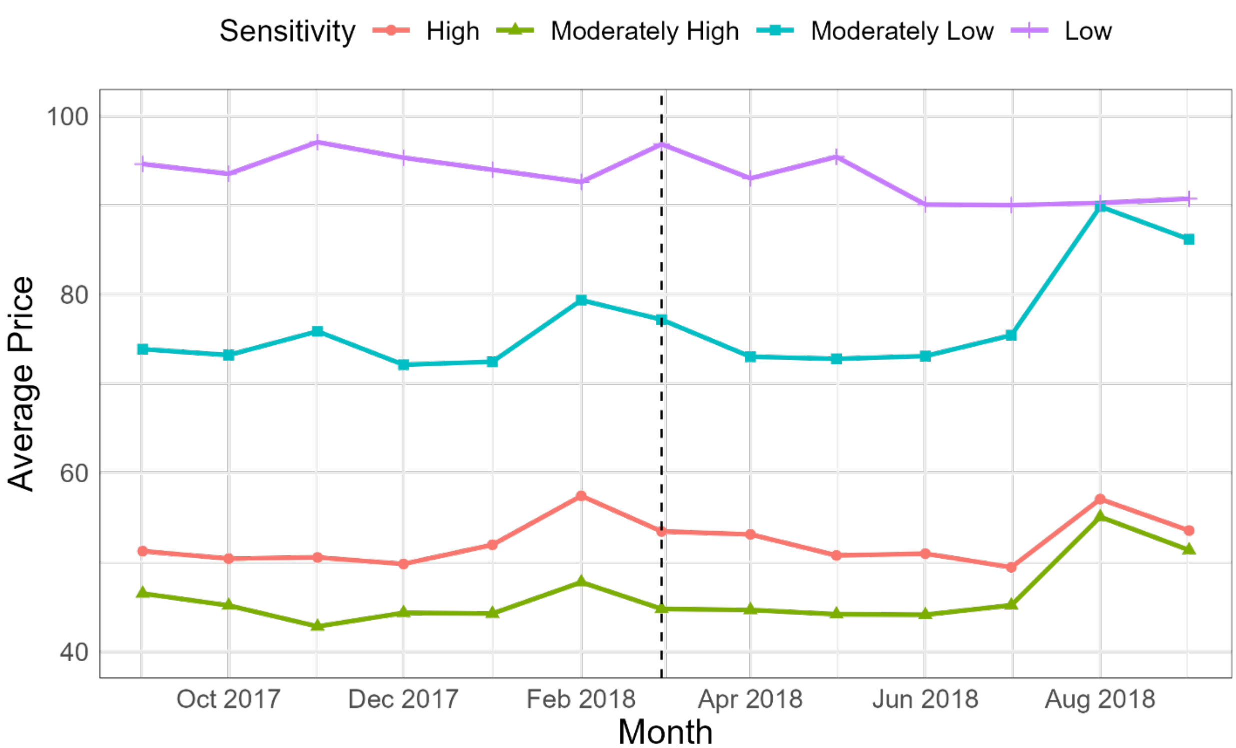


Figure A4. Average Price Over Time

Table A4. Price Changes Within ±1 Month of Feature Launch

Products	Percentage Change						
	<−10%	[-10%,-5%)	[-5%,0)	0%	(0,5%]	(5%,10%]	>10%
All	6.24%	4.96%	17.39%	51.98%	10.37%	3.02%	6.04%
Low	5.89%	3.28%	12.97%	58.05%	11.18%	2.24%	6.41%
Moderately Low	5.06%	5.00%	12.72%	57.84%	11.42%	3.02%	4.94%
Moderately High	6.46%	4.78%	15.15%	51.65%	10.23%	3.71%	8.03%
High	6.31%	5.34%	20.33%	50.46%	10.42%	2.60%	4.54%

A5. Illustrative Product Categories by Sensitivity Level

We employed the following prompt to instruct GPT-4o to classify product categories into four sensitivity levels: "Using the provided product category information, assess the product's privacy sensitivity and assign it to one of the following categories: Low, Moderately Low, Moderately High, or High. Only return the category label, with no explanation." Table A5 provides illustrative examples of product categories classified into each sensitivity level.

Table A5. Illustrative Product Categories by Sensitivity Level

Sensitivity Level	Illustrative Product Categories
High	AIDS, genital warts, male infertility, depression, vaginitis
Moderately High	Breast care, intimate fragrance, hair loss, menopause, hormonal regulation
Moderately Low	Melatonin, maca supplements, oyster extract, soy isoflavones, slimming tea
Low	Vitamins, calcium supplements, iron supplements, zinc supplements, eye health products

Appendix B. Robustness Checks

B1. Results Using Log-Transformed Dependent Variables

In our main analysis, we use the raw dependent variables to run the regression. As shown in Table B1, the results remain consistent even when the dependent variables are log-transformed.

Table B1. Results Using Log-Transformed Dependent Variables

	Dependent variable:					
	Log(Orders+1)		Log(FP_Orders+1)		Log(TP_Orders+1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.056***	0.054***	0.077***	0.074***	-0.017***	-0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Treatment × After × Is_Rural		0.008**		0.012***		-0.002
		(0.004)		(0.004)		(0.002)
Treatment × After × Household		0.015***		0.009***		0.007***
		(0.003)		(0.003)		(0.002)
Treatment × After × Coupon_Ratio		-0.023***		-0.041***		0.010***
		(0.007)		(0.007)		(0.003)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423
Within R^2	0.0009	0.0013	0.0022	0.0027	0.0003	0.0006
Overall R^2	0.242	0.242	0.232	0.232	0.289	0.290

Notes: The subgroup-specific time trends, captured by *After* × *Is_Rural*, *After* × *Household*, and *After* × *Coupon_Ratio* are controlled for and not shown. Robust standard errors clustered by consumers are reported in parentheses. *Household* and *Coupon_Ratio* are both mean-centered. Results are consistent when moderators are added separately instead of jointly. * p<0.1, ** p<0.05, *** p<0.01

B2. Sensitivity to Violation of Parallel Trend Assumption

While Figure 3 demonstrates that the parallel trend assumption is plausible in the pre-treatment period, this assumption remains untestable in the post-treatment as the counterfactual outcome of the treatment group is unobserved. To assess the robustness of our results to potential violations of this assumption, we conduct a sensitivity analysis using the HonestDiD framework (Rambachan and Roth 2023). This method quantifies how severe a deviation from parallel trends in the post-treatment period would need to be in order to invalidate the significant effects. Specifically, it calculates a parameter, denoted as $\bar{M}$, representing the ratio of allowable post-treatment trend violation relative to the worst-case deviation observed in the pre-treatment period. If the estimated effect remains significantly different from zero when $\bar{M}$ equals 1, it indicates robustness even if the post-treatment deviation were as large as the greatest pre-treatment discrepancy. As shown in Figure B2, the estimated treatment effect on total orders remains significantly positive unless $\bar{M}$ exceeds 1.5, while the effects on FP and TP orders remain significant even when $\bar{M}$ equals 2. These findings suggest that our results are fairly robust to potential violations of the parallel trend assumption.

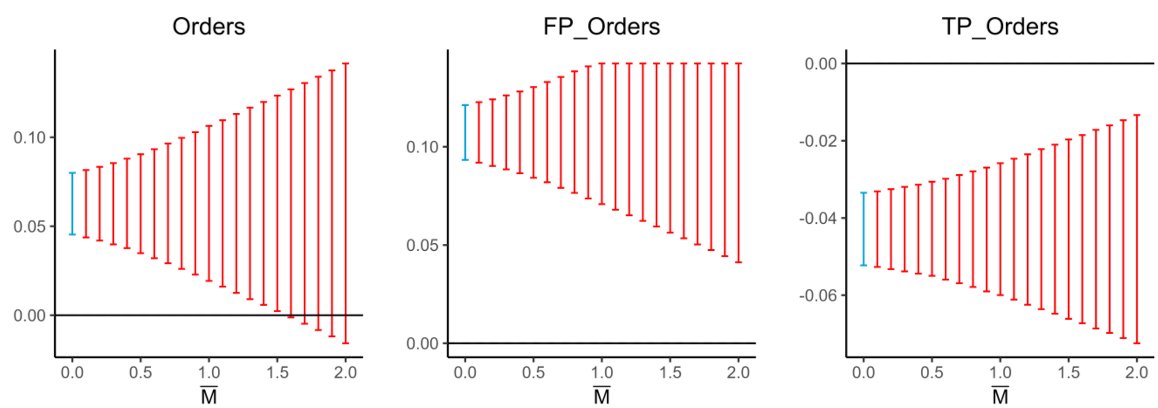


Figure B2. Sensitivity Analysis with HonestDiD

B3. Sensitivity to Selection on Unobservables

To evaluate whether our estimated effects could be explained by unobserved confounders, we conducted two complementary sensitivity analyses: Rosenbaum bounds (Rosenbaum 2002) and the selection-on-unobservables framework of Oster (2019), following Pattabhiramaiah et al. (2022). Both analyses indicate that our findings are robust to hidden bias.

We first implemented the Rosenbaum bounds analysis, which examines how strong an unobserved factor would have to be in order to nullify the estimated treatment effect. Specifically, we estimate the critical Γ, the odds ratio of treatment assignment due to unobservables, that would render the effect statistically insignificant based on Wilcoxon signed-rank tests. The Rosenbaum bounds approach requires a single post-treatment outcome per unit to assess the sensitivity of treatment effects to hidden bias (Rosenbaum 2002). Therefore, we collapse the outcome variable into consumer-level monthly averages over the post-treatment period. Specifically, we construct three variables: *Avg_Post_Orders*, *Avg_Post_FP_Orders*, and *Avg_Post_TP_Orders*, which represent the average monthly (overall/FP/TP) orders placed by each consumer following the introduction of discreet packaging. As our main analysis based on total orders revealed a positive effect of discreet packaging on demand, we are primarily concerned with the possibility of upward (positive) bias due to unobserved confounding. Accordingly, in the corresponding sensitivity analysis using *Avg_Post_Orders* as the outcome variable, we focus on the upper-bound significance level (sig+). Similarly, we focus on sig+ for *Avg_Post_FP_Orders*, and on sig– for *Avg_Post_TP_Orders*.

Table B3.1 reports the results of the Rosenbaum bounds sensitivity analysis. We increase the value of Γ in increments of 0.05, starting from 1. At each level of Γ, we compute the upper- and lower-bound significance levels, sig+ and sig–. For *Avg_Post_Orders*, the results indicate that the effect remains statistically significant up to $\Gamma = 1.6$ (sig+ = 0.003). In other words, the estimated positive treatment effect would be nullified only if there were unobserved confounders that alter the odds ratio of treatment assignment by a factor of 1.6. It is worth noting that this reflects a conservative, worst-case scenario and does not suggest that such unobserved factors necessarily exist or are strong enough to eliminate the treatment effect. Using the same approach, we obtain critical Γ values of 2.15 for *Avg_Post_FP_Orders* and 1.4 for *Avg_Post_TP_Orders*. These values are all at or above the typical range of 1.2 to 1.6 commonly reported in the empirical literature (e.g., DiPrete and Gangl 2004, Manchanda et al. 2015, Sun and Zhu 2013, Zhang et al. 2022), indicating that our estimated effects are unlikely to be driven by hidden bias of conventional magnitude.

Table B3.1. Rosenbaum Bounds Test

	Dependent variable:					
	Avg_Post_Orders		Avg_Post_FP_Orders		Avg_Post_TP_Orders	
	(1)	(2)	(3)	(4)	(5)	(6)
Γ	sig+	sig–	sig+	sig–	sig+	sig–
1	0.000	0.000	0.000	0.000	0.000	0.000
1.05	0.000	0.000	0.000	0.000	0.000	0.000
1.1	0.000	0.000	0.000	0.000	0.000	0.000
1.15	0.000	0.000	0.000	0.000	0.000	0.000
1.2	0.000	0.000	0.000	0.000	0.000	0.000
1.25	0.000	0.000	0.000	0.000	0.000	0.000
1.3	0.000	0.000	0.000	0.000	0.000	0.000
1.35	0.000	0.000	0.000	0.000	0.000	0.000
1.4	0.000	0.000	0.000	0.000	0.000	**0.001**
1.45	0.000	0.000	0.000	0.000	0.000	0.118
1.5	0.000	0.000	0.000	0.000	0.000	0.720
1.55	0.000	0.000	0.000	0.000	0.000	0.989
1.6	**0.003**	0.000	0.000	0.000	0.000	1.000
1.65	0.224	0.000	0.000	0.000	0.000	1.000
1.7	0.873	0.000	0.000	0.000	0.000	1.000
1.75	0.999	0.000	0.000	0.000	0.000	1.000
1.8	1.000	0.000	0.000	0.000	0.000	1.000
1.85	1.000	0.000	0.000	0.000	0.000	1.000
1.9	1.000	0.000	0.000	0.000	0.000	1.000
1.95	1.000	0.000	0.000	0.000	0.000	1.000
2	1.000	0.000	0.000	0.000	0.000	1.000
2.05	1.000	0.000	0.000	0.000	0.000	1.000
2.1	1.000	0.000	0.000	0.000	0.000	1.000
2.15	1.000	0.000	**0.002**	0.000	0.000	1.000
2.2	1.000	0.000	0.071	0.000	0.000	1.000
2.25	1.000	0.000	0.458	0.000	0.000	1.000
2.3	1.000	0.000	0.890	0.000	0.000	1.000
2.35	1.000	0.000	0.994	0.000	0.000	1.000
2.4	1.000	0.000	1.000	0.000	0.000	1.000
2.45	1.000	0.000	1.000	0.000	0.000	1.000
2.5	1.000	0.000	1.000	0.000	0.000	1.000

As a complementary analysis, we apply the Oster (2019) method, which relies on changes in the treatment coefficient and R^2 values from models that either include or exclude control variables to infer the potential bias from omitted variables. Following Pattabhiramaiah et al. (2022), we implement this method using a panel difference-in-differences regression on our matched sample and set the maximum attainable R^2 to 1.3 times the R^2 from the model with full controls, as recommended by Oster. Here, δ denotes the degree of selection on unobservables compared to selection on observables. As shown in Table B3.2, the resulting δ values for *Orders*, *FP_Orders*, and *TP_Orders* are 3.656, 3.245, and 2.558, respectively. These values substantially exceed the conventional threshold of $\delta = 1$, suggesting that unobserved selection would need to be at least 2.5 times as strong as observable selection to fully account for the estimated effects.

Together, these results confirm the robustness of our findings and suggest that the estimated treatment effects are unlikely to be driven by unobserved confounders.

Table B3.2. Oster Unobserved Selection Test

	Dependent variable:		
	Orders	FP_Orders	TP_Orders
	(1)	(2)	(3)
δ	3.656	3.245	2.558

B4. Within-Customer DiD Analysis

To address concerns that our results may be confounded either by seasonality or by systematic differences between treatment and control groups, we obtained one-year additional data from the platform and re-estimate the model using the period from September 2016 to August 2017 as the within-customer control (Chiou and Tucker 2022, Goldberg et al. 2024). As shown in Figure B4, purchase trends for the treatment and control groups are closely aligned in the pre-treatment period, with the only divergence reflecting reduced purchase activity around the Lunar New Year holiday—occurring in January 2017 for the control group and in February 2018 for the treatment group. Following the introduction of discreet packaging, the treatment group's purchase trend rises significantly above that of the control group, except for a temporary decline in August 2018 caused by a one-off platform-wide disruption. Table B4 reports the regression results, which remain consistent with our main findings.

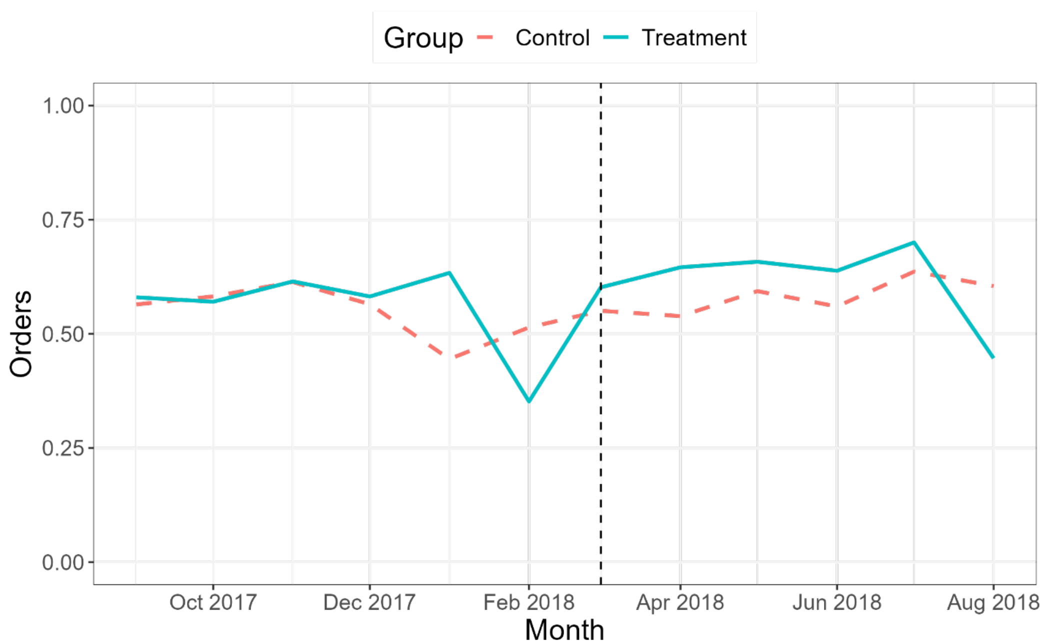


Figure B4. Purchase Trend for Within-Customer DID Analysis

Table B4. Within-Customer Analysis

	Dependent variable:					
	Orders		FP_Orders		TP_Orders	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.013*	0.017**	0.044***	0.039***	-0.027***	-0.020***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.005)	(0.004)
Treatment × After × Is_Rural		0.004		0.030**		-0.026**
		(0.021)		(0.014)		(0.013)
Treatment × After × Household		0.039***		0.047***		-0.009
		(0.014)		(0.011)		(0.008)
Treatment × After × Coupon_Ratio		-0.002		-0.077***		0.070***
		(0.027)		(0.024)		(0.010)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	448,569	448,569	448,569	448,569	448,569	448,569
Within R^2	0.0005	0.0009	0.0012	0.0016	0.0002	0.0005
Overall R^2	0.380	0.380	0.337	0.337	0.378	0.378

Notes: The subgroup-specific time trends captured by *After* × *Is_Rural*, *After* × *Household*, and *After* × *Coupon_Ratio* as well as the group dummy for *Treatment,* are controlled for and not shown. Robust standard errors clustered by consumers are reported in parentheses. *Household* and *Coupon_Ratio* are both mean-centered. Results are consistent when moderators are added separately instead of jointly. * p<0.1, ** p<0.05, *** p<0.01

B5. Stacked DiD Analysis

A potential concern with our baseline specification is that it defines treatment as the platform-wide introduction of discreet packaging in April 2018, while actual adoption was voluntary and staggered across users. To address this and better leverage variation in adoption timing, we implement a stacked difference-in-differences (DiD) design (Baker et al. 2022, Wing et al. 2024). This approach evaluates each adoption within a common relative time window, thereby avoiding the contamination from early-late adopter comparisons that can bias conventional two-way fixed effects estimators under heterogeneous treatment effects (Sun and Abraham 2021, Callaway and Sant'Anna 2021).

Specifically, we restrict the observation window to a symmetric 3-month period before and after adoption, match control users to treated users on a cohort-by-cohort basis, and then stack the resulting datasets. We estimate a DiD regression with individual and time fixed effects within each cohort, clustering standard errors at the consumer level. Figure B5 shows the corresponding parallel trend plot and Table B5 reports the regression estimates. The results are largely consistent with our baseline findings: pre-treatment trends appear flat and parallel, while post-adoption purchases rise significantly overall, driven by an increase in FP orders. At the same time, TP purchases show a modest decline, consistent with substitution away from sellers that do not offer the feature. These results reinforce the robustness of our findings.

Table B5. Results Based on Stacked DiD Design

	Dependent variable:					
	Orders		FP_Orders		TP_Orders	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.062^{***}	0.061^{***}	0.135^{***}	0.133^{***}	-0.070^{***}	-0.069^{***}
	(0.007)	(0.008)	(0.005)	(0.006)	(0.004)	(0.004)
Treatment × After × Is_Rural		0.007		0.013		-0.005
		(0.020)		(0.013)		(0.013)
Treatment × After × Household		0.039^{***}		0.018^{*}		0.022^{***}
		(0.014)		(0.010)		(0.008)
Treatment × After × Coupon_Ratio		-0.053^{**}		-0.107^{***}		0.052^{***}
		(0.026)		(0.024)		(0.009)
Cohort - Customer FE	YES	YES	YES	YES	YES	YES
Cohort - Month FE	YES	YES	YES	YES	YES	YES
Observations	391,620	391,620	391,620	391,620	391,620	391,620
Within R^2	0.0003	0.0008	0.0023	0.0031	0.0012	0.0013

Overall R^2	0.512	0.512	0.459	0.460	0.480	0.480

Notes: The subgroup-specific time trends, captured by *After* × *Is_Rural*, *After* × *Household*, and *After* × *Coupon_Ratio* are controlled for but not shown. Robust standard errors clustered by consumers are reported in parentheses. *Household* and *Coupon_Ratio* are both mean-centered. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

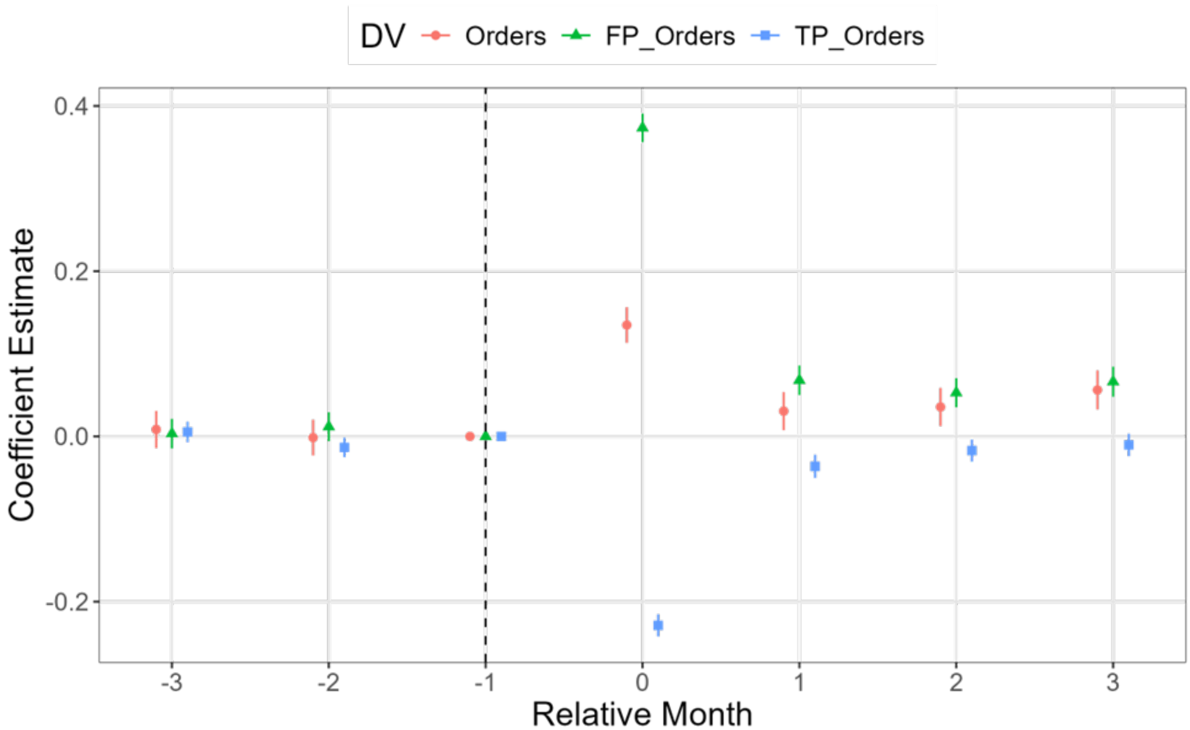


Figure B5. Parallel Trend Test based on Stacked DiD Design

B6. Cohort by Cohort Analysis

To provide a more granular view of the data, this section further presents the analysis results for each cohort separately. Table B6.1 reports the main effects, while Tables B6.2–6.4 present the heterogeneous treatment effects for different dependent variables. These findings are largely consistent with our main results.

Table B6.1. Cohort-by-Cohort DiD Results

	Dependent variable:		
	Orders	FP_Orders	TP_Orders
	(1)	(2)	(3)
Apr. 2018	0.044***	0.103***	-0.056***
	(0.013)	(0.009)	(0.008)
May. 2018	0.044***	0.107***	-0.062***
	(0.009)	(0.008)	(0.005)
Jun. 2018	0.046***	0.124***	-0.075***
	(0.010)	(0.008)	(0.005)
July. 2018	0.056***	0.134***	-0.073***
	(0.010)	(0.009)	(0.005)
Aug.2018	0.074***	0.112***	-0.028***
	(0.014)	(0.013)	(0.008)
Sept. 2018	0.106***	0.201***	-0.088***
	(0.015)	(0.014)	(0.008)

Notes: Robust standard errors clustered by consumers are reported in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table B6.2. Cohort-by-Cohort Heterogeneous Treatment Effects for Total Orders

	Dependent Variable:					
	Orders					
	Apr. 2018	May. 2018	Jun. 2018	July. 2018	Aug.2018	Sept. 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.042^{***}	0.044^{***}	0.048^{***}	0.058^{***}	0.076^{***}	0.086^{***}
	(0.013)	(0.011)	(0.011)	(0.012)	(0.015)	(0.017)
Treatment × After × Is_Rural	0.006	-0.002	-0.010	-0.009	-0.006	0.079^{**}
	(0.039)	(0.021)	(0.022)	(0.023)	(0.040)	(0.036)
Treatment × After × Household	-0.075^{*}	-0.091^{***}	0.013	-0.134^{***}	0.163^{**}	-0.108^{*}
	(0.041)	(0.035)	(0.038)	(0.039)	(0.065)	(0.064)
Treatment × After × Coupon_Ratio	0.018	0.012	0.044^{**}	0.040^{**}	-0.001	0.069^{**}
	(0.023)	(0.017)	(0.018)	(0.018)	(0.027)	(0.029)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	227,034	242,168	228,538	222,088	124,036	171,966
Within R^2	0.0005	0.0007	0.0004	0.0006	0.0004	0.0004
Overall R^2	0.460	0.413	0.355	0.391	0.354	0.358

Notes: The subgroup-specific time trends, captured by *After* × *Is_Rural*, *After* × *Household*, and *After* × *Coupon_Ratio* are controlled for and not shown. Robust standard errors clustered by consumers are reported in parentheses. *Household* and *Coupon_Ratio* are both mean-centered in the regression. Results are consistent across sequential and joint inclusion of moderators; we report the full model for brevity. $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01.

Table B6.3. Cohort-by-Cohort Heterogeneous Treatment Effects for FP Orders

	Dependent variable:					
	FP_Orders					
	Apr. 2018	May. 2018	Jun. 2018	July. 2018	Aug.2018	Sept. 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.095^{***}	0.108^{***}	0.122^{***}	0.131^{***}	0.105^{***}	0.184^{***}
	(0.010)	(0.009)	(0.009)	(0.010)	(0.013)	(0.016)
Treatment × After × Is_Rural	0.032	-0.004	0.011	0.013	0.032	0.070^{**}
	(0.021)	(0.017)	(0.019)	(0.019)	(0.036)	(0.032)
Treatment × After × Household	-0.115^{***}	-0.118^{***}	-0.032	-0.170^{***}	0.127^{**}	-0.179^{***}
	(0.037)	(0.033)	(0.036)	(0.037)	(0.063)	(0.061)
Treatment × After × Coupon_Ratio	0.011	-0.0002	0.032^{**}	0.012	-0.035	-0.003
	(0.017)	(0.015)	(0.016)	(0.016)	(0.025)	(0.027)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	227,034	242,168	228,538	222,088	124,036	171,966
Within R^2	0.0019	0.0021	0.0021	0.0025	0.0011	0.0019
Overall R^2	0.411	0.341	0.329	0.317	0.329	0.353

Notes: The subgroup-specific time trends, captured by *After* × *Is_Rural*, *After* × *Household*, and *After* × *Coupon_Ratio* are controlled for and not shown. Robust standard errors clustered by consumers are reported in parentheses. *Household* and *Coupon_Ratio* are both mean-centered in the regression. Results are consistent across sequential and joint inclusion of moderators; we report the full model for brevity. $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01.

Table B6.4. Cohort-by-Cohort Heterogeneous Treatment Effects for TP Orders

	Dependent variable:					
	TP_Orders					
	Apr. 2018	May. 2018	Jun. 2018	July. 2018	Aug.2018	Sept. 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	-0.051***	-0.063***	-0.070***	-0.068***	-0.019**	-0.091***
	(0.007)	(0.005)	(0.006)	(0.006)	(0.008)	(0.010)
Treatment × After × Is_Rural	-0.024	0.002	-0.022*	-0.021	-0.035	0.013
	(0.027)	(0.011)	(0.012)	(0.013)	(0.022)	(0.019)
Treatment × After × Household	0.041***	0.025**	0.042***	0.029**	0.041*	0.067***
	(0.015)	(0.011)	(0.012)	(0.013)	(0.021)	(0.024)
Treatment × After × Coupon_Ratio	0.008	0.010	0.015	0.031***	0.024	0.080***
	(0.014)	(0.009)	(0.010)	(0.010)	(0.015)	(0.016)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	227,034	242,168	228,538	222,088	124,036	171,966
Within R^2	0.0008	0.0010	0.0016	0.0014	0.0011	0.0013
Overall R^2	0.432	0.421	0.323	0.449	0.357	0.317

Notes: The subgroup-specific time trends, captured by *After* × *Is_Rural*, *After* × *Household*, and *After* × *Coupon_Ratio* are controlled for and not shown. Robust standard errors clustered by consumers are reported in parentheses. *Household* and *Coupon_Ratio* are both mean-centered in the regression. Results are consistent across sequential and joint inclusion of moderators; we report the full model for brevity. * p<0.1, ** p<0.05, *** p<0.01.

B7. Doubly Robust Estimator

To mitigate potential bias due to model misspecification, we implement a doubly robust estimator, which applies inverse probability weighting before running the DiD model to estimate the average treatment effect on the treated. This estimator is consistent if either the outcome model (i.e., the DiD specification) or the treatment selection model (i.e., the model to estimate propensity scores for adopting discreet packaging) is correctly specified, but not necessarily both (Callaway and Sant'Anna 2021, Sant'Anna and Zhao 2020). This design offers enhanced robustness to model misspecification. Table B7 presents the doubly robust estimates, using the same covariates from our matching procedure to predict propensity scores. The estimated treatment effects remain statistically significant and closely aligned with our main results, lending further support to the robustness of our findings.

Table B7. Results of Doubly Robust Estimators

	Dependent variable:		
	Orders	FP_Orders	TP_Orders
	(1)	(2)	(3)
Treatment × After	0.115^{***}	0.137^{***}	-0.020^{***}
	(0.007)	(0.005)	(0.004)
Bootstrap iterations	1,000	1,000	1,000
Observations	3,362,151	3,362,151	3,362,151

Notes: Robust standard errors clustered by consumers are reported in parentheses. $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01.

B8. Alternative Measure of Consumer Demand

In our main analysis, we used the number of orders as the dependent variable to examine the impact of discreet packaging introduction on consumer purchases, focusing on demand from the perspective of purchase frequency. In this section, we consider another commonly used measure of consumer demand, namely expenditure, as the dependent variable, to capture not only how often consumers purchase but also how much they spend, offering a complementary lens on consumer demand intensity (Iyengar et al. 2022, Misra et al. 2022, Narang and Shankar 2019). Given the extremely large variation in expenditure, we apply a log transformation (with one added to accommodate zero values) to ensure robust estimation. Table B8 reports the regression results when monthly expenditure is used as the dependent variable. The results are largely consistent with those from our main results, reinforcing the conclusion that the introduction of discreet packaging increases consumer demand, whether measured by purchase frequency or total spending.

Table B8. Results Using Expenditure as the Dependent Variable

	Dependent variable:					
	Log(Expenditure+1)		Log(FP_Expenditure+1)		Log(TP_Expenditure+1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.329***	0.317***	0.475***	0.459***	-0.109***	-0.108***
	(0.010)	(0.011)	(0.009)	(0.011)	(0.006)	(0.007)
Treatment × After × Is_Rural		0.050**		0.070***		-0.007
		(0.023)		(0.022)		(0.014)
Treatment × After × Household		0.058***		0.012		0.051***
		(0.020)		(0.019)		(0.012)
Treatment × After × Coupon_Ratio		-0.119***		-0.256***		0.058***
		(0.041)		(0.041)		(0.017)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423
Within R^2	0.0009	0.0012	0.0020	0.0025	0.0003	0.0006
Overall R^2	0.198	0.199	0.207	0.207	0.254	0.255

Notes: The subgroup-specific time trends, captured by *After* × *Is_Rural*, *After* × *Household*, and *After* × *Coupon_Ratio* are controlled for and not shown. Robust standard errors clustered by consumers are reported in parentheses. *Household* and *Coupon_Ratio* are both mean-centered. Results are consistent when moderators are added separately instead of jointly. $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01.

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