The Impact of Package Size on Food Consumption

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1 Introduction

The heightened prevalence of obesity and diet-related diseases in most developed countries has raised much interest in examining the effects of marketing activities on food consumption. This interest has led to a surge in experimental work focusing on evaluating the impact of food portion and package sizes on consumption. Food portion size has been singled out as one of the primary causes of higher obesity rates in the United States (Young and Nestle, 2002). Closely linked to this, food package size is considered to be one of the important environmental cues that affects consumers' food-at-home consumption (e.g., Chandon 2013). For example, the Centers for Disease Control and Prevention advise that consumers should be aware of large packages in avoiding portion size pitfalls for healthy eating. The main goal of this research is to advance our understanding of how package size affects food-at-home consumption. In our analysis, we use the package-downsizing activities by food manufacturers between 2004 and 2010 to examine how households respond to actual package-downsizing events in a market environment.

Experimental research on the effects of package and portion size on consumption generally predicts that larger package or portion sizes lead to increased food consumption, thereby increasing caloric intake (Rolls et al., 2004; Rolls, Morris and Roe, 2002; Wansink 1996; Wansink, Painter and North, 2005). An important reason why large sizes lead to increased food consumption is that consumers' size perceptions are biased. Chandon and Wansink (2007b) found that consumers underestimate actual meal size as the size of the meal increases. Similarly, some found that consumers' size perceptions are not responsive to size and shape changes and they underestimate size changes of objects (Krishna, 2006; Raghubir and Krishna, 1999). The underestimation of actual size is aggravated when objects, i.e., packages or serving containers, change in multiple dimensions as compared to one dimensional changes (Chandon and Ordabayeva, 2009). These findings are also supported by empirical work that used market data. Çakır and Balagtas (2014) found evidence that consumers are less sensitive to package size changes than to price changes, implying that downsizing can be a viable strategy to increase prices implicitly in order to pass through increases in production costs.

Price is another important factor that affects consumers' response to food portion and package size. Typically, marketers offer quantity discounts on large sizes. That is, larger size products are typically cheaper on a per unit basis than small size products. Research shows that quantity discounts can accelerate consumption (Wansink, 1996). Furthermore, quantity discounts and price promotions can lead to stockpiling which could also accelerate consumption (Chan, Narasimhan, and Zhang, 2008; Neslin and Van Heerde, 2008).

While previous literature provides some evidence on how consumers respond to food portion and package size and its underlying reasons, it has important limitations. One limitation is that previous studies primarily focus on short-term effects. However, the impact of portion and package size on consumption over longer time horizons may be important, especially with respect to health concerns. For example, consumer response can diminish over time if they are repeatedly served large packages/portions. Similarly, consumers can compensate for a large portion by eating smaller portions in subsequent meals. In other words, habituation and compensation can take place over longer time periods and these behaviors could offset short-term effects (Chandon, 2013). Also, previous research typically overlooks food purchase behavior. Because consumers purchase food prior to its consumption, factors that impact purchase behavior, such as price, promotion and availability of close competitors, need to be accounted for in order to identify the effect of package/portion size on consumption.

In this study, we overcome these limitations by using the Nielsen Homescan household panel that comprise information on food purchases in the market place. We investigate the impact of food package size by exploiting food marketers' package-downsizing strategy, where a new, smaller size product is replaced by an old, larger size. This strategy provides a unique opportunity to analyze the impact of a plausibly exogenous marketing activity on household shopping behavior. In particular, using the package-downsizing strategy we develop a novel empirical design that allows an application of the difference-in-difference (henceforth, DD) method to market data. We perform our analysis using purchase data on shelf-stable tuna (henceforth, tuna) and peanut butter (henceforth, PB) products.[1]

1.1 Package Downsizing in Tuna and Peanut Butter Markets

The tuna and PB markets in the United States are highly concentrated oligopolistic markets. In both markets the top three nationally branded tuna manufacturers hold over 70 percent of the total volume of the market. Other national brands have low national market shares, but the total store brand shares are significant with over 20 percent of each market.

Package downsizing in both markets is common. In the tuna market, brands downsized from 6 oz. and 6.5 oz. packages to 5 ounces starting in 2006. At the beginning of the study period the total volume sales of 6 oz. tuna was approximately 80 percent of the market. By 2010, 5 oz. tuna products became the norm size, comprising approximately 75 percent of the market.

Unlike tuna, there does not exist a single norm size for peanut butter. Approximately 80 percent of the PB sales are in 18 oz., 28oz., and 40oz. packages. Most of the top brands have all three popular sizes in their product lines. In 2008, two of the leading manufacturers downsized their 18 oz. packages to 16.3 ounces. However, other brands did not downsize any of their products. In 2010, the volume sales of downsized packages was approximately 20 percent of the total market.

The tuna and PB markets exhibit desirable characteristics for our research purposes. First, the degree of downsizing measured as the volume share of downsized products in total market volume is different between the markets. This is important because the degree of downsizing in a category could affect how easily consumers can switch away from downsized products. A high degree of downsizing in a product category could imply less availability of non-downsized competing products.

A second useful feature is that tuna and PB products represent two different examples of the interrelationship between package size, serving size and consumption. The impact of downsizing on purchase can be different for the products that are served and consumed differently. On the one hand, a regular PB product is designed to include multiple servings and be consumed intermittently. Also, a PB serving size does not necessarily depend on the

[1] We do not observe food consumption. However, if households consume the same proportion of the food they purchase before and after downsizing, then the impacts of package downsizing on purchase volume and consumption are the same. That is, package downsizing is assumed to have no impact on the proportion of food that is wasted, shared, or given.

package size. For example, consumers who regularly prepare PB sandwiches can easily maintain the same amount of PB spread on their sandwiches even after the package downsizing. On the other hand, a regular tuna product is not designed to be used intermittently; in most cases the package size is equal to the serving size. For example, consumers who regularly prepare tuna sandwiches will find it difficult to maintain using 6 oz. of tuna on a sandwich after the package downsizing.

Finally, a unique feature of the downsizing in the tuna and PB markets plays a key role in facilitating our research design. We observe that both tuna and PB brands are sold in multiple package sizes. However, the manufacturers downsize the products in only one of the size categories. In the section that follows, we will discuss how we exploit this observation in designing our DD analysis.

2 Empirical Strategy

Our goal is to estimate the impact of package downsizing (i.e., the treatment) on household purchase volume (i.e., the outcome). To achieve this goal, our empirical strategy is to compare purchase volume of products, which is defined below, that are affected by package downsizing (treatment group, g=1) to the changes in purchase volume of products, which are in the same product category, but are not affected by package downsizing (control group, g=0). This comparison takes a form of DD analysis. Formally, let v_{ijt} denote household i's purchase volume of product j in month t. Also, let t_c^* denote the month in which package downsizing is observed in city c. The unconditional average treatment effect is estimated as:

$$\gamma = E[v_{ijt \geq t_c^*} - v_{ijt < t_c^*} | g = 1] - E[v_{ijt \geq t_c^*} - v_{ijt < t_c^*} | g = 0], \quad (1)$$

where $E(.)$ denotes the expectation operator.

The use of DD analysis with market data to evaluate firm strategies and their implications is not common. This is mainly because with market data the formation of the treatment and control groups can be challenging, if at all possible. We define the treatment and control groups by following a strategy that is similar to those employed in the literature of mergers in retail markets (e.g., Allain et al., 2013; Houde, 2012). In this literature the treatment group is defined as the stores that are affected directly (i.e., merging stores), or indirectly (close competitors). The close competitors are determined by a pre-defined spatial proximity measure. The stores that are not close competitors are used as the control group.

In our study, we conjecture that a downsizing event could impact the volume sales of the downsized product as well as the volume sales of its close competitors. We define a product as a specific brand-size combination, such that two different sizes of a single brand are two different products. We determine a close competitor product based on its proximity to the downsized product in the product space. To fix ideas, suppose that there are two competing brands of a product (Brand 1 and Brand 2) and each brand is sold in three different package sizes (small, S; medium, M; and large, L). Suppose Brand 1 downsized only its small package size (i.e., 1-S), whereas brand 2 did not downsize any of its packages. We maintain that downsizing of 1-S could potentially affect the sales of 1-M, 2-S, and 2-M due to consumers switching brands and sizes but not the sales of 1-L and 2-L. Categorized in this way the treatment and control groups would be formed as (1-S, 1-M, 2-S, 2-M) and (1-L, 2-L), respectively.

The rationale behind these group definitions is based on an analysis of consumer switching behavior. A downsized product has less content and higher per-unit price, ceteris paribus. On the one hand, when a small product is downsized buyers of the product might switch after downsizing if they perceive the new product as "too small". In this case, assuming consumers view products as being located in characteristics space based on their package size, the medium-size packages will be more preferable to buyers of small-size products than the large size.

On the other hand, buyers might switch after downsizing if they perceive the new product as "too expensive". Similarly, in this case we would expect buyers to switch to the medium-size products rather than the large size. To illustrate, suppose buyers differ in their price sensitivities because some buyers are better informed about prices than others (Salop, 1977; Stigler, 1961). A brand manufacturer can exploit buyers' heterogeneous price sensitivity by offering quantity discounts as a tool for price discrimination (Cohen, 2008), such that larger sizes would have a lower per-unit price and appeal to more price-sensitive buyers. The self-selection of buyers into size categories would imply that buyers of small-size products are more similar in type to the buyers of medium-size products than to the buyers of the large-size products.

The DD estimator in equation 1 assumes that the purchase volume trends of both product segments would be the same in the absence of package downsizing. That is, package downsizing induces a deviation from this common trend, which is captured by group fixed effects. This identifying assumption would be tenuous if the factors that are unrelated to package downsizing affect consumption of the larger package sizes relative to the small packages. This would happen if household types were systematically different across product segments. It is likely that households who buy larger packages, and thus presumably are not affected by package downsizing, may be larger households, or households that have less storage costs, and thus have more inelastic category demand. Also, the impact of demand shocks on large-size buyers can be different than the impact on small-size buyers. In other words, the decision to downsize a specific sized product could be based on the household types. To account for this self-selection bias we will estimate the following regression DD model which includes household fixed effects and product level time varying covariates that control for the differences between the two groups:

$$\ln v_{ijt} = \alpha_0 + D_t + G_j + \gamma D_t \times G_j + \ln Z_{jt} + \lambda_i + \lambda_j + \lambda_t + \varepsilon_{ijt}, \tag{2}$$

where ln denotes the logarithmic operator, D_t is a dummy variable that takes on a value of 1 if the purchase is made post-downsizing, G_j takes on a value of 1 if the product j belongs to the downsized group. The vector $Z_{jt} = [\ln p_{jt} \; prom_{jt}]$ includes product-level information on purchase price and promotion. The regression also includes fixed effects to control for household and product fixed factors affecting purchase volume, (i.e., λ_i and λ_j, respectively) and time changing determinants of purchase volume (λ_t). The coefficient of interest is the average effect of downsizing and is captured by γ. It is important to keep in mind that because package downsizing is not randomly assigned, γ captures the average treatment effect on the treated.

In the subsequent analysis, we will separate the average effect of package downsizing into a direct and a competitive effect (Houde, 2012). The direct effect is the effect of downsizing on the purchase volume of downsized products, while the competitive effect is the effect of downsizing on the purchase volume of competing non-downsized products. To measure these disaggregate average effects we will estimate the following equation:

$$\ln v_{ijt} = \alpha_0 + D_t + G_j + \gamma_0 D_t \times G_j \times S_{jt} + \gamma_1 D_t \times G_j \times (1 - S_{jt}) + \ln Z_{jt} + \lambda_i + \lambda_j + \lambda_t + \varepsilon_{ijt}, \tag{3}$$

where S_{jt} takes on a value of one for the downsized products during the post-downsizing period. The direct and competitive effects of package downsizing are captured by the regression coefficients γ_0 and γ_1, respectively.

To account for the potential endogeneity of product price and purchase volume we take an instrumental-variables approach. We exploit the panel structure of the data and use product prices in other cities as exogenous instruments (Hausman et al., 1994; Hausman 1996). This approach relies on the correlation between the product prices in different cities due to common marginal shocks. The identifying assumption is that, after controlling for demographics and product specific effects, the stochastic disturbances in prices are independent across the cities.

3 Data

We use Nielsen homescan data on tuna and PB purchases in the 25 major Nielsen scantrack markets over a period of 7 years, 2004–2010. The data set comprises information on price and quantity of products, product characteristics, promotion, and timing of purchase for each grocery store transaction made by a large panel of U.S. households. Nielsen selects participating households based on their demographic information to construct a nationally representative sample. Each participating household is provided with a scanner to record their purchases. The dataset includes households who record a purchase of any product in at least 10 out of 12 months of the year. We conduct our analysis on a subset of households who made at least one purchase in both the pre- and post-downsizing periods. We define the first month of post-downsizing period in a city as the month that we observe the first purchase of a downsized product in that city.

To perform our DD analysis we assign each of the tuna and PB products to either the treatment or control group. We define a product as follows. First we identify the major brands in each of the product categories. In tuna and PB markets there are 6 and 13 major brands,[2] respectively. Then, we identify the container types and the major package size categories in each of the container types. For example, tuna brands are offered in can and envelope containers, comprising approximately 94 percent and 6 percent of total market volume, respectively. Similarly, PB brands are offered in plastic, glass, and can containers comprising approximately 87 percent, 11 percent, and 2 percent of the total market volume. We identify size categories in each of the container types and then define products as brand-container-size combinations. If a size category of a brand is downsized then our definition of a product would encompass both the old and the new size because the new size of a downsized product essentially replaces the old size. For example, based on our definition, 6 oz. and 5 oz. package sizes of a tuna brand are considered to be the same product. Finally, we identify products which have at least 0.1 percent share of the total market volume or at least 0.1 percent of the total purchase occasions and assign a product number. The products that are less than 0.1 percent threshold are lumped in either major sizes of "all other store brands" or "all other

[2]Each of the major brands have at least 0.5 percent of the total market volume in their respective product category.

national brands". Also, we exclude infrequently sold products such as the products that are sold only in one city. Categorized this way, the tuna sample includes 27 products that comprise over 98 percent of the total market volume, and the PB sample includes 56 products comprising over 97 percent of the total market volume.

We calculate the price variable at the product level as the average per-unit price paid for product j in month t. Similarly, we construct a promotion variable at the product level as the share of purchases of product j made with some form of discounting, *e.g.*, coupons or store discounts, in month t. For example, $prom_{jt} = 0.75$ denotes that 75 percent of the purchases of product j in time t were made with a discount, while the remaining 25 percent were made at the shelf price. The key variable of interest is the household purchase volume contracted as the average purchase volume of household i of product j in month t.

Table 1 presents summary statistics on treatment and control groups before and after downsizing. The upper (lower) panel corresponds to the tuna (PB) sample. We observe 17,011 (14,996) households in the tuna (PB) sample who on average made a purchase approximately 19 (19) times during the study period, for a total of 315,592 (282,747) purchase occasions over all households. The sample size, i.e., the number of purchase occasions, is different between the treatment and control groups for both product categories.

The average price is higher in the post-downsizing period for all groups, whereas the discount frequency remains almost the same. On average the tuna products in the control group are more expensive than the products in the treatment group. The opposite is true for the PB products, that is, on average PB products in the treatment group are more expensive than the products in the control group. In both product categories, the control products are more heavily promoted than the treated products.

The average purchase volume of tuna has decreased by approximately 1.9 oz. and 0.5 oz. in the post-downsizing period for treatment and control groups, respectively. That is, the average DD in the purchase volume of tuna is about 1.3 oz. a month. The purchase volume statistics of PB products show a different pattern. The average purchase volume of PB for the treatment group has remained almost the same in the post-downsizing period, whereas it has increased for the control group by approximately 5.3 oz. That is, the average DD in the purchase volume of PB is about 5.3 oz. a month. While these differences imply that purchase volume decreased after downsizing, it should be noted that we are not controlling for any confounding factors that could be happening at the same time as the downsizing event.

Before we turn to the results of our preliminary analysis, we investigate the key identifying assumption of the DD approach. That is, the purchase volume trends for the treatment and control groups would have been the same in the absence of package downsizing. This assumption necessitates that we observe a common trend in the pre-downsizing period for the treatment and control groups. Figure 1 shows the trends of the monthly per-household average purchase volume for the treatment and control groups in both the tuna and PB categories. The two vertical lines in each graph denote the start of the post-downsizing in the 1st city and the last city, respectively. We note that the evolution of trends are very similar during the pre-downsizing period in both product categories. This observation provides a strong support for the common trend assumption.

The evolution of purchase volume trends after the downsizing period are different. In the case of tuna it appears that downsizing coincides with a stark decrease in purchase volume for the treatment group, while control group exhibits a slight decrease. In the case of PB it appears that there is an increase for the control group while the treatment group remains stable. This

Table 1: Summary statistics on treatment and control groups

Shelf-Stable Tuna	Treatment Group		Control Group	
Number of Products	22		5	
Number of Purchase Occasions	298,694		16,898	
	Before	After	Before	After
Average Price ($)	0.1623	0.1973	0.205	0.2227
	(0.0999)	(0.1134)	(0.0634)	(0.0669)
Average Discount Frequency	0.5607	0.5655	0.8069	0.809
	(0.4903)	(0.4906)	(0.3913)	(0.3893)
Average Purchase Volume (APM)	25.0222	23.1587	22.6676	22.168
	(27.6547)	(25.0254)	(20.2088)	(16.0056)
(Post–APM) - (Pre–APM)	−1.8635		−0.4996	
DD	−1.3639			
Number of households	17,011			

Peanut Butter	Treatment Group		Control Group	
Number of Products	41		15	
Number of Purchase occasions	236,171		46,576	
	Before	After	Before	After
Average Price	0.1051	0.1213	0.0897	0.1011
	(0.0363)	(0.0405)	(0.0198)	(0.0227)
Average Discount frequency	0.5844	0.5816	0.8374	0.8165
	(0.4886)	(0.4892)	(0.3652)	(0.3834)
Purchase Volume	28.6341	28.6351	68.1928	73.5375
	(23.6404)	(25.2142)	(34.2491)	(36.2067)
(Post–APM) - (Pre–APM)	0.001		5.3447	
DD	−5.3437			
Number of households	14,996			

Notes: "Before (After)" denotes the Pre(Post)-Downsizing period. "Average purchase volume" is the average of monthly per-household purchase volume expressed in ounces. DD corresponds to the average difference-in-difference for the treated and control products. Standard deviations are in parentheses.

could be due to an increase in the overall category demand for peanut butter in the post-downsizing period.

4 Results

We estimate equations 2 and 3 by OLS, controlling for household, product and time (quarter) specific fixed-effects. Using the tuna sample, table 2 presents the estimates of equations 2 and 3 in the upper and the lower panels, respectively. The first column presents the estimates of the pure DD model without controlling for any potentially confounding factors. We estimate that, on average, package downsizing reduces purchase volume of tuna by 8.3 percent. The lower panel presents the disaggregate direct and competitive effects. Both effects are significant and have the expected signs. Accordingly, the direct effect of downsizing is negative 9.3 percent while the competitive effect is 15.7 percent. However, the R^2 of both models are less than 1% and, as discussed above, these estimates could be biased.

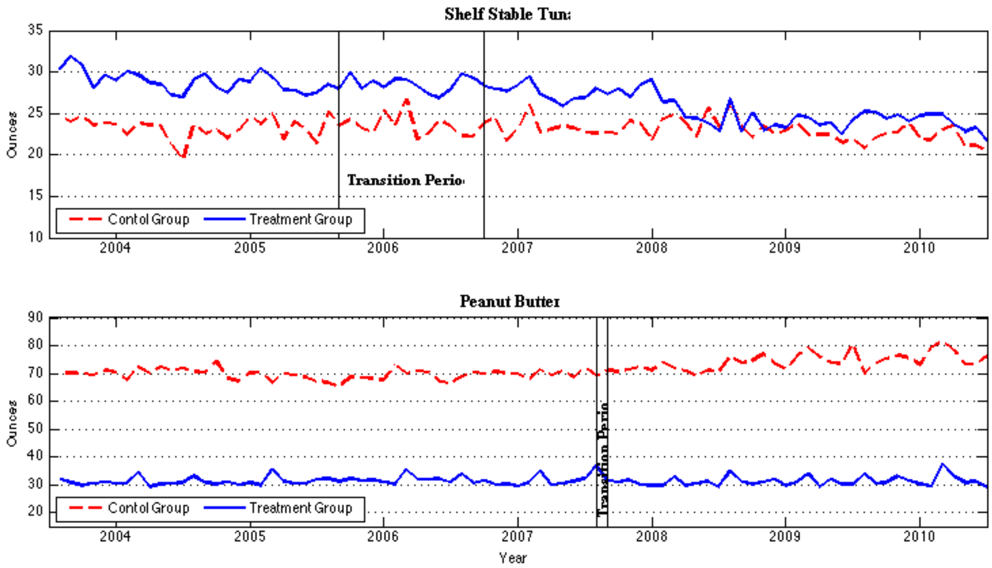

Figure 1: Evolution of the monthly per household purchase volume of shelf stable tuna and peanut butter by treatment and control groups

When we include price and discount variables, and control for household fixed-effects, the R^2 increases above 9% and we estimate that the average effect of downsizing is 1.9 percent. The price and discount effects are significant and have the expected signs; the direct effect decreases purchase volume of the downsized tuna products by 3.1 percent and the competitive effect increases purchase volume by 33.5 percent. To control for the unobserved product-specific factors we include product fixed effects. The R^2 in the upper panel of column 3 implies that the product fixed effects explain an additional 5 percent of the variation in purchase volume. The average effect of downsizing is negative 4 percent. The disaggregate results imply that most of this effect is due to households' reduced purchase volume of downsized products. That is, the direct effect decreases purchase volume of the downsized tuna products by a statistically significant 4.3 percent, while the competitive effect is insignificant. In model 4, presented in the 4^{th} column, we include time fixed effects and their interaction variables with the product fixed effects. The interaction variables control for unobserved factors that might have changed quarter by quarter for each product. Comparing these results to model 3, the estimates of average downsizing effects and the R^2 are almost the same. That is, on average package downsizing reduced the purchase volume of treated products by about 4.2 percent, and most of this effect is attributed to the direct effect.

Table 2: Difference-in-Difference Estimates of the Shelf-Stable Tuna Sample

Dependent variable: (log) monthly per–household purchase volume by products				
	M1	M2	M3	M4
Downsizing	-0.0830^{***}	-0.0196^{*}	-0.0404^{***}	-0.0415^{***}
	(0.0137)	(0.0118)	(0.0115)	(0.0115)
log(price)		-0.6388^{***}	-0.4833^{***}	-0.4649^{***}
		(0.0077)	(0.0117)	(0.0120)
Discount		0.0964^{***}	0.0600^{***}	0.0510^{***}
		(0.0086)	(0.0080)	(0.0081)
Constant	2.9499^{***}	1.9121^{***}	2.1002^{***}	2.0937^{***}
	(0.0129)	(0.0170)	(0.0443)	(0.0608)
R^2	0.0044	0.0921	0.1435	0.1441
	M1’	M2’	M3’	M4’
Downsizing x Direct	-0.0937^{***}	-0.0316^{***}	-0.0426^{***}	-0.0437^{***}
	(0.0138)	(0.0118)	(0.0115)	(0.0115)
Downsizing x Competitive	0.1573^{***}	0.3349^{***}	0.0122	0.0122
	(0.0281)	(0.0191)	(0.0218)	(0.0219)
log(price)		-0.6631^{***}	-0.4802^{***}	-0.4617^{***}
		(0.0077)	(0.0117)	(0.0120)
Discount		0.1347^{***}	0.0600^{***}	0.0510^{***}
		(0.0082)	(0.0080)	(0.0081)
Constant	2.9499^{***}	1.8655^{***}	2.1055^{***}	2.0994^{***}
	(0.0129)	(0.0170)	(0.0443)	(0.0607)
R^2	0.0065	0.1027	0.1435	0.1441
Household	No	Yes	Yes	Yes
Product	No	No	Yes	Yes
Product x Quarter	No	No	No	Yes
Observations	315,592			

Note: The variable Downsizing correspond to the interaction term Post-Downsizing × Treatment. The variable Downsizing × Direct (Downsizing × Competitive) correspond to the interaction term Post-Downsizing × Treatment× Downsized Products during Post-Downsizing (Post-Downsizing × Treatment× (1 - Downsized Products during Post-Downsizing)). The lower order terms of interactions are not reported but are included in all specifications. Clustered standard errors at the household level are reported in parentheses. *,**,*** indicate significance at the 10%, 5%, 1% level, respectively.

Table 3 presents the estimates of equations 2 and 3 using the PB sample. We follow the same estimation strategy as in the case of the tuna sample and include the fixed-effects sequentially. Similar to the tuna analysis, the overall effect of downsizing on purchase volume is negative and statistically significant, but the disaggregated effects are somewhat different.The pure DD estimates show package downsizing decreases total volume by 6.1 percent, which is largely driven by a large and statistically significant competitive effect. However, the estimated disaggregate effects are counterintuitive due to the significant negative sign on the competitive effect. When we include the price and discount variables, and control for household fixed-effects, the R^2 increases by approximately 2 percent and the estimated average effect of downsizing reduces to negative 4.1 percent. When we include product fixed effects the R^2 increases by approximately 7 percent and the estimated average effect of downsizing reduces to negative 1.9 percent. The disaggregate estimates in this case show that most of the average downsizing effect can be attributed to the direct effect, while the the competitive effect is insignificant. Finally, when we include time fixed-effects and their interaction variables with the product fixed-effects, the estimates of average downsizing effects and the R^2 remain almost the same.We estimate that the average effect of downsizing on the purchase volume of treated PB products is about 2 percent, and that most of this effect is attributed to the direct effect.

Table 3: Difference-in-Difference Estimates of the Peanut Butter Sample

Dependent variable: (log) monthly per–household purchase volume by products				
	M1	M2	M3	M4
Downsizing	-0.0612^{***}	-0.0410^{***}	-0.0194^{***}	-0.0202^{***}
	(0.0070)	(0.0056)	(0.0051)	(0.0051)
Price		-0.3479^{***}	-0.3025^{***}	-0.2904^{***}
		(0.0089)	(0.0123)	(0.0127)
Discount		0.0412^{***}	0.1249^{***}	0.1250^{***}
		(0.0051)	(0.0044)	(0.0044)
Constant	4.1284^{***}	3.1618^{***}	3.4935^{***}	3.5334^{***}
	(0.0062)	(0.0218)	(0.0444)	(0.0525)
R^2	0.3592	0.3773	0.4485	0.4491
	M1'	M2'	M3'	M4'
Downsizing x	-0.0556^{***}	-0.0908^{***}	-0.0631^{***}	-0.0641^{***}
Direct	(0.0074)	(0.0064)	(0.0064)	(0.0064)
Downsizing x	-0.0740^{***}	-0.0193^{***}	-0.0007	-0.0015
Competitive	(0.0083)	(0.0058)	(0.0052)	(0.0052)
Price		-0.3438^{***}	-0.2964^{***}	-0.2832^{***}
		(0.0088)	(0.0123)	(0.0127)
Discount		0.0582^{***}	0.1302^{***}	0.1304^{***}
		(0.0051)	(0.0044)	(0.0044)
Constant	4.1284^{***}	3.1697^{***}	3.5064^{***}	3.5487^{***}
	(0.0062)	(0.0217)	(0.0444)	(0.0526)
R^2	0.3593	0.3779	0.4489	0.4494
Household	No	Yes	Yes	Yes
Product	No	No	Yes	Yes
Product x Quarter	No	No	No	Yes
Observations	282,747			

Note: The variable Downsizing corresponds to the interaction term Post-Downsizing × Treatment. The variable Downsizing × Direct (Downsizing × Competitive) corresponds to the interaction term Post-Downsizing × Treatment× Downsized Products during Post-Downsizing period (Post-Downsizing × Treatment× (1 - Downsized Products during Post-Downsizing period)). The lower order terms of interactions are not reported but are included in all specifications. Clustered standard errors at the household level are reported in parentheses. *,**,*** indicate significance at the 10%, 5%, 1% level, respectively.

5 Conclusion

Our study contributes to the literature on the effects of packaging on consumer food purchase and consumption behavior. We examine the impact of food package size on food-at-home consumption using Nielsen Homescan household panel data. We exploit food manufacturer package downsizing strategy to track shifts in household purchase volume before and after package size changes.

In our analysis we focus on purchases of shelf-stable tuna and peanut butter products in 25 major cities between 2004 and 2010. We design a difference-in-difference analysis to compare the changes in purchase volume of products that are affected by package downsizing to the changes in purchase volume of products that are not affected by package downsizing. In subsequent analysis, we separate the average effect of package downsizing into a direct and a competitive effect. The direct effect is the effect of downsizing on the purchase volume of downsized products, while the competitive effect is the effect of downsizing on the purchase volume of competing non-downsized products. We use household, product and time (quarter) specific fixed-effects to control for unobserved confounding fixed factors.

Our main finding is that smaller package size significantly reduced household purchase volume in both product categories. Specifically, we find that, on average, package downsizing reduced the purchase volume of tuna products that are affected by downsizing by 4.2 percent. This negative impact is expected since a regular tuna product is not designed to be used intermittently. Consumers will find it difficult to maintain the same serving size of tuna after downsizing. However, considering that the degree of downsizing of tuna products was approximately 17 percent (i.e., from 6 oz. to 5 oz.) the estimate of the average treatment effect implies that consumers might have switched away from downsized products and/or increased purchase frequency. The disaggregate results show that most of the average effect is due to the impact of downsizing on purchase volume of downsized tuna products, while the impact on purchase volume of close competitors is found to be insignificant.

As for peanut butter, we find that, on average, the purchase volume of peanut butter products that are affected by downsizing decreased by 2 percent. The lower impact of downsizing on peanut butter compared to tuna can be due to i) lower degree of downsizing, approximately 9 percent (i.e., from18 oz. to 16.3 oz), ii) lower share of downsized products in the treatment group, or iii) the intermittent consumption which may lead to increased purchase frequency. Similarly, most of the average effect is due to the impact of downsizing on purchase volume of downsized PB products. The impact on purchase volume of close competitors is found to be insignificant.

In sum, the negative impacts of package downsizing on purchase volume in both product categories imply that package size is positively correlated with food-at-home consumption. This finding is consistent with the results of the experimental studies showing that larger package sizes lead to higher usage volume compared with smaller package sizes. Furthermore, we find that the percentage decrease in purchase volume due to downsizing is less than the degree of downsizing. This result implies that consumers, to some extent, might have increased their purchase frequency of the downsized products, or they might have switched away from the downsized to the competing non-downsized products. Our results show that the latter factor is insignificant.

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