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 significantly boosts the purchases of adopters. Moreover, we hypothesize and 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 on purchases between first- and third-party stores shows that the former orders increase by 8.0% while reducing the latter by only 1.7%, indicating a net gain for the platform. Despite the positive 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).

While discreet packaging may reduce friction and ease privacy concerns, it can also have unintended consequences on operations. 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

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

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. The first-party sellers account for about 75% of total sales. In March 2018, the platform introduced a free, optional discreet packaging feature for all its first-party 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.

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

The variation across customers should facilitate the identification of heterogeneous treatment effects of discreet packaging on purchases. Third, the presence of both first-party and third-party 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 leads to an overall increase in consumer purchases, boosting FP orders by 8.0% while slightly reducing TP purchases by 1.7%. 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). This pattern of results is consistent with a priori expectations on how these segments value privacy. For instance, rural consumers are deeply embedded in close-knit communities where privacy can be easily compromised (Goffman 1963). Meanwhile, households may wish to safeguard health-related privacy more so than individuals. Similarly, cherry pickers make decisions based on economic benefits like promotions and less so based on privacy (Henderson 1988, Thaler 1983). Third, the analysis of basket size and operational 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. 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. In Section 2, we outline our theoretical framework. Section 3 describes the research context and key variables. Section 4 presents our empirical approach including model-free evidence and the identification strategy. Section 5 contains the main results. Section 6 reports robustness checks. Section 7 concludes.

2. Conceptual Development

2.1. Impact of Discreet Packaging on Consumer Purchase

Discreet packaging offers a promising approach to mitigating privacy concerns by concealing the nature of pharmacy products and reducing the fear of social judgment. The reduced concern around privacy can, in turn, encourage purchases that consumers might otherwise avoid. Prior research has shown that implementing effective privacy strategies can alleviate consumer concerns and build trust. For instance, Culnan and Armstrong (1999) find that consumers are more willing to share information when privacy protections are in place. Additionally, Gal-Or et al. (2018) suggests that empowering consumers with control over their personal information is an effective strategy to reduce privacy concerns. By obscuring product details, discreet packaging effectively prevents the inadvertent disclosure of sensitive information related to consumers' health conditions, thus safeguarding their privacy. Therefore, we expect that the availability of discreet packaging makes consumers feel more secure and confident in their purchases, which can positively influence their purchasing behavior on the platform.

2.2. Moderating Effect of Consumer Location (Rural versus Urban)

Rural communities are often characterized by strong social ties and high levels of interpersonal interaction and interdependence. This close-knit social structure facilitates the flow of information, making it easier for personal health information to be observed and discussed, particularly when it deviates from prevailing social norms (Goffman 1963). In such environments, health status can become a focal point of community scrutiny, increasing the risk of social stigma. This risk is further exacerbated by disparities in the access to healthcare: rural areas often face limited availability of medical facilities and greater geographic dispersion of service providers, which restricts access to health products (Chen et al. 2019, Cyr et al. 2019). As a result, rural consumers may rely heavily on online pharmacies to meet their healthcare needs. Thus, we expect that rural consumers (as compared to urban consumers) will place greater value on the discreet packaging feature that reduces the risk of personal health information being exposed within the community, thereby avoiding potential embarrassment and maintaining privacy.

2.3. Moderating Effect of Consumption Unit (Households versus Individuals)

Lancaster (1975) suggests that household consumers differ from individual consumers in that their decisions often involve joint consumption, shared decision-making, and aggregation effects. The theory of Communication Privacy Management suggests that individuals treat private information as personal property and manage it through privacy boundaries (Petronio 2002, 2010). Within households, however, these boundaries are co-managed, and once a product enters shared spaces (e.g., mailboxes and entryways), other members may become co-owners of that information. This dynamic increases the risk of privacy boundary turbulence, where unintended disclosure occurs due to coordination breakdowns. As such, household consumers are likely to place higher value on privacy-enhancing features.

Households also tend to comprise individuals with differing levels of sensitivity, needs, and attitudes toward privacy. In privacy-sensitive contexts, such heterogeneity may lead to conflict: one member may be unconcerned about discretion, while another may strongly prefer confidentiality due to stigma or reputational concerns. Accordingly, household decisions often involve reconciling differences in these divergent preferences (Petronio 2002). To avoid friction, households may adopt the most privacy-sensitive position by default.

Moreover, stigma is not limited to the individual but can extend to those closely associated with them—a phenomenon known as courtesy stigma (Goffman 1963). In shared household environments, one member's use of stigmatized products may reflect on others, intensifying the social cost of such purchases (Struening et al. 2001, Wahl and Harman 1989). As a result, privacy-preserving features like discreet packaging may be particularly valued in household settings, where shared environments, divergent norms, and social exposure risks intersect.

2.4. Moderating Effect of Consumer Coupon Proneness

Coupon proneness refers to a consumer's higher tendency to respond to sales offers presented as coupons (Lichtenstein et al. 1990). Research indicates that coupon-prone consumers (we use the term cherry pickers interchangeably) are primarily motivated by financial incentives and the prospect of savings (Bawa and Shoemaker 1987, Mittal 1994). These consumers 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). DelVecchio (2005) further shows that deal-prone consumers respond to the relative value of promotions only when the absolute monetary savings are substantial. Collectively, this suggests that unless a feature clearly conveys economic benefit, it may receive limited attention from this segment, potentially diminishing the impact of privacy features when they lack explicit financial framing.

2.5. Hypotheses

Our theoretical arguments lead to four hypotheses for the impact of discreet packaging on demand.

H1: The introduction of discreet packaging has a positive effect on adopters' purchases of pharmacy products.

H2: The effect of discreet packaging on adopters' purchases of pharmacy products is stronger among consumers from rural areas (as compared to those from urban areas).

H3: The effect of discreet packaging on adopters' purchases of pharmacy products is stronger among household consumers (as compared to individual consumers).

H4: The effect of discreet packaging on adopters' purchases of pharmacy products is weaker among more coupon-prone consumers.

3. Data

3.1. 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. This platform operates with both first-party (FP) and third-party (TP) sellers, with each managing their logistics independently. The FP sellers account for approximately 75% of total sales. The platform introduced the discreet packaging feature for all FP products on March 29, 2018. The exterior of discreet packaging does not display any information related to the products or the platform. At checkout, consumers could request discreet packaging free of charge by checking a box, which is unselected by default. This feature is not available for TP products, as their shipping is managed by the TP sellers and is outside the control of the platform.

3.2. Variables

Our data observation window spans six months before and after the introduction of discreet packaging from the platform. The dataset contains demographic information, browsing activities, 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 68,540 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.

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 consumer- and month-level FP orders (i.e., FP_Orders_{it}) and TP orders (i.e., TP_Orders_{it}).[3]

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.

Moderators. We investigate the moderating effects of the three consumer-level characteristics discussed earlier in the section on conceptual development. 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).

[3] 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).

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. 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.

Table 1. Definitions and Descriptive Statistics of Variables

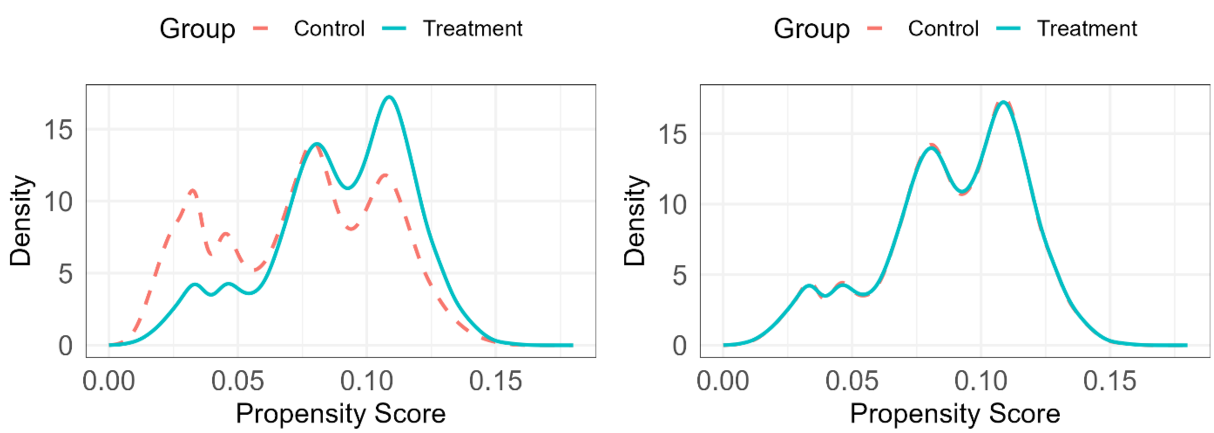
Variable	Variable definition	Observations	Mean	SD	Min	Max
Dependent variable						
$Orders_{it}$	The monthly orders of a consumer	1,227,423	0.53	1.03	0	66
FP_Orders_{it}	The monthly first-party orders of a consumer	1,227,423	0.41	0.80	0	66
TP_Orders_{it}	The monthly third-party orders of a consumer	1,227,423	0.12	0.57	0	53
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. The reported statistics are based on the matched sample, using the matching procedures described in Section 4.1. Summary statistics for the raw sample are provided in Appendix A.

4. Empirical Analysis

4.1. 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 B 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. Figure 1 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 1. Density of Propensity Scores Across Treated and Control Groups

4.2. Model-Free Evidence

Figure 2 shows the average monthly orders (log-transformed) for treatment and control groups over time, with the dashed vertical line indicating the introduction of discreet packaging on this platform.[4] Prior to the introduction, the purchase patterns of the two groups are remarkedly similar,

[4] 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.

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. In Section 6.1, we provide a formal test for parallel trends. Patterns for FP and TP orders are reported in Appendix C.

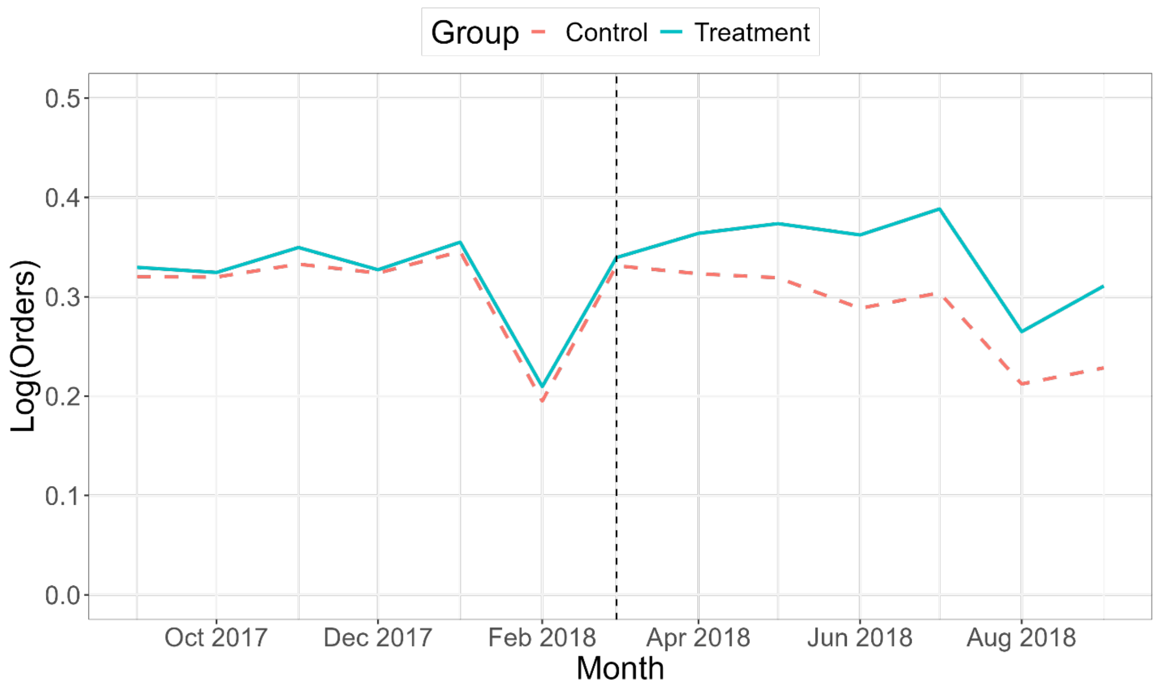


Figure 2. Purchase Trend for Treatment and Control Groups

4.3. 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.[5]

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

$$y_{it} = \beta_0 + \beta_1 \times Treatment_i \times After_t + \delta_i + \theta_t + \epsilon_{it}. \quad (1)$$

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).

$$y_{it} = \beta_0 + \beta_1 \times Treatment_i \times After_t + \beta_2 \times Treatment_i \times After_t \times Is\_Rural_i + \beta_3 \times Treatment_i \times After_t \times Household_i + \beta_4 \times Treatment_i \times After_t \times Coupon\_Ratio_i + \delta_i + \theta_t + \epsilon_{it}. \quad (2)$$

5. Results

5.1. Main Results

Table 2 presents the results with different model specifications, where the dependent variable is the logarithm of monthly orders placed by a consumer. Column 1 contains the estimates from

[5] As a robustness check, we re-estimate our model using the actual adoption time for each consumer as the intervention point (see Section 6.5 for details). The results remain highly consistent.

the baseline model with the interaction term *Treatment* × *After* capturing the average treatment effect on adopters. Columns 2 to 5 contain results from extending the baseline model with interactions based on consumer-level demographics to assess the heterogeneity in treatment effects.

Table 2. Impact of Discreet Packaging on Consumer Purchases

	Dependent variable:				
	Log(Orders)				
	(1)	(2)	(3)	(4)	(5)
Treatment × After	0.056***	0.054***	0.055***	0.056***	0.054***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Treatment × After × Is_Rural		0.008**			0.008**
		(0.004)			(0.004)
Treatment × After × Household			0.014***		0.015***
			(0.003)		(0.003)
Treatment × After × Coupon_Ratio				-0.022***	-0.023***
				(0.007)	(0.007)
Consumer FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1,227,423	1,227,423	1,227,423	1,227,423	1,227,423
Within R^2	0.0009	0.0010	0.0012	0.0010	0.0013
Overall R^2	0.242	0.242	0.242	0.242	0.242

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. Throughout the paper, we add 1 to variables before taking the log transformation. As shown in Appendix D, the results are similar when we do not log-transform the dependent variables. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

In Column 1, the coefficient on the interaction term *Treatment* × *After* is positive and statistically significant, providing support for *H1*. This result suggests that the introduction of discreet packaging significantly increases adopters' overall purchase frequency on the platform. The magnitude of the coefficient corresponds to an approximate 5.8% increase in the number of orders, calculated as exp(0.056) – 1 = 5.8%.

Moderators. The coefficients of the interaction term *Treatment* × *After* × *Is_Rural* in Columns 2 and 5 are both positive and statistically significant. This finding supports *H2* and suggests that the effectiveness of discreet packaging is stronger for rural consumers as compared to urban consumers. Columns 3 and 5 show that the interaction term *Treatment* × *After* × *Household* is positive and significant, lending support to *H3*, namely, the increase in purchases is more pronounced among household consumers as compared to individual consumers. Finally, the coefficient on the interaction term *Treatment* × *After* × *Coupon_Ratio* in Columns 4 and 5 is negative and significant. This result supports *H4* and suggests that the impact of discreet packaging is weaker among coupon-prone consumers.

5.2. Impact on Consumer Preferences

5.2.1. Impact on Preferences for Sellers

A key feature of our setting is that discreet packaging is only available for FP sellers, while TP sellers do not offer it. This asymmetry provides a unique opportunity to examine whether a privacy-enhancing feature affects how consumers allocate their purchases across different seller types. Thus, in this section, we examine how the impact of discreet packaging on consumer purchases varies across FP and TP sellers. Table 3 reports the results for both FP orders (Columns 1 – 2) and TP orders (Columns 3 – 4). Columns 1 and 3 present the overall effects, while Columns 2 and 4 incorporate interaction terms to explore heterogeneous responses across rural, household, and coupon-prone consumers. For FP sellers, the baseline model in Column 1 shows that discreet packaging increases FP purchases by 8.0% (= exp(0.077) – 1), suggesting that consumers are more inclined to buy from FP sellers when discreet packaging becomes available. Conversely, Column 3 shows that TP purchases decrease by 1.7% (= 1 – exp(–0.017)), suggesting a negative (albeit minor) spillover effect on TP purchases likely driven by a shift away from sellers lacking the feature.

Interestingly, the interaction term *Treatment* × *After* × *Is_Rural* is significantly positive in Column 2 for FP orders yet shows no significance in Column 4 for TP orders. This suggests that the differential impact between rural and urban consumers is primarily reflected in the former increasing their purchase of FP products, further indicating a higher valuation of discreet packaging among rural consumers.

Table 3. Impact of Discreet Packaging on Consumer Preferences for Sellers

	Dependent variable:			
	Log(FP_Orders)		Log(TP_Orders)	
	(1)	(2)	(3)	(4)
Treatment × After	0.077***	0.074***	-0.017***	-0.017***
	(0.002)	(0.002)	(0.001)	(0.001)
Treatment × After × Is_Rural		0.012***		-0.002
		(0.004)		(0.002)
Treatment × After × Household		0.009***		0.007***
		(0.003)		(0.002)
Treatment × After × Coupon_Ratio		-0.041***		0.010***
		(0.007)		(0.003)
Consumer FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,227,423	1,227,423	1,227,423	1,227,423
Within R^2	0.0022	0.0027	0.0003	0.0006
Overall R^2	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 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. * p<0.1, ** p<0.05, *** p<0.01.

The interaction term *Treatment* × *After* × *Household* is significantly positive for both FP and TP orders, reflecting the unique purchasing dynamics of household consumers. In Column 2, the significant result for FP orders suggests that household consumers may exhibit a stronger preference for FP products due to heightened privacy concerns or the avoidance of stigma associated with sensitive purchases. Meanwhile, the significant and positive effect in Column 4 for TP orders implies that household consumers tend to reduce their purchases of TP products to a lesser extent. This result may reflect the diverse needs within households, which makes it less feasible to entirely shift away from TP sellers.

Regardless of the dependent variable used, the direction of the moderating effect of consumer coupon proneness contrasts with the main effect of discreet packaging. Specifically, the interaction term *Treatment* × *After* × *Coupon_Ratio* is significantly negative for FP orders and significantly positive for TP orders. This result validates *H4*, suggesting that coupon-prone consumers might prioritize deals or promotions over the privacy benefits of discreet packaging, thereby rendering them less responsive to the feature.

Overall, our findings show that the introduction of discreet packaging leads to a significant increase in purchases from FP sellers (8.0%), accompanied by only a slight decline in TP orders (1.7%), resulting in a net platform-wide transaction growth (5.8%). This result underscores the effectiveness of privacy-enhancing features in driving consumer engagement.

5.2.2. Impact on Preferences for Products

We explore how discreet packaging impacts the purchase of products with different levels of sensitivity. To do so, we divide the products available on the platform into four quartiles based on the proportion of discreet packaging orders in each product category, with the first quartile representing product categories with the lowest levels of discreet packaging rate when eligible. Subsequently, we count the numbers of FP and TP orders separately for each product quartile and use them as dependent variables.[6] Table 4 presents the results, with Columns 1 – 4 corresponding to FP orders and Columns 5 – 8 to TP orders.

The results collectively strengthen our understanding of the link between the availability of discreet packaging and the purchase of products. Specifically, Columns 1 – 4 show that the impact of discreet packaging on the purchase from FP sellers increases gradually from low-sensitivity to

[6] Although our categorization on product sensitivity is based on post-treatment data as discreet packaging orders only exist in this phase, we believe this calculation is unlikely to result in major bias for several reasons. First, the calculations are based on all orders within this period, rather than only those in the sample. Second, our analysis relies on proportions rather than the absolute number of discreet packaging orders. Third, our results are similar when the products are categorized with an LLM (see Section 6.8).

high-sensitivity products, indicating that it is particularly effective for items associated with greater privacy concerns. This pattern of results suggests that discreet packaging influences consumer purchases by alleviating their privacy concerns. In contrast, Columns 5 – 8 show no clear pattern for TP orders, which is consistent with a priori expectations given the absence of discreet packaging in that channel.

Table 4. Impact of Discreet Packaging on Purchases of Products with Various Sensitivity

	Dependent variable:							
	Log(FP_Orders)				Log(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***	0.024***	0.031***	0.035***	-0.004***	-0.006***	-0.006***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)
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	0.0003	0.0005	0.0008	0.0020	0.0001	0.0001	0.0001	0.0000
Overall R^2	0.298	0.279	0.254	0.230	0.282	0.244	0.220	0.160

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

To obtain a more nuanced understanding of the results, we further delve into how different consumer segments respond to the feature across products of varying sensitivity levels. Table 5 shows the results. The interaction term *Treatment* × *After* × *Is_Rural* shows weaker significance and a smaller effect size for high-sensitivity products, in contrast to its significantly positive and stronger effect for moderately sensitive products. A possible explanation for this finding is that rural and urban consumers both tend to use discreet packaging while purchasing highly sensitive products and hence exhibit no differences. However, due to rural consumers' stronger concern over stigma, they are still prone to use discreet packaging even when purchasing moderately sensitive products, which is largely deemed unnecessary by urban consumers.

Table 5. Impact of Discreet Packaging on Purchases of Products with Various Sensitivity (with Moderating Effects of Consumer Characteristics)

	Dependent variable:							
	Log(FP_Orders)				Log(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^{***}	0.022^{***}	0.030^{***}	0.034^{***}	-0.005^{***}	-0.005^{***}	-0.006^{***}	-0.001^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)
Treatment × After × Is_Rural	0.003	0.008^{***}	0.006^{**}	0.004^{**}	0.002	-0.004^{**}	0.001	-0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Treatment × After × Household	0.010^{***}	0.004^{*}	0.001	0.014^{***}	-0.001	0.003^{***}	0.004^{***}	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Treatment × After × Coupon_Ratio	-0.007^{*}	-0.012^{***}	-0.017^{***}	-0.017^{***}	0.0001	0.002	0.006^{***}	0.002^{**}
	(0.004)	(0.004)	(0.005)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
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	0.0004	0.0007	0.0010	0.0022	0.0002	0.0002	0.0002	0.0000
Overall R^2	0.298	0.279	0.254	0.230	0.283	0.244	0.220	0.160

Notes: The subgroup-specific time trends, captured by *After* × *Is_Rural, After* × *Household*, and *After* × *Coupon_Ratio* are controlled for and not shown for brevity. 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.

We also observe a mixed pattern for consumption unit. Specifically, the moderating effect is most pronounced for high-sensitivity products, indicating that household consumers place greater value on privacy features when the potential for stigma is high. However, due to their diverse health needs, families may still purchase TP products when they offer unique benefits or meet specific health requirements not covered by FP products, which is evidenced by the positive moderating effect for moderately sensitive products in Columns 6 and 7.

We continue to find that both the positive effect on FP products and the negative effect on TP products are weaker among coupon-prone consumers, especially for the purchase of relatively sensitive products. This aligns with *H4* and further indicates that coupon-prone consumers are less responsive to non-monetary incentives.

5.3. Impact on Basket Sizes and Shipping Costs

While prior analyses have showcased the demand-side effects of discreet packaging, extant research also suggests that how the temporal demand shifts 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.

5.3.1. 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 6, indicate that the introduction of discreet packaging leads to a reduction in basket size, reflecting a shift toward more disaggregated purchasing behavior. Specifically, the average basket size decreases by 1.1% (= 1 – exp(–0.011)), suggesting that consumers place smaller orders when privacy concerns are alleviated. This effect is primarily driven by FP purchases, where basket size declines by 1.7% (= 1 – exp(–0.017)). 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 6. Impact of Discreet Packaging on Basket Sizes

	Dependent variable:		
	Log(Basket_Size)	Log(FP_Basket_Size)	Log(TP_Basket_Size)
	(1)	(2)	(3)
Treatment × After	-0.011***	-0.017***	-0.006
	(0.004)	(0.004)	(0.011)
Consumer FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	438,902	378,743	102,883
Within R^2	0.0000	0.0001	0.0000
Overall R^2	0.625	0.649	0.742

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

5.3.2. 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 6, 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.[7] Given that the vast majority of FP orders (86%) meet the platform's free-shipping threshold, the associated shipping costs are predominantly incurred by the platform. It is therefore imperative to evaluate the extent to which discreet packaging affects these costs.

We employ two complementary measures of shipping cost. The first, *Avg_Unit_Cost*, is defined as the average shipping cost per FP item within a consumer-month, measured in RMB and conditional on at least one FP order being placed. This measure captures per-unit fulfillment

[7] 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.

efficiency and mirrors our approach to analyzing basket size in Section 5.3.1. The second, *Total_Cost*, is defined as the total monthly FP shipping cost incurred by each consumer, taking a value of zero for months in which no purchases were made. It reflects the platform's aggregate logistics burden across the entire consumer base.

Table 7 reports the results. We find that the average shipping cost per item increased by 1.0% (= exp(0.010) – 1), indicating a higher per-unit fulfillment cost driven by smaller basket sizes. At the aggregate level, the total shipping cost rise dramatically by 19.0% (= exp(0.174) – 1). This sharp increase highlights 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. Thus, it is essential for platforms to carefully balance demand-generating features with operational efficiency to sustain long-term profitability.

Table 7. Impact of Discreet Packaging on Shipping Costs

	Dependent variable:	
	Log(Avg_Unit_Cost)	Log(Total_Cost)
	(1)	(2)
Treatment × After	0.010^{***}	0.174^{***}
	(0.003)	(0.003)
Consumer FE	Yes	Yes
Time FE	Yes	Yes
Observations	378,743	1,227,423
Within R^2	0.0001	0.0022
Overall R^2	0.648	0.207

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

6. 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 more detail below.

Table 8. Summary of Robustness Checks

Analysis	Objective	Location
Parallel trend test	Testing the parallel trend assumption	Section 6.1
Sensitivity to violation of parallel trend assumption	Assessing robustness to violations of the parallel trend assumption	Section 6.2
Sensitivity to selection on unobservables	Examining robustness to selection on unobservables	Section 6.3
Doubly robust estimator	A model robust to misspecification in outcome or treatment selection model	Section 6.4
Cohort-based DiD analysis	Robustness to the definition of treatment	Section 6.5
Alternative measure of consumer demand	Robustness to the choice of dependent variable	Section 6.6
Alternative measure of coupon proneness	Robustness to an alternative measure of coupon proneness	Section 6.7
Using LLM to measure product sensitivity	Robustness to the definition of product sensitivity	Section 6.8

6.1. 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:

$$y_{it} = \gamma_0 + \sum_{k=-7}^{-2} \eta_k \times Treatment_i \times Month_{T+k} + \sum_{k=0}^{5} \eta_k \times Treatment_i \times Month_{T+k} + \delta_i$$
$$+\theta_t + \epsilon_{it}. \tag{3}$$

Here, T represent the month when discreet packaging became available on the platform (i.e., April 2018 as explained in Section 3.2). Similar to Equation (1), δ_i and θ_t represent consumer and month level fixed effects, respectively. 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, supporting the validity of the parallel trend assumption in the pre-treatment period.

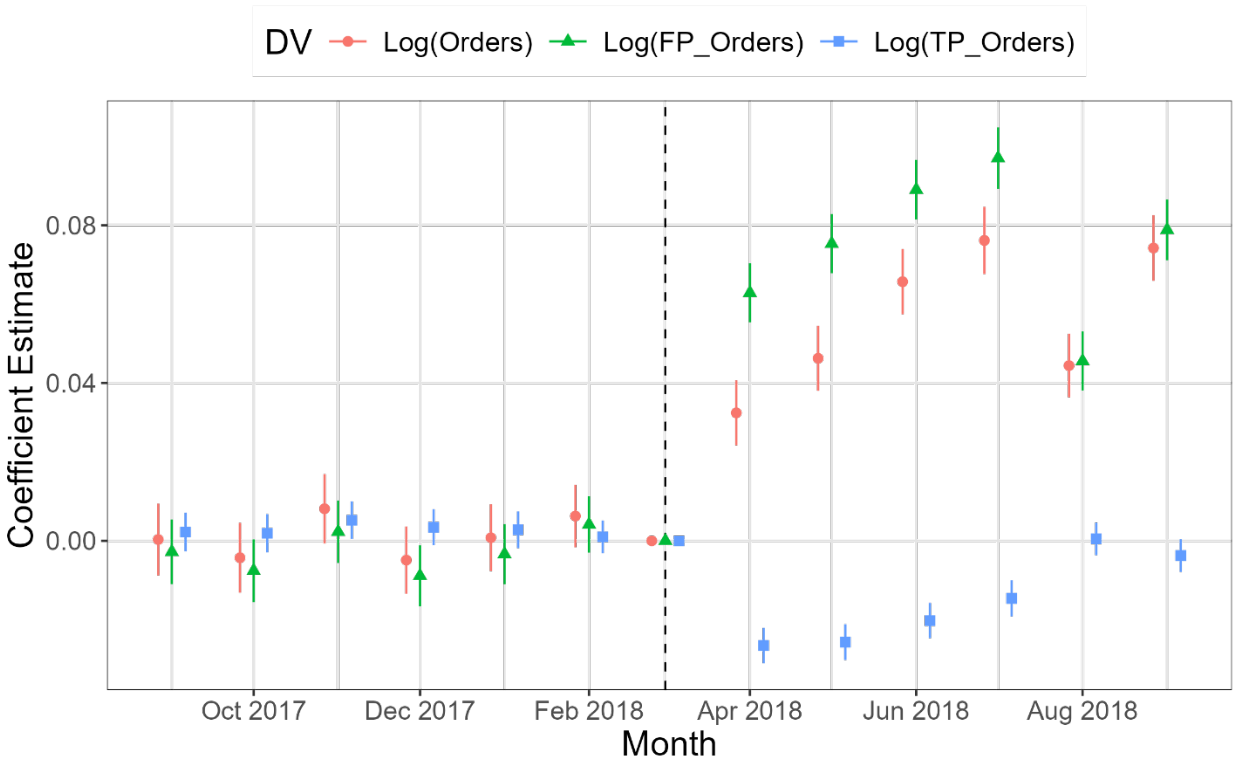


Figure 3. Parallel Trend Test

6.2. 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 4, 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.

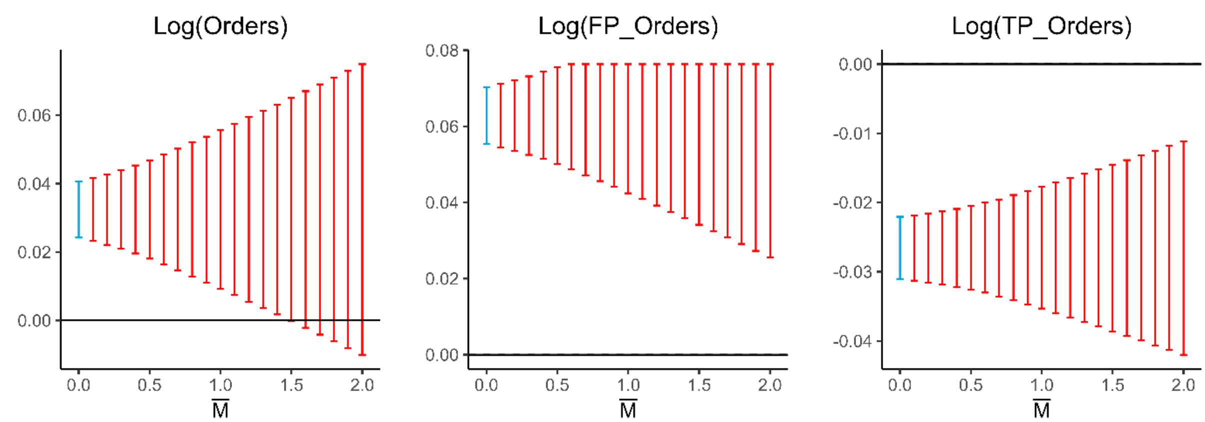


Figure 4. Sensitivity Analysis with HonestDiD

6.3. Sensitivity to Selection on Unobservables

To evaluate the extent to which our estimated treatment effects could be explained by unobserved confounders, following Pattabhiramaiah et al. (2022), we conduct two complementary sensitivity analyses: Rosenbaum bounds (Rosenbaum 2002) and the selection-on-unobservables framework proposed by Oster (2019).

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 9 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 $\Gamma = 1.65$ (sig+ = 0.043). 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 1.65. 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 2.30 for *Avg_Post_FP_Orders* and 1.45 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 9. Rosenbaum Bounds Test

	Dependent variable:					
	Log (Avg_Post_Orders)		Log (Avg_Post_FP_Orders)		Log (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	0.000
1.45	0.000	0.000	0.000	0.000	0.000	**0.047**
1.5	0.000	0.000	0.000	0.000	0.000	0.534
1.55	0.000	0.000	0.000	0.000	0.000	0.963
1.6	0.000	0.000	0.000	0.000	0.000	1.000
1.65	**0.043**	0.000	0.000	0.000	0.000	1.000
1.7	0.568	0.000	0.000	0.000	0.000	1.000
1.75	0.978	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	0.000	0.000	0.000	1.000
2.2	1.000	0.000	0.000	0.000	0.000	1.000
2.25	1.000	0.000	0.000	0.000	0.000	1.000
2.3	1.000	0.000	**0.015**	0.000	0.000	1.000
2.35	1.000	0.000	0.190	0.000	0.000	1.000
2.4	1.000	0.000	0.648	0.000	0.000	1.000
2.45	1.000	0.000	0.947	0.000	0.000	1.000
2.5	1.000	0.000	0.998	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 10, the resulting δ values for log-transformed *Orders*, *FP_Orders*, and *TP_Orders* are 3.603, 3.295, and 2.808, respectively. These values substantially exceed the conventional threshold of $\delta = 1$, suggesting that unobserved selection would need to be at least 2.8 times as strong as observable selection to fully account for the estimated effects.

Table 10. Oster Unobserved Selection Test

	Dependent variable:		
	Log(Orders)	Log(FP_Orders)	Log(TP_Orders)
	(1)	(2)	(3)
δ	3.603	3.295	2.808

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

6.4. 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 11 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 11. Results of Doubly Robust Estimators

	Dependent variable:		
	Log(Orders)	Log(FP_Orders)	Log(TP_Orders)
	(1)	(2)	(3)
Treatment × After	0.064***	0.080***	-0.012***
	(0.003)	(0.003)	(0.002)
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.

6.5. Cohort-Based DiD Analysis

In the main analysis, to mitigate endogeneity concerns, we define the treatment as the platform-wide introduction of discreet packaging, using the launch date as the treatment point for all users in the treated group. To complement this classical DiD design, we also implement a cohort-based DiD analysis. In this approach, treatment is defined by the actual adoption of discreet packaging, and consumers who adopted in the same month are grouped into distinct treatment cohorts. The cohort-based approach is also commonly used in marketing research (e.g., McCarthy et al. 2017), likely because it facilitates cleaner identification of behavioral changes around the moment of adoption and allows for more precise, temporally aligned matching of treated and control users. To that end, we split treated users into six monthly cohorts based on their adoption date and, for each cohort, match control users who also placed orders in the same calendar month, using the same procedure employed in the main analysis. For simplicity, our analysis focuses on the pooled data across all cohorts, with the cohort-specific analyses presented in Appendix F.

Table 12 reports regression results from the pooled cohort sample. We find that when using feature adoption as the treatment, the results remain largely consistent with those obtained under the feature introduction specification. While the heterogeneous treatment effects appear slightly less significant in some specifications, this is likely due to the more stringent construction of the control group in the cohort-based design, which requires control users to have made at least one purchase in the adoption month of the corresponding treatment cohort. As a result, the control group consists only of active users from each adoption month, making our estimates relatively conservative and more likely to reflect a lower bound of the true effect. This consistency of results indicates that whether the treatment is defined as the platform's introduction of discreet packaging or consumers' actual adoption, the estimated treatment effects remain robust, providing strong evidence of the discreet packaging's positive influence on consumers' purchases.

Table 12. Results Using Pooled Cohorts Sample

	Dependent variable:					
	Log(Orders)		Log(FP_Orders)		Log(TP_Orders)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.021***	0.020***	0.065***	0.063***	-0.040***	-0.039***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Treatment × After × Is_Rural		0.002		0.010**		-0.007**
		(0.005)		(0.005)		(0.003)
Treatment × After × Household		0.006		-0.006		0.013***
		(0.004)		(0.004)		(0.002)
Treatment × After × Coupon_Ratio		-0.025***		-0.058***		0.023***
		(0.008)		(0.008)		(0.003)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,215,830	1,215,830	1,215,830	1,215,830	1,215,830	1,215,830
Within R^2	0.0480	0.0483	0.0390	0.0396	0.0109	0.0111
Overall R^2	0.274	0.274	0.255	0.255	0.299	0.299

Notes: The cohort-specific and subgroup-specific time trends, captured by *After*, *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.

6.6. 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). Table 13 reports the regression results when log-transformed 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 13. Results Using Expenditure as the Dependent Variable

	Dependent variable:					
	Log(Expenditure)		Log(FP_Expenditure)		Log(TP_Expenditure)	
	(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.

6.7. Alternative Measure of Coupon Proneness

In our main analysis, we used the variable *Coupon_Ratio* to measure consumers' coupon proneness. To ensure our findings are not driven by how coupon proneness is measured, we also use a binary variable, *Has_Coupon*, which is set to 1 if a consumer used a coupon before the feature launch and is 0 otherwise. Consumers who have coupon usage experience are classified as cherry pickers. This approach avoids distortions from low purchase frequency. Table 14 shows the estimated moderating effects when the coupon proneness is measured with *Has_Coupon*. The interaction term *Treatment* × *After* × *Has_Coupon* remains significantly negative for *FP_Orders*. This consistency of results suggests the robustness of our findings.

Table 14. Results Using Alternative Definition of Coupon Proneness

	Dependent variable:					
	Log(Orders)		Log(FP_Orders)		Log(TP_Orders)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.056***	0.056***	0.077***	0.078***	-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 × Has_Coupon		-0.006		-0.013***		0.001
		(0.004)		(0.004)		(0.002)
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	0.0022	0.0022	0.0039	0.0003	0.0003
Overall R^2	0.242	0.243	0.232	0.233	0.289	0.289

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

6.8. Using LLM to Measure Product Sensitivity

In Section 5.2.2, we employ a data-drive approach to categorize products into four levels of sensitivity. Although this method is relatively objective, it relies on data observed after the introduction of discreet packaging, which may raise concerns about defining sensitivity based on future outcomes. To address this issue, we utilize GPT-4o to classify product categories into four sensitivity levels and re-run the analysis. The results, presented in Table 15 and Table 16, show that LLM-based classification yields findings highly consistent with those in Section 5.2.2, suggesting that our findings are not driven by how we measure product sensitivity.

Table 15. Impact of Discreet Packaging on Purchases of Products with Various Sensitivity (LLM-Defined Product Sensitivity)

	Dependent variable:							
	Log(FP_Orders)				Log(TP_Orders)			
	Low	Moderately Low	Moderately High	High	Low	Moderately Low	Moderately High	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × After	0.010^{***}	0.008^{***}	0.027^{***}	0.058^{***}	-0.002^{***}	-0.002^{***}	-0.007^{***}	-0.011^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.0003)	(0.001)	(0.001)
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	0.0006	0.0019	0.0000	0.0000	0.0001	0.0002
Overall R^2	0.192	0.179	0.254	0.260	0.145	0.149	0.228	0.283

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

Table 16. Impact of Discreet Packaging on Purchases of Products with Various Sensitivity (with Moderating Effects of Consumer Characteristics, LLM-Defined Product Sensitivity)

	Dependent variable:							
	Log(FP_Orders)				Log(TP_Orders)			
	Low	Moderately Low	Moderately High	High	Low	Moderately Low	Moderately High	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × After	0.009^{***}	0.007^{***}	0.026^{***}	0.057^{***}	-0.002^{***}	-0.002^{***}	-0.007^{***}	-0.011^{***}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.0004)	(0.0004)	(0.001)	(0.001)
Treatment × After × Is_Rural	0.003^{**}	0.004^{***}	0.008^{***}	0.005^{*}	0.0002	0.001	0.0004	-0.002
	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Treatment × After × Household	0.005^{***}	0.003^{***}	0.004^{*}	0.015^{***}	0.0003	-0.001	0.004^{***}	0.002
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Treatment × After × Coupon_Ratio	-0.007^{***}	0.0005	-0.014^{***}	-0.031^{***}	0.001	0.002^{*}	0.002	0.007^{***}
	(0.003)	(0.002)	(0.005)	(0.006)	(0.001)	(0.001)	(0.002)	(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	0.0003	0.0003	0.0007	0.0022	0.0001	0.0001	0.0002	0.0005
Overall R^2	0.192	0.179	0.254	0.260	0.145	0.149	0.228	0.283

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. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

7. 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 only a slight 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.

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 insights highlight the value of developing targeted strategies that address the varying priorities of diverse consumer groups.

Third, our study provides valuable insights into the role of privacy innovations in shaping platform competition. The introduction of discreet packaging for FP products has an overall positive and lasting impact on the platform, with sustained growth in both total consumer order volume and FP product purchases. Although the effect on TP product purchases is slightly negative and short-lived, it highlights the strategic importance of discreet packaging as a market differentiator. These findings illustrate how privacy-focused innovations can redefine the competitive dynamics between FP and TP products, providing practical guidance for practitioners navigating platform competition.

Finally, through the analysis on basket sizes and shipping costs, we document the trade-off associated with the introduction of the privacy feature. While discreet packaging enhances consumer purchases, it also increases order fragmentation (smaller, more frequent orders), which may lead to higher fulfillment and shipping costs. The shift towards smaller, more frequent orders can strain logistics efficiency and require greater operational capacity to maintain service quality. These findings highlight while such features can enhance consumer engagement, it is important to perform a careful cost-benefit analysis.

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.

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Online Appendices

Appendix A. Full Sample Statistics

Table A1. Definitions and Descriptive Statistics of Variables of 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
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.

Appendix B. Balance Check

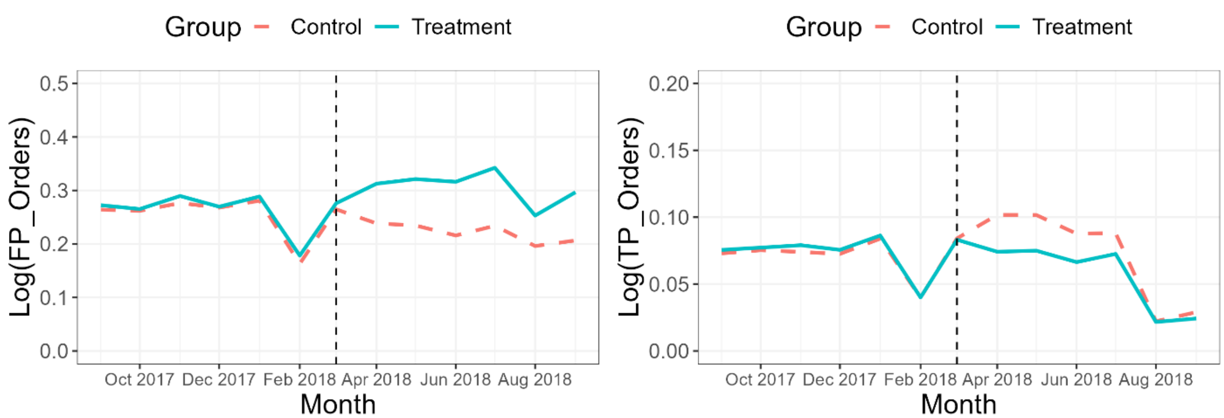
Table B1 provides an overview of the variables used for propensity score matching and the balance check statistics post-matching. The results demonstrate that the treatment and control groups achieve comparable characteristics following the matching process.

Table B1. 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

Appendix C. Purchase Trend for FP and TP Products

Figure C1 displays the monthly average orders (log-transformed) of FP and TP Products from 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 slight, temporary decline compared to the control group. This finding suggests that discreet packaging significantly increased consumers' demand for FP products with minimal impact on the demand for TP products.



(a) FP_Orders (b) TP_Orders

Figure C1. Purchase Trends for FP and TP Products

Appendix D. Results Using Raw Dependent Variables

In our main analysis, we use the log-transformed dependent variables due to the highly-skewed distribution of our raw data. As shown in Table D1, the results remain consistent even when the dependent variables are left untransformed.

Table D1. Results Using Raw Dependent Variables

	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 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.

Appendix E. Inverse Probability of Treatment Weighting

Our main analysis relies on propensity score matching to adjust for observable differences between treated and control units. As a robustness check, we also apply inverse probability of treatment weighting (IPTW), an alternative method that retains the full sample of users but reweighs them to achieve balance (Austin and Stuart 2015). The results remain highly consistent with our main findings, supporting the robustness of our estimates.

Table E1. Results from the IPTW Sample

	Dependent variable:					
	Log(Orders)		Log(FP_Orders)		Log(TP_Orders)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.060***	0.059***	0.092***	0.088***	-0.023***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Treatment × After × Is_Rural		0.005		0.015***		-0.007
		(0.005)		(0.004)		(0.005)
Treatment × After × Household		0.021***		0.012***		0.014***
		(0.004)		(0.004)		(0.004)
Treatment × After × Coupon_Ratio		-0.030***		-0.062***		0.017***
		(0.007)		(0.007)		(0.004)
Consumer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,026,558	4,026,558	4,026,558	4,026,558	4,026,558	4,026,558
Within R^2	0.0014	0.0019	0.0046	0.0055	0.0005	0.0015
Overall R^2	0.258	0.259	0.233	0.234	0.343	0.344

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.

Appendix F. Details of Cohort-Based Analysis

Figure F1 shows the results of the overall parallel trend test for the pooled cohort sample.[8] The coefficients of all leads are close to zero, indicating no significant differences between the treatment and control groups prior to feature adoption. However, after adoption, the purchase patterns of treatment and control consumers diverge significantly. Specifically, treatment consumers show a substantial and sustained increase in demand for FP products throughout our observation window. In contrast, purchases of TP products decrease during the first three months following adoption, but this effect is smaller and not persistent. These findings are consistent with the results observed in our main analysis.

To provide a more granular view of the data, this section further presents the analysis results for each cohort separately. Table F1 reports the main effects, while Tables F2–F4 present the heterogeneous treatment effects for different dependent variables. These findings are largely consistent with our main results.

[8] We select period -2 as the reference period as -1 appears to be an outlier in the pre-treatment period.

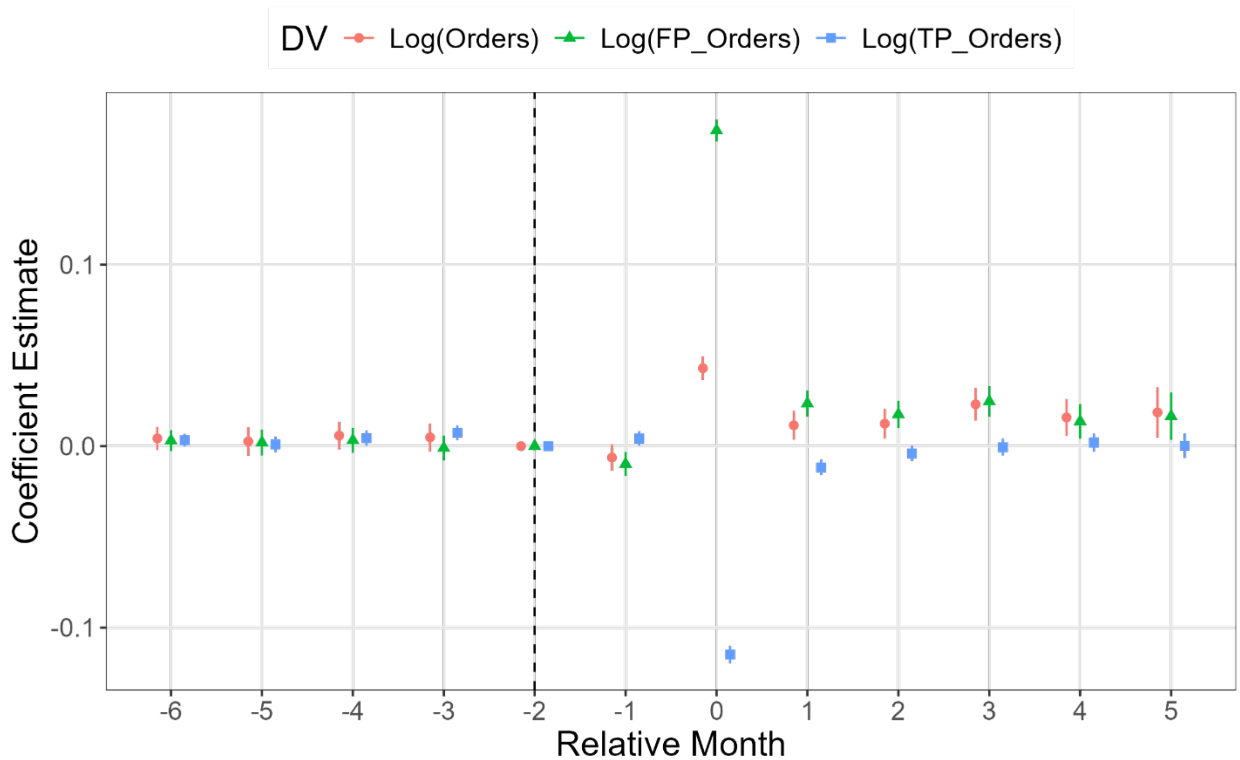


Figure F1. Parallel Trend Test Using Pooled Cohorts Sample

Table F1. Main Effect Based on the Cohorts Sample

	Dependent variable:		
	Log(Orders)	Log(FP_Orders)	Log(TP_Orders)
	(1)	(2)	(3)
Apr. 2018	0.019***	0.058***	-0.035***
	(0.004)	(0.004)	(0.003)
May. 2018	0.019***	0.059***	-0.039***
	(0.004)	(0.004)	(0.002)
Jun. 2018	0.019***	0.067***	-0.045***
	(0.004)	(0.004)	(0.002)
July. 2018	0.020***	0.073***	-0.047***
	(0.004)	(0.004)	(0.002)
Aug.2018	0.024***	0.052***	-0.019***
	(0.006)	(0.006)	(0.004)
Sept. 2018	0.036***	0.103***	-0.058***
	(0.005)	(0.005)	(0.005)

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

Table F2. Heterogeneous Treatment Effect Based on the Cohorts Sample (with Log(Orders) as the Dependent Variable)

	Dependent Variable:					
	Log(Orders)					
	Apr. 2018	May. 2018	Jun. 2018	July. 2018	Aug.2018	Sept. 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.017***	0.020***	0.020***	0.019***	0.026***	0.028***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.007)	(0.006)
Treatment × After × Is_Rural	0.010	-0.004	-0.004	0.007	-0.009	0.032**
	(0.011)	(0.009)	(0.010)	(0.010)	(0.014)	(0.013)
Treatment × After × Household	0.0004	0.001	0.015*	0.016**	-0.002	0.027***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.012)	(0.011)
Treatment × After × Coupon_Ratio	-0.025	-0.032**	-0.002	-0.044***	0.064**	-0.033
	(0.018)	(0.016)	(0.016)	(0.015)	(0.026)	(0.024)
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	0.0010	0.0008	0.0004	0.0003	0.0002	0.0003
Overall R^2	0.370	0.351	0.335	0.351	0.343	0.337

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 F3. Heterogeneous Treatment Effect Based on the Cohorts Sample (with Log(FP_Orders) as the Dependent Variable)

	Dependent variable:					
	Log(FP_Orders)					
	Apr. 2018	May. 2018	Jun. 2018	July. 2018	Aug.2018	Sept. 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	0.053***	0.060***	0.065***	0.069***	0.051***	0.095***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
Treatment × After × Is_Rural	0.020**	-0.004	0.007	0.018*	0.004	0.034***
	(0.009)	(0.008)	(0.009)	(0.009)	(0.013)	(0.012)
Treatment × After × Household	-0.005	-0.007	0.006	0.0002	-0.026**	-0.014
	(0.008)	(0.007)	(0.008)	(0.008)	(0.012)	(0.011)
Treatment × After × Coupon_Ratio	-0.054***	-0.060***	-0.036**	-0.079***	0.037	-0.099***
	(0.017)	(0.015)	(0.016)	(0.015)	(0.025)	(0.023)
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	0.0024	0.0023	0.0022	0.0023	0.0008	0.0016
Overall R^2	0.337	0.320	0.308	0.315	0.333	0.339

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 F4. Heterogeneous Treatment Effect Based on the Cohorts Sample (with Log(TP_Orders) as the Dependent Variable)

	Dependent variable:					
	Log(TP_Orders)					
	Apr. 2018	May. 2018	Jun. 2018	July. 2018	Aug.2018	Sept. 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × After	-0.033***	-0.039***	-0.042***	-0.045***	-0.015***	-0.060***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Treatment × After × Is_Rural	-0.009	-0.0001	-0.014**	-0.010	-0.013	0.008
	(0.007)	(0.005)	(0.006)	(0.006)	(0.010)	(0.011)
Treatment × After × Household	0.006	0.006	0.012**	0.018***	0.016*	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.009)
Treatment × After × Coupon_Ratio	0.021***	0.019***	0.026***	0.022***	0.030***	0.049***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.012)	(0.015)
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	0.0014	0.0016	0.0021	0.0022	0.0011	0.0019
Overall R^2	0.344	0.306	0.284	0.312	0.311	0.273

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.

Appendix G. Detailed Results of Parallel Trend Tests

Table G1 presents the results of the parallel trend tests for the matched sample. The coefficients of the leads during the pretreatment period are consistently close to zero, indicating that the parallel trend assumption is plausible in the pre-treatment period.

Table G1. Parallel Trend Test Results for the Classical DiD Design

	Dependent variable:		
	Log(Orders)	Log(FP_Orders)	Log(TP_Orders)
Leads/Lags (Calendar Month)	(1)	(2)	(3)
Treatment × Month2017-09	0.0003	-0.003	0.002
	(0.005)	(0.004)	(0.002)
Treatment × Month2017-10	-0.004	-0.008*	0.002
	(0.005)	(0.004)	(0.002)
Treatment × Month2017-11	0.008*	0.002	0.005**
	(0.004)	(0.004)	(0.002)
Treatment × Month2017-12	-0.005	-0.009**	0.003
	(0.004)	(0.004)	(0.002)
Treatment × Month2018-01	0.001	-0.003	0.003
	(0.004)	(0.004)	(0.002)
Treatment × Month2018-02	0.006	0.004	0.001
	(0.004)	(0.004)	(0.002)
Treatment × Month2018-03		The Baseline	
Treatment × Month2018-04	0.032***	0.063***	-0.027***
	(0.004)	(0.004)	(0.002)
Treatment × Month2018-05	0.046***	0.075***	-0.026***
	(0.004)	(0.004)	(0.002)
Treatment × Month2018-06	0.066***	0.089***	-0.020***
	(0.004)	(0.004)	(0.002)
Treatment × Month2018-07	0.076***	0.097***	-0.015***
	(0.004)	(0.004)	(0.002)
Treatment × Month2018-08	0.044***	0.046***	0.0005
	(0.004)	(0.004)	(0.002)
Treatment × Month2018-09	0.074***	0.079***	-0.004*
	(0.004)	(0.004)	(0.002)
Consumer FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	1,227,423	1,227,423	1,227,423
Within R^2	0.0011	0.0025	0.0005
Overall R^2	0.242	0.232	0.290

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

References

Austin PC, Stuart EA (2015) Moving towards Best Practice When Using Inverse Probability of Treatment Weighting (IPTW) Using the Propensity Score to Estimate Causal Treatment Effects in Observational Studies. *Statistics in Medicine* 34(28):3661–3679.