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Research Note

A Comparison of Within-Household Price Sensitivity Across Online and Offline Channels

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We use a unique data set to estimate the price sensitivities of households in online and offline shopping channels when the same households shop across channels. We observe households that shop interchangeably at the online and the offline stores in the same grocery chain and investigate their purchase behavior in specific product categories. Although nearly 90% of households in our sample shop both at online and offline stores, we find that, across 12 vastly different product categories, these households exhibit lower price sensitivities when they shop online than when they shop offline. Our analysis accounts for observed and unobserved household heterogeneity as well as price endogeneity. The results hold for large basket-share categories and small basket-share categories, for consumer packaged goods and nonpackaged goods, for categories that are more likely to be purchased online because of their bulkiness or heaviness, and for categories that are more likely to be purchased offline because of their “sensory” nature. Households’ price sensitivities are also closely related to demographics and inversely related to how far the households are located from the offline stores. Reasons for the lower price sensitivities in the online medium are discussed.

Key words: Price sensitivity; Internet; scanner panel data; logit demand model; endogeneity

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1. Introduction

Will the same consumers exhibit different price sensitivities when they shop online than when they shop offline? If so, are they more or less price sensitive in the Internet shopping medium than in a physical store? Because consumer price sensitivity directly affects a firm’s pricing strategy and profits, an empirical understanding of consumers’ price responses across these two different shopping media will help firms better price their products for different channels and thus earn higher profits.

Empirical findings with actual data on the effect of the Internet on price competition, price dispersion, and consumer price sensitivity are mixed, even for physically identical products such as books and CDs.¹ Bailey (1998) finds that average levels of prices for books and CDs were higher online between 1996

and 1997, implying less price competition online; Brynjolfsson and Smith (2000) find that the average prices for books and CDs were lower online in 1999, implying more price competition online than offline. Shankar et al. (2001) study how the online medium affects (a) the importance of price and (b) the value of price search in the hospitality industry. Comparing online and offline shopper groups, they find that the online medium does not have a main effect on the importance of price, but it does increase the perceived value of price search and thus increases price sensitivity. Nevertheless, some website tactics, such as the degree of interactivity and the depth of information provision, actually reduce price sensitivity.

Smith and Brynjolfsson (2001) find that customers at an Internet book shopbot are twice as sensitive to changes in shipping fees and sales tax than to changes in item price. Brown and Goolsbee (2002) find that Internet comparison sites make the life insurance industry more competitive and reduce insurance policy prices. Clemons et al. (2002) find that airline

¹ Some theoretical and experimental studies (besides the empirical ones discussed here) are Alba et al. (1997), Bakos (1997), He and Chen (2006), Lal and Sarvary (1999), and Lynch and Ariely (2000).

ticket prices from online travel agents vary substantially, even after controlling for ticket quality. Cooper (2006) finds that online prices are lower and significantly less dispersed than offline prices for contact lenses, but the differences are less pronounced for advertised products.

The above studies all deal with nongrocery items, and none of them compares price sensitivities for the *same* individuals. Grocery shopping differs from nongrocery shopping in two important ways. First, grocery shopping is a frequent and repetitive activity and can be a burden for individuals, and second, although competition for groceries tends to be local, that for nongroceries such as books and CDs is global. Furthermore, many online grocers are virtual monopolies in their markets for the online medium. Thus, conclusions about nongrocery products might not apply to grocery items.

Research on online grocery shopping has focused on comparing features such as brand loyalty and price sensitivities across online and offline channels using *separate* online and offline panels while controlling for self-selection related issues. Degeratu et al. (2001) investigate how brand name, price, and other search attributes affect consumer choice behavior in online and conventional supermarkets. They find that the importance of brand name varies across category, price sensitivity is higher online because of the stronger signaling effect of online price cuts, and the combined effect of price and promotion is lower online than offline. Andrews and Currim (2004) find that online consumers are less price sensitive and prefer larger sizes. Danaher et al. (2003) find that high market share brands enjoy a loyalty advantage in the online store. In all these studies, the online and offline customers come from two separate samples; therefore, observed differences in shopping behavior might not be caused by the shopping media, but might be inherent in these two groups of consumers (although Danaher et al. 2003 explicitly account for this in their analysis). Zhang and Krishnamurthi (2004) use a household panel data set of online purchases to measure the impact of promotions on households' purchase behavior. Lewis et al. (2006) find a significant effect of nonlinear shipping and handling fees on consumers' online purchase incidence and expenditure decisions for groceries. The latter two studies deal only with the Internet medium, while this paper looks at both online and offline channels.

In this paper, we investigate how the same households respond to grocery prices differently in the online store than in the offline stores of the same chain. Our analysis is based on a unique household scanner panel data set. We observe a panel of households that make grocery shopping trips interchangeably to the Internet store and to the physical

stores of the same grocery chain, with almost 90% of households shopping across these channels. For each trip, we observe the entire basket of both packaged and nonpackaged goods. Our empirical analysis is conducted on 12 product categories, including big basket-share categories (yogurt and milk) and small basket-share categories (liquid fabric softener and dish detergent); packaged goods (paper towels and frozen pizza) and nonpackaged goods (oranges and potatoes); and categories that are more likely to be purchased online because of their bulkiness or heaviness (toilet paper and cooking oil) and more likely to be purchased offline because of their "sensory" nature (bread and oranges). We provide detailed results for one category (frozen pizza) and summary results for other categories.

We specify a random coefficients logit model for purchase incidence and brand choice conditional on store choice. Quantity choices are accounted for by explicitly incorporating different package sizes into the model specification. Our estimation accounts for observed and unobserved household heterogeneity as well as for price endogeneity. We allow the distribution of price coefficient, the effects of demographics on price response, brand loyalty, and the effects of outside good utility shifters to differ across offline and online channels. We find that the same households exhibit lower price sensitivities when they shop online than when they shop offline. The results hold across 12 vastly different product categories. We discuss reasons for our findings.

The rest of the paper proceeds as follows. We describe the data in §2, set up the econometric model in §3, and detail the estimation in §4. We report findings in §5 and conclude in §6.

2. Data

2.1. The Grocery Retailer

Our data come from a major grocery retail chain in Spain. The data are for one metro area, where the retailer has 200 physical stores. The retailer started online operations in 2001 and was the only successful online grocery store in Spain during the period of our data collection. The online store is teamed up with 17 of the chain's physical stores in the metro area for grocery supply. Online orders are processed by these offline stores. After placing an order online, a household can either go to one of these 17 stores to pick up the order for no charge or have the basket delivered to its doorstep (delivery fee of €4.5 for orders under €90, or free otherwise). An important feature of grocery stores in the metro area is that they do not always have parking lots, so consumers usually walk or take public transport to do grocery shopping. About 60% of the physical stores in this chain also provide home

delivery service. The delivery charge for offline shopping is €3.5 for orders below €90 and free otherwise.

The retailer has a Hi-Lo chainwide promotion policy and practices zone pricing for the offline stores. There are two offline price zones. Roughly, stores in the low-income area belong to the low-price zone, and those in the high-income area belong to the high-price zone. Average prices across *all* categories in the high-price zone are about 3% higher. When this retailer started the online business, it applied the prices in the high-price offline zone to the online store.

Finally, price cuts are usually the same across channels. The retailer's store week is the same as the calendar week, and promotions are usually run on a weekly basis; thus, weekday prices are the same as weekend prices.

2.2. Household Panel Data

We obtained household panel data on 2,733 households from this retailer. To be included in the panel, the household needs to have made at least one online purchase at the retailer's online store *prior* to the data collection. So all households in our panel are online shoppers, although some of them do not make any online trips during the data-collection period. We observe all trips both to the online store and to the offline stores in this grocery chain from 12/2002 to 11/2003. For each trip, we observe the entire basket of both packaged and nonpackaged goods. For each item, we have prices, units bought, and a detailed description. We compute a distance measure between the households and the stores based on each household's zip code information and each store's street location.

Of the panel households, 41.3% reside in the low-price zone and 58.7% in the high-price zone. Eighty-nine percent of the panel households are "mixed" shoppers—shopping both at the online and offline stores—10.2% are pure online shoppers, and 0.8% are pure offline shoppers. Of the households in the

low-price zone, 87.3% are mixed shoppers and 11.8% are pure online shoppers; of the households in the high-price zone, 90.2% are mixed shoppers and 9.2% are pure online shoppers. The dropout rate among these online shoppers is very low, in contrast with what is found in other studies (Danaher et al. 2003). The households on average made 43.3 shopping trips during the one-year period: 38.3 trips for households in the low-price zone and 46.8 trips for households in the high-price zone. Of the trips, 27.9% occurred to stores in the low-price zone, 55.5% to stores in the high-price zone, and 16.6% to the online store. However, the online store accounts for 37.9% of grocery spending, the low-price zone accounts for 16.8%, and the high-price zone accounts for 45.3%. Consequently, the online basket size is much larger than the offline basket size.

Table 1 shows the distribution of shopping trips and mean basket size across zones for households in the two different price zones. Interestingly, cross-zone shopping is common among these households, particularly for those in the low-price zone. Households in the low-price zone made 18.9% of their trips to the online store and 14.6% to the high-price zone, and households in the high-price zone made only 15.3% of their trips to the online store and 5.5% to the low-price zone, even though the former have to pay higher prices in the online store and in the high-price zone, and the latter benefit more from cross-zone shopping.

The mixed shoppers made 49.4 trips in total, with 6.6 online and 42.8 offline. The pure online and pure offline shoppers each made 13 trips or 56 trips, respectively. The mixed shoppers behave like pure online shoppers when shopping online and like pure offline shoppers when shopping offline. The online basket for mixed shoppers is €129.5, as compared to €121.2 for the pure online shoppers, and the offline basket for mixed shoppers is €43.1, as compared to €43.3 for the pure offline shoppers. The mixed shoppers buy 29 categories and 41 items on an average online trip; the

Table 1 Distribution of Shopping Trips and Mean Basket Size by Price Zone

	Number and percent of shopping trips across zone				Mean basket size by zone (€)			
	Low-price zone	High-price zone	Online	Total	Low-price zone	High-price zone	Online	Total
Households in low-price zone								
No. of trips	25.5	5.6	7.2	38.3	32.8	49.9	119.5	51.7
Percent distribution	66.5	14.6	18.9	100.0				
Households in high-price zone								
No. of trips	2.6	37.1	7.1	46.8	40.8	45.3	134.0	58.6
Percent distribution	5.5	79.3	15.3	100.0				
All households								
No. of trips	12.0	24.0	7.2	43.3	33.8	45.7	127.9	56.0
Percent distribution	27.9	55.5	16.6	100.0				

corresponding numbers for the pure online shoppers are 22 and 31. The mixed shoppers buy 12 categories and 16 items on an offline trip; the corresponding numbers for the pure offline shoppers are 13 and 17. So it appears that the shopping media change consumers' behavior, and the same consumers behave differently in the online medium than in the offline medium.

There are no significant differences in observed demographics across the pure online shoppers and the mixed shoppers, a result consistent with the sample selection criterion. Mean family size and number of adults for pure online shoppers are 2.90 (standard deviation [s.d.] is 1.73) and 2.33 (s.d. is 1.53); the corresponding numbers for the mixed shoppers are 3.39 (s.d. is 1.41) and 2.26 (s.d. is 1.01). So although demographic characteristics might still explain differences in price sensitivities across households, findings of differences in price sensitivities across channels are more likely attributable to channels themselves.

Danaher et al. (2003) note that even when one has access to a mixed shopper panel such as ours, there could be unobserved factors such as stockouts (in offline stores) that could explain differences in elasticities across channels. Such factors could result in greater offline brand switching, from which one might erroneously infer higher online brand loyalty. Although such factors could certainly exist, factors such as stockouts are more likely to occur for promoted items. If households purchase nonpromoted items as a consequence, this is likely to lower offline price elasticities, which works against our findings and is therefore unlikely to explain our results. Furthermore, our results are consistent across 12 categories, indicating that it is not a category-specific finding.

2.3. The Frozen Pizza Category

In the frozen pizza category, 1,514 households make at least one purchase. Table 2 summarizes their demographics. Interestingly, there do not appear to be large differences in demographics of pizza buyers across

zones. Of these pizza buyers, 4.4% are pure online shoppers, 4.2% are pure offline shoppers, and 91.4% are mixed shoppers. Again, there are no significant differences in the observed demographics across different types of shoppers. These households make 65,613 shopping trips, with 9,872 online and 57,741 offline; 18.9% of the trips involve purchases of frozen pizza. The purchase incidences for online and offline trips are 39.2% and 15.3%, respectively. Table 3 reports the mean prices and conditional (on purchase) market shares of each of the listed 15 items.

The raw data suggest that households are less responsive to price changes in the online store than in the offline stores. For example, the regular prices for the 600-g Buitoni pizza increased by 3.3% in both offline and online stores from week 22 on. Before the price change, the total numbers of purchases for the online and offline stores are 63 and 73, respectively; these numbers after the change are 101 and 64. In the same periods, the total numbers of purchases of the 340-g Buitoni pizza, which did not experience a shift in regular prices, increase from 94 to 115 for the online store and from 64 to 94 for the offline stores.

3. Model

We follow the standard random utility approach for the demand model. We assume that on a given shopping trip, a household either chooses an alternative that gives it the highest utility in the category or chooses not to purchase in the category. We do not model a household's store choice decision explicitly but focus on purchase incidence and brand choice, because we believe that store choice is a much more complicated issue and that one category alone usually is not able to drive a household's store choice decision. On a shopping trip in week t , household h 's indirect utility of choosing alternative ω (brand j of size b and flavor f) from store s is given by

$$U_{h\omega st} = \alpha_{h\omega} + D_h \gamma + (I_{st}^{on} \beta_{h,on} + I_{st}^{off} \beta_{h,off})(Y_h - P_{\omega st}) \\ + (I_{st}^{on} \eta_{on} + I_{st}^{off} \eta_{off})I_{h\omega, t-1} + \xi_{\omega st} + \varepsilon_{h\omega st}, \quad (1)$$

where $\alpha_{h\omega}$ is household h 's intrinsic preference for alternative ω , $\alpha_{h\omega} = \alpha_{hj} + \alpha_{hb} + \alpha_{hf}$; D_h includes family size, numbers of preschool children and elders, and distance to the closest offline store; γ is the effect of demographics; I_{st}^{on} and I_{st}^{off} are indicators for online and offline purchases, and $\beta_{h,on}$ and $\beta_{h,off}$ are online and offline price response parameters; Y_h is income; $P_{\omega st}$ is alternative ω 's price in store s in week t ; $I_{h\omega, t-1}$ equals 1 if alternative ω is purchased on the previous trip, and η_{on} and η_{off} are state-dependence parameters; $\xi_{\omega st}$ is alternative ω 's unobserved portion of mean utility that varies with t and s ; and $\varepsilon_{h\omega st}$ is household h 's idiosyncratic utility. The

Table 2 Household Demographics by Zone

	Low-price zone (37%)		High-price zone (63%)		Total	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
Family size	3.38	1.16	3.62	1.47	3.56	1.38
No. of pre-school children (<6 years)	0.56	0.72	0.52	0.88	0.56	0.83
No. of school-age children (6–18 years)	0.51	0.79	0.65	1.02	0.60	0.95
No. of adults (19–65 years)	2.23	0.84	2.38	1.05	2.33	0.98
No. of elders (>65 years)	0.08	0.35	0.07	0.30	0.07	0.32
Distance to closest store (km)	0.57	0.35	0.77	0.31	0.69	0.34

Table 3 Prices and Market Shares of Frozen Pizza

Brand	Size (g)	Flavor	Mean price/kg		Market share conditional on purchase incidence		
			Low-price	High price	Low-price	High-price	Online
Buitoni	340	Cheese	7.95	8.46	1.76	2.09	3.15
Buitoni	410	Cheese	7.81	7.87	3.30	2.28	3.98
Buitoni	600	Cheese	8.35	8.70	1.67	1.65	2.97
Private label	425	Cheese	4.92	5.02	5.18	6.46	7.73
Private label	450	Bacon/ham	4.65	4.73	10.12	6.94	11.55
Tarradella	350	Others	6.15	6.26	3.30	7.07	6.07
Tarradella	410	Cheese	5.37	5.49	15.46	15.76	13.49
Tarradella	425	Bacon/ham	5.18	5.29	7.87	3.63	4.68
Tarradella	425	Others	5.18	5.29	4.35	3.65	5.81
Tarradella	425	Ham/cheese	5.18	5.29	11.66	15.05	10.65
Tarradella	435	Others	5.06	5.17	15.46	12.68	8.71
Tarradella	450	Others	4.89	5.00	3.95	2.87	4.57
Tarradella	650	Ham/cheese	5.88	6.08	1.39	1.69	2.04
Tarradella	2 × 225	Cheese	6.40	6.78	5.15	6.99	5.97
Tarradella	2 × 225	Bacon/ham	6.40	6.78	9.38	11.18	8.63
Mean/total			5.96	6.15	100.00	100.00	100.00

unobserved attribute $\xi_{\omega st}$ accounts for factors such as features or displays that are not part of our data but could influence household utilities. $\xi_{\omega st}$ is store specific, because some factors such as displays are likely to differ across stores: the online store cannot have the same displays as the offline ones. Furthermore, they could potentially be correlated with price. No-purchase utility is given by

$$U_{h0st} = X_{ht}(I_{st}^{on}\theta_{on} + I_{st}^{off}\theta_{off}) + (I_{st}^{on}\beta_{h,on} + I_{st}^{off}\beta_{h,off})Y_h + \varepsilon_{h0st}, \quad (2)$$

where X_{ht} includes following variables: (1) weather dummy, (2) weekday dummy, (3) purchase quantity on the last trip/household size, (4) an indicator that takes the value 1 if the basket size excluding pizza exceeds €90 (to check whether a household buys pizza only because it wants to take advantage of the free delivery option), and (5) an indicator that takes the value 1 if the household purchased pizza on any of the two most recent trips (to capture inventory effects but mitigating the endogeneity problem associated with using inventory or time elapsed since last purchase). Assuming that $\varepsilon_{h\omega st}$ follows an extreme value distribution yields the logit probability of alternative choice

$$S_{h\omega st} = \exp(\alpha_{h\omega} + D_h\gamma - [I_{st}^{on}\beta_{h,on} + I_{st}^{off}\beta_{h,off}]P_{\omega st} + (I_{st}^{on}\eta_{on} + I_{st}^{off}\eta_{off})I_{h\omega, t-1} + \xi_{\omega st}) \cdot \left(\exp(V_{h0st}) + \sum_{\omega'=1}^{\Omega} \exp(\alpha_{h\omega'} + D_h\gamma - [I_{st}^{on}\beta_{h,on} + I_{st}^{off}\beta_{h,off}]P_{\omega' st} + (I_{st}^{on}\eta_{on} + I_{st}^{off}\eta_{off})I_{h\omega', t-1} + \xi_{\omega' st}) \right)^{-1}. \quad (3)$$

$V_{h0st} \equiv X_{ht}(I_{st}^{on}\theta_{on} + I_{st}^{off}\theta_{off})$, and Ω is the set of alternatives available to households. Intrinsic preferences for brand and product attributes vary across consumers as follows: $\alpha_{hj} \sim N(\bar{\alpha}_j, \sigma_j^2)$, $\alpha_{hb} \sim N(\bar{\alpha}_b, \sigma_b^2)$, and $\alpha_{hf} \sim N(\bar{\alpha}_f, \sigma_f^2)$. We allow the distribution of price response parameter and the impact of demographics on price sensitivity to differ across online and offline channels as follows (Chintagunta et al. 2003):

$$\begin{pmatrix} \beta_{h,on} \\ \beta_{h,off} \end{pmatrix} \sim N \left(\begin{bmatrix} \bar{\beta}_{on} + DP_h\lambda_{on} \\ \bar{\beta}_{off} + DP_h\lambda_{off} \end{bmatrix}, \Sigma_{\beta} \right).$$

In addition to the four demographics in D_h , DP_h also includes (1) an indicator for the store zone that a household resides in (to check whether households living in different price zones exhibit different price sensitivity) and (2) an indicator taking the value 1 if basket size, excluding pizza, exceeds €90 (to check whether households are more price sensitive if buying pizza has no effect on delivery charge). λ_{on} and λ_{off} are the effects of demographics on online and offline price response. We average the choice probabilities across households to obtain alternative ω 's market share

$$S_{\omega st} = \frac{1}{H} \sum_{h=1}^H S_{h\omega st}. \quad (4)$$

4. Estimation

We estimate the demand parameters by combining maximum likelihood estimation (MLE) for the heterogeneity parameters with a two-stage least-squares (2SLS) regression to recover the mean parameters of the heterogeneity distribution and to control for the potential price endogeneity problem. To simplify notation, let $\delta_{\omega st}$ be the mean utility of alternative ω

across households and $\mu_{h\omega st}$ be the household-specific deviations from the mean, which are defined respectively as

$$\delta_{\omega st} \equiv \bar{\alpha}_j + \bar{\alpha}_b + \bar{\alpha}_f - (I_{st}^{on} \bar{\beta}_{on} + I_{st}^{off} \bar{\beta}_{off}) P_{\omega st} + \xi_{\omega st}, \quad (5)$$

$$\begin{aligned} \mu_{h\omega st} \equiv & (\alpha_{hj} - \bar{\alpha}_j) + (\alpha_{hb} - \bar{\alpha}_b) + (\alpha_{hf} - \bar{\alpha}_f) + D_h \gamma \\ & - [I_{st}^{on} (\beta_{h,on} - \bar{\beta}_{on}) + I_{st}^{off} (\beta_{h,off} - \bar{\beta}_{off})] P_{\omega st} \\ & + (I_{st}^{on} \eta_{on} + I_{st}^{off} \eta_{off}) I_{h\omega, t-1}. \end{aligned} \quad (6)$$

Defining $\delta \equiv \{\delta_{\omega st}, \omega = 1, \dots, \Omega, s = 1, \dots, S, t = 1, \dots, T\}$ and $\Theta \equiv \{\gamma, \lambda_{on}, \lambda_{off}, \sigma_j, \sigma_b, \sigma_f, \Sigma, \theta_{on}, \theta_{off}\}$, we can rewrite Equation (3) as

$$S_{h\omega st} = \frac{\exp(\delta_{\omega st} + \mu_{h\omega st})}{\exp(V_{h0st}) + \sum_{\omega'=1}^{\Omega} \exp(\delta_{\omega' st} + \mu_{h\omega' st})}. \quad (7)$$

Because of the presence of unobserved product characteristics $\xi_{\omega st}$ that might be correlated with price, we cannot use standard MLE to obtain consistent estimates of the mean parameters $\bar{\alpha}$ and $\bar{\beta}$ together with the heterogeneity distribution parameters. We use the two-stage procedure suggested by Berry (1994) and implemented by Goolsbee and Petrin (2004) with individual choice data. In the first stage, we concentrate out the likelihood function and search only over the space of $\{\Theta\}$. This involves the following three steps:

(1) For any candidate values of $\{\Theta\}$ and vector of mean utilities δ , calculate the likelihood that a given household chooses alternative ω from store s in a given week t , and integrate over households' choice probabilities to obtain market shares.

(2) Given $\{\Theta\}$, solve for vector $\delta(\Theta)$ that matches observed market shares $S_{\omega st}$ to model predicted shares $\hat{S}_{\omega st}$ by a nonlinear search routine: $\delta(\Theta) = \arg \min |S_{\omega st} - \hat{S}_{\omega st}|$.

(3) Maximize the likelihood function by choosing $\{\delta(\Theta), \Theta\}$.

As usual formulas for the standard errors of $\{\Theta\}$ will not apply because of sampling errors in the observed market shares, we compute them as in Goolsbee and Petrin (2004). In the second stage, we project the estimated $\hat{\delta}$ onto brand intercepts, product attributes, and price to recover the mean parameters $(\bar{\alpha}, \bar{\beta})$, as in Equation (5). In this stage, because prices might be correlated with the unobserved product attributes, we use M exogenous variables $Z_{\omega st}$ as instruments for the endogenous prices. We use prices of pizza ingredients as instruments: flour, bacon, pepperoni, and cheese. The first-stage R -squared is 82.5%. We account for the estimation error in $\hat{\delta}$ from the first stage by using a generalized 2SLS procedure.² An advantage of this approach is that we do not need to make

any specific parametric assumptions about the price-generating process, nor do we need to specify a parametric distribution for ξ .

5. Results

5.1. Demand Parameter Estimates for Frozen Pizza

In Table 4, we report the model estimates for frozen pizza. A comparison of OLS and 2SLS parameter estimates reveals the importance of accounting for price endogeneity. We also find that it is important to account for both observed and unobserved household heterogeneity. Households are heterogeneous in their intrinsic preferences for brand and size and in their price sensitivities. Interestingly, consumers are more heterogeneous in online price response than in offline price response: The coefficients of variation for the online and offline stores are 0.342 and 0.065, respectively. This might be because online shoppers come both from the high-price zone and the low-price zone; when these households shop offline, they primarily shop in the price zone where they live, as shown in Table 1. Another possible reason for the higher online price heterogeneity might be that online sales could be coming from (a) households that make purchases online because they value other attributes such as convenience more and are therefore less price sensitive, and (b) households that value convenience and are also more responsive to promotions; the online shopping medium might make in-store comparison of price and some non-price attributes much easier for the latter group. The former group tends to be price inelastic and the latter group relatively more price elastic. Our discussion below will focus on the model with both observed and unobserved household heterogeneity.

We find that households living farther away from a store are less likely to purchase pizza. This is because in the city we study, households usually walk or take public transportation to do grocery shopping and therefore have to carry the basket home. This might be also because households living far away might be afraid that the pizzas will thaw if they travel a long distance. Households with elders are less likely to purchase pizza, possibly because they have more time to cook.

The majority of price-demographic interactions are significant, and the significant interactions are of the same sign for the online store as for the offline stores, implying that households with similar demographics exhibit similar behaviors across the two channels. A household's distance to the store is negatively related to price sensitivity: The farther a household lives from a store, the less price sensitive it is. This is likely because households closer to a store are more likely to obtain price and promotion information, for

² Please refer to the Technical Appendix at <http://mktsci.journal.informs.org/> for the technical details of the two-stage estimation procedure.

Table 4 Demand Model Estimates (Standard Errors) for Frozen Pizza

	Without unobserved heterogeneity		With unobserved heterogeneity		
	OLS	2SLS	OLS	2SLS	Heterogeneity
Buitoni (α_f)	−6.291 (0.103)	−3.097 (0.576)	−6.707 (0.107)	−2.796 (0.517)	1.386 (0.204)
Private label (α_f)	−4.787 (0.100)	−1.682 (0.560)	−5.787 (0.104)	−1.986 (0.503)	1.435 (0.159)
Tarradella (α_f)	−4.871 (0.085)	−1.713 (0.569)	−5.190 (0.089)	−1.323 (0.509)	0.990 (0.172)
Size 1 (600 g) (α_b)	0.157 (0.079)	0.226 (0.059)	0.142 (0.083)	0.227 (0.067)	0.209 (0.052)
Size 2 (425 g) (α_b)	−0.006 (0.052)	0.086 (0.041)	−0.057 (0.054)	0.055 (0.045)	0.094 (0.059)
Size 3 (410 g) (α_b)	0.873 (0.070)	0.873 (0.051)	0.514 (0.073)	0.514 (0.058)	0.320 (0.142)
Size 4 (350 g) (α_b)	0.284 (0.076)	0.286 (0.055)	−0.115 (0.079)	−0.113 (0.063)	1.044 (0.193)
Size 5 (435 g) (α_b) t	1.162 (0.076)	1.196 (0.055)	1.099 (0.079)	1.140 (0.063)	0.632 (0.201)
Size 6 (650 g) (α_b)	−1.483 (0.082)	−1.323 (0.066)	−1.536 (0.086)	−1.339 (0.073)	0.179 (0.104)
Size 7 (2 × 225 g) (α_b)	0.167 (0.076)	0.256 (0.057)	−0.485 (0.079)	−0.376 (0.064)	1.159 (0.192)
Flavor 1 (cheese) (α_f)	0.420 (0.076)	0.377 (0.056)	0.474 (0.079)	0.421 (0.063)	0.073 (0.127)
Flavor 2 (bacon/ham) (α_f)	0.761 (0.059)	0.695 (0.044)	0.738 (0.062)	0.657 (0.050)	0.097 (0.102)
Mean online price (β_{on})	0.099 (0.012)	−0.413 (0.093)	0.082 (0.012)	−0.546 (0.083)	0.187 (0.055)
Mean offline price (β_{off})	−0.046 (0.012)	−0.573 (0.094)	−0.033 (0.012)	−0.676 (0.084)	0.044 (0.012)
Online-offline price sensitivity correlation					−0.091 (0.039)
Demographic effect on incidence (γ)					
Closest distance	−0.493 (0.081)			−0.513 (0.072)	
Family size	0.145 (0.022)			0.104 (0.084)	
Children	−0.276 (0.043)			−0.247 (0.139)	
Elders	−0.547 (0.069)			−0.496 (0.058)	
	Online	Offline	Online	Offline	
Price-demo interaction (λ):					
Closest distance	0.058 (0.013)	0.057 (0.014)	0.054 (0.005)	0.067 (0.006)	
Family size	−0.021 (0.004)	−0.025 (0.004)	−0.018 (0.006)	−0.020 (0.006)	
Children	0.037 (0.008)	0.034 (0.007)	0.033 (0.005)	0.034 (0.008)	
Elders	0.028 (0.010)	0.050 (0.012)	0.031 (0.005)	0.049 (0.005)	
Household zone	−0.005 (0.002)	−0.013 (0.026)	0.004 (0.005)	−0.006 (0.005)	
Basket size threshold	0.012 (0.003)	−0.045 (0.094)	0.020 (0.005)	−0.008 (0.006)	
State dependence parameter(η)	1.299 (0.082)	1.175 (0.101)	0.978 (0.057)	0.652 (0.088)	
Effect on no-purchase (θ)					
Weather dummy	0.034 (0.035)	0.020 (0.026)	0.025 (0.044)	0.021 (0.045)	
Weekday dummy	0.088 (0.018)	0.302 (0.025)	0.030 (0.050)	0.278 (0.044)	
Lagged purchase quantity	−0.699 (0.030)	−0.327 (0.007)	−0.473 (0.044)	−0.038 (0.055)	
Basket size threshold	−0.006 (0.023)	−0.931 (0.057)	−0.254 (0.047)	−1.025 (0.048)	
Previous purchase indicator	−0.873 (0.037)	−0.456 (0.021)	−0.475 (0.054)	−0.056 (0.079)	
Value of objective function		58,779		52,982	

instance, through more frequent store visits. This is consistent with Fox and Hoch (2005), who find that the propensity to cherry pick is inversely related to shoppers' geographic distance to nearby stores. Large families are more price sensitive, which is consistent with the economic theory (Becker 1965) and with previous research (e.g., Ainslie and Rossi 1998). The coefficient for the basket-size indicator is positive, implying that households are less price sensitive once their basket size, excluding pizza, exceeds the free delivery threshold. This is because large-basket trips are more likely to be planned trips and less likely to be cherry-picking trips than are small-basket trips and households are less price sensitive on planned trips.

We now examine the effects of mean utility drivers for the no-purchase option.

5.1.1. Effect of Basket Size and Free Delivery Threshold. When a household's basket, not including pizza, already exceeds the free delivery threshold, it is *more* likely to purchase frozen pizza, both for the online and offline trips, because the coefficient for the no-purchase option is significantly negative and the effect more pronounced for the offline trips than for the online trips. This implies that a household seldom considers individual categories on a large-basket trip, which is consistent with the fact that large-basket trips are more likely to be planned trips.

5.1.2. Lagged Purchase Quantity and Previous Purchase Indicators. We expect that the more a household purchased on previous trips, the less likely it will purchase on the current trip. This effect is not significant for the offline trips while for the online

Table 5 Price Elasticity (Standard Error) Across Channels*

	Unconditional			Conditional on purchase incidence		
	Online	Offline	Ratio	Online	Offline	Ratio
Buitoni 340 g cheese	−4.376 (0.742)	−5.573 (0.645)	0.785	−4.282 (0.724)	−5.428 (0.626)	0.789
Buitoni 410 g cheese	−4.525 (0.767)	−5.775 (0.668)	0.784	−4.409 (0.745)	−5.632 (0.650)	0.783
Buitoni 600 g cheese	−2.572 (0.436)	−3.339 (0.386)	0.770	−2.419 (0.409)	−3.159 (0.365)	0.766
Private label 425 g cheese	−2.418 (0.410)	−3.144 (0.364)	0.769	−2.240 (0.379)	−2.891 (0.334)	0.775
Private label 450 g bacon/ham	−4.064 (0.689)	−5.284 (0.611)	0.769	−3.936 (0.665)	−5.126 (0.591)	0.768
Tarradella 350 g others	−3.232 (0.548)	−4.175 (0.483)	0.774	−3.112 (0.526)	−4.009 (0.463)	0.776
Tarradella 410 g cheese	−2.767 (0.470)	−3.615 (0.418)	0.765	−2.509 (0.424)	−3.186 (0.368)	0.788
Tarradella 425 g bacon/ham	−2.734 (0.464)	−3.523 (0.408)	0.776	−2.644 (0.447)	−3.374 (0.389)	0.784
Tarradella 425 g others	−2.729 (0.463)	−3.528 (0.408)	0.773	−2.622 (0.443)	−3.403 (0.393)	0.771
Tarradella 425 g ham/cheese	−2.691 (0.457)	−3.487 (0.403)	0.772	−2.496 (0.422)	−3.071 (0.354)	0.813
Tarradella 435 g others	−2.632 (0.447)	−3.405 (0.394)	0.773	−2.447 (0.414)	−2.976 (0.344)	0.822
Tarradella 450 g others	−2.585 (0.438)	−3.337 (0.386)	0.775	−2.498 (0.422)	−3.244 (0.374)	0.770
Tarradella 650 g ham/cheese	−3.144 (0.533)	−4.041 (0.467)	0.778	−3.037 (0.513)	−3.928 (0.453)	0.773
Tarradella 2 × 225 g cheese	−3.531 (0.599)	−4.478 (0.518)	0.788	−3.478 (0.588)	−4.419 (0.510)	0.787
Tarradella 2 × 225 g bacon/ham	−3.500 (0.594)	−4.454 (0.515)	0.786	−3.388 (0.573)	−4.249 (0.490)	0.798
Overall	−3.167 (0.537)	−4.077 (0.472)	0.777	−3.034 (0.513)	−3.873 (0.447)	0.783

*Standard errors are computed via bootstrapping.

trips, we get the opposite: The coefficients are negative, implying that households are more likely to make a purchase. This confirms that when a household makes an online trip, it buys everything, regardless of inventory levels. This could help explain the lower online price sensitivity. Because of the much larger items and categories purchased online, households might not pay careful attention to prices of individual items.

The online medium makes consumers more inertial, as is shown by the online state-dependence coefficient (0.978) being higher than the offline one (0.652). The higher online inertia is further proved by the smaller numbers of unique brands and items bought by a household in the online store than in the offline stores. Over the one-year period, households on average bought 1.2 unique brands (s.d. = 0.5) and 2.2 unique items (s.d. = 1.4) in the online store (across all trips); the corresponding numbers for the offline stores are 1.4 (s.d. = 0.6) and 2.9 (s.d. = 2.0), respectively. This holds across all 12 categories investigated. This helps explain the lower online price sensitivity discussed below. The Internet shopping medium helps households create various shopping lists such as the previous purchase list. When a consumer is busy, she can simply click on the list to fill the basket, without looking at the content of the list.

5.2. Online/Offline Price Sensitivity

Households are less price sensitive when shopping online than when shopping offline. The corresponding elasticity estimates are reported in Table 5. The average unconditional online price elasticity is 3.17, about 78% of the offline price elasticity (4.08). We use bootstrapping to compute the asymptotic covariance

matrix and conduct a mean difference test (Johnson and Wichern 2002) on the vectors of online and offline price elasticities. We find the online–offline elasticity differences are statistically significant at the 5% level. A paired comparison test on equal elasticities across the two channels gives a *t*-statistic of 18.1, rejecting the hypothesis of equal elasticities across channels.

There are several possible reasons for consumers' lower sensitivity to price when shopping online. First, consumers are more likely to shop online when they are subject to time pressure. For example, we find consumers are more likely to shop online on weekdays.³ When consumers are pressured for time, they will search less and make fewer price comparisons within the store and are thus likely to be less price sensitive. This is consistent with previous research on time pressure and search and cherry-picking behavior. Urbany et al. (1996) and Putrevu and Ratchford (1997) find that time pressure is negatively related to search. Fox and Hoch (2005) find that the likelihood of cherry picking is higher on weekends than on weekdays. Second, the household is able to create various shopping lists at the Internet store to facilitate future shopping. These shopping lists reduce total shopping time but also reduce consumers' search and price comparisons. As a result, households become more inertial in the online store, as is shown by the much larger online state-dependence parameter estimate. They might make purchases before seeing the prices of the items in the basket. This is consistent with Howard and Sheth's (1969) theory of routinized response behavior. Third, the online store provides

³ On weekdays, online traffic accounts for 18.4% of total store traffic, but on weekends it accounts for only 8.9%.

easier-to-obtain nonprice information (e.g., nutrition facts). According to Lynch and Ariely (2000), consumers become less price sensitive when they are provided with more nonprice information. Fourth, the online grocery store is the only successful online store and therefore is a virtual monopoly for the online shopping medium in this market. This reduces consumers' comparison shopping across stores. When households decide to shop online, they know the store is the "only show in town" and accept the prevailing prices. Last but not least, grocery shopping is a frequent and repetitive activity and can be a burden for most people. Online grocery shopping is primarily a convenience good, and consumers might be willing to pay a premium for the associated convenience. Studies find that consumers do not consider price as the most important factor in choosing an online store for grocery shopping. In a survey by Morganosky and Cude (2000), 73% of e-grocery shoppers report convenience and time saving as primary reasons for using the Internet to buy groceries.

The unconditional elasticities described above are the result of two factors: the price response coefficient and purchase incidence. Everything else being the same, the higher online purchase incidence will result in a decrease in the relative magnitude of online/offline own price elasticity. To investigate the effect of price response alone, we compute the conditional (on purchase) price elasticities, shown in the right panel of Table 5. The conditional market shares are not much different across the two channels, so the conditional price elasticities are primarily determined by the online and offline price response parameters. The mean conditional online and offline price elasticities are 3.03 and 3.87, respectively.

Key findings from our analysis are as follows. We find that it is important to account for price endogeneity and observed and unobserved consumer heterogeneity. Household demographics influence both purchase incidence and price response. Larger households are more price sensitive, and households living farther away from a store are less price sensitive. Households exhibit more inertia in the online channel. Households are less price sensitive but more heterogeneous in price response when shopping online.

5.3. Robustness Checks

We check whether our parameter estimates and conclusions are sensitive to model specification and whether the differences across online and offline price elasticities can be attributed to other factors.

5.3.1. Price Zone and Price Sensitivity. We checked whether households also exhibit zone-specific price sensitivity and whether it is a household's location in a particular price zone that causes the lower online price sensitivity. For this, in addition to

including a household's residential zone as one demographic variable that affects price sensitivity, we also did the following: (a) Under the current model specification, we allowed the two offline price zones to have different mean price coefficients. We found these effects are not statistically different. (b) We estimated a separate random coefficients logit model for households in both the low-price and the high-price zones and obtained lower online price sensitivities for both types of households. (c) We estimated a random coefficients logit model for the offline trips only, allowing the two offline price zones to have different price coefficients. Again we found the two price coefficients are not statistically different.⁴ Therefore, we conclude that the lower online price sensitivity is not caused by the different price zones.

5.3.2. Variance-Covariance Matrix for Alternative Preferences. Because our frozen pizza data have 15 choice alternatives, estimating a full variance-covariance matrix for the alternative preferences implies estimating 120 parameters. To reduce the computational burden, we used a characteristics approach and decomposed the alternative preferences into preferences for brand, size, and flavor. A second approach is to estimate a factor-analytic model for the alternative preferences (Elrod and Keane 1995). We estimated a two-factor model, and the imputed online and offline price elasticities are -3.34 and -4.47 , respectively, with an online/offline ratio of 0.75. This compares to -3.17 and -4.08 with a ratio of 0.78 for our model.

5.3.3. Number of Trips, Purchase Incidence, and Basket Size. The online and offline stores differ substantially in number of trips, purchase incidence, and basket size. To check whether the online and offline price sensitivity estimates are affected only by these factors, we re-estimated the model for the following cases: (a) drop small (basket $<€50$ or $<€70$) offline trips such that online and offline stores are comparable in terms of number of trips, purchase incidence, and basket size; and (b) randomly select offline trips such that online and offline stores are comparable in terms of number of trips. We find that online price sensitivities are lower in all cases. Even when online and offline have roughly the same number of trips, purchase incidence, and basket size, the online price sensitivity is still only 82% of the offline. Therefore, we can conclude that our estimated price sensitivity differences across the two channels are not caused by differences in number of trips, purchase incidence, or

⁴ Our modeling approach requires at least one purchase incidence for each item in each zone week; thus, we cannot take this approach for (b) and (c). Instead, we estimated random coefficients logit models not accounting for price endogeneity. Consequently, the magnitudes of price effects are much smaller, but the relative relationships still hold.

basket size. This is further confirmed by our analysis in other categories as discussed below.

5.3.4. Purchase Quantities. We have shown that households are less price sensitive in purchase incidence and brand choice when shopping online than when shopping offline. One possible reason for this is that households are more responsive to online promotions and purchase in greater quantities. If so, the lower online price sensitivity in purchase incidence and brand choice will be compensated by the higher online price sensitivity in purchase quantity. We check all categories and find that households do not seem to be more responsive to online promotions than offline promotions by buying more in promotion weeks. The reason might be that if households are less sensitive in purchase incidence and brand choice when shopping online because of factors such as time pressure, ignorance of promotions, or distractions by nonprice information, they are also unlikely to purchase more of the promoted items.

5.3.5. The Effect of Regular Price Change versus Promotional Price Change. Households might respond differently to regular price changes than to promotional price changes. We find that one item experienced a level shift in regular price, but the magnitude was much smaller than promotional price cuts, so the observed differences were largely caused by promotional price changes. Nevertheless, we repeated the analysis after dropping the four-week period following the level shift in one item's regular price and obtained similar results.

5.4. Price Sensitivities for Other Categories

To check whether the above conclusions hold in other categories, we extend the analysis to 11 more categories—yogurt, shelf-stable milk, cooking oil, toilet paper, square bread, eggs, liquid fabric softener, packed oranges, paper towels, packed potatoes, and

liquid dish detergent. These categories differ substantially in basket share and purchase incidence across the online and offline channels. They include large categories such as yogurt and milk and small categories such as packed potatoes and paper towels; categories that are more likely to be purchased online because of their bulkiness or heaviness, such as toilet paper and milk, as well as categories that are more likely to be purchased offline because of their “sensory” nature, such as bread and oranges; and conventional consumer packaged goods as well as non-consumer packaged goods, such as packed oranges and potatoes. We report the major results in Table 6 and put the detailed estimates in the appendix. We can see that across all categories, households are always less price sensitive when shopping online than when shopping offline. The ratio of online/offline price elasticities ranges from 0.44 to 0.88.

6. Conclusion

In this paper, we use a unique data set to examine the same consumers' price sensitivity across online and offline channels. We observe the same households that shop interchangeably at the online store and at the offline stores in the same grocery chain and investigate their purchase behavior in specific product categories. Nearly 90% of households shop at both online and offline stores. More importantly, across 12 vastly different product categories, these households exhibit lower price sensitivities when they shop online than when they shop offline. There could be several reasons for these findings, including constraints on time and the convenience of online shopping; greater inertia online because of factors such as the presence of “shopping lists,” availability of nonprice information, and absence of online alternatives to this supermarket.

Table 6 Channel-Specific Price Elasticity for Other Categories

	Percent of purchases by zone			Share of basket (%)			Purchase incidence (%)			Price elasticity: OLS		Price elasticity: 2SLS		
	High-price zone	Low-price zone	Online	Online	Offline	Total	Online	Offline	Total	Online	Offline	Online	Offline	Ratio
Yogurt	47.55	21.88	30.57	3.97	5.21	4.72	71.92	33.20	44.28	0.571	−0.247	−2.035	−2.950	0.689
Shelf-stable milk	37.46	22.32	40.22	6.07	3.15	4.31	82.95	26.17	35.53	−1.387	−3.185	−2.595	−4.428	0.586
Cooking oil	37.29	16.36	46.35	3.40	1.92	2.52	54.97	12.68	19.36	0.791	−1.173	−1.820	−3.980	0.457
Toilet paper	35.29	13.89	50.81	2.21	1.04	1.51	59.69	11.33	19.23	0.008	−1.591	−1.716	−3.390	0.506
Square bread	51.02	23.17	25.81	0.75	1.31	1.09	45.57	23.88	27.09	0.468	0.096	−3.339	−3.790	0.881
Egg	50.92	22.46	26.62	0.57	0.90	0.77	44.47	20.73	24.19	−0.235	−0.626	−3.427	−4.012	0.854
Liquid fabric softener	35.41	13.06	51.53	1.00	0.51	0.70	39.12	6.73	11.72	−1.038	−2.777	−2.336	−4.090	0.571
Packed orange	55.29	14.58	30.13	0.61	0.75	0.69	27.13	10.18	12.54	−1.205	−2.142	−2.874	−3.916	0.734
Paper towel	34.27	12.67	53.06	0.75	0.34	0.50	49.89	8.58	15.33	−0.944	−2.087	−1.973	−4.034	0.489
Packed potato	46.28	15.46	38.26	0.55	0.54	0.54	33.38	9.48	12.96	−0.350	−1.599	−2.449	−3.829	0.640
Liquid dish detergent	37.52	13.81	48.67	0.65	0.37	0.48	28.20	5.77	9.33	−0.260	−2.082	−2.439	−4.372	0.558

One extension to the current exercise is to explicitly incorporate purchase quantity decisions and decompose price elasticity into the elasticity of purchase incidence, brand choice, and purchase quantity. As shown in our robustness checks, we see that an identical price reduction across channels does not result in a bigger online response in purchase quantity than in the offline channel. Nevertheless, the actual quantity purchased could vary across channels and needs to be considered. Studying channel choice is another worthwhile endeavor, because the information available to the household at the time of making the store choice decision is not typically observed in the data.

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Appendix

In this appendix, we report summary statistics and demand parameter estimates for the other 11 categories—yogurt, shelf-stable milk, cooking oil, toilet paper, square bread, eggs, liquid fabric softener, packed oranges, paper towels, packed potatoes, and liquid dish detergent.

In Table A.1 we report summary statistics for these categories, including the distribution of shopper types, distribution of shopping trips and purchases across channels and price zones, unique numbers of brands and items ever bought in each channel by each household, and mean quantities per purchase by channel. Households are more likely to make a purchase in a particular category when they visit the online store than when they visit offline stores: The ratio of online/offline purchase incidence ranges from 1.91 for square bread to 5.81 for paper towels. For any given category, households tend to buy larger quantities in the online store than in the offline stores: The online/offline quantity ratio ranges from 1.13 for packed oranges to 2.13 for shelf-stable milk. However, households exhibit less variety seeking and focus on fewer brands and items when shopping online than when shopping offline: The online/offline ratio of numbers of unique items ever bought ranges from 0.39 for square bread to 0.94 for toilet paper.

In Tables A.2, A.3, and A.4, we report estimates of the key demand parameters, including the main price effect and demographic effects on purchase incidence, on price sensitivity, and on the no-purchase decision. Common findings are: (1) households are always less price sensitive in the online store than in the offline stores; (2) the farther a household lives from a physical store, the less price sensitive it is; (3) households exhibit higher inertia in the online store than in the offline store; (4) most demographics have significant effects on purchase incidence, price sensitivity, and

the no-purchase decision; (5) households in different price zones exhibit similar price sensitivities; (6) households do not seem to take advantage of the free delivery option when purchasing in a particular category, because when their basket size already exceeds the free delivery threshold, they are *more* likely to make a purchase in the category, which is true for both online and offline channels; (7) inventory levels do not seem to play a big role in a household's category purchase decision in the online store: in 8 of the 11 categories, the higher the lagged purchase quantity/household size, the more likely it is that a household makes a purchase; and (8) it is important to explicitly account for price endogeneity, as the imputed price elasticities are much smaller for the OLS model than for the 2SLS model.

1. Yogurt

Yogurt is one of the largest basket-share categories, accounting for 4.7% of total grocery spending, 4.0% of online grocery spending, and 5.2% of offline grocery spending. There are 4 brands and 144 items in this category. At least one purchase in the yogurt category is made by 2,577 households, of which 92.3% are "mixed shoppers" and 6.9% pure online shoppers. These households made 115,868 shopping trips during the one-year period, with 15.4% online and 84.6% offline. Of the shopping trips, 44.3% involve purchases of yogurt—71.9% for online trips and 33.2% for offline trips. The online store accounts for 30.6% of yogurt purchases, the high-price zone accounts for 47.6%, and the low-price zone accounts for 21.9%. Prices in the high-price zone are on average 4.3% higher than in the low-price zone, with a s.d. of 3.8%. Households on average have selected 4.4 unique items (s.d. = 4.7) when shopping online, compared with 9.6 unique items (s.d. = 8.1) when shopping offline.

The online and offline price elasticities are -2.035 and -2.950 , respectively, with a ratio of 0.689. Larger households, households with children, and households with elders are more likely to buy yogurt. In both channels, households with elders are more price sensitive and households with children are less price sensitive. The ratio of online/offline state dependence parameters is 1.191. Households are more likely to buy yogurt online during weekdays.

2. Shelf-Stable Milk

Shelf-stable milk is also one of the largest basket-share categories, accounting for 4.3% of total grocery spending, 6.1% of online grocery spending, and 3.2% of offline grocery spending. There are 11 brands and 53 items in this category. There are 2,675 households that make at least one purchase in the shelf-stable milk category, of which 89.5% are "mixed shoppers" and 9.8% pure online shoppers. These households made 116,285 shopping trips during the one-year period, with 16.5% online and 83.5% offline. Of the shopping trips, 35.5% involve purchases of shelf-stable milk: 83.0% for online trips and 26.2% for offline trips. The online store accounts for 40.2% of shelf-stable milk purchases, the high-price zone accounts for 37.5%, and the low-price zone accounts for 22.3%. Prices in the high-price zone are on average 2.1% higher than in the low-price zone (s.d. = 2.4%). Households on average selected 2.0 unique items (s.d. = 1.5) when shopping online, compared to 3.0 unique items (s.d. = 2.6) when shopping offline.

Table A.1 Summary Statistics for the Eleven Categories

	Yogurt	Shelf-stable milk	Cooking oil	Toilet paper	Square bread	Eggs	Liquid fabric softener	Packed oranges	Paper towels	Packed potatoes	Liquid dish detergent
No. of households	2,577	2,675	2,421	2,632	2,321	2,292	1,949	1,533	2,431	1,981	2,342
Shopper type											
Percent Pure online	6.91	9.76	8.55	9.5	5.73	5.8	7.8	4.76	9.09	5.35	8.5
Percent Pure offline	0.81	0.79	0.78	0.72	0.86	0.83	0.72	0.78	0.78	0.86	0.77
Percent Mixed	92.28	89.46	90.67	89.78	93.41	93.37	91.48	94.46	90.13	93.79	90.73
No. of total trips	115,868	116,285	109,709	115,878	108,137	107,608	89,820	76,251	107,460	96,139	107,993
Percent Online	15.41	16.48	15.79	16.34	14.8	14.58	15.43	13.94	16.35	14.56	15.87
Percent Offline	84.59	83.52	84.21	83.66	85.2	85.42	84.57	86.06	83.65	85.44	84.13
No. of purchases*	109,930	52,447	25,446	23,078	33,446	27,043	11,152	9,859	16,936	13,195	11,094
Percent Online	30.57	40.22	46.35	50.81	25.81	26.62	51.53	30.13	53.06	38.26	48.67
Percent Offline	69.43	59.78	53.65	49.19	74.19	73.38	48.47	69.87	46.94	61.74	51.33
Percent High-price zone	47.55	37.46	37.29	35.29	51.02	50.92	35.41	55.29	34.27	46.28	37.52
Percent Low-price zone	21.88	22.32	16.36	13.89	23.17	22.46	13.06	14.58	12.67	15.46	13.81
No. of purchase trips	51,309	41,314	21,237	22,287	29,296	26,032	10,530	9,564	16,476	12,459	10,072
Percent Online	25.03	38.48	44.83	50.71	24.89	26.8	51.47	30.17	53.21	37.5	47.99
Percent Offline	74.97	61.52	55.17	49.29	75.11	73.2	48.53	69.83	46.79	62.5	52.01
Percent High-price zone	50.16	38.89	38.4	35.48	51.4	50.87	35.33	55.28	34.29	46.99	37.99
Percent Low-price zone	24.81	22.63	16.78	13.82	23.7	22.33	13.2	14.55	12.5	15.51	14.02
No. of brands	9	11	12	3	7	6	5	0	4	0	5
No. of items	144	53	38	12	39	18	35	7	9	14	18
Total # of unique brands ever bought by each household across all trips											
Online mean	1.16	1.42	1.34	1.10	1.00	1.41	1.33	—	1.32	—	1.40
Online s.d.	0.77	0.88	1.02	0.66	0.82	0.70	0.62	—	0.53	—	0.62
Offline mean	1.71	1.76	1.43	1.13	1.76	2.16	1.54	—	1.61	—	1.54
Offline s.d.	1.14	1.41	1.31	0.91	1.14	1.05	0.79	—	0.71	—	0.74
Online/offline	0.68	0.81	0.94	0.97	0.57	0.65	0.86	—	0.82	—	0.91
Total # of unique items ever bought by each household across all trips											
Online mean	4.37	1.99	1.75	1.44	1.22	1.69	1.66	1.49	1.45	1.81	1.74
Online s.d.	4.70	1.51	1.47	1.06	1.36	1.03	1.04	0.80	0.72	1.14	0.96
Offline mean	9.57	2.97	1.93	1.54	3.14	3.37	2.09	2.18	2.01	2.55	2.04
Offline s.d.	8.09	2.59	1.91	1.38	2.45	2.01	1.47	1.27	1.09	1.63	1.24
Online/offline	0.46	0.67	0.91	0.94	0.39	0.50	0.79	0.68	0.72	0.71	0.85
Purchase quantity per trip											
Online mean	3.82	11.54	2.71	1.39	1.47	1.42	1.56	1.36	1.52	1.26	1.42
Online s.d.	3.01	9.59	2.11	0.98	0.96	0.80	1.03	0.82	1.20	0.64	0.92
Offline mean	2.49	5.43	1.87	1.15	1.21	1.21	1.25	1.20	1.16	1.11	1.22
Offline s.d.	1.91	5.98	1.45	0.63	0.58	0.52	0.65	0.52	0.55	0.37	0.63
Online/offline	1.53	2.13	1.45	1.21	1.21	1.17	1.25	1.13	1.31	1.14	1.16
Price ratio(Hi/Lo)											
Mean	1.043	1.021	1.020	1.026	1.034	1.036	1.015	1.011	1.025	1.021	1.026
s.d.	0.038	0.024	0.026	0.024	0.030	0.036	0.026	0.034	0.027	0.058	0.025

*Purchases of multiple varieties in one trip are counted as multiple purchases.

The online and offline price elasticities are -2.595 and -4.428 , respectively, with a ratio of 0.586 . Larger households are less likely to buy shelf-stable milk, while households with children and elders are more likely to buy. Larger households and households with children are less price sensitive in the online store. Households with elders are more price sensitive in the online channel but less price sensitive in the offline channel. The ratio of online/offline state dependence parameters is 1.149 . Households are more likely to buy shelf-stable milk online on weekdays.

3. Cooking Oil

Cooking oil is a large basket-share category, accounting for 2.5% of total grocery spending, 3.4% of online grocery

spending, and 1.9% of offline grocery spending. There are 12 brands and 38 items in this category; 2,421 households make at least one purchase in the cooking oil category, of which 90.7% are mixed shoppers and 8.6% pure online shoppers. These households made 109,709 shopping trips during the one-year period, with 15.8% online and 84.2% offline; 19.4% of the shopping trips involved purchases of cooking oil: 55.0% for online trips and 12.7% for offline trips. The online store accounts for 46.4% of cooking oil purchases, the high-price zone accounts for 37.3% , and the low-price zone accounts for 16.4% . Prices in the high-price zone are on average 2.0% higher than in the low-price zone, with a standard deviation of 2.6% . Households on average selected 1.8 unique items (s.d. = 1.5) when shopping online,

Table A.2 Demand Parameter Estimates for Yogurt, Shelf-Stable milk, Cooking Oil, and Toilet Paper

	Yogurt		Shelf-stable milk		Cooking oil		Toilet paper	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Main price effect								
Mean: OLS	0.034	−0.041	−0.185	−0.789	0.350	−0.501	−0.109	−0.609
Mean: 2SLS	−0.892	−0.998	−0.495	−1.101	−0.817	−1.676	−0.783	−1.293
Heterogeneity	0.490	0.242	0.104	0.178	0.065	0.015	0.607	0.351
Online-offline price sensitivity correlation	−0.029		0.181		0.085		0.019	
Demographic effect on purchase incidence								
Closest distance	0.033		−0.107		−0.008		−0.017	
Family size	0.040		−0.073		n.s.		−0.071	
Children	0.100		0.048		−0.015		−0.163	
Elders	0.102		0.075		0.004		0.019	
Price-demographics interactions								
Closest distance	0.005	0.009	0.013	0.020	0.013	0.015	0.003	n.s.
Family size	0.017	−0.019	0.010	n.s.	0.005	0.008	0.017	n.s.
Children	0.036	0.003	0.007	−0.013	−0.033	−0.035	0.030	0.008
Elders	−0.056	−0.053	−0.016	0.010	0.009	0.009	0.009	0.032
Household zone	0.008	0.019	0.023	0.040	0.012	0.013	0.033	0.017
Basket size threshold	0.021	0.021	0.004	0.006	0.011	0.032	−0.020	−0.020
State dependence parameter	1.021	0.857	1.162	1.011	0.895	0.441	1.499	0.767
Demographic effects on no purchase								
Weather dummy	−0.017	−0.007	−0.006	−0.019	0.102	n.s.	n.s.	−0.016
Weekday dummy	−0.027	0.129	0.008	0.111	−0.017	0.076	−0.179	0.102
Lagged purchase quantity	−0.435	−0.252	−0.027	0.498	−0.035	0.267	−0.064	0.368
Basket size threshold	−0.088	−0.949	−0.009	−1.248	−0.305	−1.189	−0.327	−1.509
Previous purchase indicator	−0.445	−0.210	−0.059	−0.249	−0.278	n.s.	0.269	0.298

Note. n.s. = not significant.

compared to 1.9 unique items (s.d. = 1.9) when shopping offline.

The online and offline price elasticities are −1.820 and −3.980, respectively, with a ratio of 0.457. Larger households and households with children are less likely to buy cooking oil, while households with elders are more likely to buy. In both channels, larger households and households with elders are less price sensitive; households with children are more price sensitive. The ratio of online/offline state dependence parameters is 2.029. Households are more likely to buy cooking oil online on weekdays.

4. Toilet Paper

Toilet paper is a medium-sized basket-share category, accounting for 1.5% of total grocery spending, 2.2% of online grocery spending, and 1.0% of offline grocery spending. There are 3 brands and 12 items in this category; 2,632 households make at least one purchase in the toilet paper category, of which 89.8% are mixed shoppers and 9.5% are pure online shoppers. These households made 115,878 shopping trips during the one-year period, with 16.3% of trips online and 83.7% offline. Of the shopping trips, 19.2% involve purchases of toilet paper, 59.7% for online trips and 11.3% for offline trips. The online store accounts for 50.8% of toilet paper purchases, the high-price zone accounts for 35.3%, and the low-price zone accounts for 13.9%. Prices in the high-price zone are on average 2.6% higher than in the low-price zone (s.d. = 2.4%). Households

on average selected 1.4 unique items (s.d. = 1.1) when shopping online, compared to 1.5 unique items (s.d. = 1.4) when shopping offline.

The online and offline price elasticities are −1.716 and −3.390, respectively, with a ratio of 0.506. Larger households and households with children are less likely to buy toilet paper, while households with elders are more likely to buy. In both channels, larger households, households with elders, and households with children are less price sensitive. The ratio of online/offline state dependence parameters is 1.954. On weekdays households are more likely to buy cooking oil online, while on weekends they are more likely to buy offline.

5. Square Bread

Square bread is one of the medium-sized basket-share categories, accounting for 1.1% of total grocery spending, 0.8% of online grocery spending, and 1.3% of offline grocery spending. There are 7 brands and 39 items in this category, and 2,321 households make at least one purchase in this category, of which 93.4% are mixed shoppers and 5.7% are pure online shoppers. These households made 108,137 shopping trips during the one-year period, with 14.8% online and 85.2% offline; 27.1% of the trips involved purchases of square bread—45.6% for online trips and 23.9% for offline trips. The online store accounts for 25.8% of square bread purchases, the high-price zone accounts for 51.0%, and the low-price zone accounts for 23.2%. Prices in the high-price zone are on average 3.4% higher than the

Table A.3 Demand Parameter Estimates for Square Bread, Eggs, Liquid Fabric Softener, and Packed Oranges

	Square bread		Eggs		Liquid fabric softener		Packed oranges	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Main price effect								
Mean: OLS	0.158	0.041	−0.097	−0.276	−0.738	−2.080	−0.939	−1.786
Mean: 2SLS	−1.328	−1.461	−1.749	−2.030	−1.991	−3.335	−2.413	−3.282
Heterogeneity	0.084	0.013	0.013	0.008	0.061	0.024	0.610	0.078
Online-offline price sensitivity correlation		−0.024		0.014		0.005		0.370
Demographic effect on purchase incidence								
Closest distance		−0.007		0.020		0.106		0.126
Family size		0.011		0.029		0.016		−0.031
Children		0.014		n.s.		−0.039		0.076
Elders		−0.025		n.s.		n.s.		−0.004
Price-demographics interactions								
Closest distance	0.004	0.004	0.003	n.s.	0.002	n.s.	0.091	0.085
Family size	−0.008	−0.005	−0.004	−0.011	−0.004	−0.005	−0.069	−0.008
Children	0.010	0.002	−0.006	−0.017	n.s.	n.s.	0.161	−0.083
Elders	−0.047	−0.019	n.s.	0.002	n.s.	n.s.	−0.052	0.071
Household zone	−0.034	n.s.	−0.017	n.s.	0.001	0.010	−0.225	−0.008
Basket size threshold	0.072	0.080	−0.003	−0.005	0.005	0.014	n.s.	−0.075
State dependence parameter	1.041	0.913	1.271	0.978	1.126	0.643	0.768	0.334
Demographic effects on no purchase								
Weather dummy	−0.026	0.023	0.018	n.s.	0.028	−0.028	n.s.	n.s.
Weekday dummy	0.110	0.128	−0.034	0.110	−0.116	0.050	n.s.	0.038
Lagged purchase quantity	−0.155	0.142	0.255	0.566	−0.047	0.168	−0.101	n.s.
Basket size threshold	−0.356	−0.630	−0.265	−1.001	−0.428	−1.338	n.s.	−1.218
Previous purchase indicator	−0.427	−0.189	−0.139	0.076	0.073	0.105	−0.453	−0.374

Note. n.s. = not significant.

low-price zone, with a standard deviation of 3.0%. Households on average selected 1.2 unique items (s.d. = 1.4) when shopping online, compared to 3.1 unique items (s.d. = 2.5) when shopping offline.

The online and offline price elasticities are −3.339 and −3.790, respectively, with a ratio of 0.881. Larger households and households with children are more likely to buy square bread, and households with elders are less likely to buy. In both channels, larger households and households with elders are more price sensitive, and households with children are less price sensitive. The ratio of online/offline state dependence parameters is 1.140.

6. Eggs

Eggs is one of the small basket-share categories, accounting for 0.8% of total grocery spending, 0.6% of online grocery spending, and 0.9% of offline grocery spending. There are 6 brands and 18 items in this category, and 2,292 households make at least one purchase in the egg category, of which 93.4% are mixed shoppers and 5.8% are pure online shoppers. These households made 107,608 shopping trips during the one-year period, with 14.6% online and 85.4% offline; 24.2% of the shopping trips involved purchases of eggs: 44.5% for online trips and 20.7% for offline trips. The online store accounts for 26.6% of egg purchases, the high-price zone accounts for 50.9%, and the low-price zone accounts for 22.5%. Prices in the high-price zone are on average 3.6% higher than in the low-price zone, with a standard deviation of 3.6%. Households on average selected

1.7 unique items (s.d. = 1.0) when shopping online, compared to 3.4 unique items (s.d. = 2.0) when shopping offline.

The online and offline price elasticities are −3.427 and −4.012, respectively, with a ratio of 0.854. Larger households are more likely to buy eggs; number of children and number of elders have no effect on egg purchase. In both channels, larger households and households with children are more price sensitive. The ratio of online/offline state dependence parameters is 1.301. On weekdays, households are more likely to buy eggs online, while on weekends, they are more likely to buy offline.

7. Liquid Fabric Softener

Liquid fabric softener is one of the small basket-share categories, accounting for 0.7% of total grocery spending, 1.0% of online grocery spending, and 0.5% of offline grocery spending. There are 5 brands and 35 items in this category, and 1,949 households make at least one purchase in the liquid fabric softener category, of which 91.5% are mixed shoppers and 7.8% are pure online shoppers. These households made 89,820 shopping trips during the one-year period, with 15.4% online and 84.6% offline; 11.7% of the shopping trips involved purchases of liquid fabric softener—39.1% for online trips and 6.7% for offline trips. The online store accounts for 51.5% of liquid fabric softener purchases, the high-price zone accounts for 35.4%, and the low-price zone accounts for 13.1%. Prices in the high-price zone are on average 1.5% higher than the low-price zone, with a standard deviation of 2.6%. Households on average

Table A.4 Demand Parameter Estimates for Paper Towel, Packed Potatoes, and Liquid Dish Detergent

	Paper towels		Packed potatoes		Liquid dish detergent	
	Online	Offline	Online	Offline	Online	Offline
Main price effect						
Mean: OLS	−0.611	−1.414	−0.566	−2.320	−0.099	−0.622
Mean: 2SLS	−1.640	−2.991	−3.726	−5.543	−0.754	−1.286
Heterogeneity	0.133	0.031	0.021	0.013	0.004	0.042
Online-offline price sensitivity correlation		0.017		−0.007		0.075
Demographic effect on purchase incidence						
Closest distance		−0.012		0.003		0.015
Family size		−0.072		0.009		n.s.
Children		−0.148		−0.012		−0.068
Elders		0.008		0.003		0.049
Price-demographics interactions						
Closest distance	n.s.	0.003	0.001	0.002	0.002	0.009
Family size	0.031	0.026	0.010	0.003	0.005	0.001
Children	0.040	0.029	−0.002	−0.006	n.s.	−0.004
Elders	0.002	0.004	0.002	0.002	−0.001	0.001
Household zone	0.025	0.020	−0.002	−0.002	0.012	0.014
Basket size threshold	−0.018	−0.019	0.004	0.010	0.012	0.040
State dependence parameter	0.980	0.352	0.997	0.411	0.865	0.364
Demographic effects on no purchase						
Weather dummy	0.055	−0.021	0.040	−0.084	0.032	−0.043
Weekday dummy	−0.163	0.094	0.065	0.102	−0.065	0.043
Lagged purchase quantity	−0.116	0.129	−0.048	0.085	−0.076	0.147
Basket size threshold	−0.498	−1.457	−0.322	−1.238	−0.420	−1.235
Previous purchase indicator	0.214	0.216	−0.151	0.146	0.152	0.222

Note. n.s. = not significant.

selected 1.7 unique items (s.d. = 1.0) when shopping online, compared to 2.1 unique items (s.d. = 1.5) when shopping offline.

The online and offline price elasticities are −2.336 and −4.090, respectively, with a ratio of 0.571. Larger households are more likely to buy liquid fabric softener, and households with children are less likely to buy. In both channels, larger households are more price sensitive. The ratio of online/offline state dependence parameters is 1.819. On weekdays, households are more likely to buy liquid fabric softener online; on weekends, they are more likely to buy offline.

8. Packed Oranges

Packed oranges is one of the small basket-share categories, accounting for 0.7% of total grocery spending, 0.6% of online grocery spending, and 0.8% of offline grocery spending. Packed oranges are not branded. There are 7 items in this category. At least one purchase in the packed oranges category was made by 1,533 households, of which 94.5% are mixed shoppers and 4.8% pure online shoppers. These households made 76,251 shopping trips during the one-year period, with 13.9% online and 86.1% offline; 12.5% of these trips involved purchases of packed oranges—39.1% for online trips and 6.7% for offline trips. The online store accounts for 30.1% of packed orange purchases, the high-price zone accounts for 55.3%, and the low-price zone accounts for 14.6%. Prices in the high-price zone are on

average 1.1% higher than in the low-price zone, with a standard deviation of 3.4%. Households on average selected 1.5 unique items (s.d. = 0.8) when shopping online, compared to 2.2 unique items (s.d. = 1.3) when shopping offline.

The online and offline price elasticities are −2.874 and −3.916, respectively, with a ratio of 0.734. Larger households and households with elders are less likely to buy packed oranges; households with children are more likely to buy. Larger households are more price sensitive in both channels. Households with children are less price sensitive online but more price sensitive offline; households with elders are more price sensitive online but less price sensitive offline.

9. Paper Towels

Paper towels is one of the small basket-share categories, accounting for 0.5% of total grocery spending, 0.8% of online grocery spending, and 0.3% of offline grocery spending. There are four brands and nine items in this category; 2,431 households make at least one purchase in the paper towel category, of which 90.1% are mixed shoppers and 9.1% are pure online shoppers. These households made 107,460 shopping trips during the one-year period, 16.4% online and 83.7% offline, and 15.3% of the shopping trips involved purchases of paper towels: 49.9% for online trips and 8.6% for offline trips. The online store accounts for 53.1% of paper towel purchases, the high-price zone accounts for 34.3%, and the low-price zone accounts for 12.7%. Prices in the high-price zone are on average 2.5%

higher than in the low-price zone, with a standard deviation of 2.7%. Households on average selected 1.5 unique items (s.d. = 0.7) when shopping online, as compared to 2.0 unique items (s.d. = 1.1) when shopping offline.

The online and offline price elasticities are -1.973 and -4.034 , respectively, with a ratio of 0.489. Larger households and households with children are less likely to buy paper towels, and households with elders are more likely to buy. In both channels, larger households, households with children and households with elders are less price sensitive. The ratio of online/offline state dependence parameters is 2.784. On weekdays, households are more likely to buy paper towels online; on weekends, they are more likely to buy offline.

10. Packed Potatoes

Packed potatoes is a small basket-share category, accounting for 0.5% of total grocery spending, 0.5% of online grocery spending, and 0.5% of offline grocery spending. Packed potatoes are not branded, and there are 14 items in this category; 1,981 households make at least one purchase in the packed potato category, of which 93.8% are mixed shoppers and 5.4% are pure online shoppers. These households made 96,139 shopping trips during the one-year period, 14.6% online and 85.4% offline. Of these shopping trips, 13.0% involve purchases of packed potatoes: 33.4% for online trips and 9.5% for offline trips. The online store accounts for 38.3% of packed potato purchases, the high-price zone accounts for 46.3%, and the low-price zone accounts for 15.5%. Prices in the high-price zone are on average 2.1% higher than in the low-price zone, with a standard deviation of 5.8%. Households on average have selected 1.8 unique items (s.d. = 1.1) when shopping online, compared to 2.6 unique items (s.d. = 1.6) when shopping offline.

The online and offline price elasticities are -2.449 and -3.829 , respectively, with a ratio of 0.640. Larger households and households with elders are more likely to buy packed potatoes; households with children are less likely to buy. In both channels, larger households and households with elders are less price sensitive, and households with children are more price sensitive. The ratio of online/offline state dependence parameters is 2.426.

11. Liquid Dish Detergent

Liquid dish detergent is also a small basket-share category, accounting for 0.5% of total grocery spending, 0.7% of online grocery spending, and 0.4% of offline grocery spending. There are 5 brands and 18 items in this category; 2,342 households make at least one purchase in the liquid dish detergent category, of which 90.7% are mixed shoppers and 8.5% are pure online shoppers. These households made 107,993 shopping trips during the one-year period, with 15.9% online and 84.1% offline, and 9.3% of the shopping trips involved purchases of liquid dish detergent: 28.2% for online trips and 5.8% for offline trips. The online store accounts for 48.7% of liquid dish detergent purchases,

the high-price zone accounts for 37.5%, and the low-price zone accounts for 13.8%. Prices in the high-price zone are on average 2.6% higher than in the low-price zone, with a standard deviation of 2.5%. Households on average selected 1.7 unique items (s.d. = 1.0) when shopping online, compared to 2.0 unique items (s.d. = 1.2) when shopping offline.

The online and offline price elasticities are -2.439 and -4.372 , respectively, with a ratio of 0.558. Households with children are less likely to buy liquid dish detergent, and households with elders are more likely to buy. In both channels, larger households are more price sensitive. Households with elders are less price sensitive offline but more price sensitive online. The ratio of online/offline state dependence parameters is 2.376. On weekdays, households are more likely to buy liquid dish detergent online; on weekends, they are more likely to buy offline.

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