

How does online shopping affect offline price sensitivity?

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Abstract

The rapid rise of e-commerce has transformed consumer behavior, prompting questions about how online adoption influences offline shopping. We examine whether consumers who adopt online shopping with a retailer become more price-sensitive in their subsequent offline purchases with that retailer. Using transaction-level data from a large Brazilian pet supplies retailer operating both online and offline, we compare “adopters”—customers who began shopping online after a period of offline-only purchasing—with “non-adopters” who remained offline-only. We estimate a discrete choice logit model with individual-level heterogeneity, using a novel algorithm to handle high-dimensional fixed effects and address price endogeneity. We then apply a staggered difference-in-differences approach to the estimated price elasticities and obtain the Average Treatment Effect on the Treated (ATT). We find that offline price sensitivity increases significantly after online adoption in three out of four product categories, particularly in items with low switching costs, such as pet hygiene. Counterfactual pricing simulations show that incorporating these behavioral spillovers into pricing strategies can increase firm profits by up to 4.1%. These results underscore the importance of recognizing cross-channel effects in consumer behavior and contribute to the literature on pricing and multichannel retailing by identifying online adoption as a key driver of offline price sensitivity.

Keywords: Multichannel Retailing, Online Shopping, Price Elasticity, Pricing

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1 Introduction

Over the past two decades, online shopping has grown rapidly, driven by the widespread adoption of computers and smartphones. U.S. e-commerce sales more than doubled from \$571 billion in 2019 to approximately \$1.19 trillion in 2024, and the share of e-commerce in total US retail sales has grown from 15.4% to 22.7% over the same period (Haleem 2025). Consumers are increasingly adapting to the convenience of online shopping and allocating a large portion of their spending to online channels (McKinsey & Company 2023). This shift has prompted traditional brick-and-mortar retailers such as Walmart, Target, and Costco to expand into e-commerce channels and adopt multichannel strategies.

Given the rise of online shopping, a natural question that arises for retailers is whether online shopping influences how consumers shop *offline*, and if so, how? In this paper, we focus on an important aspect of consumer behavior – their price sensitivity. Specifically, we seek to answer two key research questions – (1) Does adopting online shopping affect consumers’ offline price sensitivity? If so, does offline price sensitivity increase or decrease post-online adoption? (2) What are the implications of such cross-channel spillovers on retailers’ offline pricing strategies and profits? Given the migration of consumers from offline stores to multi-channel shopping, quantifying the existence and impact of cross-channel externalities (in particular, the effect of online shopping on offline shopping behavior) is important, both for improving our understanding of consumer behavior as well as for optimizing firm strategies in multi-channel settings.

While there is a rich literature studying the determinants of price sensitivity, this literature largely focuses on determinants of price elasticities *within* a channel (see §2 for a detailed discussion). By contrast, our focus is on the externalities or spillover across channels. From a conceptual perspective, there are reasons why we may expect offline price sensitivity to increase post-online adoption as well as reasons that suggest the opposite. On the one hand, online shopping may make consumers less price sensitive and more brand loyal because online recommendation systems promote easy repeat purchases and lead to habit formation by highlighting prior purchases, e.g., “Buy again” or “Frequently purchased items” (Danaher et al. 2003; Chu et al. 2008). This increase in brand loyalty in online settings could spill over to offline shopping occasions and may make consumers more brand loyal and less price-sensitive offline too (after adopting online shopping). On the other hand, online shopping makes it easy for consumers to engage in price comparisons (due to features like sorting by price and lower search costs of browsing through many options on an app or website). This habit of checking and comparing prices online can potentially carry over to offline settings, and consumers become more aware of price differences in physical stores as well. Another potential reason that may make consumers more price-sensitive after adopting online shopping is that, in many contexts, prices are lower online than offline (Brynjolfsson and Smith 2000; Cooper 2006). Being exposed to lower prices for the same products online can make in-store prices seem inflated by comparison, prompting greater scrutiny of the prices of different brands. Finally, recent research suggests that when consumers are exposed to a wider variety of prices (which is likely to occur when they adopt online shopping), they become more price-sensitive (Aparicio et al. 2024). Therefore, the question of whether the adoption of online shopping affects offline price sensitivity, and if so, in which direction, is an empirical one.

We address this question using data from a large pet supplies retailer in Brazil that sells through both online and offline channels. The dataset includes detailed transaction-level information for all customers across both channels from January 1, 2019, to June 30, 2021. In our data, we observe some consumers who were initially offline-only and made their first online purchase with the retailer, while others remained offline-only throughout. This allows us to track the offline purchases of adopters, both pre- and post-adoption, and also all purchases of those consumers who remained offline only. We focus on four major product categories: dog food, cat food, dog hygiene, and cat hygiene, which together account for more than 50% of the retailer’s total revenue. These categories are also relatively frequently purchased and are characterized by a good amount of price variation both across brands and across time, which allows us to measure individual-level price elasticities at the monthly level.

From an empirical perspective, a key question relates to the estimand of interest and how to measure it. Note that adopting online shopping is a consumer-level decision, i.e., firms cannot randomly assign consumers to adopt online shopping. Therefore, we cannot quantify the Average Treatment Effect (ATE) of adopting online shopping on offline price sensitivity. In addition, even if obtaining the ATE was possible, firms cannot act on it because they cannot force consumers to adopt online shopping. Therefore, obtaining the ATE is not only impractical but also lacks actionable implications. Hence, we focus on identifying the Average Treatment Effect on the Treated (ATT), which captures the impact of treatment on those who adopted online shopping.

Our empirical strategy consists of two steps. In the first stage, we specify and estimate a discrete choice logit model for each category, controlling for unobserved customer heterogeneity in brand preferences. In our model, we allow price elasticity to be a function of the extent to which a given consumer adopts online shopping at a point in time, measured by the cumulative fraction of their online spending with the retailer up to that point in time. This modeling approach allows us to measure the effect of interest and examine how the price elasticity of consumers who have adopted online shopping diverges over time from those who have not. We encounter two challenges in estimating this demand model. First, maximum likelihood estimation of a non-linear model, such as the logit model, is quite challenging in the presence of high-dimensional fixed effects (customer-brand fixed effects in our case). To accommodate these high-dimensional fixed effects, we build on the Minorization-Maximization algorithm proposed by Chen et al. (2021). We extend the Chen et al. (2021) algorithm (that uses a multinomial logit model with no alternative specific characteristics) to a more general setting where covariates vary by individual, by alternative, and also over time. We then apply this algorithm to our setting for estimation. Second, we must address potential endogeneity in prices using our observational data (Nevo 2001). To that end, we use costs as an instrument (Berry 1994) in conjunction with a control function approach (Villas-Boas and Winer 1999; Petrin and Train 2010). We then use the estimates from this model to compute customer-month-level price elasticities.

In the second stage, we use the estimated customer-month-level price elasticities of adopters and non-adopters from the first stage to estimate our ATT of interest, which is the effect of adopting online shopping on customer price elasticities. Again, our observational data pose some challenges for the identification of the

ATT. First, consumers in our sample are either treated or untreated in each time period, and we do not observe their counterfactual outcomes in the unobserved condition (i.e., their behaviors if they had not adopted online shopping). Moreover, the staggered timing of online adoption among different consumers requires careful computation and aggregation of treatment effects (Goodman-Bacon 2021; Callaway and Sant’Anna 2021; Baker et al. 2022). To deal with this, we employ a staggered difference-in-differences (DID) framework, as proposed by Callaway and Sant’Anna (2021), utilizing the variation in staggered adoption timing of online shopping. We identify different cohorts of consumers who adopt online shopping (i.e., adopters) in each month of our data and compare changes in their behavior to those of a control group of customers who shop exclusively offline throughout the observation period (i.e., non-adopters).

Our main finding is that consumers become *more* price sensitive in their offline shopping trips after adopting online shopping for three out of four categories. The relative increase in offline price elasticity, defined as the ATT relative to the pre-adoption average price elasticity of the treated group is heterogeneous across categories. We find a large effect in the dog and cat hygiene categories (where price elasticity increases by 72.7% and 34.7%, respectively). We also observe a significant but smaller increase in the dog food category (8.4%) and no effect for cat food. The heterogeneity across categories can likely be explained by differences in switching costs to different brands. While pet owners face little risk in trying a new lower-priced hygienic mat for their pet, changing the brand of food can be much trickier due to the pets’ stronger preferences for shape, smell, and texture in food, particularly for cats (Nichelason 2024). We also provide a series of tests and alternative specifications that establish the robustness of our results and provide additional empirical support for the generalizability of our findings.

Our findings have significant managerial implications for firms’ pricing strategies. Based on our empirical results, we consider counterfactual pricing scenarios and document the value of correctly accounting for the online adoption effect on offline prices. We first consider a uniform pricing strategy, where all customers pay the same price, and the firm correctly accounts for the online adoption effect when optimizing prices. We demonstrate that this approach can increase the firm’s offline profit (summed across the three categories where there is a significant online adoption effect) by 1.17%, compared to a scenario where the manager does not account for the online adoption effect in their demand model and attempts to set optimal offline prices. Next, we perform a similar comparison under a personalized pricing scenario, where the firm can personalize prices (similar to Rossi et al. (1996); Smith et al. (2023); Jain et al. (2024)). We show that incorporating the customer’s online spend in the behavioral features in the demand model and optimizing prices based on this demand model increase profits by 4.1% (compared to a setting where the firm does not include the online adoption effect in the demand model but still personalizes prices). Together, these counterfactual results suggest correctly accounting for online spend in offline demand models can help retailers improve their pricing and personalization strategies.

In sum, our paper makes two main contributions to the literature. First, from a substantive perspective, we contribute to the literature on price sensitivity and multichannel retailing by identifying a new determinant of offline price sensitivity: the adoption of online shopping. We demonstrate that consumers become more

price-sensitive in the offline channel after adopting online shopping. This finding is important and distinct from previous research, which has mainly focused on cross-sectional or within-household comparisons of price sensitivity between online and offline settings (Degeratu et al. 2000; Chu et al. 2008, 2010). Second, from a managerial perspective, our counterfactual simulations suggest that incorporating the online adoption effects into price elasticity measurements and subsequent price optimization can significantly improve retailer profits. Overall, these findings highlight the importance of correctly accounting for cross-channel spillovers in retailers' marketing decisions.

The rest of the paper is organized as follows. In §2, we discuss the related literature, and in §3, we discuss the setting and data. In §4, we document descriptive evidence, and in §5, we specify the firm's problem and provide an overview of the empirical strategy. §6 presents the demand model, and §7 presents the ATT estimates of online adoption on offline price sensitivity. §8 discusses the generalizability and robustness checks of our main results. In §9, we perform counterfactual simulations and provide managerial implications for retailers' offline pricing and profitability. Finally, in §10, we summarize our findings and discuss some directions for future research.

2 Literature

Our study relates to multiple streams of literature on the determinants of price elasticity, optimal pricing, and multi-channel retailing in marketing and economics.

First, our work relates to the large literature in marketing and economics that has focused on documenting the drivers of consumers' price sensitivity. Prior research has identified various determinants of price sensitivity, particularly in grocery settings. These include (1) macroeconomic conditions, such as GDP growth and inflation rates (Gordon et al. 2013; Tellis 1988; Bijmolt et al. 2005); (2) marketing interventions, such as advertising (Kanetkar et al. 1992; Kaul and Wittink 1995; Kalra and Goodstein 1998; Jedidi et al. 1999) and promotions (Mela et al. (1997); Jedidi et al. (1999); Kopalle et al. (1999)); (3) brand strength (Guadagni and Little 1983; Kamakura and Russell 1989; Guadagni and Little 2008); (4) consumer loyalty (Danaher et al. 2003); (5) time between purchase and consumption (Joo et al. 2020). Early research has also examined the relationship between customer demographic characteristics – age, education, income, and household size – and price sensitivity using household-level scanner panel data (Rossi and Allenby 1993; Narasimhan 1984; Bawa and Shoemaker 1987, 1989). However, later studies have concluded these relationships are generally weak, suggesting that demographics do not explain a large portion of the variation in household-level price sensitivity (Hoch et al. 1995; Rossi et al. 1996).

We consider the adoption of online shopping as a novel factor that may affect consumers' offline price sensitivity. Given the rise of digitization and online shopping, this factor can be particularly important for multi-channel retailers (who are increasingly investing in online channels). Existing literature provides some insights into how consumer behavior differs between online and offline channels. Early studies focusing on cross-sectional comparisons find that consumers exhibit lower price sensitivity and less brand switching when shopping online compared to offline (Degeratu et al. 2000; Andrews and Currim 2004). Danaher et al. (2003) shows that high market share brands exhibit greater brand loyalty online, whereas low market share

brands exhibit greater brand loyalty in offline stores. However, these studies are “cross-sectional” in nature, i.e., they compare the set of consumers shopping offline vs. those shopping online, who may be very different from each other. More recent research has shifted toward within-household analysis. For example, Chu et al. (2008) compare price sensitivity in online and offline grocery shopping within the same household and find that consumers are generally less price-sensitive online. Further, Chu et al. (2010) investigate the role of household characteristics in moderating price sensitivity across channels. However, none of this research looks into *if* and *how* the *adoption* of online shopping affects consumers’ offline price sensitivity, which is the focus of our paper. This is an important question since consumers in many traditional brick-and-mortar settings are increasingly adopting online shopping and becoming multi-channel shoppers. If the adoption of online shopping systematically changes consumers’ offline shopping behavior, then firms need to account for these changes in their pricing and promotion strategies.

Our research also relates to the literature on how price sensitivity estimates can affect firms’ strategic business decisions and policy interventions. A recent stream of work has looked at how we can use consumer-level demand models to design targeted pricing and promotion strategies to maximize profit (Smith et al. 2023; Dubé and Misra 2023; Jain et al. 2024). We build on this work and show that accurately accounting for consumers’ online adoption status can improve firms’ pricing decisions and profitability. More broadly, from a policy and research perspective, accurate measures of price sensitivity can help policy-makers and managers assess market power, competitive dynamics, and the welfare implications of price targeting (Kadiyali et al. 2000; Nevo 2001; Chintagunta et al. 2002; Dubé and Misra 2023; Beresteanu et al. 2024). While we do not focus on public policy and competition in this work, our paper suggests that the adoption of online shopping is an important factor affecting price sensitivity that policymakers and researchers should consider when making policy recommendations in multi-channel settings.

Finally, our study contributes to the broader multichannel retailing literature; see Zhang et al. (2010) and Cui et al. (2021) for comprehensive overviews. One key stream of research highlights that online and offline channels can function as complements (Avery et al. 2012; Wang and Goldfarb 2017; Bell et al. 2018) or substitutes (Forman et al. 2009; Li 2021; Shriver and Bollinger 2022), depending on the context. Other studies have examined how digitization affects consumer shopping behavior across channels, focusing on spend patterns and purchase volume (Wang et al. 2015; Narang and Shankar 2019; Biswas et al. 2024), brand exploration (Pozzi 2012), and purchase variety (Chintala et al. 2023). Building on this body of work, our study provides new insights into multichannel strategy (Neslin 2022) by investigating changes in offline price sensitivity when consumers adopt online shopping.

3 Setting and Data

3.1 Setting

We study consumers’ offline purchase behavior and price sensitivity using data from a leading pet supplies retailer in Brazil. This firm operates in a multichannel environment, with over 200 brick-and-mortar stores nationwide and a digital presence through both a mobile app and an e-commerce website. The retailer offers a broad selection of pet-related products, including food, medicines, hygiene and grooming items, toys,

and accessories. To track consumer purchases across online and offline channels, the retailer uses Brazil’s National Identification Number, which provides a unique identifier for each customer. Online purchases - whether through the app or website - require customers to log into their accounts, making all such transactions traceable to individual IDs. For brick-and-mortar purchases, customers provide their ID at checkout, although it is not mandatory. According to the retailer, around a quarter of offline transactions are not associated with a customer ID, and this rate has remained stable throughout the study period.

The dataset spans 30 months, from January 1, 2019, to June 30, 2021, and covers all transactions (online and offline) linked to identifiable customers. Each transaction includes a unique order ID and detailed product-level information, such as price, quantity, brand, category (e.g., dry food or hygiene), and purchase channel.

3.2 Dataset Construction

We now discuss how we construct the dataset used for our empirical analysis.

Selection of Product Categories: We focus on the four top-selling non-medical categories: Dry Dog Food, Dry Cat Food, Dog Hygiene (i.e., Hygienic Mats), and Cat Hygiene (i.e., Sands). These categories account for more than 50% of the focal retailer’s revenue (see Table 1). Products within these four major categories are generally measured in comparable units, allowing us to construct brand-level prices per unit.

We exclude certain categories from our analysis. First, we exclude medical products such as prescription drugs and anti-flea medication (second category shown in Table 1) because many products in this category require a doctor’s prescription and purchase does not depend solely on consumers’ preferences. Further, medical products can be quite differentiated and target specific ailments, and as such, do not serve as natural substitutes for each other. Second, we exclude all small categories that account for less than 3% of the total sales revenue during the observation period, e.g., snacks and toys. Products in these categories are often unique, serve diverse functions, and are not necessarily natural substitutes for each other.

Table 1: Top Categories Ranked By Total Sales (Offline and Online) During the Observation Period.

Category	Share of sales(%)	Cumulative share (%)
Dry Dog Food	32.62	32.62
Medical	12.18	44.80
Dry Cat Food	9.41	54.21
Dog Hygiene	5.48	59.68
Cat Hygiene	3.62	63.30

Selection of Brands and Stock Keeping Units (SKUs): Each category contains a large number of pack sizes and SKUs per brand. First, within each category, we focus on specific pack size(s) to ensure that the price variation for each brand is captured accurately – this avoids the need to aggregate price movements across a number of different pack sizes. Focusing on a narrow set of pack sizes to study brand choice within a category is common in the brand choice literature (e.g. Allenby and Rossi (1998); Kim et al. (2002); Chintagunta et al. (2005); Dubé et al. (2010)). The pack sizes we select for each category are as follows: 15KG for dry dog food, 10 KG for dry cat food, 80cm × 60cm 30-piece mats for dog hygiene, and silica cat sand (1.6KG,

1.8KG, and 2.0KG) for cat hygiene. We provide a detailed discussion of the reasons for selecting these pack sizes in Web Appendix §A.1.1.

Next, we aggregate SKUs to the brand level and estimate consumer preferences and price elasticities at the brand level for each product category, similar to Hitsch et al. (2021); Gordon et al. (2013). Specifically, we follow a two-step process for each category. First, for each category, we select the top-selling brands and SKUs that are comparable in usage and are substitutes for each other. Next, we aggregate prices and costs (our instrumental variable to deal with price endogeneity) to the brand level from the SKU level, following the approach described in Hitsch et al. (2021). We provide details on both these steps in Web Appendix §A.1.

Selection of Customers: For each category, we restrict our sample to only those consumers who only purchase the specific pack size of interest for that category (as defined earlier), without switching to any other pack sizes within the same category. Next, given that the goal of our study is to investigate the effect of consumers' adoption of online shopping¹ on their *offline* price sensitivity, we need to ensure that we have sufficiently long pre- and post-adoption periods for each adopter in our sample to effectively measure price elasticities. Therefore, we focus on customers who adopt online shopping in the middle of our observation period, i.e., July 1st, 2019 – June 30th, 2020. So our 30-month data period is divided into three phases: a pre-adoption period (January 1st, 2019 – June 30th, 2019) when all adopters are in their pre-adoption phase, an adoption period (July 1st, 2019 – June 30th, 2020) during which time the adopters in our sample make their first online purchase, and a post-adoption period (July 1st, 2020 - June 30th, 2021), when all the adopters in our sample are in their post-adoption phase. To clarify, a given adopter's pre- and post-adoption phases are defined as the months before and after they make their first online purchase. Non-adopters only shop offline through the entire data period.

We now outline the criteria used to select adopters and non-adopters for each product category below. *Adopters* in a given category must satisfy the following criteria:

- Made their first-ever online purchase (in any product category, not just the focal category) between July 1st, 2019, and June 30th, 2020.
- Made at least one offline purchase in the focal category both before and after online adoption.

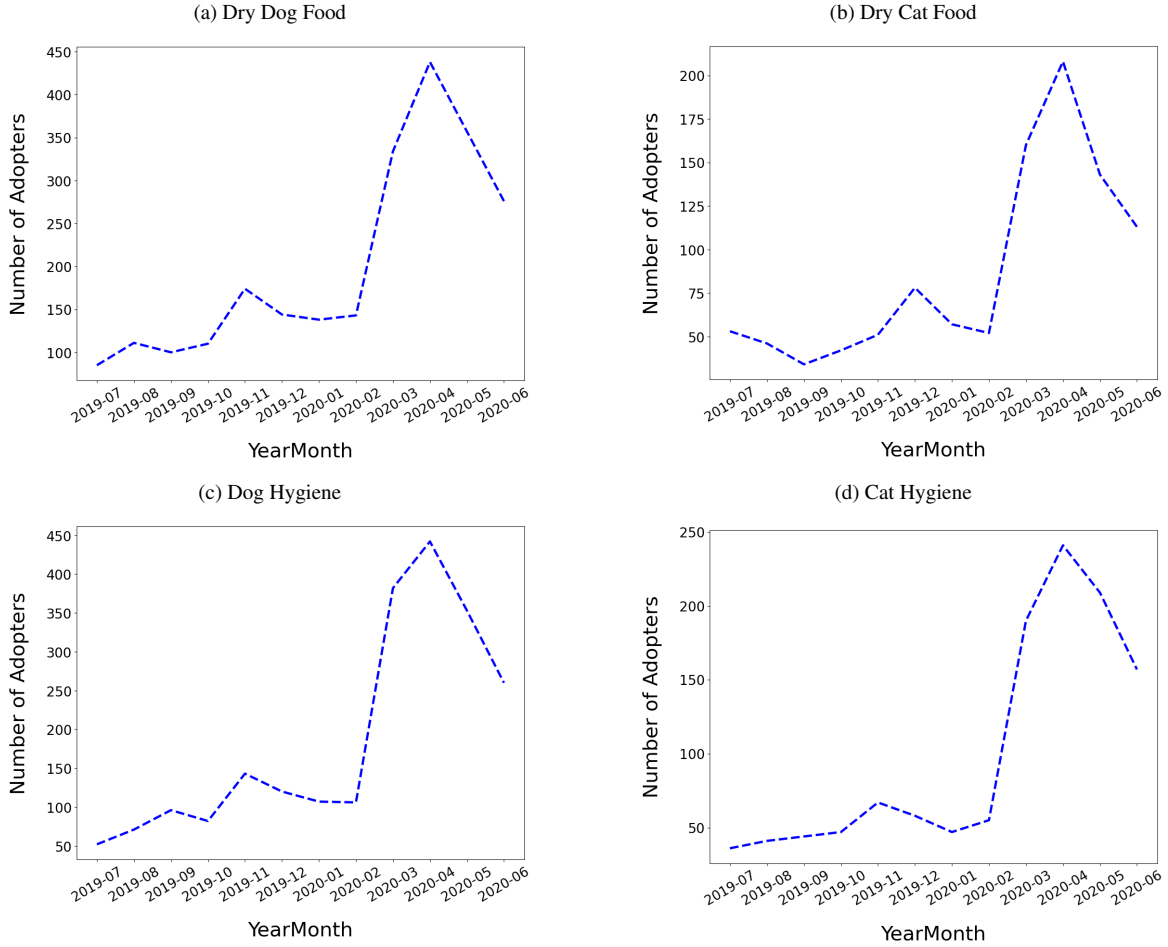
Overall, this gives us 12 cohorts of adopters, where each cohort represents the month in which the user adopted online shopping. For example, the first cohort of adopters consists of users who adopted online shopping during July 2019 while the twelfth cohort consists of users who adopted online shopping during June 2020. Figure A1 in Web Appendix A.1.3 shows stylistic examples of users in different cohorts. Figure 1 shows the number of adopters across the different periods in each category. Notice that there is a spike in the number of adopters during March–April 2020, which is likely driven by the onset of the COVID-19 pandemic. Our analysis is agnostic to the reasons for adopting online shopping, and in our empirical analysis, we will allow for the possibility that these cohorts may be different from earlier/later cohorts.

Non-adopters in a given category must meet the following criteria:

¹“Adoption of online shopping” refers to a customer making his/her first online purchase with the focal retailer in *any* category, and not just one of the four focal categories.

- Did not make any online purchases at any point during the entire observation period.
- Made at least one offline purchase in the category during both the pre-adoption (i.e., January 1st, 2019 – June 30th, 2019) and the post-adoption periods (i.e., July 1st, 2020 – June 30th, 2021).

Figure 1: Sample Sizes of Adopters by Cohorts and Product Category. Corresponding sample sizes for each cohort are shown in Table A1 in Web Appendix A.1.3.



Estimation Sample Construction: For each customer in a given category (both adopters and non-adopters), we organize the data into a panel that captures purchase occasions and brand choices for individual customers over time. Specifically, we define purchase occasions at the customer-month level. If a customer visits a physical store of the retailer during a month and purchases in any category (not limited to the categories we focus on in this study), that customer-month is included as a purchase occasion for all four categories. If a customer makes no purchases in any category during the month, that customer-month is not included as a purchase occasion. In other words, a purchase occasion represents any customer-month during which we observe any offline interaction with the retailer (similar to week-store visit in Gordon et al. (2013)) ².

²Based on our definition of purchase occasion, if a customer visits multiple times in a month, it is treated as one purchase occasion.

For each purchase occasion, we identify the brand chosen by the consumer as the brand which has positive spend.³ If the customer does not have positive spend on any brand during a purchase occasion, we label it as choosing the outside option (i.e., “no-purchase”).

3.3 Summary Statistics

We now present some summary statistics on the estimation sample.

First, we find that there are systematic differences in the demographics (age, income, and gender) of adopters and non-adopters across all four categories. Across all categories, women tend to adopt online shopping more than men. In addition, online adopters tend to be younger and higher-income households. This makes intuitive sense because younger and higher-income consumers are often more familiar with online technology and seek time-saving and convenient shopping options. Details of these demographic characteristics are shown in Web Appendix A.2.

Next, Table 2 summarizes the category-level statistics, including the number of brands, sample sizes for adopters and non-adopters (as defined above), the total number of purchase occasions, and the number of purchase occasions that contain a brand purchase within each category.

Table 2: Summary Statistics By Category

	Dry Dog Food	Dry Cat Food	Dog Hygiene	Cat Hygiene
Number of Brands	8	4	4	4
Number of Adopters	2,410	1,037	2,214	1,192
Number of Non-Adopters	7,938	2,297	3,582	2,725
Number of Purchase Occasions	136,411	45,443	78,253	55,410
Purchase Occasions with a Category Purchase	99,233	27,623	40,183	42,596

Table 3: Summary Statistics of Prices and Costs

	Dry Dog Food	Dry Cat Food	Dog Hygiene	Cat Hygiene
Mean Price	10.17	11.89	2.28	12.25
SD Price	2.82	2.40	0.28	2.46
Mean Cost	6.29	8.04	0.96	4.95
SD Cost	2.32	3.39	0.29	1.54

In our data, customers, by and large, do not purchase from more than one store in a month. More than 96% of customer-month-level purchase occasions involve purchases from a single store. When we process the choice data for each category, for the minor fraction of purchase occasions that involve more than one store, we label these customer-month purchase occasions with the store where the customer spent the most within that category during the month so that each customer-month level purchase occasion is associated with a single store.

³We rarely observe customer-month purchase occasions that involve a purchase of more than one brand. All product categories have fewer than 0.86% of total purchase occasions (e.g., including those with multiple visits to a single store in a month, visits to multiple stores and a single visit) with multiple brand purchases. For these few purchase occasions with multiple brand purchases, we assign the brand with the largest spend for that customer during the month, similar to previous brand choice literature, e.g. Erdem and Keane (1996). Some researchers have handled this issue differently, for instance, by having each brand chosen count as an independent single-brand purchase occasion (Krishnamurthi and Raj 1988; Chib et al. 2004). Since the fraction of purchases is so small, we do not think this decision makes a material impact on our results.

Finally, in Table 3, we show some summary statistics of the prices and costs for each category. Specifically, we show the mean and standard deviation (SD) of the brand price (or cost) per pack size unit (e.g, KG or piece) for each category, for the estimation sample. These values are calculated by averaging across all purchase occasions and brands. Specifically, the mean price for category c is calculated as: $\text{Mean Price}_c = \frac{1}{N_c} \frac{1}{J_c} \sum_{t=1}^{N_c} \sum_{j=1}^{J_c} \text{Price}_{jt}$ where Price_{jt} is the price of brand j on the purchase occasion t . N_c is the total number of purchase occasions in category c , and J_c is the number of brands of category c . The standard deviation is computed as $\text{SD Price}_c = \sqrt{\frac{1}{N_c} \frac{1}{J_c} \sum_{t=1}^{N_c} \sum_{j=1}^{J_c} (\text{Price}_{jt} - \text{Mean Price}_c)^2}$. The mean cost and SD cost are defined similarly.⁴ Overall, we see that the data contain significant price and cost variation for each category. This variation is important and helps us estimate price elasticities.

4 Descriptive Analysis

We now present some descriptive analysis that examines if/how the adoption of online shopping changes consumer behavior during their offline shopping trips in the post-adoption period. Specifically, we focus on two variables that can capture changes in *within-customer* offline price sensitivity:

- Price Paid: Conditional on making an offline purchase in the focal category, do adopters shift toward lower-priced after online adoption (compared to non-adopters)?
- Category Purchase Frequency: Conditional on an offline purchase occasion (as defined earlier), do adopters purchase the focal category less frequently after they adopt online shopping, compared to non-adopters?

4.1 Price Paid

Table 4: Two-Way Fixed Effects Model Estimates – $\ln(\text{Price_Paid})$

Dependent Variable:	$\ln(\text{Price_Paid})$			
Model:	Dry Dog Food (1)	Dry Cat Food (2)	Dog Hygiene (3)	Cat Hygiene (4)
<i>Variables</i>				
$\mathcal{I}\{\text{Adopter}_i\} \times \mathcal{I}\{t \geq T_i^{\text{adopt}}\}$	-0.0102* (0.0040)	-0.0106** (0.0038)	-0.0046 (0.0030)	-0.0160* (0.0063)
<i>Fixed-effects</i>				
Customer	Yes	Yes	Yes	Yes
YearMonth	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	99,233	27,623	40,183	42,596
R ²	0.89566	0.70460	0.62699	0.66927
Within R ²	0.00030	0.00065	0.00012	0.00074

Clustered (Customer & YearMonth) standard-errors in parentheses

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

⁴All price and cost figures are inflation-adjusted. Brazil exhibited significant inflation during our study period, and adjusting for inflation is crucial to reflect the real price changes. The adjustment is relative to the first observation period, January 2019.

We now examine how the prices paid by adopters change after online adoption (compared to non-adopters). To that end, we focus on all offline purchase orders (made by adopters and non-adopters) that contain a focal category purchase and estimate the following two-way fixed-effects regression for each category at the customer-order level:

$$\ln(\text{Price_Paid})_{it} = \delta \times \mathcal{I}\{\text{Adopter}_i\} \times \mathcal{I}\{t \geq T_i^{\text{adopt}}\} + \text{Customer}_i + \text{YearMonth}_t + \epsilon_{it}, \quad (1)$$

where $\mathcal{I}\{\text{Adopter}_i\}$ is an indicator variable which is 1 for adopters and 0 for non-adopters. T_i^{adopt} is the adoption time of customer i , and $\mathcal{I}\{t \geq T_i^{\text{adopt}}\}$ is an indicator which is 1 if the order t is during customer i 's post-adoption period. We also include customer-fixed effects, Customer_i , to measure the within-customer change, and time-fixed effects, YearMonth_t , to control for time-specific unobserved shocks. A negative δ indicates that adopters, on average, pay lower prices or shift towards the lower end of the price distribution after adopting online shopping, relative to non-adopters. A positive δ would indicate the opposite.

Table 4 presents the within-customer changes in the prices paid by adopters relative to non-adopters, controlling for customer and date fixed-effects. Across all product categories, we see that adopters pay lower prices offline after they adopt shopping online in the retailer, compared to non-adopters. Further, three of the categories show a statistically significant effect at the 5% level of significance. In Web Appendix B Table A3, we repeat this analysis with the percentile of price paid as the dependent variable (instead of $\ln(\text{Price_Paid})$) and find consistent results – customers shift towards lower-priced products during their offline purchases after adopting online shopping. Together, these results suggest that, conditional on purchasing, consumers are paying lower prices, possibly because they are more price-sensitive.

4.2 Category Purchase Frequency

Table 5: Two-Way Fixed Effects Model Estimates - BuyCategory

Dependent Variable:	BuyCategory			
Model:	Dry Dog Food (1)	Dry Cat Food (2)	Dog Hygiene (3)	Cat Hygiene (4)
<i>Variables</i>				
$\mathcal{I}\{\text{Adopter}_i\} \times \mathcal{I}\{t \geq T_i^{\text{adopt}}\}$	-0.0751*** (0.0077)	-0.0497*** (0.0109)	-0.0617*** (0.0075)	-0.0654*** (0.0106)
<i>Fixed-effects</i>				
Customer	Yes	Yes	Yes	Yes
YearMonth	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	136,411	45,443	78,253	55,410
R ²	0.30479	0.25032	0.23015	0.26662
Within R ²	0.00147	0.00066	0.00113	0.00121

Clustered (Customer) standard-errors in parentheses

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

Next, we examine how the frequency of adopters’ purchase of a given category in the offline channel changes compares to non-adopters. Specifically, during each offline purchase occasion, we construct a binary dependent variable, $\mathcal{I}\{\text{BuyCategory}_{it}\}$, which equals 1 if customer i buys the focal category in purchase occasion t , and 0 otherwise. We then estimate the following two-way fixed effects regression at the customer-month purchase occasion level:

$$\mathcal{I}\{\text{BuyCategory}_{it}\} = \delta \times \mathcal{I}\{\text{Adopter}_i\} \times \mathcal{I}\{t \geq T_i^{\text{adopt}}\} + \text{Customer}_i + \text{YearMonth}_t + \epsilon_{it} \quad (2)$$

As before, we include customer and year-month fixed effects. The coefficient δ captures the change in the probability of buying the category for adopters relative to non-adopters after adoption.

Table 5 shows the results on this estimation. We find that, conditional on a purchase occasion, adopters purchase dog food and cat food 7.5% and 5.0% less frequently than non-adopters in the offline channel after they begin using the retailer’s online channel. Similarly, adopters buy dog and cat hygiene 6.2% and 6.5% less frequently than non-adopters, respectively. These findings suggest that, compared to non-adopters, adopters are more likely to choose the “no-purchase” option when they start shopping online.

In summary, both the descriptive analyses suggests that consumers are less likely to buy the focal category offline and when they do buy, they pay lower prices, on average. Together these findings provide some suggestive evidence for potentially higher offline price sensitivity after online adoption. In the next few sections, we build on these findings and estimate customer-level price elasticities as a function of their online adoption status and then quantify the effect of online adoption on offline price elasticities.

5 Firm’s Problem and Overview of Empirical Strategy

The primary objective of the firm is to quantify the causal effect of consumers’ adoption of online shopping on their offline price sensitivity, compared to consumers who shop exclusively offline. However, quantifying this impact presents both methodological challenges and limited managerial relevance for several reasons.

First, adopting the online channel is a consumer-level decision, and firms cannot randomly assign consumers to adopt the online channel or remain offline-only through field experiments. This makes it impossible to directly measure the Average Treatment Effect (ATE) of online adoption on consumers’ offline price sensitivity. Second, although firms could implement an intent-to-treat (ITT) design - such as randomly offering incentives to some offline-only consumers to encourage their online adoption - this approach still does not give us ATE given that some consumers would never adopt online ⁵. Third, even if a firm could somehow identify a significant effect of adopting online shopping on consumers’ offline price sensitivity, it cannot force consumers to choose a specific channel. Therefore, obtaining the ATE is not only impractical but also lacks actionable implications. Instead, the main quantity of interest for the firm is the change in offline price sensitivity among consumers who adopt online shopping compared to those who continue to shop exclusively offline i.e. the Average Treatment Effect on the Treated (ATT). Measuring this would help

⁵We do not obtain ATE under the ITT design, since the causal quantity obtained from 2SLS estimators represents the Average Causal Response, which is a weighted sum of individual treatment effects where weights are compliance scores; For more details, see Angrist and Imbens (1995); Syrgkanis et al. (2019); Mummalaneni et al. (2023).

firms adjust their offline pricing strategies in response to their customers adopting online shopping. Thus, our goal is to identify the ATT of online adoption on offline price sensitivity.

We adopt a two-step empirical strategy to solve this problem:

- First, we measure category-level own-price elasticities at the customer-month level: In §6, we use a logit brand choice model where each consumer’s price sensitivity coefficient varies with the extent of their online spending and include customer-brand fixed effects. To address price endogeneity, we use the control functions approach (Petrin and Train 2010), using wholesale cost as an instrument. To efficiently estimate the model given a large number of customer-brand fixed effects, we implement a Minorization-Maximization (MM) algorithm for the logit model (Chen et al. 2021).
- Next, we use the estimated elasticities in the first step to measure the change in offline price elasticities due to online adoption. In §7, we use a staggered difference-in-differences approach (Callaway and Sant’Anna 2021) to estimate the ATT of online adoption on offline price elasticities after accounting for differences in the timing of adoption between different adopter cohorts.

6 Demand Model

6.1 Choice Model and Utility Specification

For each category, we use a logit model of brand choice (Guadagni and Little 1983; Chintagunta et al. 1991) to estimate offline price elasticities at customer-brand-month-level. Suppose that for a given category, there are J brands indexed by $j = 1, 2, \dots, J$ plus an outside option indexed by 0. The utility that consumer i obtains from choosing brand j during offline purchase occasion t is given by ⁶:

$$U_{ijt} = \alpha_0 \text{Price}_{jt} + \alpha_1 \text{cumPercOnlineSpend}_{it} + \alpha_2 \text{Price}_{jt} \times \text{cumPercOnlineSpend}_{it} + \alpha_3 \mathcal{I}\{\text{BuyLastMonth}_{ijt}\} + \delta_{ij} + \epsilon_{ijt} \quad \forall j \in \{1, \dots, J\} \quad (3)$$

In this utility specification, Price_{jt} is the price of brand j during purchase occasion t . We allow a consumer’s price sensitivity coefficient to depend on their cumulative percentage of online spending, denoted as $\text{cumPercOnlineSpend}_{it}$. This variable represents the proportion of the customer’s total spending with the retailer that has occurred online up to the purchase occasion t since their first transaction with the retailer. We use this continuous variable to allow for variation in the online adoption effect based on the *extent* of a consumer’s online spend. We also consider an alternate specification where we use a binary online adoption indicator in §8.2.1. The coefficient α_0 represents the baseline price sensitivity for purely offline customers. The interaction coefficient α_2 reflects how price sensitivity changes as consumers spend more online. A negative α_2 would suggest that higher online spending share leads to greater offline price sensitivity.⁷ The variable $\mathcal{I}\{\text{BuyLastMonth}_{ijt}\}$ is an indicator that equals 1 if customer i purchased brand j at the previous purchase occasion $t - 1$, and 0 otherwise, capturing state dependence via α_3 . The customer-brand fixed

⁶Here, we use a single index t to denote a purchase occasion, which contains both the time (YearMonth) and store information associated with the purchase occasion.

⁷Interaction terms in logit and other nonlinear models are best interpreted via marginal effects or elasticities (Ai and Norton 2003).

effects δ_{ij} capture consumer i 's time-invariant preference for brand j . These fixed effects capture systematic time-invariant consumer-level heterogeneity in brand preferences. However, including these high-dimensional fixed effects introduces some estimation challenges which we discuss in §6.3. The term ϵ_{ijt} is an idiosyncratic error term. Finally, the utility of choosing the outside option is normalized as $U_{i0t} = 0 + \epsilon_{i0t}$ where ϵ_{i0t} also follows an i.i.d. Type I extreme value distribution.

6.2 Price Endogeneity

A common challenge in estimating price elasticities with observational choice data is price endogeneity. This issue arises when the error term, ϵ_{ijt} , contains some time-varying unobserved demand shocks that may be correlated with prices; e.g., if promotions or advertising are correlated with prices. To address this, we apply the control function approach for two endogenous variables, Price_{jt} and $\text{Price}_{jt} \times \text{cumPercOnlineSpend}_{it}$ (Petrin and Train 2010; Wooldridge 2015). We use the weighted wholesale cost indices for each brand j (constructed as described in §3.2), Cost_{jt} , as the instrument. Intuitively, cost is correlated with a brand's price but not correlated with unobserved demand shocks, and it is a standard instrument for correcting price endogeneity in the demand estimation literature (Berry et al. 1995; Berry and Haile 2021).

To obtain control functions for two endogenous variables, we run the following two regressions and obtain the residuals; see (Aparicio et al. 2024) for a similar use case of this approach.

$$\text{Price}_{jt} = \gamma_1 \text{Cost}_{jt} + \text{Brand}_j + \text{Store}_t + \text{YearMonth}_t + \xi_{jt}^{(1)} \quad (4)$$

$$\text{Price}_{jt} \times \text{cumPercOnlineSpend}_{it} = \gamma_2 \text{Cost}_{jt} + \gamma_3 \text{Cost}_{jt} \times \text{cumPercOnlineSpend}_{it} + \gamma_4' \text{Control}_{ijt} + \xi_{ijt}^{(2)} \quad (5)$$

Here, Control_{ijt} is a vector of control variables (e.g., $\text{cumPercOnlineSpend}_{it}$, $\mathcal{I}\{\text{BuyLastMonth}_{ijt}\}$, Customer_i , Brand_j , YearMonth_t). Next, following Petrin and Train (2010), the original error term in the utility specification, ϵ_{ijt} , can be decomposed as follows:

$$\epsilon_{ijt} = \lambda_1 \text{CF_Price}_{jt} + \lambda_2 \text{CF_Price_cumPercOnlineSpend}_{ijt} + \tilde{\epsilon}_{ijt} \quad (6)$$

where $\tilde{\epsilon}_{ijt}$ is assumed to follow i.i.d. Type I extreme value distribution. We then include two control functions into the utility equation as additional regressors, which is now given by:

$$\begin{aligned} U_{ijt} &= \alpha_0 \text{Price}_{jt} + \alpha_1 \text{cumPercOnlineSpend}_{it} + \alpha_2 \text{Price}_{jt} \times \text{cumPercOnlineSpend}_{it} \\ &+ \alpha_3 \mathcal{I}\{\text{BuyLastMonth}_{ijt}\} + \delta_{ij} + \lambda_1 \text{CF_Price}_{jt} + \lambda_2 \text{CF_Price_cumPercOnlineSpend}_{ijt} + \tilde{\epsilon}_{ijt} \quad (7) \\ &= \psi_{ijt} + \tilde{\epsilon}_{ijt} \quad \forall j \in \{1, \dots, J\}, \end{aligned}$$

where ψ_{ijt} is the deterministic part of the utility term and $\psi_{i0t} = 0$ for the outside option. Under the Type I extreme value assumption for $\tilde{\epsilon}_{ijt}$, the probability that consumer i chooses brand j at shopping occasion t is given by the following formula:

$$Pr_{ijt} = \frac{\exp(\psi_{ijt})}{\sum_{j'=0}^J \psi_{ij't}} \quad (8)$$

Let $\psi_{it} = (\psi_{i0t}, \psi_{i1t}, \psi_{i2t}, \dots, \psi_{iJt}) \in \mathbb{R}^{J+1}$ be the vector of nominal utilities and $\mathbf{y}_{it} = (y_{i0t}, y_{i1t}, \dots, y_{iJt}) \in \mathbb{R}^{J+1}$ be the binary choice outcomes for consumer i at shopping occasion t , with $y_{ijt} = 1$ if consumer i chooses brand j at shopping occasion t and 0 otherwise. The likelihood of consumer i at purchase occasion t is given by:

$$l(\psi_{it}; \mathbf{y}_{it}) = \prod_{j=0}^J (Pr_{ijt}(\psi_{it}))^{y_{ijt}} \quad (9)$$

The log-likelihood function over all consumers and purchase occasions can be written as

$$\mathcal{L}(\theta) = \sum_{i=1}^N \sum_{t \in T_i} \log l(\psi_{it}; \mathbf{y}_{it}) \quad (10)$$

where T_i is the set of purchase occasions associated with customer i . The parameter vector of interest is $\theta = \{\alpha_0, \alpha_1, \alpha_2, \alpha_3, \lambda_1, \lambda_2, \{\delta_{ij}\}_{i=1, \dots, N; j=1, \dots, J}\}$. Note that this is a high-dimensional parameter vector – in addition to population parameters such as α s and λ s, we also have customer-brand fixed-effects (δ_{ijs}), which scale with the sample size.

6.3 Estimation

Our main estimation strategy follows the standard two-step approach used in control function approaches; see (Petrin and Train 2010) for details. However, the key additional challenge in our setting comes from the presence of the high-dimensional customer-brand fixed-effects. We now discuss both the overview of our estimation strategy and also provide a summary of the solution concept that we adopt to address the high-dimensional fixed-effects.

First, we run OLS regressions for Price_{jt} in Equation (4) and $\text{Price}_{jt} \times \text{cumPercOnlineSpend}_{it}$ in Equation (5), respectively. We then obtain the residuals, CF_Price_{jt} and $\text{CF_Price_cumPercOnlineSpend}_{ijt}$, which serve as control functions. Second, we include these residuals as additional regressors in the logit model (i.e., Equation (7)). In a standard setting, estimation can proceed as usual at this stage. However, since we have a large number of customer-brand fixed effects (δ_{ij}), standard maximum likelihood estimation becomes computationally infeasible. To overcome this, we adopt a Minorization-Maximization (MM) algorithm for the logit model with fixed effects, an efficient estimation method proposed by Chen et al. (2021). The MM algorithm transforms the non-linear optimization problem (i.e., MLE estimation) into a sequence of simpler problems by iteratively constructing and maximizing a surrogate transfer minorization function $S(\cdot)$ that minorizes the log-likelihood (James 2017). The transfer minorization function $S(\cdot)$ is less than the log-likelihood function everywhere except at the current best guess of the parameters, where it is equal. Chen et al. (2021) derives a transfer minorization function for the standard multinomial logit model in which there are no alternative-specific time-varying covariates in the utility function. In the theorem below, we extend their proof to cover a fully flexible logit model with covariates that may vary by individual, by alternative (brand), and over time. We then derive the corresponding transfer minorization function $S(\cdot)$ for the log-likelihood \mathcal{L} .

Theorem. Let $\mathcal{L}(\boldsymbol{\theta})$ be the log-likelihood of the logit model, defined as in Equation (10). Let $S(\boldsymbol{\theta}; \boldsymbol{\theta}^{(k)})$ be defined as:

$$S(\boldsymbol{\theta}; \boldsymbol{\theta}^{(k)}) = \mathcal{L}(\boldsymbol{\theta}^{(k)}) + \frac{1}{2} \sum_{i,j,t} h_j(\boldsymbol{\psi}_{it}^{(k)}; \mathbf{y}_{it})^2 - \frac{1}{2} \sum_{i,j,t} [\psi_{ijt}^{(k)} + h_j(\boldsymbol{\psi}_{it}^{(k)}; \mathbf{y}_{it}) - \psi_{ijt}^{(k)}]^2, \quad (11)$$

where

$$h_j(\boldsymbol{\psi}_{it}^{(k)}; \mathbf{y}_{it}) = \frac{\partial \log l(\boldsymbol{\psi}_{it}^{(k)}; \mathbf{y}_{it})}{\partial \psi_{ijt}^{(k)}} = y_{ijt} - Pr_{ijt}(\boldsymbol{\psi}_{it}^{(k)}) \quad (12)$$

$$\boldsymbol{\psi}_{it}^{(k)} = (\psi_{i0t}^{(k)}, \psi_{i1t}^{(k)}, \psi_{i2t}^{(k)}, \dots, \psi_{iJt}^{(k)}) \quad (13)$$

Here, $h_j(\boldsymbol{\psi}_{it}^{(k)}; \mathbf{y}_{it})$ is the j th entry of the gradient vector of log-likelihood with respect to the nominal utility of alternative j , $\psi_{ijt}^{(k)}$. $\boldsymbol{\psi}_{it}^{(k)}$ denotes the vector of nominal utilities for consumer i at iteration k . Then, the function $S(\boldsymbol{\theta}; \boldsymbol{\theta}^{(k)})$ is a transfer minorization of $\mathcal{L}(\boldsymbol{\theta})$.

Proof. See Web Appendix C.1.

Based on the Theorem 1 and proof from Chen et al. (2021), the iterative sequence $\boldsymbol{\theta}^{(k+1)} = \arg \max_{\boldsymbol{\theta}} S(\boldsymbol{\theta}; \boldsymbol{\theta}^{(k)})$, $k = 0, 1, \dots$, converges to a local, if not global, maximum of $\mathcal{L}(\boldsymbol{\theta})$.⁸

Equation (11) is a second-order Taylor expansion of the log-likelihood function at $\boldsymbol{\theta}^{(k)}$. The model parameters we are searching over in the iterative MM algorithm ($\boldsymbol{\theta}$, rather than $\boldsymbol{\theta}^{(k)}$), appear only in the third term. Because the only term in $S(\boldsymbol{\theta}; \boldsymbol{\theta}^{(k)})$ that depends on $\boldsymbol{\theta}$ is the sum of squared residuals, maximizing $S(\boldsymbol{\theta}; \boldsymbol{\theta}^{(k)})$ is equivalent to minimizing this least squares objective, and the coefficients can be obtained by regressing $\psi_{ijt}^{(k)} + h_j(\boldsymbol{\psi}_{it}^{(k)}; \mathbf{y}_{it})$ on the vector of explanatory variables $\mathbf{x}_{ijt} = \{\text{Price}_{jt}, \text{cumPercOnlineSpend}_{it}, \text{Price}_{jt} \times \text{cumPercOnlineSpend}_{it}, \mathcal{I}\{\text{BuyLastMonth}_{ijt}\}, \text{CF_Price}_{jt}, \text{CF_Price_cumPercOnlineSpend}_{ijt}, \delta_{ij}\}$ in the utility function. This linearization allows us to exploit standard panel data methods despite a large number of fixed effects δ_{ij} .

In summary, the MM-based estimation algorithm that we employ is as follows:

- Initialization: Set the initial parameter estimates $\boldsymbol{\theta}^{(0)}$ including all customer-brand fixed effects as zero.
- Iterative Steps:
 1. Minorization step: Given $\boldsymbol{\theta}^{(k)}$, calculate $h_j(\boldsymbol{\psi}_{it}^{(k)}; \mathbf{y}_{it})$ and obtain $\psi_{ijt}^{(k)} + h_j(\boldsymbol{\psi}_{it}^{(k)}; \mathbf{y}_{it})$.
 2. Maximization step: Regress $\psi_{ijt}^{(k)} + h_j(\boldsymbol{\psi}_{it}^{(k)}; \mathbf{y}_{it})$ on the vector of variables \mathbf{x}_{ijt} in the utility equation (7).
 3. Repeat until convergence, that is, $\|\boldsymbol{\theta}^{(k+1)} - \boldsymbol{\theta}^{(k)}\|_{\infty} < 10^{-3}$.

Since the estimated residuals from the first stage enter the estimation in the second stage, the standard errors in the second step estimation tend to be downward biased, although the parameter estimates themselves are consistent (Wooldridge 2010). Therefore, we use block bootstrapping with 500 replications, which treats

⁸For more details, please refer to the proof of Theorem 1 in Chen et al. (2021), which shows the convergence of this iterative estimator to the true parameters.

individual customers as blocks. In each replication, we resample the same number of customers as in the original sample with replacement, re-estimate the demand model, and then obtain the bootstrapped standard errors for the demand parameters and price elasticities (Cameron 2005).

6.4 Demand Model Parameter Estimates

Table 6 presents the estimation results of the demand model based on Equation (7). The standard errors of the parameter estimates are derived using block bootstrap with 500 replications. All the price coefficients are negative and statistically significant. The price interaction terms are also negative and significant for dry dog food and for dog and cat hygiene categories but are insignificant for dry cat food. We discuss the potential sources for this heterogeneity in §7.1.

The coefficient of the interaction term in the logit model should not be interpreted directly. Instead, the correct way to interpret the interaction effect is to calculate the marginal effect and price elasticity (Ai and Norton 2003; Karaca-Mandic et al. 2012). Accordingly, we calculate price elasticities using the statistically significant coefficients, as specified in Equation (14) and discuss their implications in the next section.

Table 6: Coefficient Estimates of Demand Model - Main Results

<i>Variables</i>	Dry Dog Food	Dry Cat Food	Dog Hygiene	Cat Hygiene
Price	-0.3159*** (0.0235)	-0.1603*** (0.0188)	-1.2464*** (0.123)	-0.221*** (0.0209)
cumPercOnlineSpend	-0.3357 (0.4601)	-1.4046 (1.0888)	8.7512*** (1.8675)	3.4655** (1.0615)
Price * cumPercOnlineSpend	-0.1115** (0.0421)	0.018 (0.091)	-4.1601*** (0.8197)	-0.284*** (0.0713)
BuyLastMonth	0.1512*** (0.0273)	-0.5037*** (0.0451)	-0.1821*** (0.0284)	0.3247*** (0.0295)
CF_Price	0.0515 (0.0293)	0.0468 (0.0258)	0.1911 (0.1815)	0.2805*** (0.0279)
CF_Price_cumPercOnlineSpend	0.0227 (0.0803)	-0.0604 (0.1232)	3.6335*** (1.0007)	0.3006** (0.0936)
Customer_Brand_FE	Yes	Yes	Yes	Yes
Observations	136,411	45,443	78,253	55,410
Log-likelihood	-84210.21	-30698.052	-55444.644	-37327.537

Bootstrapped standard-errors in parentheses via 500 replications

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

7 ATT of Online Adoption on Offline Price Elasticity

Now that we have the demand parameter estimates, we then measure the category-level own-price elasticity and formalize the ATT of online adoption on offline price elasticity. In §7.1, we present the elasticity estimates from the estimation procedure. Next, in §7.2, we perform a within-customer comparison of adopters' offline price elasticity before and after the adoption of online shopping. In §7.3, we formalize the changes in offline price elasticity due to the adoption of online shopping using a staggered difference-in-differences (DID) model.

7.1 Elasticity Estimates

Given the demand model parameters, we can then derive a customer i 's own-price elasticity for brand j in a purchase occasion t as shown below:

$$\eta_{ijt} = \frac{\partial Pr_{ijt}}{\partial Price_{jt}} \cdot \frac{Price_{jt}}{Pr_{ijt}} = (\alpha_0 + \alpha_2 \times \text{cumPercOnlineSpend}_{it}) \times Price_{jt} \times (1 - Pr_{ijt}) \quad (14)$$

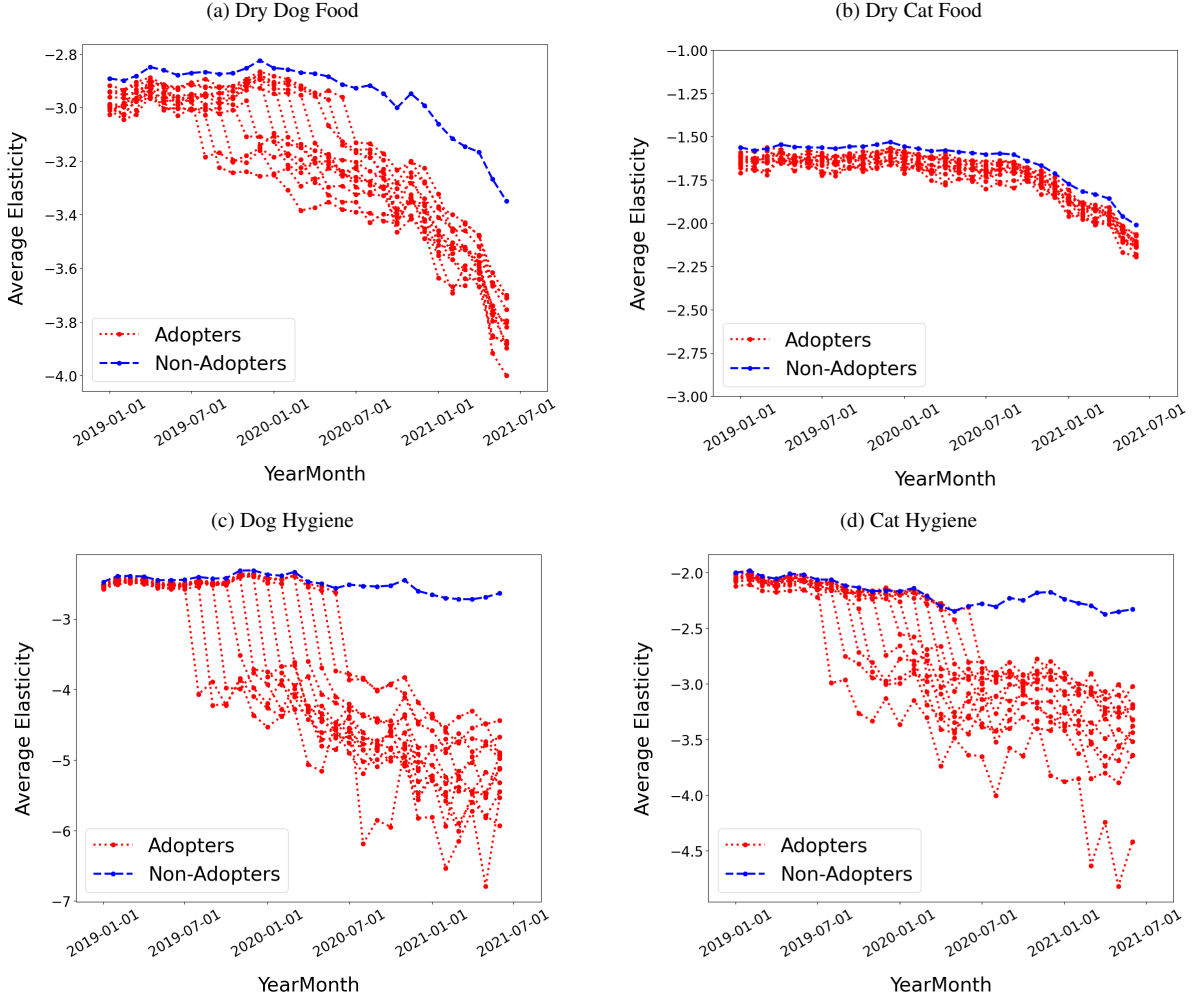
To estimate category-level own-price elasticity, we proceed in two steps. First, for each customer i , brand j in the customer-month purchase occasion t , we calculate the own-price elasticity η_{ijt} using Equation (14). We then average across the J brands to obtain a customer-month level own-price elasticity for each category, denoted by $\tilde{\eta}_{it} = \frac{1}{J} \sum_{j'} \eta_{ij't}$. Hereafter, we let t index the calendar time (i.e., year-month) rather than a purchase occasion. $\tilde{\eta}_{it}$ serves as the dependent variable in our subsequent regression analysis.

For easier interpretation, we further calculate the monthly average elasticity for each adopter and non-adopter cohort by taking the cross-sectional mean across all customers' own-price elasticities within that cohort. Figure 2 shows these monthly average offline price elasticities for both adopters and non-adopters of these product categories. The dashed line represents the baseline for non-adopters, while the twelve dotted lines represent adopter cohorts, each defined by the month in which customers first purchased online between July 2019 and June 2020.

Before online adoption, consumers' offline price elasticities closely mirror those of non-adopters, suggesting comparable pre-trends. However, after adopting online shopping, adopters consistently become more price sensitive in their offline shopping. The magnitude of the increase in offline price elasticity is most pronounced for dog hygiene and cat hygiene, moderate for dry dog food, and barely visible for dry cat food. The sharp increases in elasticities for the hygiene categories are likely due to the fact that these products have low switching costs: owners face little risk in trying a new hygienic mat for their dog if it is lower priced, with other attributes like pad size being standardized. The smaller changes to price elasticities in the two pet food categories, and a zero effect for cat food, is likely due to the fact that brand switching is not so simple in the case of pet food. Changing a dog's or cat's diet entails palatability trials, digestive risks, and rejection. Cats in particular, are very picky eaters and have especially strong food preferences in terms of shape, smell and texture (Nichelason 2024). Since the main coefficient of interest in Table 6 for cat food is not statistically significant at the 5% level, and the elasticity figure also shows no effect for cat food, we drop this category in our subsequent analyses.

In sum, Figure 2 provides clear visual evidence supporting the idea that adoption of online shopping heightens consumers' offline price elasticity. Furthermore, this pattern holds true across all cohorts, as well as for the dry dog food and dog and cat hygiene categories. For cat food, we find a null effect; hence, we drop the category from our subsequent analyses. A drawback of the plots above is that we don't control for common time-specific shocks and/or unobserved customer heterogeneity. In the next few sections, we address these confounds using within-customer and staggered difference-in-differences (DID) analysis.

Figure 2: Average price elasticity between adopters (shown in twelve dotted lines) and non-adopters (shown in one dashed line) for each category.



7.2 Within-Customer Analysis

We now quantify how adopters' offline price elasticity changes after they start shopping online at the focal retailer. We estimate two model specifications on the sample of adopters for each category:

$$\tilde{\eta}_{it} = \phi_0 + \phi_1 \times \mathcal{I}\{t \geq T_i^{\text{adopt}}\} + e_{it} \quad (15)$$

$$\tilde{\eta}_{it} = \text{Customer}_i + \text{YearMonth}_t + \phi_2 \times \mathcal{I}\{t \geq T_i^{\text{adopt}}\} + e_{it}, \quad (16)$$

where the binary indicator $\mathcal{I}\{t \geq T_i^{\text{adopt}}\}$ indicates the post-online-adoption period, which equals 1 if customer i has adopted online shopping at time t , and 0 otherwise. Customer_i and YearMonth_t are customer- and year-month fixed effects, which control for individual-specific time-invariant unobserved heterogeneity and time-specific unobserved shocks, respectively. Finally, because the outcome variable is an estimate (rather

than data), we bootstrap standard errors. Specifically, we employ a block bootstrap with 500 replications, treating individual customers as blocks (as described in §6) to obtain standard errors.

Table 7 presents the parameter estimates (and bootstrapped standard errors) for these categories. We find that the coefficient on $\mathcal{I}\{t \geq T_i^{\text{adopt}}\}$ is consistently negative across all specifications and categories. This suggests that, on average, adopters become more sensitive in offline channels in these product categories after adopting online shopping (even after controlling for customer and time fixed effects).

Table 7: Within-Customer Analysis of Offline Price Elasticity - Main Results

Dependent Variable:	Offline Price Elasticity					
Model:	Dry Dog Food		Dog Hygiene		Cat Hygiene	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
Constant	-2.935*** (0.2142)		-2.464*** (0.2429)		-2.125*** (0.1998)	
$\mathcal{I}\{t \geq T_i^{\text{adopt}}\}$	-0.3870*** (0.0759)	-0.1173* (0.0543)	-1.916*** (0.3563)	-0.7239** (0.2361)	-0.8860*** (0.1727)	-0.3347** (0.1250)
<i>Fixed-effects</i>						
Customer		Yes		Yes		Yes
YearMonth		Yes		Yes		Yes
<i>Fit statistics</i>						
Observations	29,416	29,416	28,375	28,375	15,081	15,081
R ²	0.31325	0.86657	0.34866	0.72137	0.37526	0.75980
Within R ²		0.04011		0.03352		0.03960

Bootstrapped standard-errors in parentheses via 500 replications

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

Although this pre/post comparison isolates within-customer changes, it remains a before-after contrast confined to adopters. It does not control for common time-varying or macro shocks that could have affected the trend of price elasticities of both adopters and non-adopters. To effectively address this issue, we need to construct a counterfactual or control group of non-adopters, who were also offline customers of the firm in the pre-adoption period and continue to be offline only. To address this issue, we outline a difference-in-differences strategy in the next section.

7.3 Difference-In-Differences (DID) Analysis

To estimate the causal effect of interest – the average treatment effect on the treated (ATT), we use a difference-in-differences (DID) approach. This method compares adopters with non-adopters before and after online adoption. As a baseline specification, we estimate the following two-way fixed effects (TWFE) model:

$$\tilde{\eta}_{it} = \text{Customer}_i + \text{YearMonth}_t + \phi_{TWFE} \times \mathcal{I}\{\text{Adopter}_i\} \times \mathcal{I}\{t \geq T_i^{\text{adopt}}\} + e_{it}. \quad (17)$$

Here, ϕ_{TWFE} is our parameter of interest. $\mathcal{I}\{\text{Adopter}_i\}$ is a binary indicator that is 1 if customer i is an adopter and 0 otherwise. $\mathcal{I}\{t \geq T_i^{\text{adopt}}\}$ is a binary indicator equal to 1 if the year-month t is in the post-online

adoption phase of customer i . We present the estimation results of the two-way fixed effects estimator in Table A4 in Web Appendix §D. The estimates show that there is a significant increase in price elasticity for adopters post-adoption, as indicated by the negative and significant coefficient on ϕ_{TWFE} for these categories.

Although TWFE regression is widely used in empirical studies involving staggered adoption, it only provides consistent estimates of ATT under the assumption of homogeneous treatment effects, a condition that is rarely met in practice; see De Chaisemartin and d’Haultfoeuille (2020); Callaway and Sant’Anna (2021); Sun and Abraham (2021); Goodman-Bacon (2021) for detailed discussions of this issue. Specifically, Goodman-Bacon (2021) shows that the TWFE estimator (ϕ_{TWFE}) effectively represents a weighted average of all possible 2-by-2 combinations of pairwise difference-in-differences comparisons between groups of units treated at different times.

To address this issue, we adopt the staggered difference-in-differences (DID) framework proposed by Callaway and Sant’Anna (2021), hereafter referred to as the CS estimator as our main specification. The CS estimator addresses the biases associated with TWFE estimators by eliminating problematic comparisons between late-treated and already-treated units and has been applied recently in the marketing and economics literature (Ang 2021; Braghieri et al. 2022; Bekkerman et al. 2023). This method is particularly suited to our context, because we have customers adopting online shopping over a one year period, in 12 cohorts (one cohort per month). As discussed earlier, because there were exogenous events during this time period (e.g., the onset of COVID-19), it is possible that the ATT is different across cohorts. Therefore, we use this estimator in our main analysis and then supplement the analysis with TWFE estimates as a robustness check (which provide similar results in terms of direction and magnitude). We refer the reader to the original paper for a discussion of the technical details of how the CS estimator works. The main idea is to identify the Average Treatment Effect on the Treated (ATT) for each post-treatment period, for consumers who are treated at different times, and then calculate the overall treatment effect as a weighted average of these ATTs. In our context, the ATT in month t for customers who adopt online shopping in month g can be defined as:

$$ATT(g, t) = \mathbb{E}[\tilde{\eta}_{it}(g) - \tilde{\eta}_{it}(0) | G_{ig} = 1], \quad (18)$$

where $\tilde{\eta}_{it}(g)$ is the observed elasticity of customer i at month t who adopts online shopping in month g . G_{ig} is a binary indicator which is set to one if the customer i adopts online shopping in month g . Since the adoption window in our study spans from July 2019 to June 2020, g ranges from 7 to 18. $\tilde{\eta}_{it}(0)$ represents the potential outcome (i.e. counterfactual elasticity) of customer i at month t , if they did not adopt online shopping. Under the “no anticipation of treatment” assumption from CS, $\tilde{\eta}_{it}(0) = \tilde{\eta}_{it}(g)$ for all $t < g$. In other words, the offline price elasticity of any customer i during the pre-treatment period does not depend on whether and when customer i adopts online shopping, and this represents the counterfactual elasticity if they had not adopted online shopping.

As discussed by Callaway and Sant’Anna (2021), this effect, $ATT(g, t)$, can be identified provided that parallel pre-trends hold. We provide a test of parallel pre-trends in Figure A7 in Web Appendix §E.3.

The overall treatment effect (θ_o) is then calculated as a weighted average of $ATT(g, t)$ for all periods post-adoption across all groups:

$$\theta_o = \frac{1}{C_o} \sum_g \sum_{t>g} w_g ATT(g, t) \quad (19)$$

where w_g is the weight assigned to units in group g , which is the proportion of the number of online adopters in treatment group g relative to the total number of adopters. C_o normalizes the weights to sum to one.

We present the overall treatment effect estimates (θ_o) in Table 8. Since the customer-month level price elasticities are themselves estimates from our demand model with confidence intervals around them (and not directly observed from data), we compute standard errors for our ATT estimates using customer-level block bootstraps with 500 replications. Figure A3 in Web Appendix §D shows the bootstrapped distribution of these ATT estimates. The results in Table 8 suggest that consumers become more price-sensitive in the offline channel after they adopt online shopping, and this finding is consistent across these categories. The effect is stronger for the dog and cat hygiene categories, consistent with the elasticity visualization in Figure 2. To help with interpretation, we calculate the relative magnitude of the elasticity increase in percentage terms by dividing the ATT by the average pre-adoption price elasticity of adopters and show these percentage changes in the second row of Table 8. The most substantial effects are observed for dog hygiene and cat hygiene categories; offline price elasticity increases by 72.7% (i.e., -1.792 / -2.464) for dog hygiene and 34.7% (i.e., -0.738 / -2.125) for cat hygiene. The increase in offline price elasticity is lower for dry dog food, at 8.4% (i.e., -0.248 / -2.935). As discussed in §7.1, the pronounced increase in offline price elasticity for hygiene products (vs. dry food products) is likely driven by the lower switching costs associated with trying new brands of hygiene mats or other hygiene-related items. In summary, consistent with the descriptive evidence earlier, we find that consumers become more price-sensitive in their offline shopping trips when they start shopping online.

Table 8: ATT of Online Adoption on Offline Price Elasticity Over All Post-Adoption Period (CS Estimator)

Dependent Variable: Model:	Offline Price Elasticity		
	Dry Dog Food (1)	Dog Hygiene (2)	Cat Hygiene (3)
ATT	-0.2482** (0.0945)	-1.7922*** (0.3678)	-0.7381*** (0.1794)
ATT Relative to Adopters' Pre-Adoption Elasticity	8.4%	72.7%	34.7%
Observations	136,411	78,253	55,410

Bootstrapped standard-errors in parentheses via 500 replications

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

8 Generalizability and Robustness Checks

We now discuss the generalizability of our findings, provide some extensions, and present a series of tests and alternative specifications to establish the robustness of our findings.

8.1 Generalizability

We now discuss the generalizability of our findings and provide some evidence in favor of portability to other settings.

First, consumers may adopt online shopping for different reasons, and a natural question is whether our results are specific to consumers who adopt online shopping for certain reasons but not others. To examine this question, we leverage the fact that our observation period starts before the onset of the COVID-19 pandemic and continues through it. The cohorts that adopted from July 2019 to Feb 2020 are likely to have done so organically, while those who adopted from March 2020 are likely to have done so for exogenous reasons, i.e., the COVID-19 pandemic. Indeed, there is a big surge in online adoptions starting March 2020 (see Figure 1). We use this exogenous shock in the reason for adoption across cohorts to examine this issue. Overall, we find that the reason why a consumer switches to online shopping does not seem to have a significant impact on post-adoption price sensitivity: the ATT of cohorts that switched during the COVID-19 pandemic is similar to that of cohorts that switched organically before the onset of COVID-19 (see Figure 2). This suggests that the online adoption effect is not sensitive to the reasons that drive a consumer’s decision to adopt online shopping.

Second, we examine the extent to which our results are likely to be driven by the fact that online prices are slightly lower than offline prices in our setting. To that end, we examine the magnitude of the price differences between online and offline channels in our study (see details in Web Appendix E.1). We find that online prices are only 2–6% lower than offline in our data. Furthermore, the variation in prices explained by channel is significantly smaller than the variation in prices explained by SKU-level differences – across all categories, only 4% of the variation in prices is explained by channels, whereas when we include SKU fixed effects, this increases to 65%. Overall, these data patterns suggest that the differences between online and offline prices are relatively small and are unlikely to be the primary driver of our results. Other potential mechanisms, such as consumers becoming more accustomed to comparing prices across brands or their exposure to a wider variety of prices, are likely to be at play as well (as discussed in §1). Thus, we expect that our results are likely to generalize to other empirical settings where online prices are the same or higher than offline prices.⁹

Nevertheless, we note that we are unable to tease out the exact source of these effects because we lack granular data on consumers’ search and shopping behavior in the online channel. We do not observe online click-stream data, so we cannot comment on price search behavior online or the variety of prices seen online. We also do not observe any search behavior in offline stores. Further, while there are some differences in offline prices across physical stores at any given point in time, we do not have a sufficiently large proportion

⁹In practice, there is considerable heterogeneity in whether online prices are lower, the same, or higher than offline prices across retailers, countries, and product categories (Cavallo 2017).

of stores that are consistently higher or lower priced than others throughout our entire time period. Therefore, we cannot conduct a clean test of whether the effect we observe is driven more by price differences across the offline and online channels, the variety of prices that the consumer sees, or changes in search behavior that occur after adopting online shopping. We hope that future research can further dis-entangle which of these mechanisms are at play and to what extent. Further studies of such spillover effects in other countries, product categories, and retailers can also provide a more comprehensive understanding of the extent to which these effects manifest in different settings.

8.2 Robustness checks

We first examine alternative demand specifications in §8.2.1 and then consider matching methods and alternative control groups in §8.2.2 and 8.2.3, respectively.

8.2.1 Alternative Demand Specifications

We now consider two different demand model specifications:

- **Binary online adoption variable:** In our main demand model, we use the continuous variable $\text{cumPercOnlineSpend}_{it}$ to capture how consumers' offline price sensitivity changes after adopting online shopping. We now consider an alternative specification where we treat online adoption as a binary treatment. To that end, we use the binary indicator, $\text{Post_OnlineAdoption}_{it}$, which takes value one if customer i has adopted online shopping by time t , and zero otherwise. We substitute $\text{cumPercOnlineSpend}_{it}$ with $\text{Post_OnlineAdoption}_{it}$ in Equation (3), and also modify the corresponding control function term accordingly. We estimate revised demand model and compute the average elasticity at the customer-month level for each product category following the same steps as before. The details of the model and estimation results are provided in Web Appendix §E.2. The conclusions from this alternative demand model and the corresponding ATT estimates are consistent with our main results.
- **Accounting for a potential change in state dependence or brand loyalty due to online adoption:** In our main model, we include customer-brand fixed effects to capture time-invariant preferences and use $\mathcal{I}\{\text{BuyLastMonth}_{jt}\}$ to capture the state dependence. We now consider a specification with an additional control variable, $\mathcal{I}\{\text{BuyLastMonth}_{jt}\} \times \text{cumPercOnlineSpend}_{it}$, which captures the interaction between state dependence (e.g., repeated purchase of a brand) and the share of online spending. This can account for any effects that online adoption may have on brand loyalty.

The utility specifications and the estimation results from these two exercises are shown in Web Appendix §E.2. We find that the results are consistent with our main specification. We also do not find evidence of significant changes to offline brand loyalty after consumers adopt online shopping.

8.2.2 Matching and IPW Approaches to Control for Selection on Observables

Consumers self-select into adopting a retailer's online channel (or not), and as shown in Web Appendix §A.2, there are some systematic differences between adopters and non-adopters in terms of observable characteristics like demographics. In general, such differences are not an issue as long as the parallel pre-trends assumption holds (see Chapter 5 of Angrist and Pischke (2008) and Roth et al. (2023) for additional

discussions). To that end, we consider the pre-adoption trends in price elasticities between adopters and non-adopters and verify that the parallel pre-trends assumption holds in Web Appendix §E.3.

Nevertheless, differences in characteristics between groups may still potentially lead to differences in price elasticities over time in some way that is not showing up in the first few months of data or is not being accounted for in our model. For instance, there may be some factor that affects younger customers who are more likely to adopt online shopping, and only shows up in the later part of our data period. To provide additional credibility to our findings and to ensure that they are robust to any time-varying factors correlated with observable characteristics, we use propensity score-based methods like Inverse Propensity Weighting (IPW) and Propensity Score Matching (PSM) to account for differences in observable characteristics between the groups, which improves the comparability between the groups. These methods improve covariate balance, discard poorly matched customers, and make our results more robust to model misspecification with respect to any time-varying factors that are correlated with observable characteristics.

We perform the propensity score estimation and matching for each adoption cohort separately. Specifically, we define the pre-adoption period separately for each cohort and measure pre-adoption variables (e.g., monthly average spend) using all purchase data up to the month of adoption (Gu and Kannan 2021). For example, when identifying matched non-adopters for customers who adopt in July 2019, we measure the pre-adoption variables for both adopters and non-adopters using the data up to June 30, 2019, and estimate the propensity score model for the adoption cohort in July 2019. We repeat this process for each cohort and estimate twelve different propensity score models corresponding to each monthly adoption cohort. We compute propensity scores with a logistic regression model and the variables included are demographics (e.g., gender, age, and household income) and pre-adoption purchase variables (i.e. average monthly spend, number of unique orders, unique brands, and unique categories). With the estimated propensity scores, we use our CS estimator to estimate the ATT using both IPW and PSM methods. The propensity score model specification and detailed results from the IPW and PSM methods are shown in Web Appendix E.4. We find that our conclusions remain the same.

8.2.3 Alternative Control Groups

While we do our best to account for differences in observable characteristics between adopters and non-adopters in §8.2.2, it may be that there are certain time-specific unobserved factors that only affect adopters or would-be adopters, or disproportionately affect them more than non-adopters, thus potentially making non-adopters an unsuitable control group. We conduct an additional robustness check, leveraging the fact that we have multiple cohorts of consumers who adopted online shopping at different times. Following Narang and Shankar (2019) and Manchanda et al. (2015), we consider an alternative specification where later adopter cohorts serve as control groups for earlier adopter cohorts. Since all of these cohorts adopt online shopping at some point, the differences in any time-specific unobservables (that correlate with factors that drive the decision of whether a consumer chooses to adopt online shopping or not) should be minimized across these different adoption cohorts, at least relative to non-adopters. The results from this alternative CS estimator are shown in Web Appendix §E.5. Overall, we see that the conclusions remain similar to those from our main

specification, i.e., that consumers become more offline price-sensitive after adopting online shopping.

9 Implications for Retailer Pricing and Profitability

So far, we have established that when consumers begin to shop online, their price sensitivity in the offline channel increases. We now examine how the retailer should modify its offline pricing strategy in response to these customer-level changes. In particular, given the firm’s current level of online adoption, how much *offline* profit can be gained by properly accounting for the change in price elasticity relative to a scenario where the firm ignores this effect? To quantify the profit implications, we conduct counterfactual analyses that compare offline profits under pricing policies that incorporate the online adoption effect vs. those that do not. In §9.1, we first outline how a *naive* retailer who ignores the online adoption effect would (incorrectly) estimate the offline price elasticities. Next, in §9.2, we characterize the profit-maximizing prices that would be set under the true demand model (accounting for the online adoption effect) and under the naive demand model (ignoring the online adoption effect) for two pricing strategies: uniform pricing and personalized pricing. In §9.3, we describe how we compute the profits under four potential counterfactual pricing strategies and quantify the profit implications of accounting for the online adoption effect. We also mention some caveats of our counterfactual results.

9.1 Naive demand model without adoption effect

First, we characterize how a naive retailer would estimate consumers’ offline price sensitivities. In this case, we assume that the retailer uses a demand model that does not account for online adoption effects.

Following notation of the demand model in Equation (7) in §6, we specify the mean utility for consumer i choosing brand j at purchase occasion t in this case as follows:

$$\tilde{\psi}_{ijt} = \tilde{\alpha}_0 \text{Price}_{jt} + \tilde{\alpha}_1 \mathcal{I}\{\text{BuyLastMonth}_{ijt}\} + \tilde{\beta}_1 \text{CF.Price}_{jt} + \tilde{\delta}_{ij} \quad \forall j \in \{1, \dots, J\} \quad (20)$$

Here, $\tilde{\alpha}_0$ is the *naive* estimate of the price sensitivity parameter. $\tilde{\alpha}_1$ and $\tilde{\beta}_1$ are coefficients for the state dependence variable and price control function, respectively, and $\tilde{\delta}_{ij}$ denotes customer-brand fixed effects. The corresponding choice probability for consumer i choosing brand j on purchase occasion t is then given by $\tilde{P}_{r_{ijt}} = \frac{\exp(\tilde{\psi}_{ijt})}{1 + \sum_{j'=1}^J \exp(\tilde{\psi}_{ij't})}$. We follow the estimation procedure described in §6.3 and report the parameter estimates in Table A20 in Web Appendix F. Compared to the parameter estimates in Table 6, we find that the estimated price coefficient $\tilde{\alpha}_0$ from the naive model reflects a weighted average of price sensitivities for both adopters and non-adopters. This naive estimate serves as a key input for computing the counterfactual profit-maximizing prices that the retailer would set if they ignored the effect of online adoption.

9.2 Optimal Offline Price Characterization Under Counterfactual Scenarios

We now characterize the profit-maximizing offline prices for a given month, under two pricing strategies: (1) Uniform pricing, where all consumers who visit an offline store during a particular time period see the same price for a given brand, and (2) Personalized pricing, where each consumer may potentially receive a different price vector depending on their demographics, prior purchase behavior, and under our demand model, their

online shopping status (whether they have adopted online shopping and how much of their cumulative spend is on the online channel). In practice, the personalized pricing strategy would need to be implemented using targeted coupons (Rossi et al. 1996). Personalized pricing is being increasingly adopted by firms in retail settings and has been the focus of recent research in marketing (Dubé and Misra 2023; Smith et al. 2023; Jain et al. 2024). Therefore the impact of the online adoption effect on both uniform and personalized pricing is of interest for managers.

Let \mathcal{M}_k be a generic demand model, where the subscript k denotes the model used. Specifically, \mathcal{M}_N denotes the Naive model defined in Equation (20), whereas \mathcal{M}_O refers to *Our* model in Equation (7). We now characterize the optimal offline pricing for a generic demand model \mathcal{M}_k and then derive the profit-maximizing price vectors for both the uniform and personalized pricing strategies.

Let N be the market size, which is the number of offline shoppers who make at least one offline store visit during the month. Since we focus on monthly profit, we drop the month index (t) for notational simplicity. Let $\mathbf{p} \in \mathcal{R}^{J \times 1}$ denote the price vector, with p_j being the price of brand j . We use the notation p_j for price here (instead of Price_j) since price is now a decision variable rather than an observable. Under the naive model \mathcal{M}_N , the mean utility for consumer i choosing brand j based on Equation (20) can be written as:

$$\psi_{ij}(\mathbf{p}; \mathcal{M}_N) = \tilde{\alpha}_0 p_j + \tilde{\alpha}_1 \mathcal{I}\{\text{BuyLastMonth}_{ij}\} + \tilde{\beta}_1 \text{CF_Price}_j + \tilde{\delta}_{ij}$$

In contrast, the mean utility of our demand model \mathcal{M}_O based on Equation (7) can be written as:

$$\begin{aligned} \psi_{ij}(\mathbf{p}; \mathcal{M}_O) = & \alpha_0 p_j + \alpha_1 \text{cumPercOnlineSpend}_i + \alpha_2 p_j \times \text{cumPercOnlineSpend}_i \\ & + \alpha_3 \mathcal{I}\{\text{BuyLastMonth}_{ij}\} + \lambda_1 \text{CF_Price}_j + \lambda_2 \text{CF_Price_cumPercOnlineSpend}_{ij} + \delta_{ij} \end{aligned}$$

9.2.1 Uniform Pricing

Under uniform pricing, the retailer maximizes the expected profit per customer, defined as:

$$R(\mathbf{p}; \mathcal{M}_k) = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^J (p_j - m_j) \times \text{Pr}_{ij}(\mathbf{p}; \mathcal{M}_k) = \frac{1}{N} \sum_{i=1}^N R_i(\mathbf{p}; \mathcal{M}_k) \quad (21)$$

where m_j is the cost of brand j . $\text{Pr}_{ij}(\mathbf{p}; \mathcal{M}_k) = \frac{\exp(\psi_{ij}(\mathbf{p}; \mathcal{M}_k))}{1 + \sum_{j'=1}^J \exp(\psi_{ij'}(\mathbf{p}; \mathcal{M}_k))}$ refers to the choice probability of consumer i for brand j given price vector \mathbf{p} and demand model \mathcal{M}_k , and $R_i(\mathbf{p}; \mathcal{M}_k)$ represents customer i 's profit contribution. By taking the derivative of $R(\mathbf{p}; \mathcal{M}_k)$ with respect to each brand's price p_j , we characterize the optimal uniform pricing condition under a demand model \mathcal{M}_k :

Definition 1. Profit-Maximizing Uniform Price under Model \mathcal{M}_k : Let $\alpha_i^{\mathcal{M}_k}$ denote the price sensitivity estimate for each customer i under model \mathcal{M}_k . Then the optimal uniform price vector $\mathbf{p}_* = (p_{*,1}, \dots, p_{*,J})'$

satisfies the following system of equations:

$$p_{*,j} - m_j = c_j(\mathbf{p}_*; \mathcal{M}_k) + \sum_{i=1}^N w_{ij}(\mathbf{p}_*; \mathcal{M}_k) R_i(\mathbf{p}_*; \mathcal{M}_k), \quad (22)$$

where $c_j(\mathbf{p}_*; \mathcal{M}_k) = -\sum_{i=1}^N \frac{Pr_{ij}(\mathbf{p}_*; \mathcal{M}_k)}{\sum_{i'=1}^N \alpha_{i'}^{\mathcal{M}_k} Pr_{i'j}(\mathbf{p}_*; \mathcal{M}_k)}$ and $w_{ij}(\mathbf{p}_*; \mathcal{M}_k) = \frac{\alpha_i^{\mathcal{M}_k} Pr_{ij}(\mathbf{p}_*; \mathcal{M}_k)}{\sum_{i'=1}^N \alpha_{i'}^{\mathcal{M}_k} Pr_{i'j}(\mathbf{p}_*; \mathcal{M}_k)}$. Further, when we use the naive model, $\alpha_i^{\mathcal{M}_N} = \tilde{\alpha}_0$ and when we use our model, the $\alpha_i^{\mathcal{M}_O} = \alpha_0 + \alpha_2 \times \text{cumPercOnlineSpend}_i$.

This formulation gives us J equations corresponding to J unknown prices. We can numerically solve for the optimal price vectors based on this system of J equations for a given demand model \mathcal{M}_k . See Web Appendix §F.2 for detailed proofs and derivations.

We denote the profit-maximizing uniform prices solution for a given demand model \mathcal{M}_k as $\mathbf{p}_*^{U, \mathcal{M}_k}$, and $k \in \{N, O\}$. Specifically, $\mathbf{p}_*^{U, \mathcal{M}_N}$ denotes the profit-maximizing uniform prices under the naive model \mathcal{M}_N and $\mathbf{p}_*^{U, \mathcal{M}_O}$ denotes the profit-maximizing uniform prices under our model \mathcal{M}_O .

9.2.2 Personalized Pricing

We now consider a personalized pricing strategy where the firm can tailor prices to each customer based on their price elasticity through targeted coupons and email campaigns. Personalized pricing is now commonly used by firms in retail settings and has been the focus of recent research in marketing (Rossi et al. 1996; Smith et al. 2023; Jain et al. 2024).

Here, the retailer's objective is to maximize the profit for each customer i :

$$R_i(\mathbf{p}^i; \mathcal{M}_k) = \sum_{j=1}^J (p_j^i - m_j) \times Pr_{ij}(\mathbf{p}^i; \mathcal{M}_k), \quad (23)$$

where $\mathbf{p}^i \in \mathcal{R}^{J \times 1}$ is the personalized price vector offered to customer i . As before, let $Pr_{ij}(\mathbf{p}^i; \mathcal{M}_k) = \frac{\exp(\psi_{ij}(\mathbf{p}^i; \mathcal{M}_k))}{1 + \sum_{j'=1}^J \exp(\psi_{ij'}(\mathbf{p}^i; \mathcal{M}_k))}$ denote the probability that customer i chooses brand j under model \mathcal{M}_k given price \mathbf{p}^i . Following Jain et al. (2024), we show that there exists a unique globally optimal revenue and price vector characterized by a fixed-point equation and derive the optimal price vector as follows.

Definition 2. Profit-Maximizing Personalized Price under Model \mathcal{M}_k : The optimal personalized price vector under model \mathcal{M}_k for any customer i , $\mathbf{p}_*^{i, \mathcal{M}_k} := \arg \max_{\mathbf{p}^i \in \mathcal{R}_{\geq 0}^{J \times 1}} R_i = R_i(\mathbf{p}^i; \mathcal{M}_k)$ satisfies:

$$p_{*,j}^i - m_j = -\frac{1}{\alpha_i^{\mathcal{M}_k}} + R_i, \quad (24)$$

where $p_{*,j}^i$ is the optimal price for brand j for customer i , $\alpha_i^{\mathcal{M}_k}$ is the price sensitivity estimate of customer i .

Further, $R_i(\mathbf{p}_*^i; \mathcal{M}_k)$ is the solution of the fixed point equation:

$$R_i(\mathbf{p}_*^i; \mathcal{M}_k) = -\frac{1}{\alpha_i^{\mathcal{M}_k}} \sum_{j=1}^J \exp(-1 + \alpha_i^{\mathcal{M}_k} \cdot m_j + v_{ij}(\mathcal{M}_k)) \exp(\alpha_i^{\mathcal{M}_k} \cdot R_i(\mathbf{p}_*^i; \mathcal{M}_k)), \quad (25)$$

where $v_{ij}(\mathcal{M}_k)$ represents the sum of all remaining terms in the utility for customer i and brand j under model \mathcal{M}_k that do not include price.

Notice that Equation (25) has a unique solution since the left-hand side is increasing and starts from zero, and the right-hand side is positive at $R_i(\mathbf{p}_*^i; \mathcal{M}_k) = 0$ and decreasing. Following Jain et al. (2024), we use a binary search algorithm to obtain the optimal $R_i(\mathbf{p}_*^i; \mathcal{M}_k)$ for each individual consumer i and then calculate her optimal price vector $\mathbf{p}_*^{i, \mathcal{M}_k}$. The detailed proofs for personalized pricing definitions are shown in Web Appendix §F.3. Finally, we denote the profit-maximizing personalized prices for each customer i under the naive and our model as $\mathbf{p}_*^{i, \mathcal{M}_N}$ and $\mathbf{p}_*^{i, \mathcal{M}_O}$, respectively.

9.3 Profit Evaluation under Counterfactual Scenarios

We now consider four counterfactual scenarios that allow for different pricing strategies (uniform vs. personalized pricing) and whether the retailer accounts for the online adoption effect (naive vs. our model). Each scenario is characterized by its input parameters, including the individual price sensitivity parameter α_i and the mean utility function $\psi_{ij}(\mathbf{p}; \mathcal{M}_k)$ as defined in §9.2. Specifically, we consider four counterfactual scenarios, where the firm sets profit-maximizing prices:

- Uniform Price using the Naive Model, denoted by $\mathbf{p}_*^{U, \mathcal{M}_N}$.
- Uniform Price using Our Model, denoted by $\mathbf{p}_*^{U, \mathcal{M}_O}$.
- Personalized Price under the Naive Model, denoted by $\mathbf{p}_*^{i, \mathcal{M}_N}$ for customer i .
- Personalized Price under Our Model, denoted by $\mathbf{p}_*^{i, \mathcal{M}_O}$ for customer i .

The counterfactual analysis consists of two steps: (1) Optimal price calculation and (2) Profit evaluation. In the optimal price calculation step, we numerically solve for the optimal uniform and personalized price vectors under both our model and the naive model, as described in §9.2.1 and §9.2.2. Next, in the profit evaluation step, we take the optimal price from Step 1 and evaluate the counterfactual profit using Our model \mathcal{M}_O (which we treat as the true model that accounts for the online adoption effect). This gives us the counterfactual profits for all four scenarios described above.

Next, we define how much the firm would gain if it uses our model instead of the naive model and engages in uniform pricing, as follows:

$$\Delta \text{Gain from Uniform Pricing (\%)} = \frac{R(\mathbf{p}_*^{U, \mathcal{M}_O}; \mathcal{M}_O) - R(\mathbf{p}_*^{U, \mathcal{M}_N}; \mathcal{M}_O)}{R(\mathbf{p}_*^{U, \mathcal{M}_N}; \mathcal{M}_O)} \quad (26)$$

Similarly, we can define the gains from using our model instead of the naive model for the personalized

pricing case:

$$\Delta \text{Gain from Personalized Pricing (\%)} = \frac{\sum_{i=1}^N R_i(\mathbf{p}_*^{i, \mathcal{M}_O}; \mathcal{M}_O) - \sum_{i=1}^N R_i(\mathbf{p}_*^{i, \mathcal{M}_N}; \mathcal{M}_O)}{\sum_{i=1}^N R_i(\mathbf{p}_*^{i, \mathcal{M}_N}; \mathcal{M}_O)} \quad (27)$$

Finally, we simulate the four counterfactual scenarios using data from June 2021. We focus on the last month of the observational period to provide a clear interpretation of the firm’s *monthly* incremental profit and to avoid any time-specific variations across months that could complicate the interpretation. Table A21 in Web Appendix F.4 summarizes the sample sizes for each category included in this counterfactual study (i.e., customers defined in §3.2 with a purchase occasion in June 2021).

We now discuss the results of our counterfactual analysis. Under uniform pricing, we find that using our model (accounts for the online adoption effect) to optimize prices, increases monthly profit by 1.17% compared to pricing using the naive model. Further, under personalized pricing, using our model to optimize prices increases monthly profit by 4.1% compared to pricing using a naive model. Overall, these results suggest that the retailer can benefit from accounting for the effect of online adoption on consumers’ offline price sensitivity when optimizing their offline pricing decisions. Further, the magnitude of these gains is non-trivial, economically meaningful and consistent with the earlier literature on personalization (Rossi et al. 1996; Yoganarasimhan et al. 2023; Rafieian and Yoganarasimhan 2023).

Overall, our findings highlight an important yet overlooked managerial implication for multichannel retailers: retailers need to incorporate online adoption effects into offline pricing strategies, and doing so can improve retailers’ profitability in the offline channel, regardless of whether pricing is uniform or personalized. Further, the magnitude of these gains is economically meaningful. As retailers continue to expand their multichannel operations, adjusting for this effect in offline pricing becomes increasingly important.

Nevertheless, our counterfactual results should be interpreted carefully, with the appropriate caveats. First, it is possible that consumers’ likelihood of shopping offline changes under the counterfactual pricing strategy. However, consistent with the earlier literature studying brand choice within channels, (Danaher et al. 2003; Chu et al. 2008), we do not model the channel choice decision (Valentini et al. 2011), and this can potentially bias our counterfactual results. Second, we abstract away from retailer-level competition, and we do not model consumers’ choices between different retailers and how changes to offline prices may affect these choices (Bell et al. 1998). Again, this is outside of the scope of our data. Finally, our counterfactual policy estimates are based on model-based estimates rather than based on off-policy IPW evaluation (such as Smith et al. (2023)). This is because there is insufficient overlap in price distributions between monopolistic profit-maximizing prices and observed prices in the data. Nevertheless, in line with model-based evaluation similar to Rossi et al. (1996), these counterfactual analyses provide important insights into the potential gains from accounting for the effect of online adoption on offline pricing. We hope that future research can build on our findings and make further progress on these issues.

10 Conclusions

The rapid growth of e-commerce has fundamentally reshaped consumer behavior, but its spillover effects on offline shopping dynamics remain understudied. In this paper, we investigate how the adoption of online shopping influences consumers' offline price sensitivity, utilizing transaction-level data from a multichannel pet supplies retailer in Brazil. We find that consumers who adopt online shopping become more price-sensitive in their offline purchases. The relative increase in offline price elasticity, defined as the ATT relative to the pre-adoption average price elasticity of the treated group, is quite heterogeneous across categories, with a 72.7% and a 34.7% increase for dog hygiene and cat hygiene categories, and a smaller increase of 8.4% for dog food. We find no effect on cat food, presumably because it is hard to switch brands easily in this category.

From a substantive standpoint, our results contribute to the literature on price elasticity by identifying online adoption as a novel determinant of offline price sensitivity. For practitioners, our findings have significant implications on retailer offline pricing and profitability, emphasizing the need for multichannel retailers to account for the online adoption effect (i.e., heightened offline price sensitivity) in both uniform and personalized offline pricing decisions. Counterfactual simulations demonstrate that accounting for cross-channel spillovers can boost offline profits by $\approx 1 - 4\%$, depending on whether the retailer has the flexibility to personalize prices.

Finally, our paper opens many avenues for future research. First, future research could explore whether these effects generalize to other markets (e.g., non-discretionary goods or regions with lower e-commerce penetration) and investigate mediating factors, such as the role of mobile price-checking apps or subscription models. Further, while our paper documents one aspect of consumer behavior (price sensitivity), multi-channel shopping can induce other spillover effects from one channel to another. For instance, product categories purchased offline may change after adopting online shopping (Huyghe et al. 2017), and there may be cross-media effects between channels (Joo et al. 2014; Du et al. 2019). Future research can investigate other such spillover effects and their effect on cross-channel purchases. Ultimately, as retail continues to evolve toward omnichannel integration, understanding these interdependencies will be critical for both academics and firms aiming to thrive in a digitally transformed landscape.

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Web Appendices

A Appendix to Setting and Data

A.1 Details of Dataset Construction

A.1.1 Selection of Brands and Stock Keeping Units (SKUs)

For each product category (i.e., dry dog food, dry cat food, dog hygiene and cat hygiene), we focus on a single pack size that accounts for the largest sales revenue and offers sufficient brand representation. Our goal is to study consumer brand choice and price elasticity, so consistent with previous brand choice literature (Allenby and Rossi 1998; Kim et al. 2002; Chintagunta et al. 2005; Dubé et al. 2010) we focus on a market (i.e., single most popular pack size within each category) that initially (as of January 1st, 2019 - June 30th, 2019) features at least three brands. We exclude any market with fewer than three brands or with one brand contributing more than 60% of total sales. Applying these criteria yields the top one selling pack sizes for each category during the observation period: 15KG adult daily dry dog food, 10.1KG adult daily dry cat food, and an 80cm \times 60cm dog hygiene mat containing 30 pieces.

However, we observe high market concentration for certain cat hygiene pack sizes. The 12KG, 4KG, and 3KG sizes are among the top-selling segments (e.g., ranked 1st, 3rd, and 4th in offline sales). However, each has less than three brands, and a single brand contributes over 60% of sales revenue (85%, 63%, and 88%, respectively), making these pack sizes unsuitable for brand choice analysis. Furthermore, the excluded pack sizes differ significantly in sand types, compositions, and functional characteristics, limiting their substitutability in the consumer’s mind. For example, 3KG pack sizes SKUs are primarily made from cereal- and vegetable-based materials that are eco-friendly, bio-degenerate, lightweight, and prone to scattering, whereas 4KG and 12KG pack sizes consist of granulated smectite clay, which is heavy, non-biodegradable and derived from mine materials. Hence, these pack sizes cater to distinct functional needs and consumer preferences.¹⁰ The differences in product attributes and target consumer preferences complicate defining a cohesive market that includes these pack sizes. In addition, even if 4KG and 12KG pack sizes are grouped into a single market, the top brand still accounts for 77% of the sales, leaving little room for brand choice analysis.

Consequently, we focus on silica cat sand in the 1.6KG, 1.8KG, and 2.0KG, which together account for 29% of the store’s cat sand sales. Among these, the 1.8KG size is the second largest in the offline cat sand sales. Despite slight variations in pack sizes across brands, all three pack sizes offer the same sand category (i.e., silica), and we observe significant overlap in consumer purchases. Specifically, among customers who purchased the 1.8KG size at least once during the sample period, 28% also purchased the 1.6KG pack size, and 20% also purchased the 2.0KG pack size during the observation period, indicating a clear overlap of consumer preferences in this segment.

After defining the market with the top one selling pack size for each category, we rank brands by offline

¹⁰For a similar reason, we exclude the 10KG pack size, which ranks 6th and sells sands with pine and wood.

sales in descending order and include those that collectively account for at least 80% of the sales, following earlier literature (Gordon et al. 2013). The remaining brands are grouped into a single ‘Other Brand’ for each product category, ensuring broad market coverage.

A.1.2 Price and Cost Index Calculations

We construct brand-level price indices for each category by aggregating SKU-level price data from *offline* transactions (Gordon et al. 2013; Hitsch et al. 2021). First, we construct a store-SKU-month level price matrix from the available transactions data. To begin with, this price matrix could contain both outliers and missing values. Any observed price that is more than four times higher than or less than one-quarter of the median price for each SKU (across all store-month observations) is treated as an outlier and labeled as missing, following Hitsch et al. (2021). This process filters out unreasonable prices before imputing any missing values of store-SKU-month price (when there is no sale or there is an outlier). For these missing prices, we use the highest observed price from the previous three months for the same SKU at the same store to impute the missing value (Gordon et al. 2013). Finally, we exclude SKUs for a particular store and week if we have never observed them being sold in that store previously.

Next, we aggregate SKUs to create brand-level price indices by converting all SKU prices to a per-unit basis for comparable units. All product categories (e.g., dry food and cat sands) are measured by price per kilogram (KG) except for hygienic mats, which are measured by price per piece. Following the approach of Hitsch et al. (2021), the brand price for brand j at store s in month t , denoted as BrandPrice_{jst} , is calculated as the weighted average price per unit across all SKUs in that brand in the defined market. The weights are based on each SKU’s share of offline sales within the brand at that store over the full 30-month data period.

$$\text{Brand_Price}_{jst} = \sum_{k \in C_{js}} w_{jsk} \times \text{SKU_Price}_{jstk}, \quad (\text{A1})$$

where the weight of SKU k is $w_{jsk} = \frac{\text{Store_Sales}_{jsk}}{\sum_{k' \in C_{js}} \text{Store_Sales}_{jsk'}}$, and Store_Sales_{jsk} is the total offline sales of SKU k for brand j at store s from January 1, 2019 to June 30, 2021. C_{js} represents the set of SKUs for brand j available at store s , and SKU_Price_{jstk} is the price of SKU k for brand j sold in store s during month t , as recorded in the store-SKU-month price matrix.

We then apply a similar approach to construct a store-SKU-month level cost matrix based on wholesale cost data, and aggregate SKU-level costs to create brand-level cost indices that correspond to each price index. These cost indices serve as the instrument for addressing price endogeneity, as discussed in Section §6. Finally, we use Brazil’s Extended National Consumer Index (IPCA) to obtain inflation-adjusted prices and costs (Brazil Institute of Geography and Statistics (IBGE) 2024), with January 2019, the first month of observation, as the base period.

A.1.3 Supplementary material for Selection of Customers

Figure A1 illustrates three examples of adopters defined in §3.2, including adopters whose first online purchase in any category during August 2019, April 2020, and June 2020, respectively. Table A1 presents the sample sizes for each adoption cohort and each category.

Figure A1: Staggered Adoption Cohorts of Online Shopping (12 Adoption Cohorts from July 2019 to June 2020)

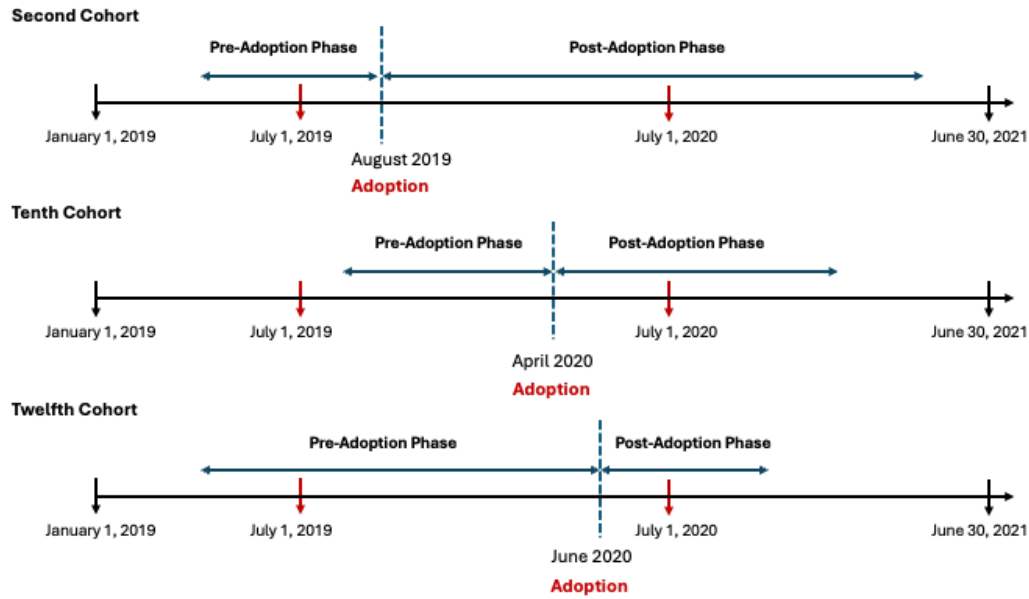


Table A1: Adopters Sample Size by Adoption Time - By Product Category

Adoption Month	Dry Dog Food	Dry Cat Food	Dog Hygiene	Cat Hygiene
2019-07	85	53	52	36
2019-08	111	46	71	41
2019-09	100	34	96	44
2019-10	110	42	82	47
2019-11	174	51	143	67
2019-12	144	78	120	58
2020-01	138	57	107	47
2020-02	143	52	106	55
2020-03	334	160	382	190
2020-04	438	208	442	241
2020-05	357	143	353	209
2020-06	276	113	260	157
Total	2410	1037	2214	1192

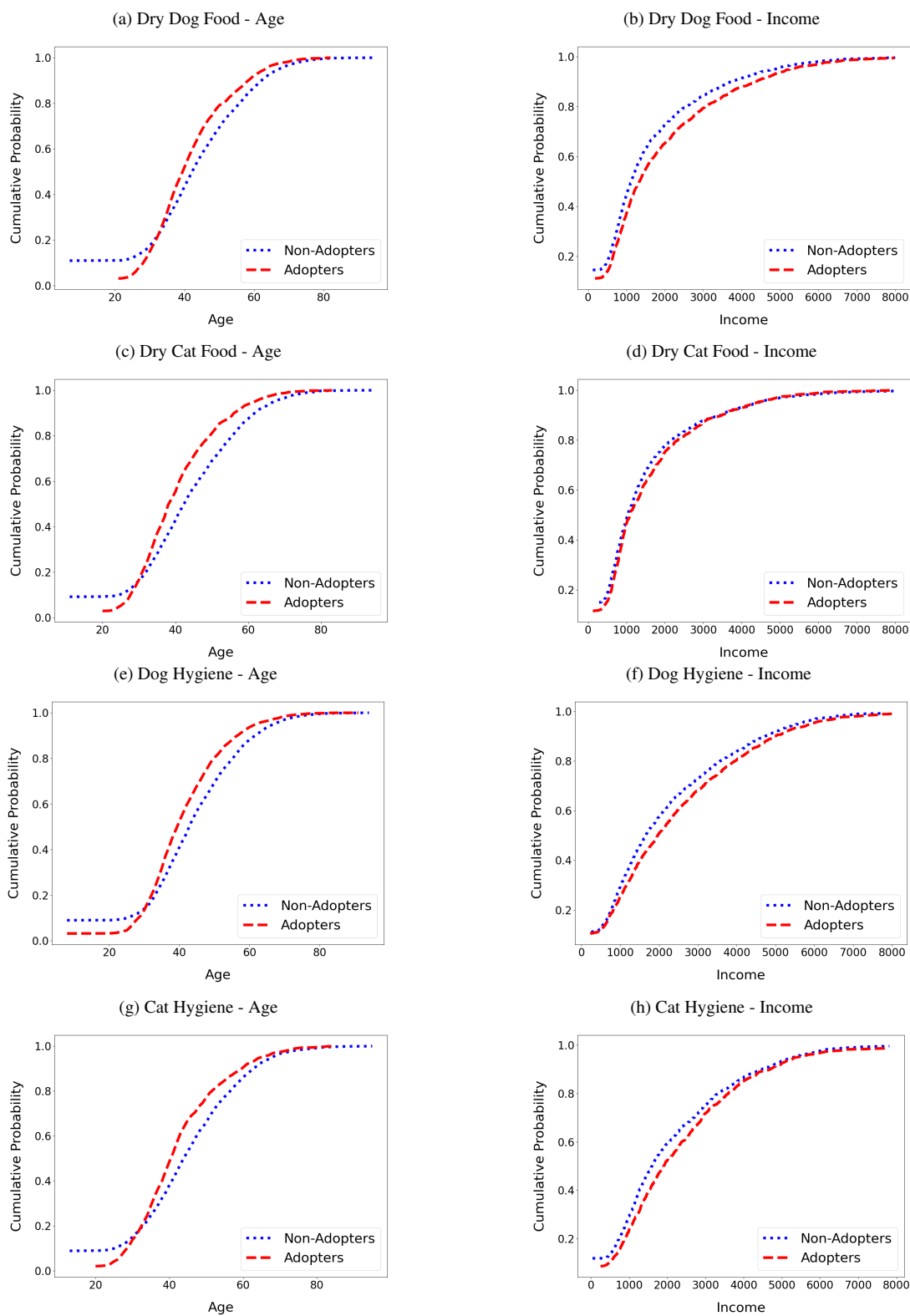
A.2 Summary Statistics for Customer Demographics

We summarize the customer demographics for each product category. Table A2 presents the gender distribution for the different product categories amongst adopters and non-adopters. In all categories, adopters exhibit a higher proportion of women compared to non-adopters. For example, in the dry dog food category, 48% of adopters are female, whereas only 32.6% of non-adopters are female. Figure A2 shows the cumulative age and income distributions for adopters and non adopters. The height of the leftmost point on each curve represents the fraction of customers with missing age or income information. Across all categories, adopters tend to be younger compared to non-adopters. In terms of monthly household income, adopters generally exhibit higher incomes relative to compared to non-adopters.

Table A2: Gender by Product Categories

Gender	Dry Dog Food		Dry Cat Food		Dog Hygiene		Cat Hygiene	
	Adopters	Non-Adopters	Adopters	Non-Adopters	Adopters	Non-Adopters	Adopters	Non-Adopters
Female	0.480	0.326	0.570	0.418	0.601	0.470	0.602	0.462
Male	0.398	0.522	0.286	0.417	0.285	0.379	0.279	0.387
NaN	0.122	0.152	0.144	0.165	0.113	0.152	0.118	0.151
Total	1	1	1	1	1	1	1	1

Figure A2: Customer demographics of adopters and non-adopters of product category - age and monthly household income



B Appendix to Descriptive Analysis

B.1 Supplementary Result: Percentile Price Paid

As a robustness check for the results in §4, Table A3 presents the within-customer changes in the percentile of prices paid by adopters relative to non-adopters, controlling for customer and year-month fixed effects. The percentile of price paid is calculated by first constructing the empirical price distribution for each month, based on all transactions in that month involving SKUs from the focal category. Each transaction price is then ranked relative to this monthly price distribution to obtain its percentile.

Table A3: Two-Way Fixed Effects Model Estimates - Percentile.Price.Paid

Dependent Variable:	Percentile.Price.Paid			
Model:	Dry Dog Food (1)	Dry Cat Food (2)	Dog Hygiene (3)	Cat Hygiene (4)
<i>Variables</i>				
$\mathcal{I}\{\text{Adopter}_i\} \times \mathcal{I}\{t \geq T_i^{\text{adopt}}\}$	-1.437** (0.4141)	-3.318** (0.9727)	-0.9569 (0.6351)	-4.104*** (1.100)
<i>Fixed-effects</i>				
Customer	Yes	Yes	Yes	Yes
YearMonth	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	99,233	27,623	40,183	42,596
R ²	0.86731	0.61190	0.50654	0.42914
Within R ²	0.00057	0.00135	0.00010	0.00126
<i>Clustered (Customer & YearMonth) standard-errors in parentheses</i>				
<i>Signif. Codes: ***: 0.001, **: 0.01, *: 0.05</i>				

C Appendix to Model and Estimation

C.1 Proof for Minorization-Maximization Estimation

Proof of Theorem. We show that $S(\boldsymbol{\theta}; \boldsymbol{\theta}^{(k)})$ is a minorization of $\mathcal{L}(\boldsymbol{\theta}^{(k)})$ at $\boldsymbol{\theta}^{(k)}$ for maximization by checking the following requirements.

- $S(\boldsymbol{\theta}; \boldsymbol{\theta}^{(k)}) \leq \mathcal{L}(\boldsymbol{\theta}^{(k)})$. For a given consumer i at purchase occasion t , we denote the choice probability of consumer i toward brand j during purchase occasion t as Pr_{ijt} :

$$l(\boldsymbol{\psi}_{it}; \mathbf{y}_{it}) = \prod_j \left(\frac{\exp(\psi_{ijt})}{1 + \sum_{j=1}^J \exp(U_{ijt})} \right)^{y_{ijt}} \quad (\text{A2})$$

$$h_j(\boldsymbol{\psi}_{it}; \mathbf{y}_{it}) = \frac{\partial \log l(\boldsymbol{\psi}_{it}; \mathbf{y}_{it})}{\partial \psi_{ijt}} = y_{ijt} - Pr_{ijt} \quad (\text{A3})$$

$$h_{jk}(\boldsymbol{\psi}_{it}; \mathbf{y}_{it}) = \frac{\partial^2 \log l(\boldsymbol{\psi}_{it}; \mathbf{y}_{it})}{\partial \psi_{ijt} \partial \psi_{ikt}} = \begin{cases} -Pr_{ijt}(1 - Pr_{ikt}), & j = k, \\ Pr_{ijt}Pr_{ikt}, & j \neq k. \end{cases} \quad (\text{A4})$$

The Taylor expansion of $\log l(\boldsymbol{\psi}_{it})$ at $\tilde{\boldsymbol{\psi}}_{it}$ is

$$\log l(\boldsymbol{\psi}_{it}; \mathbf{y}_{it}) = \log l(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it}) + (\boldsymbol{\psi}_{it} - \tilde{\boldsymbol{\psi}}_{it})' \nabla \log l(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it}) + \frac{1}{2} (\boldsymbol{\psi}_{it} - \tilde{\boldsymbol{\psi}}_{it})' \nabla^2 \log l(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) (\boldsymbol{\psi}_{it} - \tilde{\boldsymbol{\psi}}_{it}).$$

Where

$$\begin{aligned} \nabla^2 \log l(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) &= \begin{bmatrix} h_{11}(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) & h_{12}(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) & \cdots & h_{1J}(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) \\ h_{21}(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) & h_{22}(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) & \cdots & h_{2J}(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) \\ \vdots & \vdots & \ddots & \vdots \\ h_{J1}(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) & h_{J2}(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) & \cdots & h_{JJ}(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) \end{bmatrix} \\ &= \begin{bmatrix} -Pr_{i1t}(1 - Pr_{i1t}) & Pr_{i1t}Pr_{i2t} & \cdots & Pr_{i1t}Pr_{iJt} \\ Pr_{i2t}Pr_{i1t} & -Pr_{i2t}(1 - Pr_{i2t}) & \cdots & Pr_{i2t}Pr_{iJt} \\ \vdots & \vdots & \ddots & \vdots \\ Pr_{iJt}Pr_{i1t} & Pr_{iJt}Pr_{i2t} & \cdots & -Pr_{iJt}(1 - Pr_{iJt}) \end{bmatrix} \end{aligned}$$

We have $\nabla^2 \log l(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) \geq -I$, i.e., $\nabla^2 \log l(\boldsymbol{\psi}_{it}^*; \mathbf{y}_{it}) + I$ is semi-positive definite.

Therefore,

$$\begin{aligned}
\log l(\boldsymbol{\psi}_{it}; \mathbf{y}_{it}) &\geq \log l(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it}) + (\boldsymbol{\psi}_{it} - \tilde{\boldsymbol{\psi}}_{it})' \nabla \log l(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it}) - \frac{1}{2} (\boldsymbol{\psi}_{it} - \tilde{\boldsymbol{\psi}}_{it})' (\boldsymbol{\psi}_{it} - \tilde{\boldsymbol{\psi}}_{it}) \\
&= \log l(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it}) - (\tilde{\boldsymbol{\psi}}_{it} - \boldsymbol{\psi}_{it})' \nabla \log l(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it}) - \frac{1}{2} (\tilde{\boldsymbol{\psi}}_{it} - \boldsymbol{\psi}_{it})' (\tilde{\boldsymbol{\psi}}_{it} - \boldsymbol{\psi}_{it}) \\
&= \log l(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it}) - \sum_j h_j(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it}) (\tilde{\psi}_{ijt} - \psi_{ijt}) - \frac{1}{2} \sum_j (\tilde{\psi}_{ijt} - \psi_{ijt})^2 \\
&= \log l(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it}) + \frac{1}{2} \sum_j h_j(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it})^2 - \frac{1}{2} \sum_j (\tilde{\psi}_{ijt} + h_j(\tilde{\boldsymbol{\psi}}_{it}; \mathbf{y}_{it}) - \psi_{ijt})^2. \quad (\text{A5})
\end{aligned}$$

For now, we derive a lower bound for $\log l(\boldsymbol{\psi}_{it}; \mathbf{y}_{it})$, the log-likelihood for each choice instance (i.e., customer-month purchase occasion). The log-likelihood function is its sum over user i and time t . We substitute $\boldsymbol{\psi}_{it}$ and $\tilde{\boldsymbol{\psi}}_{it}$ with the nominal utility $\mathbf{x}'_{ijt}\boldsymbol{\alpha} + \delta_{ij}$ and nominal utility evaluated at the current estimates in the k_{th} iteration $\mathbf{x}'_{ijt}\boldsymbol{\alpha}^{(k)} + \delta_{ij}^{(k)}$, respectively. Summing over all customers over all periods, the log-likelihood $\mathcal{L}(\boldsymbol{\theta})$ satisfies

$$\begin{aligned}
\mathcal{L}(\boldsymbol{\theta}) &\geq \mathcal{L}(\boldsymbol{\theta}^{(k)}) + \frac{1}{2} \sum_{i,j,t} h_j(\tilde{\boldsymbol{\psi}}_{it}^{(k)}; \mathbf{y}_{it})^2 - \frac{1}{2} \sum_{i,j,t} (\tilde{\psi}_{ijt}^{(k)} + h_j(\tilde{\boldsymbol{\psi}}_{it}^{(k)}; \mathbf{y}_{it}) - \mathbf{x}'_{ijt}\boldsymbol{\alpha} - \delta_{ij})^2 \\
&= \mathcal{L}(\boldsymbol{\theta}^{(k)}) + \frac{1}{2} \sum_{i,j,t} h_j(\mathbf{x}'_{ijt}\boldsymbol{\alpha}^{(k)} + \delta_{ij}^{(k)}; \mathbf{y}_{it})^2 \\
&\quad - \frac{1}{2} \sum_{i,j,t} (\mathbf{x}'_{ijt}\boldsymbol{\alpha}^{(k)} + \delta_{ij}^{(k)} + h_j(\mathbf{x}'_{ijt}\boldsymbol{\alpha}^{(k)} + \delta_{ij}^{(k)}; \mathbf{y}_{it}) - \mathbf{x}'_{ijt}\boldsymbol{\alpha} - \delta_{ij})^2
\end{aligned} \quad (\text{A6})$$

where the RHS of the above inequality is $S(\boldsymbol{\theta}; \boldsymbol{\theta}^{(k)})$.

- $S(\boldsymbol{\theta}^{(k)}; \boldsymbol{\theta}^{(k)}) = \mathcal{L}(\boldsymbol{\theta}^{(k)})$.

By definition,

$$\begin{aligned}
S(\boldsymbol{\theta}^{(k)}; \boldsymbol{\theta}^{(k)}) &= \mathcal{L}(\boldsymbol{\theta}^{(k)}) + \frac{1}{2} \sum_{i,j,t} h_j(\tilde{\boldsymbol{\psi}}_{it}^{(k)}; \mathbf{y}_{it})^2 - \frac{1}{2} \sum_{i,j,t} (\tilde{\psi}_{ijt}^{(k)} + h_j(\tilde{\boldsymbol{\psi}}_{it}^{(k)}; \mathbf{y}_{it}) - \mathbf{x}'_{ijt}\boldsymbol{\alpha}^{(k)} - \delta_{ij}^{(k)})^2 \\
&= \mathcal{L}(\boldsymbol{\theta}^{(k)}) + \frac{1}{2} \sum_{i,j,t} h_j(\tilde{\boldsymbol{\psi}}_{it}^{(k)}; \mathbf{y}_{it})^2 - \frac{1}{2} \sum_{i,j,t} h_j(\tilde{\boldsymbol{\psi}}_{it}^{(k)}; \mathbf{y}_{it})^2 \\
&= \mathcal{L}(\boldsymbol{\theta}^{(k)})
\end{aligned} \quad (\text{A7})$$

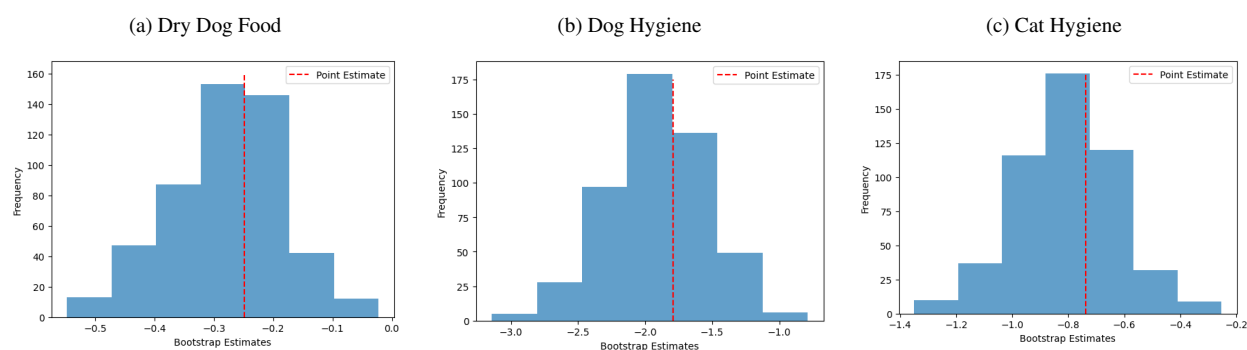
D Appendix to Difference-in-Differences (DID) Analysis

D.1 Bootstrapped distribution of ATT estimates

Since the customer-month level price elasticities are estimates and not directly observed from data, to obtain correct standard errors, we perform a customer-level block bootstrap with 500 replications. This includes (1) resampling customers with replacement; (2) re-estimating the demand model on each bootstrapped dataset; (3) using the estimated coefficients from that replication to compute price elasticities at the customer-month level (e.g., insignificant demand model coefficients evaluated based on the analytical standard error in the current bootstrap iteration is set to 0); (4) estimating the ATT via staggered DID based on these elasticity estimates; (5) plotting and calculating the bootstrapped standard errors for the ATT and demand parameters.

Figure A3 presents the bootstrapped distribution of ATT estimates — that is, the effect of online adoption on price elasticity, based on 500 replications.

Figure A3: Bootstrapped distribution of Overall ATT Estimates based on 500 replications with the point estimate Table 8.



D.2 Two-Way Fixed Effects (TWFE) Estimates

Table A4 provides TWFE estimates of online adoption on offline price elasticities estimated from the main demand model described in Equation (7).

Table A4: Two-Way Fixed Effects Estimate - Offline Price Elasticity

Dependent Variable: Model:	Offline Elasticity		
	Dry Dog Food (1)	Dog Hygiene (2)	Cat Hygiene (3)
<i>Variables</i>			
PostOnlineAdoption	-0.2145** (0.0697)	-1.544*** (0.3308)	-0.6368*** (0.1605)
<i>Fixed-effects</i>			
CUSTOMER.ID	Yes	Yes	Yes
MONTHSTART	Yes	Yes	Yes
<i>Fit statistics</i>			
Observations	136,411	78,253	55,410
R ²	0.91126	0.76395	0.82317
Within R ²	0.24557	0.32091	0.32582

Bootstrapped standard-errors in parentheses via 500 replications

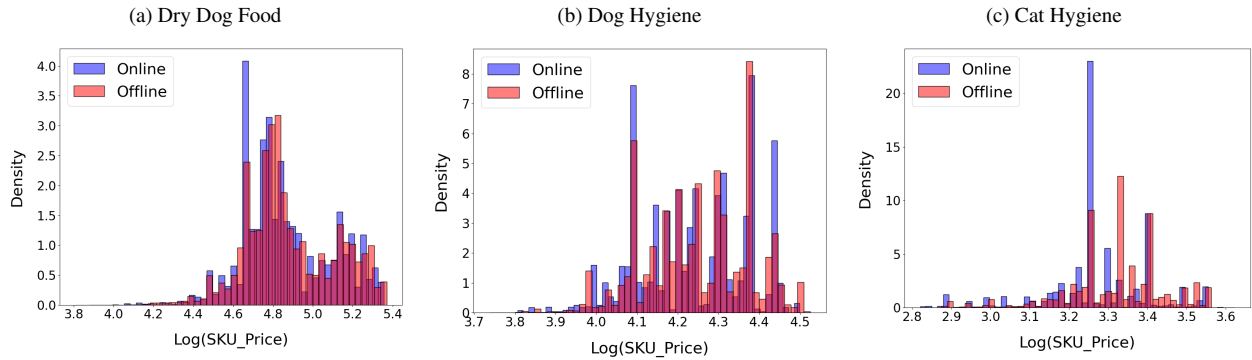
Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

E Appendix to Generalizability and Robustness Checks

E.1 Detailed Results for the Role of Price Difference Across Channels

Figure A4 presents the probability density function (PDF) of offline and online prices (in natural log scale) for each category at the SKU-Store-Date level. While there is substantial price variation across SKUs, the central tendency, skewness, and dispersion of distributions for online and offline channels are quite similar. The substantial overlap in online and offline price distribution suggests no systematic difference between online and offline prices overall.

Figure A4: Distribution of Online and Offline Prices (Natural Log Scale) over SKU-Date - PDF



To formally compare offline and online prices, we construct a sample at the SKU-Channel-Store-Date level. Each row represents the price of a specific SKU on a particular channel (online or offline) at a specific

store and date. We then estimate the following model:

$$\ln(\text{SKU_Price}_{kstc}) = \beta \times \text{isOnline}_c + \text{SKU}_k + \text{Date}_t + \epsilon_{kstc} \quad (\text{A8})$$

where the SKU_Price_{kstc} refers to the selling price of SKU k of store s at time t . The index c refers to the online or offline channel. Here, a negative β would indicate that, on average, online prices are lower than offline prices for the same SKU on the same date, and vice versa. Table A5 presents the regression result for comparing online and offline prices in Equation (A8) for three categories. Table A6 presents the regression results of decomposing SKU price variation for each category. Column (1) of Table A6 only includes the channel indicator, *isOnline*, and Column (2) includes both channel indicator and SKU fixed effects. Comparing the R-squared values in Table A6, we see that the price variation across channels is far smaller than the price variation across SKUs.

Table A5: Descriptive Analysis - Online vs. Offline Prices at the SKU-Date Level

Dependent Variable:	ln(SKU_Price)		
Model:	Dry Dog Food (1)	Dog Hygiene (2)	Cat Hygiene (3)
<i>Variables</i>			
isOnline	-0.0322*** (0.0022)	-0.0361* (0.0135)	-0.0607*** (0.0087)
<i>Fixed-effects</i>			
SKU	Yes	Yes	Yes
DATE	Yes	Yes	Yes
<i>Fit statistics</i>			
Observations	554,191	328,323	244,723
R ²	0.95202	0.98493	0.91763
Within R ²	0.01819	0.00912	0.02441
<i>Clustered (SKU & DATE) standard-errors in parentheses</i>			
<i>Signif. Codes: ***: 0.001, **: 0.01, *: 0.05</i>			

Table A6: Descriptive Analysis - SKU-Level Price Variation Decomposition. Compared to column 1, column 2 controls for SKU fixed effects, indicating that after holding SKU constant, the price variation attributable to the online-offline channel is very small.

Dependent Variable:			ln(SKU_Price)			
	Dry Dog Food		Dog Hygiene		Cat Hygiene	
Model:	(1)	(2)	(1)	(2)	(1)	(2)
<i>Variables</i>						
Constant	4.941***		4.043***		3.224***	
	(0.0439)		(0.1420)		(0.0769)	
isOnline	0.0659*	-0.0313***	-0.0123	-0.0382*	-0.0726*	-0.0594***
	(0.0287)	(0.0025)	(0.0269)	(0.0135)	(0.0304)	(0.0087)
<i>Fixed-effects</i>						
SKU		Yes		Yes		Yes
<i>Fit statistics</i>						
Observations	554,191	554,191	328,323	328,323	244,723	244,723
R ²	0.00398	0.89516	1.61×10^{-5}	0.95365	0.00309	0.84228
Within R ²		0.00797		0.00333		0.01235

Clustered (SKU & DATE) standard-errors in parentheses

Signif. Codes: ***: 0.001, **: 0.01, *: 0.05

E.2 Detailed Results for Alternative Demand Model Specifications

E.2.1 Results for Alternate Demand Specification with Binary Adoption Variable

The alternative demand model specification is given by:

$$\begin{aligned} \psi_{ijt} = & \alpha_0 \text{Price}_{jt} + \alpha_1 \text{Post_OnlineAdoption}_{it} + \alpha_2 \text{Price}_{jt} \times \text{Post_OnlineAdoption}_{it} \\ & + \alpha_3 \mathcal{I}\{\text{BuyLastMonth}_{ijt}\} + \beta_1 \text{CF_Price}_{jt} + \beta_2 \text{CF_Price_Post_OnlineAdoption}_{ijt} + \delta_{ij} \quad \forall j \in \{1, \dots, J\} \end{aligned} \quad (\text{A9})$$

To address the endogeneity of Price_{jt} and its interaction with $\text{Post_OnlineAdoption}_{it}$, we use the control function approach with instruments Cost_{jt} and $\text{Cost}_{jt} \times \text{Post_OnlineAdoption}_{it}$, and construct two control function terms, CF_Price_{jt} and $\text{CF_Price_Post_OnlineAdoption}_{ijt}$. We then estimate the above demand model and compute the average elasticity at the customer-month level for each product category following the same steps as before. The results are shown below.

Table A7 presents the estimates of the demand model. The standard errors for the demand parameters are based on the customer-level block bootstrap with 500 replications.

Table A8 presents the ATT estimates of offline price elasticity from CS Estimator based on the demand model in Equation (A9). The standard errors for the ATT estimates and the demand model parameters are based on the customer-level block bootstrap with 500 replications; See Figure A5.

Table A7: Coefficient Estimates of Demand Model in Equation (A9) - Binary Online Adoption Variable

<i>Variables</i>	Dry Dog Food	Dry Cat Food	Dog Hygiene	Cat Hygiene
Price	-0.3031*** (0.0171)	-0.1577*** (0.0202)	-1.0463*** (0.1123)	-0.2038*** (0.0199)
Post_OnlineAdoption	-0.0834 (0.1341)	-0.2483 (0.398)	2.1377*** (0.3641)	1.8521*** (0.3083)
Price * Post_OnlineAdoption	-0.034** (0.0123)	-0.004 (0.0337)	-1.0684*** (0.159)	-0.1432*** (0.0218)
BuyLastMonth	0.1561*** (0.0273)	-0.4977*** (0.0451)	-0.1802*** (0.0283)	0.3216*** (0.0295)
CF_Price	0.042 (0.0237)	0.039 (0.0268)	0.0572 (0.1622)	0.2797*** (0.0261)
CF_Price.Post_OnlineAdoption	0.0521** (0.0175)	0.038 (0.0343)	0.6873** (0.2196)	0.0609* (0.0256)
Customer_Brand_FE	Yes	Yes	Yes	Yes
Observations	136,411	45,443	78,253	55,410
Log-likelihood	-84085.187	-30700.989	-55426.656	-37292.32

Bootstrapped standard-errors in parentheses via 500 replications

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

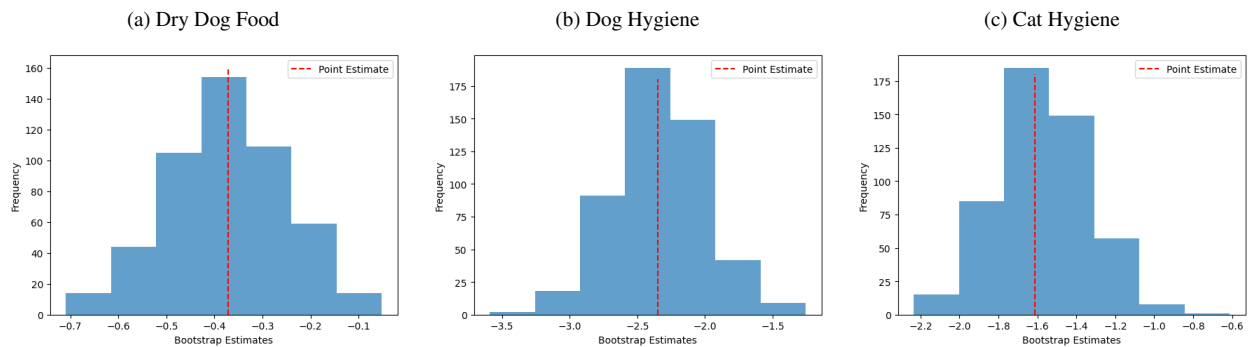
Table A8: ATT of Online Adoption on Offline Price Elasticity (CS Estimator) - Binary Adoption Variable

Dependent Variable:	Offline Price Elasticity		
	Dry Dog Food (1)	Dog Hygiene (2)	Cat Hygiene (3)
Model:			
CS	-0.3711** (0.1224)	-2.3513*** (0.3407)	-1.614*** (0.2353)
Observations	136,411	78,253	55,410

Bootstrapped standard-errors in parentheses via 500 replications

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

Figure A5: Bootstrapped distribution of Overall ATT Estimates based on 500 replications with the point estimate from Table A8.



E.2.2 Results for Alternate Demand Model Controlling for State Dependence due to Online Adoption

The alternative utility specification is given by:

$$\begin{aligned}\psi_{ijt} = & \alpha_0 \text{Price}_{jt} + \alpha_1 \text{cumPercOnlineSpend}_{it} + \alpha_2 \text{Price}_{jt} \times \text{cumPercOnlineSpend}_{it} \\ & + \alpha_3 \mathcal{I}\{\text{BuyLastMonth}_{ijt}\} + \alpha_4 \mathcal{I}\{\text{BuyLastMonth}_{ijt}\} \times \text{cumPercOnlineSpend}_{it} \\ & + \beta_1 \text{CF_Price}_{jt} + \beta_2 \text{CF_Price_cumPercOnlineSpend}_{ijt} + \delta_{ij} \quad \forall j \in \{1, \dots, J\}\end{aligned}\quad (\text{A10})$$

We estimate this model and again obtain the customer-month level average elasticity for each category as before. Table A9 presents the estimates of the demand model. The standard errors for the demand model parameters are based on the customer-level block bootstrap with 500 replications.

Table A9: Coefficient Estimates of Demand Model in Equation (A10) - Controlling for Interaction between Online Spend and Brand Loyalty

<i>Variables</i>	Dry Dog Food	Dry Cat Food	Dog Hygiene	Cat Hygiene
Price	-0.3157*** (0.0159)	-0.1618*** (0.0172)	-1.2497*** (0.1142)	-0.2209*** (0.0186)
cumPercOnlineSpend	-0.3383 (0.4039)	-1.5509 (1.2012)	8.6901*** (1.8059)	3.4632*** (0.9725)
Price * cumPercOnlineSpend	-0.1092** (0.0366)	0.0227 (0.0994)	-4.1435*** (0.7895)	-0.284*** (0.0661)
BuyLastMonth	0.1592*** (0.0278)	-0.5249*** (0.047)	-0.1894*** (0.0294)	0.3242*** (0.0306)
CF_Price	0.0521* (0.0219)	0.048 (0.0245)	0.1936 (0.1673)	0.2803*** (0.0247)
CF_Price_cumPercOnlineSpend	0.0212 (0.0719)	-0.0595 (0.1169)	3.6167*** (0.9742)	0.3009** (0.0915)
BuyLastMonth * cumPercOnlineSpend	-0.3059 (0.2918)	1.0106** (0.3853)	0.2991 (0.3022)	0.0133 (0.2768)
Customer_Brand_FE	Yes	Yes	Yes	Yes
Observations	136,411	45,443	78,253	55,410
Log-likelihood	-84209.589	-30693.216	-55438.072	-37327.394

Bootstrapped standard-errors in parentheses via 500 replications

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

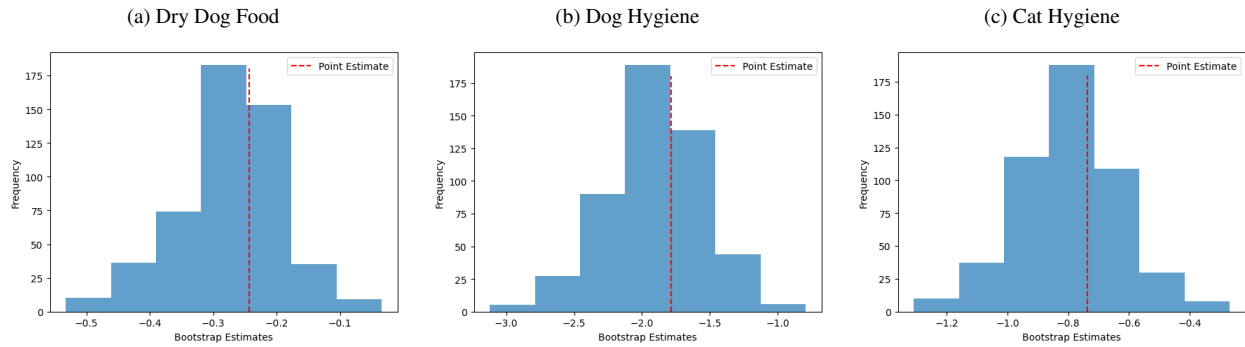
Table A10 presents the ATT estimates of offline price elasticity from the CS estimator based on the demand model in Equation (A10). The standard errors for the ATT estimates are based on the customer-level block bootstrap with 500 replications; See Figure A6.

Table A10: ATT of Online Adoption on Offline Price Elasticity (CS Estimator) - Controlling for State Dependence due to Online Adoption

Dependent Variable: Model:	Offline Price Elasticity		
	Dry Dog Food (1)	Dog Hygiene (2)	Cat Hygiene (3)
CS	-0.2429** (0.0797)	-1.7868*** (0.3544)	-0.7382*** (0.1668)
Observations	136,411	78,253	55,410

Bootstrapped standard-errors in parentheses via 500 replications
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

Figure A6: Bootstrapped distribution of Overall ATT Estimates based on 500 replications with the point estimate from Table A10.



E.3 Detailed results for testing the Parallel Pre-Trend Assumption

A fundamental condition for the credibility of the estimates presented in §7.3 is the parallel trends assumption. We assess it with an event-study figure following Callaway and Sant’Anna (2021). Figure A7 plots the point estimates and 95% bootstrapped confidence interval for each pre- and post-treatment period, and shows that all pre-treatment coefficients are insignificant from zero. We do not exhibit discernible pre-trends. In addition, the p-values from the Wald tests of the pre-trend assumption are greater than 5% level of significance in each category. We therefore conclude that the parallel trend assumption is reasonably satisfied throughout the analysis.

E.4 Detailed Results for Matching, IPW Approaches to Control for Selection on Observables

For each of the adoption cohorts under a product category, we estimate the following propensity score model:

$$\text{PropensityScore}_i = f(X_i^T \theta), \quad (\text{A11})$$

where $f(\cdot)$ is the logit link function where $f(X_i^T \theta) = \frac{1}{1 + \exp(-X_i^T \theta)}$. $\theta \in \mathcal{R}^{M \times 1}$ is a column vector of coefficients. $X_i \in \mathcal{R}^{M \times 1}$ is a column vector with M covariates of customer i , including demographics (e.g., gender, age and income) and the pre-adoption monthly purchase average measured using data up to the adoption period of the adoption cohort. For example, for customers who adopted in July 2019, we measure the pre-adoption variables for both adopters and non-adopters using the data up to June 30, 2019, and estimate the propensity score model for the adoption cohort in July 2019.

Tables A11 and A12 present the propensity score model estimates for the twelve adoption cohorts in the dry dog food, dog hygiene and cat hygiene categories, respectively. Similarly, Tables A13 and A14 provide results for dog hygiene and Tables A15 and A16 provide results for cat hygiene. We find that certain observables, such as being female, having a high household income, and having a high pre-adoption monthly spend, increase the likelihood of adopting online shopping.

Using the predicted propensity score, we apply the R package *MatchIt* to conduct one-to-one nearest neighbor matching with replacement for each adoption cohort Stuart et al. (2011). For each product category, we first estimate the ATT using the CS based on the matched sample, with results shown in Web Appendix §E.4 Table A17. Second, we estimate the ATT using the CS estimator with the inverse propensity score weighting (IPW) method, with results shown in Table A18. These findings are consistent with our main results, demonstrating that consumers become more price sensitive offline after adopting online shopping. Detailed results are below.

Figure A7: Parallel Pre-Trends Evaluation and Dynamic Effect during the Pre- and Post-Adoption Periods

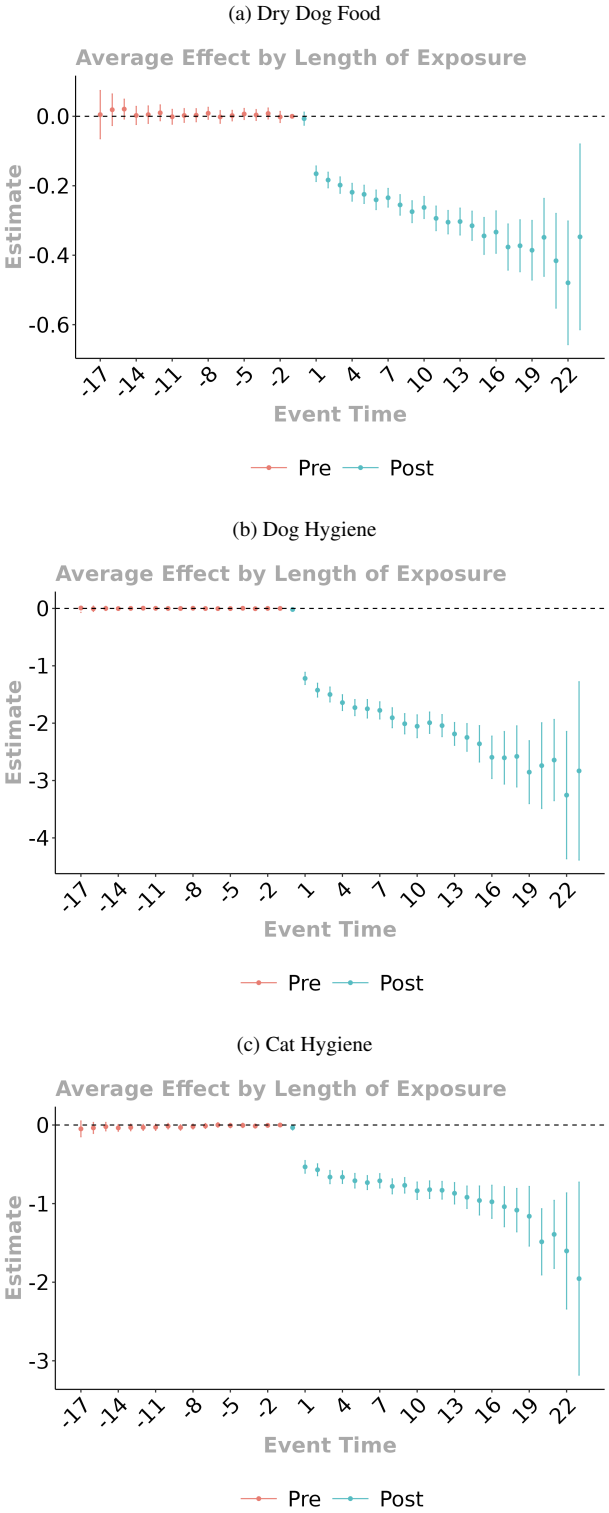


Table A11: Propensity Score Logit Model for Dry Dog Food - Adopter Cohorts between 2019-07 and 2019-12 vs. Non-Adopters

	<i>Dependent variable:</i>					
	Adopter					
	2019-07	2019-08	2019-09	2019-10	2019-11	2019-12
Gender_Female	0.288*** (0.078)	0.382*** (0.072)	0.671*** (0.078)	1.030*** (0.073)	0.655*** (0.062)	0.283*** (0.064)
Gender_NoInformation	-0.944*** (0.155)	-0.177 (0.111)	0.354*** (0.104)	-0.114 (0.122)	0.367*** (0.083)	-0.180 (0.095)
Age \geq 50	-0.599*** (0.166)	-0.874*** (0.175)	-0.354* (0.160)	-0.777*** (0.153)	-1.654*** (0.111)	-1.523*** (0.112)
Age30_40	0.140 (0.161)	0.667*** (0.163)	0.410** (0.156)	-0.047 (0.149)	-0.269** (0.100)	-0.677*** (0.106)
Age40_50	-0.077 (0.163)	0.134 (0.165)	-0.143 (0.161)	0.204 (0.145)	-1.012*** (0.106)	-0.891*** (0.107)
Age_NoInformation	-1.798*** (0.272)	-1.188*** (0.226)	-1.496*** (0.245)	-2.105*** (0.267)	-2.036*** (0.163)	-2.120*** (0.174)
Income<1000	-0.417*** (0.105)	-0.302** (0.102)	0.038 (0.093)	-0.047 (0.088)	-0.256*** (0.075)	-0.314*** (0.081)
Income \geq 2000	0.223* (0.095)	0.762*** (0.088)	0.149 (0.093)	0.043 (0.088)	0.197** (0.073)	0.181* (0.077)
Income_NoInformation	-0.063 (0.120)	0.060 (0.116)	-0.272* (0.125)	-0.651*** (0.129)	-0.363*** (0.097)	-0.075 (0.097)
AvgSpendPerMonth	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.0002** (0.0001)	0.0001 (0.0001)
AvgQuantitiesPerMonth	-0.095*** (0.025)	-0.108*** (0.024)	-0.058** (0.018)	0.010* (0.005)	-0.008 (0.008)	0.010 (0.009)
AvgUniqueItemsPerMonth	-0.221* (0.105)	0.231* (0.090)	-0.507*** (0.105)	-0.444*** (0.090)	-0.235** (0.074)	-0.166* (0.079)
AvgUniqueOrdersPerMonth	0.200** (0.075)	-0.653*** (0.102)	-0.195* (0.084)	-0.555*** (0.102)	0.048 (0.062)	-0.027 (0.071)
AvgUniqueBrandsPerMonth	0.298* (0.145)	0.148 (0.133)	0.662*** (0.151)	0.778*** (0.150)	0.188 (0.121)	0.365** (0.126)
AvgUniqueSubcategoriesPerMonth	0.132 (0.164)	-0.079 (0.175)	1.189*** (0.181)	-0.129 (0.183)	0.243 (0.164)	-0.306 (0.162)
AvgUniqueCategoriesPerMonth	0.046 (0.142)	0.019 (0.159)	-1.069*** (0.160)	0.172 (0.158)	0.222 (0.144)	0.522*** (0.155)
Intercept	-2.549*** (0.178)	-2.504*** (0.180)	-2.851*** (0.177)	-2.536*** (0.165)	-1.535*** (0.117)	-1.311*** (0.118)
Observations	8,023	8,049	8,038	8,048	8,112	8,082
Log Likelihood	-2,586.499	-2,989.092	-2,841.850	-2,963.057	-4,088.072	-3,736.394
Akaike Inf. Crit.	5,206.999	6,012.184	5,717.700	5,960.113	8,210.144	7,506.788

Note:

*p<0.05; **p<0.01; ***p<0.001

Table A12: Propensity Score Logit Model for Dry Dog Food - Adopter Cohorts between 2020-01 and 2020-06 vs. Non-Adopters

	<i>Dependent variable:</i>					
	Adopter					
	2020-01	2020-02	2020-03	2020-04	2020-05	2020-06
Gender_Female	0.677*** (0.065)	0.473*** (0.064)	0.386*** (0.048)	0.658*** (0.044)	0.736*** (0.047)	0.475*** (0.050)
Gender_NoInformation	-0.223* (0.105)	-0.331** (0.103)	-0.098 (0.070)	0.176** (0.062)	0.134* (0.067)	-0.072 (0.074)
Age \geq 50	-0.957*** (0.118)	-0.966*** (0.129)	-1.150*** (0.093)	-1.143*** (0.084)	-0.923*** (0.090)	-1.165*** (0.097)
Age30_40	-0.378** (0.115)	-0.105 (0.122)	-0.313*** (0.090)	-0.403*** (0.083)	-0.060 (0.088)	-0.113 (0.092)
Age40_50	-0.682*** (0.118)	-0.363** (0.124)	-0.698*** (0.091)	-0.602*** (0.083)	-0.602*** (0.090)	-0.742*** (0.095)
Age_NoInformation	-2.308*** (0.215)	-2.600*** (0.256)	-1.399*** (0.119)	-2.220*** (0.127)	-2.318*** (0.151)	-1.690*** (0.136)
Income<1000	-0.211* (0.082)	0.212** (0.080)	0.051 (0.061)	-0.223*** (0.055)	-0.061 (0.058)	-0.470*** (0.060)
Income \geq 2000	0.115 (0.079)	0.163* (0.083)	0.481*** (0.058)	0.335*** (0.053)	0.210*** (0.057)	-0.334*** (0.061)
Income_NoInformation	-0.093 (0.100)	-0.149 (0.106)	-0.159* (0.078)	-0.450*** (0.071)	-0.215** (0.074)	-0.570*** (0.078)
AvgSpendPerMonth	0.0004*** (0.0001)	0.0002 (0.0001)	0.0005*** (0.0001)	0.0004*** (0.0001)	0.001*** (0.0001)	0.0001 (0.0001)
AvgQuantitiesPerMonth	-0.051** (0.016)	-0.008 (0.012)	-0.011 (0.008)	0.009 (0.007)	-0.013 (0.008)	-0.034** (0.011)
AvgUniqueItemsPerMonth	-0.285** (0.095)	-0.557*** (0.099)	-0.156* (0.061)	-0.076 (0.054)	-0.028 (0.069)	-0.029 (0.076)
AvgUniqueOrdersPerMonth	-0.223** (0.085)	-0.409*** (0.084)	-0.558*** (0.066)	-0.455*** (0.062)	-0.786*** (0.075)	-0.267*** (0.065)
AvgUniqueBrandsPerMonth	0.553*** (0.143)	1.275*** (0.150)	0.286** (0.103)	-0.134 (0.086)	0.413*** (0.113)	0.547*** (0.119)
AvgUniqueSubcategoriesPerMonth	0.015 (0.184)	-0.410* (0.181)	0.467*** (0.126)	0.088 (0.126)	-0.627*** (0.155)	-0.426* (0.166)
AvgUniqueCategoriesPerMonth	0.243 (0.165)	0.279 (0.178)	0.025 (0.121)	0.836*** (0.122)	0.907*** (0.139)	0.374* (0.149)
Intercept	-1.852*** (0.132)	-2.011*** (0.136)	-1.158*** (0.099)	-0.870*** (0.091)	-1.039*** (0.099)	-0.715*** (0.101)
Observations	8,076	8,081	8,272	8,376	8,295	8,214
Log Likelihood	-3,577.410	-3,603.534	-6,105.810	-7,120.955	-6,365.540	-5,585.395
Akaike Inf. Crit.	7,188.819	7,241.067	12,245.620	14,275.910	12,765.080	11,204.790

Note:

*p<0.05; **p<0.01; ***p<0.001

Table A13: Propensity Score Logit Model for Dog Hygiene - Adopter Cohorts between 2019-07 and 2019-12 vs. Non-Adopters

	<i>Dependent variable:</i>					
	Adopter					
	2019-07	2019-08	2019-09	2019-10	2019-11	2019-12
Gender_Female	0.809*** (0.118)	0.697*** (0.105)	0.552*** (0.089)	0.267** (0.092)	0.436*** (0.075)	0.253** (0.080)
Gender_NoInformation	-0.169 (0.197)	0.501*** (0.145)	-0.695*** (0.164)	-0.035 (0.135)	0.076 (0.109)	0.037 (0.116)
Age \geq 50	-0.636* (0.275)	-1.062*** (0.198)	-1.063*** (0.171)	-0.713*** (0.183)	-0.771*** (0.165)	-1.237*** (0.170)
Age30_40	0.610* (0.261)	-0.246 (0.192)	-0.244 (0.164)	-0.264 (0.179)	0.077 (0.160)	-0.046 (0.159)
Age40_50	0.148 (0.264)	-0.400* (0.194)	-0.705*** (0.167)	-0.442* (0.179)	-0.103 (0.160)	-0.354* (0.161)
Age_NoInformation	-0.059 (0.303)	-1.842*** (0.302)	-2.730*** (0.358)	-1.562*** (0.266)	-0.930*** (0.208)	-2.127*** (0.277)
Income<1000	-0.354* (0.176)	-0.558*** (0.163)	-0.183 (0.124)	0.186 (0.119)	0.167 (0.099)	-0.492*** (0.117)
Income \geq 2000	0.307* (0.127)	0.345** (0.107)	-0.239* (0.101)	-0.286** (0.104)	0.074 (0.084)	-0.043 (0.087)
Income_NoInformation	0.535** (0.165)	-0.225 (0.169)	0.540*** (0.123)	-0.029 (0.143)	-0.043 (0.119)	0.009 (0.122)
AvgSpendPerMonth	0.001*** (0.0001)	0.001*** (0.0001)	0.0004** (0.0001)	0.001*** (0.0001)	0.0002 (0.0001)	0.001*** (0.0001)
AvgQuantitiesPerMonth	-0.147*** (0.036)	0.015 (0.009)	-0.148*** (0.029)	-0.029 (0.016)	-0.039** (0.013)	-0.087*** (0.020)
AvgUniqueItemsPerMonth	-0.043 (0.115)	-0.249*** (0.072)	-0.013 (0.089)	-0.145 (0.078)	-0.327*** (0.071)	-0.149 (0.092)
AvgUniqueOrdersPerMonth	-0.065 (0.091)	0.187** (0.069)	-0.684*** (0.095)	-0.455*** (0.091)	-0.149* (0.061)	-0.103 (0.092)
AvgUniqueBrandsPerMonth	0.475*** (0.141)	0.462*** (0.123)	0.448*** (0.136)	0.399** (0.123)	0.425*** (0.114)	-0.253* (0.129)
AvgUniqueSubcategoriesPerMonth	0.161 (0.167)	0.023 (0.161)	0.199 (0.169)	0.048 (0.151)	0.655*** (0.141)	1.241*** (0.178)
AvgUniqueCategoriesPerMonth	-0.463** (0.161)	-0.239 (0.156)	0.068 (0.157)	0.095 (0.146)	-0.305* (0.134)	-0.512*** (0.152)
Intercept	-3.145*** (0.296)	-2.318*** (0.223)	-1.544*** (0.196)	-1.800*** (0.205)	-1.721*** (0.186)	-1.348*** (0.182)
Observations	3,634	3,653	3,678	3,664	3,725	3,702
Log Likelihood	-1,353.099	-1,680.290	-1,967.035	-1,897.595	-2,712.319	-2,353.311
Akaike Inf. Crit.	2,740.197	3,394.581	3,968.071	3,829.189	5,458.638	4,740.623

Note:

*p<0.05; **p<0.01; ***p<0.001

Table A14: Propensity Score Logit Model for Dog Hygiene - Adopter Cohorts between 2020-01 and 2020-06 vs. Non-Adopters

	<i>Dependent variable:</i>					
	Adopter					
	2020-01	2020-02	2020-03	2020-04	2020-05	2020-06
Gender_Female	0.627*** (0.092)	0.370*** (0.086)	0.413*** (0.056)	0.582*** (0.054)	0.571*** (0.057)	0.435*** (0.063)
Gender_NoInformation	0.579*** (0.123)	0.172 (0.121)	−0.093 (0.083)	−0.333*** (0.085)	0.053 (0.084)	−0.056 (0.093)
Age \geq 50	−1.372*** (0.171)	−1.130*** (0.168)	−1.080*** (0.114)	−0.834*** (0.119)	−1.256*** (0.121)	−1.169*** (0.128)
Age30_40	−0.134 (0.157)	−0.341* (0.162)	−0.483*** (0.114)	−0.122 (0.118)	−0.318** (0.118)	−0.274* (0.123)
Age40_50	−0.802*** (0.163)	−0.800*** (0.165)	−0.964*** (0.114)	−0.261* (0.117)	−0.675*** (0.119)	−0.825*** (0.125)
Age_NoInformation	−1.945*** (0.252)	−2.592*** (0.286)	−2.108*** (0.162)	−1.115*** (0.148)	−1.837*** (0.160)	−2.046*** (0.184)
Income<1000	0.277* (0.118)	−0.157 (0.125)	−0.118 (0.081)	−0.144 (0.077)	−0.222** (0.081)	−0.182* (0.090)
Income \geq 2000	0.304** (0.100)	0.246** (0.095)	0.430*** (0.062)	0.331*** (0.060)	0.233*** (0.062)	0.263*** (0.069)
Income_NoInformation	−0.080 (0.144)	0.119 (0.134)	−0.263** (0.096)	−0.317*** (0.092)	−0.059 (0.093)	−0.137 (0.105)
AvgSpendPerMonth	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.0005*** (0.0001)
AvgQuantitiesPerMonth	−0.150*** (0.024)	−0.007 (0.007)	0.011 (0.008)	−0.046*** (0.012)	−0.009 (0.009)	−0.014 (0.009)
AvgUniqueItemsPerMonth	0.140 (0.085)	−0.345*** (0.075)	−0.139** (0.054)	0.056 (0.065)	−0.185** (0.058)	0.138* (0.070)
AvgUniqueOrdersPerMonth	−0.124 (0.084)	−0.080 (0.088)	−0.172*** (0.038)	−0.498*** (0.064)	−0.372*** (0.067)	−0.605*** (0.084)
AvgUniqueBrandsPerMonth	−0.050 (0.133)	0.436*** (0.113)	0.087 (0.091)	−0.224* (0.102)	0.242** (0.093)	−0.292* (0.116)
AvgUniqueSubcategoriesPerMonth	0.951*** (0.171)	0.664*** (0.156)	0.487*** (0.116)	0.922*** (0.126)	0.502*** (0.131)	0.919*** (0.147)
AvgUniqueCategoriesPerMonth	−0.616*** (0.154)	−0.769*** (0.160)	−0.139 (0.113)	−0.257* (0.117)	−0.264* (0.135)	−0.394** (0.139)
Intercept	−2.091*** (0.196)	−1.383*** (0.190)	−0.282* (0.125)	−0.497*** (0.134)	−0.247 (0.132)	−0.426** (0.141)
Observations	3,689	3,688	3,964	4,024	3,935	3,842
Log Likelihood	−2,067.730	−2,175.618	−4,499.026	−4,832.667	−4,400.367	−3,656.464
Akaike Inf. Crit.	4,169.460	4,385.235	9,032.052	9,699.334	8,834.733	7,346.928

Note:

*p<0.05; **p<0.01; ***p<0.001

Table A15: Propensity Score Logit Model for Cat Hygiene - Adopter Cohorts between 2019-07 and 2019-12 vs. Non-Adopters

	<i>Dependent variable:</i>					
	Adopter					
	2019-07	2019-08	2019-09	2019-10	2019-11	2019-12
Gender_Female	0.835*** (0.141)	0.450*** (0.129)	0.986*** (0.130)	0.823*** (0.131)	0.526*** (0.107)	0.364*** (0.107)
Gender_NoInformation	0.055 (0.229)	0.315 (0.179)	−0.655* (0.259)	0.164 (0.195)	0.034 (0.158)	−0.424* (0.179)
Age \geq 50	−0.024 (0.361)	−0.217 (0.353)	−0.605* (0.277)	−0.916*** (0.218)	−0.503 (0.264)	−0.764** (0.236)
Age30_40	1.468*** (0.352)	1.077** (0.345)	0.730** (0.270)	−0.334 (0.219)	1.052*** (0.254)	0.182 (0.234)
Age40_50	0.302 (0.361)	0.325 (0.349)	0.057 (0.269)	−0.929*** (0.222)	0.504* (0.255)	0.031 (0.229)
Age_NoInformation	−15.840 (380.738)	−0.103 (0.404)	−16.557 (382.142)	−17.598 (380.148)	−1.475*** (0.408)	−1.916*** (0.394)
Income<1000	0.269 (0.229)	−0.407* (0.182)	−0.334* (0.161)	−0.417* (0.199)	−0.544*** (0.153)	−0.396* (0.171)
Income \geq 2000	1.356*** (0.171)	−0.137 (0.134)	−0.495*** (0.126)	0.368** (0.130)	0.076 (0.110)	0.440*** (0.117)
Income_NoInformation	0.072 (0.281)	−0.148 (0.187)	−1.423*** (0.255)	−0.066 (0.193)	−0.364* (0.171)	−0.507* (0.200)
AvgSpendPerMonth	0.001** (0.0002)	0.001*** (0.0001)	0.001*** (0.0002)	0.002*** (0.0002)	−0.0001 (0.0001)	0.0002 (0.0002)
AvgQuantitiesPerMonth	0.018* (0.008)	−0.003 (0.008)	0.005 (0.009)	−0.076*** (0.015)	0.044*** (0.006)	0.009 (0.008)
AvgUniqueItemsPerMonth	−0.213* (0.090)	0.101 (0.053)	−0.104 (0.079)	0.241** (0.078)	−0.649*** (0.094)	−0.268** (0.082)
AvgUniqueOrdersPerMonth	−0.076 (0.109)	−0.176* (0.084)	−0.340** (0.104)	−0.804*** (0.116)	−0.962*** (0.126)	−0.716*** (0.115)
AvgUniqueBrandsPerMonth	0.116 (0.186)	−0.003 (0.117)	0.143 (0.138)	−0.528*** (0.157)	0.813*** (0.172)	−0.002 (0.159)
AvgUniqueSubcategoriesPerMonth	0.417 (0.225)	−0.514** (0.160)	−0.142 (0.206)	−0.009 (0.206)	0.608** (0.207)	−0.093 (0.193)
AvgUniqueCategoriesPerMonth	−0.786*** (0.228)	0.757*** (0.167)	0.394* (0.198)	0.798*** (0.211)	−0.209 (0.196)	1.401*** (0.194)
Intercept	−3.263*** (0.401)	−3.235*** (0.371)	−2.481*** (0.299)	−2.102*** (0.253)	−2.167*** (0.268)	−2.533*** (0.256)
Observations	2,761	2,766	2,769	2,772	2,792	2,783
Log Likelihood	−908.558	−1,079.992	−1,078.742	−1,114.206	−1,440.825	−1,336.839
Akaike Inf. Crit.	1,851.117	2,193.985	2,191.483	2,262.411	2,915.651	2,707.678

Note:

*p<0.05; **p<0.01; ***p<0.001

Table A16: Propensity Score Logit Model for Cat Hygiene - Adopter Cohorts between 2020-01 and 2020-06 vs. Non-Adopters

	<i>Dependent variable:</i>					
	Adopter					
	2020-01	2020-02	2020-03	2020-04	2020-05	2020-06
Gender_Female	0.798*** (0.131)	0.887*** (0.122)	0.490*** (0.071)	0.459*** (0.068)	0.357*** (0.068)	0.702*** (0.078)
Gender_NoInformation	0.835*** (0.164)	0.334 (0.176)	−0.072 (0.108)	0.224* (0.094)	−0.370*** (0.106)	0.232* (0.111)
Age \geq 50	−0.962*** (0.253)	−1.164*** (0.202)	−0.881*** (0.141)	−0.896*** (0.130)	−1.128*** (0.132)	−1.857*** (0.133)
Age30_40	0.505* (0.240)	−0.194 (0.195)	−0.145 (0.142)	−0.237 (0.131)	−0.319* (0.133)	−0.801*** (0.130)
Age40_50	−0.014 (0.240)	−0.816*** (0.199)	−0.727*** (0.141)	−0.629*** (0.130)	−0.890*** (0.133)	−1.147*** (0.128)
Age_NoInformation	−0.407 (0.298)	−2.189*** (0.370)	−2.352*** (0.237)	−2.549*** (0.231)	−1.864*** (0.190)	−3.821*** (0.344)
Income<1000	−0.463** (0.174)	0.008 (0.140)	−0.241* (0.104)	0.499*** (0.091)	−0.160 (0.095)	−0.097 (0.107)
Income \geq 2000	0.122 (0.124)	−0.463*** (0.123)	0.428*** (0.077)	0.465*** (0.075)	0.038 (0.074)	0.307*** (0.082)
Income_NoInformation	−0.508* (0.205)	−0.588** (0.194)	−0.516*** (0.131)	0.224* (0.108)	−0.367** (0.113)	−0.214 (0.128)
AvgSpendPerMonth	−0.002*** (0.0003)	0.0004* (0.0002)	−0.00003 (0.0001)	0.0003** (0.0001)	−0.00001 (0.0001)	−0.0002 (0.0001)
AvgQuantitiesPerMonth	0.031** (0.012)	0.012 (0.010)	0.008 (0.006)	−0.001 (0.006)	0.008 (0.006)	0.012 (0.007)
AvgUniqueItemsPerMonth	−0.673*** (0.108)	−0.410*** (0.091)	−0.090* (0.040)	−0.029 (0.038)	−0.072 (0.045)	−0.146* (0.058)
AvgUniqueOrdersPerMonth	−0.330** (0.119)	−0.696*** (0.112)	−0.214*** (0.060)	−0.482*** (0.068)	−0.512*** (0.066)	−0.174** (0.058)
AvgUniqueBrandsPerMonth	0.586** (0.192)	0.323* (0.157)	0.167 (0.085)	0.006 (0.085)	−0.135 (0.093)	0.205 (0.111)
AvgUniqueSubcategoriesPerMonth	0.745** (0.253)	0.984*** (0.169)	0.073 (0.115)	−0.027 (0.095)	0.787*** (0.128)	0.762*** (0.157)
AvgUniqueCategoriesPerMonth	0.231 (0.240)	−0.441** (0.161)	0.326** (0.117)	0.642*** (0.111)	−0.109 (0.127)	−0.721*** (0.162)
Intercept	−2.797*** (0.274)	−1.602*** (0.220)	−0.789*** (0.157)	−0.740*** (0.147)	−0.040 (0.142)	−0.024 (0.151)
Observations	2,772	2,780	2,915	2,966	2,934	2,882
Log Likelihood	−1,163.361	−1,274.134	−2,813.474	−3,215.689	−3,002.450	−2,487.669
Akaike Inf. Crit.	2,360.722	2,582.269	5,660.947	6,465.378	6,038.899	5,009.338

Note:

*p<0.05; **p<0.01; ***p<0.001

Table A17: ATT of Online Adoption on Offline Price Elasticity (CS Estimator) - Propensity Score Matching based on each adoption cohort's time of adoption

Dependent Variable: Model:	Offline Price Elasticity		
	Dry Dog Food (1)	Dog Hygiene (2)	Cat Hygiene (3)
CS	-0.2473** (0.0945)	-1.788*** (0.3678)	-0.7409*** (0.1794)
Observations	58,580	50,913	29,039

Bootstrapped standard-errors in parentheses via 500 replications
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

Table A18: ATT of Online Adoption on Offline Price Elasticity (CS Estimator) - IPW

Dependent Variable: Model:	Offline Price Elasticity		
	Dry Dog Food (1)	Dog Hygiene (2)	Cat Hygiene (3)
CS	-0.2479** (0.0945)	-1.7903*** (0.3678)	-0.7399*** (0.1793)
Observations	136,411	78,253	55,410

Bootstrapped standard-errors in parentheses via 500 replications
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

E.5 ATT Estimates - Using Not-Yet-Treated Adopters as Control Groups

Table A19 presents ATT estimates using Not-Yet-Treated adopters as the control group, as discussed in §8.2.3.

Table A19: ATT of Online Adoption on Offline Price Elasticity (CS Estimator) - Only Use Not-Yet-Treated Adopters as Comparison Units

Dependent Variable: Model:	Offline Price Elasticity		
	Dry Dog Food (1)	Dog Hygiene (2)	Cat Hygiene (3)
CS	-0.1685* (0.0814)	-1.1729*** (0.3006)	-0.5222*** (0.1533)
Observations	29,416	28,375	15,081

Bootstrapped standard-errors in parentheses via 500 replications
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

F Appendix to Counterfactual Analysis

F.1 Estimation Result for Naive Demand Model

Table A20 provides the estimates for the naive demand model described in 9.1 specified by Equation (20).

Table A20: Coefficient Estimates of the Naive Demand Model

<i>Variables</i>	Dry Dog Food	Dog Hygiene	Cat Hygiene
Price	-0.3808*** (0.0237)	-1.5921*** (0.1129)	-0.2822*** (0.0189)
BuyLastMonth	0.1581*** (0.0316)	-0.1772*** (0.0299)	0.3306*** (0.0289)
CF_Price	0.1068*** (0.0279)	0.5272** (0.1847)	0.3522*** (0.0261)
Customer_Brand_FE	Yes	Yes	Yes
Observations	136,411	78,253	55,410
Log-likelihood	-84222.285	-55490.014	-37358.772

Bootstrapped standard-errors in parentheses via 500 replications
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05*

F.2 Derivation of Profit Maximizing Uniform Offline Price

First, we derive the market-level profit maximizing uniform offline price for each brand in a given month t that t maximizes category-level offline profit. We drop the index t (month) in the following derivation for simplicity.

Let \mathcal{M}_k be a generic demand model, and the superscript k denotes the model used. Let N be the market size, which is the number of offline shoppers who make at least one store visit during the month. The expected profit per customer is:

$$R(\mathbf{p}; \mathcal{M}_k) = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^J (p_j - m_j) \times \frac{\exp(\psi_{ij}(\mathbf{p}; \mathcal{M}_k))}{1 + \sum_{j'=1}^J \exp(\psi_{ij'}(\mathbf{p}; \mathcal{M}_k))} = \frac{1}{N} \sum_{i=1}^N R_i(\mathbf{p}; \mathcal{M}_k) \quad (\text{A12})$$

where i indexes consumers, j indexes brands, m_j is the cost for brand j , and $R_i(\mathbf{p}; \mathcal{M}_k)$ is customer i 's profit contribution given price vector \mathbf{p} . Customer i 's offline price sensitivity is $\alpha_i = \alpha_i^{\mathcal{M}_k}$ under model \mathcal{M}_k . For notational convenience, we use α_i for the following derivation. Let $e_{ij} = \exp(\psi_{ij}(\mathbf{p}; \mathcal{M}_k))$ and $\Lambda_i(e) = \sum_{j \in [J]} e_{ij}$ under model \mathcal{M}_k . In our context, $k \in N, O$ and we are interested in the uniform pricing under two demand models, including a naive model (\mathcal{M}_N) defined in Equation (20) and our model (\mathcal{M}_O) defined in Equation (7).

To find the profit-maximizing price vector \mathbf{p}_* , we take the first derivative of $R(\mathbf{p}; \mathcal{M}_k)$ with respect to each brand j 's price p_j . The resulting first-order condition (FOC) for the price of brand j , p_j , is:

$$\frac{\partial R(\mathbf{p}; \mathcal{M}_k)}{\partial p_j} = \frac{1}{N} \sum_{i=1}^N \frac{\alpha_i e_{ij}}{1 + \Lambda_i(e)} \left[\frac{1}{\alpha_i} + (p_j - m_j) - \frac{\sum_{l=1}^J (p_l - m_l) e_{il}}{1 + \Lambda_i(e)} \right] \quad (\text{A13})$$

The profit-maximizing price vector \mathbf{p}_* satisfies the following condition for each brand j :

$$\frac{1}{N} \sum_{i=1}^N \frac{\alpha_i e_{ij}}{1 + \Lambda_i(e)} \left[\frac{1}{\alpha_i} + (p_{*,j} - m_j) - \frac{\sum_{l=1}^J (p_{*,l} - m_l) e_{il}}{1 + \Lambda_i(e)} \right] = 0 \quad (\text{A14})$$

Let $Pr_{ij}(\mathbf{p}; \mathcal{M}_k) = \frac{e_{ij}}{1 + \Lambda_i(e)}$ be the choice probability of consumer i and brand j . Substituting this into the FOC for each brand j yields:

$$\begin{aligned} (p_{*,j} - m_j) \sum_{i=1}^N \alpha_i Pr_{ij}(\mathbf{p}_*; \mathcal{M}_k) &= - \sum_{j=1}^N Pr_{ij}(\mathbf{p}_*; \mathcal{M}_k) + \sum_{i=1}^N \alpha_i Pr_{ij}(\mathbf{p}_*; \mathcal{M}_k) R_i(\mathbf{p}_*; \mathcal{M}_k) \\ p_{*,j} - m_j &= - \sum_{i=1}^N \frac{Pr_{ij}(\mathbf{p}_*; \mathcal{M}_k)}{\sum_{i'=1}^N \alpha_{i'} Pr_{ij'}(\mathbf{p}_*; \mathcal{M}_k)} + \sum_{i=1}^N \frac{\alpha_i Pr_{ij}(\mathbf{p}_*; \mathcal{M}_k)}{\sum_{i'=1}^N \alpha_{i'} Pr_{ij'}(\mathbf{p}_*; \mathcal{M}_k)} \times R_i(\mathbf{p}_*; \mathcal{M}_k) \quad (\text{A15}) \\ p_{*,j} - m_j &= c_j(\mathbf{p}_*; \mathcal{M}_k) + \sum_{i=1}^N w_{ij}(\mathbf{p}_*; \mathcal{M}_k) R_i(\mathbf{p}_*; \mathcal{M}_k) \end{aligned}$$

where $c_j(\mathbf{p}_*; \mathcal{M}_k) = - \sum_{i=1}^N \frac{Pr_{ij}(\mathbf{p}_*; \mathcal{M}_k)}{\sum_{i'=1}^N \alpha_{i'} Pr_{ij'}(\mathbf{p}_*; \mathcal{M}_k)}$ and $w_{ij}(\mathbf{p}_*; \mathcal{M}_k) = \frac{\alpha_i Pr_{ij}(\mathbf{p}_*; \mathcal{M}_k)}{\sum_{i'=1}^N \alpha_{i'} Pr_{ij'}(\mathbf{p}_*; \mathcal{M}_k)}$. This formulation results in J equations corresponding to the J unknown prices to solve, with the j_{th} row equation given by Equation (22). The optimal price vector is given by $\mathbf{p}_* = \mathbf{m} + \mathbf{c}(\mathbf{p}_*) + \mathbf{W}(\mathbf{p}_*)' \mathbf{R}(\mathbf{p}_*)$. We numerically solve for the profit-maximizing price vectors based on a system of J FOC equations.

F.3 Derivation of Profit-maximizing Personalized Offline Prices

We next consider a personalized pricing strategy where the firm can tailor prices to each customer's elasticity and implement it through targeted coupons and email campaigns. The objective is to maximize each consumer i 's expected offline profit, defined as:

$$R_i(\mathbf{p}^i; \mathcal{M}_k) = \sum_{j=1}^J (p_j^i - m_j) \times \frac{\exp(\psi_{ij}(\mathbf{p}^i; \mathcal{M}_k))}{1 + \sum_{j'=1}^J \exp(\psi_{ij'}(\mathbf{p}^i; \mathcal{M}_k))} \quad (\text{A16})$$

where $\mathbf{p}^i \in R^{J \times 1}$ represents the personalized price vector for customer i . $\psi_{ij}(\mathbf{p}^i; \mathcal{M}_k)$ refers to the mean utility of a generic demand model \mathcal{M}_k . Specifically, $k \in N, O$ in our context and we are interested in the personalized pricing under two demand models, including a naive model (\mathcal{M}_N) defined in Equation (20) and our model (\mathcal{M}_O) defined in Equation (7).

The first-order condition for maximizing consumer i 's profit with respect to brand j 's price is given by:

$$\begin{aligned} p_{*,j}^i - m_j &= -\frac{1}{\alpha_i} + \frac{\sum_{l=1}^J (p_{*,l}^i - m_l) e_{il}}{1 + \Lambda_i(e)} \\ &= -\frac{1}{\alpha_i} + R_i(\mathbf{p}_*^{i, \mathcal{M}_k}; \mathcal{M}_k) \end{aligned} \quad (\text{A17})$$

Denote $R_i = R_i(\mathbf{p}_*^{i, \mathcal{M}_k}; \mathcal{M}_k)$ as customer i 's optimal profit evaluated at the profit maximizing price vector of customer i . Multiply by e_{ij} and sum over all brands $j \in [J]$:

$$\begin{aligned} \sum_{j=1}^J (p_{*,j}^i - m_j) e_{ij} &= -\sum_{j=1}^J \frac{e_{ij}}{\alpha_i} + \frac{\sum_{j=1}^J e_{ij} \left(\sum_{l=1}^J (p_{*,l}^i - m_l) e_{il} \right)}{1 + \Lambda_i(e)} \\ [1 + \Lambda_i(e)] R_i &= -\sum_{j=1}^J \frac{e_{ij}}{\alpha_i} + R_i \sum_{j=1}^J e_{ij} \\ R_i &= -\sum_{j=1}^J \frac{e_{ij}}{\alpha_i} \\ &= -\sum_{j=1}^J \frac{\exp(\alpha_i p_{*,j}^i + v_{ij})}{\alpha_i} \\ &= -\frac{1}{\alpha_i} \sum_{j=1}^J \exp(-1 + \alpha_i m_j + v_{ij}) \exp(\alpha_i R_i) \end{aligned} \quad (\text{A18})$$

where v_{ij} refers to the sum of all remaining terms that does not include price but affect the utility. Specifically, for our model \mathcal{M}_O , $v_{ij}(\mathcal{M}_O) = \alpha_1 \text{cumPercOnlineSpend}_i + \alpha_3 \mathcal{I}\{\text{BuyLastMonth}_{ij}\} + \lambda_1 \text{CF_Price}_j + \lambda_2 \text{CF_Price_cumPercOnlineSpend}_{ij} + \delta_{ij}$. For the naive model \mathcal{M}_N , $v_{ij}(\mathcal{M}_N) = \tilde{\alpha}_1 \mathcal{I}\{\text{BuyLastMonth}_{ij}\} + \tilde{\beta}_1 \text{CF_Price}_j + \tilde{\delta}_{ij}$. Here, for each individual customer i , $R_i = g(R_i)$, and this equation has a unique solution since the left-hand side is increasing and starts from zero, and the right-hand side is positive at $R_i = 0$

and decreasing. We use the binary search to obtain the optimal R_i for each individual consumer i and then calculate her profit-maximizing price vector under model \mathcal{M}_k , denoted as $\mathbf{p}_*^{i, \mathcal{M}_k}$.

F.4 Appendix to Counterfactual Scenarios

Table A21 shows the sample size for each category included in the counterfactual study (i.e., customers defined in §3.2 with a purchase occasion in June 2021).

Table A21: Sample Sizes for the Counterfactual Study - By Category

	Dry Dog Food	Dog Hygiene	Cat Hygiene	Total
Adopters	765	838	450	2425
Non-Adopters	2879	1400	1165	6314
Total	3644	2238	1615	8739

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