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The Impact of Walmart Supercenter Conversion on Consumer Shopping Behavior

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This paper presents an empirical study of the impact of Walmart supercenter conversion on consumer shopping behavior. By using a difference-in-difference estimator, we find that Walmart gains 41% in weekly revenue from the conversion. Decomposing the revenue gains into components attributable to store visits and per-visit expenditures, we find that the majority of these gains were due to larger expenditures, with a much smaller impact from store visits. By contrast, among competing retailers, grocery stores experience the most significant loss (20% weekly revenue) mostly from fewer store visits, with a much smaller impact attributable to per-visit expenditure. Taken together, these findings show that consumers may benefit from reduced shopping costs by making fewer overall trips and increasing their Walmart basket sizes. In addition, we find that overall revenue gains for Walmart from conversion outweigh the small cannibalization loss at the existing Walmart supercenters located farther away. Finally, from category-level analyses, we find evidence of increases in category-level spending in preexisting categories in the converted supercenter. However, we also find that positive demand externality is more pronounced in food categories, mainly as a result of increased purchase incidence. We discuss the implications of our findings for academics and retail managers.

Keywords: Walmart supercenter; retailer competition; demand externality; revenue economy of scope; one-stop shopping; consumer shopping behavior; interformat competition
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1. Introduction

Wal-Mart Stores, Inc., the world's largest retail firm, has changed the landscape of the U.S. and Canadian retail industry considerably in the past four decades through its ruthless focus on competitiveness and efficiency, achieved through a combination of cost-saving technologies and efficient supply chain networks. The opening of a new Walmart store in any location typically has a substantial impact on consumers and incumbent retailers. Therefore, empirical studies on Walmart are abundant.

Empirical studies on Walmart's effects on retail markets have focused on competitor sales, pricing, assortment, stockouts, and propensity to exit (Jia 2008, Ellickson and Grieco 2013). For example, previous research has found that incumbent supermarkets lose 17% of store sales after Walmart supercenter entry, mostly from a reduction in store traffic (Singh et al. 2006). Incumbent supermarkets reduce prices 1%–3% (Basker and Noel 2009) and raise quality by reducing stockouts (Matsa 2011) after Walmart supercenter entry. Ailawadi et al. (2010) found significant variations in incumbent retailers' reactions in pricing and assortment after Walmart supercenter entry in three different retail formats: supermarkets, drugstores, and mass merchandisers. They also found that incumbents' reactions significantly affected their sales outcomes. Research has also shown that Walmart increases consumer surplus (Hausman and Leibtag 2007) and supplier profits as a result of market expansion (Huang et al. 2012).

However, little is known about how consumer shopping behavior—both store visits and per-visit expenditure—changes at Walmart and competing retailers across multiple channels after Walmart supercenter conversion (i.e., the expansion of a traditional discount format store by adding new departments such as fresh food, produce, and frozen food). This is partly due to data limitations, since large-scale consumer panel data are required together with detailed information on Walmart supercenter entry or conversion to gain insights into changes in consumer shopping behavior. To our knowledge, only one study (Singh et al. 2006) has investigated consumer shopping behavior at supermarkets after Walmart supercenter entry. However, even this study is silent about consumer shopping behavior at Walmart and competing retailers in other channels (i.e., mass merchandisers, drugstores, and warehouse clubs). There is a clear need to examine consumer shopping behavior at Walmart and other channels to obtain a holistic picture of multichannel shopping behavior. Therefore, we investigate the important question of how retail store scope expansion (i.e., an increase in the number of categories offered by a store) affects consumer shopping behavior by using Walmart supercenter conversion as a working example in this study.[1]

We find that Walmart gains 41% in weekly revenue from the conversion and the increase in Walmart traffic (10%) is much smaller than the increase in per-visit expenditure (31%). We also find that positive demand spillover effects into food categories are pronounced, mainly because of an increase in purchase incidence. In other words, a greater number of Walmart shopping trips involve food category purchases after supercenter conversion. By contrast, nonfood categories, which are farther away from newly added departments both in physical distance and category association, do not benefit from positive demand spillover effects. This contradicts the commonly held belief among industry analysts that Walmart offers lower prices on food to increase traffic into the supercenters with the goal of selling higher-margin general merchandise, which potentially treats the entire food business as a loss leader (Singh et al. 2006).

In addition, we find that among competing retail channels, grocery stores experience the most significant loss (20% decrease in weekly spending) mostly from fewer store visits, with a much smaller impact from per-visit expenditure. However, mass merchandisers, drugstores, and warehouse clubs are not affected by Walmart supercenter conversions, which is very different from the case of Walmart supercenter entry (Ailawadi et al. 2010). Finally, we find that the overall revenue gain from Walmart supercenter conversions outweighs the small cannibalization loss at the existing Walmart supercenters, which are located farther away.

Our findings of asymmetric demand externality in food and nonfood categories have important implications on how retailers should manage their merchandise in the case of store scope expansion. For example, retailers should carefully consider physical distance and category association so as to benefit from positive demand spillover from retail scope expansion. Our results are also important for understanding how competitive impacts of retail scope expansion are different from the case of new retail store entry. Our results suggest that competing retailers that have more overlaps with the expanded scope suffer more in the case of supercenter conversion.

This study contributes to research on demand externalities from spatial colocation by providing direct empirical measurements of demand externality in the case of Walmart supercenter conversion, which is a significant phenomenon in the retail industry (Gould et al. 2005, Clifford 2011, Datta and Sudhir 2011, Sen et al. 2011, Vitorino 2012). Our research is also related to the store choice literature (Bell and Lattin 1998, Bell et al. 1998, Briesch et al. 2009, Fox et al. 2004, Cleeren et al. 2010) and multicategory shopping literature (Manchanda et al. 1999, Seetharaman et al. 2005).

We organize the remainder of this paper as follows: §2 describes the data, provides details on household selection, and presents key summary statistics; §3 presents our estimation strategy and results; and in §4 we discuss our findings and conclude.

2. Data

2.1. Data Description

Our analysis uses two main sources of data: (1) consumer panel data and (2) Walmart store location and opening/conversion date data. Nielsen collects consumer panel data through home scanners (Homescan data). The data set contains detailed information on participating households' shopping behavior during the period April 2003–September 2006. The data cover all major retail channels, including grocery stores, mass merchandisers, supercenters, drugstores, and warehouse clubs. Moreover, the data include information on panelist households' shopping behavior at Walmart. During the period covered by our data, Walmart did not provide point-of-sales data to Nielsen or Information Resources, Inc. (IRI). However, Homescan data enable us to directly measure the impact of Walmart supercenter conversion on consumer shopping behavior at both Walmart and competing retail channels. We convert the trip-level data into weekly data and compute the weekly spending, weekly count of visits, and weekly average per-visit expenditure for each household at Walmart stores and competing retail channels.

Along with the records on shopping trips and per-visit expenditures, we have product-category-level data, such as purchase timing and total category spending, for four food categories and five nonfood categories: ready-to-eat (RTE) cereal, mayonnaise, coffee, cola, batteries, toothpaste, vitamin and mineral supplements, cold/sinus/allergy medicine, and linen and window furniture coverings. This allows us to analyze the impact of Walmart supercenter conversion at the product-category level. We focus on product categories that already exist in discount format stores

[1] More than 60% of Walmart supercenter openings have been brought about by the conversion of existing Walmart discount stores, based on our calculations of Walmart supercenter openings between October 2004 and January 2006. We note that most existing studies do not investigate Walmart supercenter conversion.

before supercenter conversion to examine whether there is positive demand externality to these categories after supercenter conversions. We convert the original data to compute weekly category spending for each household.

Finally, the Homescan data set also includes details on household locations, which can be inferred from the five-digit zip codes of households' home addresses. By using Google's geocoding service, we obtain the longitudes and latitudes of five-digit zip code centroids for each household and use them in our empirical analysis.

The second data set provides information on Walmart stores. This data set lists the address, store number (store ID), store type (i.e., supercenter or discount store), and opening date (or conversion date if the store is a supercenter converted from a discount store) for each Walmart store. This store information up to 2006 is constructed by Holmes (2011).[2] We add new information up to December of 2009 based on announcements on Walmart's website. We supplement this data set by combining the longitudes and latitudes of store locations from TDLinx and Google's geocoding service.

An important feature of our data sets is that we have detailed location data for both households and Walmart stores. This allows us to compute the distances from a particular Walmart store to a specific household. As discussed in §2.2, the selection of households for our analysis relies heavily on the rich location details in these data sets.

2.2. Household Selection: Treatment and Control Households

We focus on Walmart supercenter conversions between October 2003 and January 2006 and refer to this period as the "focal period."[3] Walmart opened 353 new supercenters in the United States during the focal period. Of the new openings, the majority (213 supercenters, or 60.3%) were converted from traditional discount stores. We identify the Walmart discount stores that experienced supercenter conversions during the focal period as the treatment Walmart stores to select treatment households. More specifically, we select treatment households on the basis of the following four conditions:

(i) The household's distance from a treatment Walmart discount store is less than 15 miles.

(ii) The household's distance to the other Walmart stores (including preexisting stores and new entries during the sample period) is more than or equal to 15 miles.

(iii) The household stays in the panel for at least 100 days before and after the conversion.

(iv) The household records at least one shopping trip to any retailer in any five-week period.

Conditions i and ii ensure that the treatment Walmart store is the nearest Walmart store to the treatment households. Condition ii also ensures that the influence of the other Walmart stores on the treatment households' shopping behavior is limited. Condition iii ensures that we have adequate shopping histories of the households before and after the supercenter conversions. Finally, condition iv enables us to exclude the households that may not have faithfully reported their shopping behavior.

We also identify the control Walmart discount stores to select control households in a similar manner. The control stores are Walmart discount stores that do not undergo supercenter conversions during the sample period but experience supercenter conversions right after the sample periods (i.e., between October 2006 and December 2009). We discuss subsequently how this definition minimizes potential selection biases. We select control households using the same four conditions above but replace the treatment store with a control store.[4] The household selection criteria result in 778 households for our analysis: 337 treatment households and 441 control households.

We emphasize that we chose the stores that experienced conversions right after the sample period as control Walmart stores. Thus, control Walmart stores differ from treatment Walmart stores only in the timing of their conversion to supercenters. An important question is whether the selection criterion—namely, the timing of conversion—is correlated with changes in consumer shopping behavior. If the local factors that Walmart uses and that can potentially cause selection biases are either not time varying or vary reasonably slowly over time, our choice of control Walmart stores ensures that there are no systematic differences between the control and the treatment Walmart stores. Moreover, the difference in conversion timing can be affected by exogenous random factors (permits from state and local authorities, construction, additional staff hiring, etc.), which will reduce systematic differences between treatment and control households. In summary, our careful choice of control Walmart stores and control households helps us avoid selection biases. In §2.3, we report key

[2] For more details on the data collection procedure, see Holmes (2011).

[3] Note that our sample period is from April 2003 to September 2006. To observe consumers' behavior before and after Walmart conversions, we use roughly six-month buffer periods before and after the focal period.

[4] To select control households, we also modify condition iii to "the household stays in the panel for at least 200 days," since the control stores do not undergo supercenter conversions during the sample period.

Table 1 Panel Households' Shopping Behavior at Walmart Stores

Parameter	Value
No. of total households (HHs)	823
No. of Walmart-shopping HHs	778 (94.5%)
Observations (weeks)	89,260
Purchase observations (weeks)	42,903 (48.1%)
Weekly spending ($, excluding no purchases)	
Average	74.14
SD	83.08
Median	49.75
Max	1,442.33
Min	0.19
No. of control HHs	441
No. of treatment HHs	337
Shop at Walmart before and after conversion	320 (95.0%)
Shop at Walmart before conversion only	8 (2.4%)
Shop at Walmart after conversion only	9 (2.7%)

summary statistics of treatment and control households and find that the two groups are similar before conversion.

Traditional discount stores and supercenters have a trading radius of 15 miles (Ailawadi et al. 2010). Accordingly, we use a 15-mile boundary in our selection of treatment and control households.[5] After household selection, we include all the retail stores that the households have shopped at, regardless of distance.

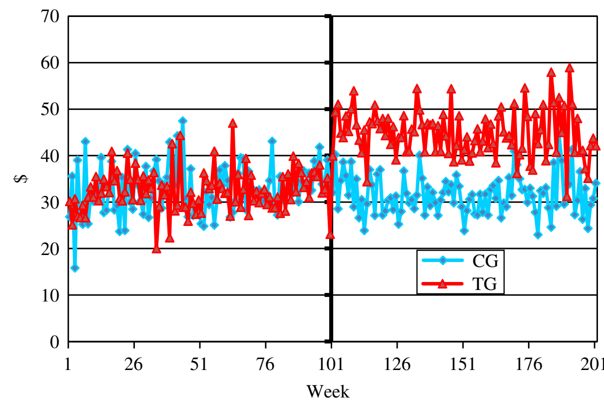
2.3. Descriptive Statistics

We provide key descriptive statistics of our panel data. Table 1 summarizes the panel households' shopping behavior at Walmart stores. In our data, 94.5% of households shop at Walmart stores at least once. The sample households shop at Walmart stores in approximately 48% of observed sample weeks, and the average weekly spending conditional on purchase is approximately $74. Of treatment households that experience a supercenter conversion of the nearest Walmart store during the sample period, 95.0% shop both before and after the conversion, 2.4% shop before conversion only, and 2.7% shop after conversion only. This observation indicates that the conversion creates only a small number of new shoppers.

Figure 1 shows the average weekly Walmart spending, including no shopping (i.e., zero spending), of treatment and control households over time. In particular, for the treatment households, we arrange the weekly Walmart spending data around the conversion date of the treatment Walmart stores and compute the averages for 100 weeks before and after the conversion. For the comparison, we arrange the control households' spending data around the conversion date of the nearest treatment Walmart stores. This is equivalent to a random timing assignment because

[5] For the robustness of analysis, we also use 10- and 5-mile boundaries to select households and confirm that the main findings are the same. These results are available upon request from the authors.

Figure 1 (Color online) Weekly Walmart Spending Before and After Supercenter Conversion



Notes. The vertical line in the center of the panel denotes the supercenter conversion week. CG, control group; TG, treatment group.

the treatment Walmart stores are too far for the control households to visit. Confirming this, the weekly spending of control households shows no trend. We observe the significant increase in weekly spending after the conversion of the nearest Walmart store in treatment households. This provides support for the positive revenue effect of Walmart conversion. Finally, weekly spending trends before conversion in the two groups are very similar, which ensures the propriety of the difference-in-difference approach to be used in §3.

In Tables 2 and 3, we report the average weekly spending, average weekly count of visits, and average weekly per-visit expenditure at Walmart stores and grocery stores, respectively, before and after the conversion. As in Figure 1, we use the conversion date of the nearest treatment Walmart stores to define "before conversion" and "after conversion" periods of control households. Control households show no significant change in weekly spending either at Walmart stores or at grocery stores. By contrast, treatment households show a slight increase in visits and a substantial increase in per-visit expenditure at Walmart stores, resulting in a 37% increase in weekly spending. Moreover, the spending of treatment households at grocery stores shows a substantial decrease (−21%), mostly as a result of the decrease in the count of store visits. In §3, we formally examine the influence of Walmart supercenter conversions on grocery stores, mass merchandisers, drugstores, and warehouse clubs, after controlling for temporal shocks and household heterogeneity.

In Table 4, we compare two key demographic variables that might influence households' shopping behavior: income and household size. The table indicates that the two groups are very similar in terms of income and household size. This further ensures the validity of our difference-in-difference approach to be used in §3.

Table 2 Walmart Supercenter Conversion and Shopping Behaviors at Walmart Stores

	Weekly spending ($)		Weekly visit		Per-visit expenditure ($)	
Group	Before conversion	After conversion	Before conversion	After conversion	Before conversion	After conversion
Treatment	32.54	44.54	0.76	0.79	43.59	58.44
Control	32.86	31.14	0.73	0.63	47.11	51.06

Table 3 Walmart Supercenter Conversion and Shopping Behavior at Grocery Stores

	Weekly spending		Weekly visit		Per-visit expenditure	
Group	Before conversion	After conversion	Before conversion	After conversion	Before conversion	After conversion
Treatment	49.1	38.55	1.73	1.33	33.26	33.5
Control	55.07	55.45	1.73	1.54	38.19	43.06

Table 4 Demographic Variables of Treatment and Control Group Households

	Income		*Household size*	
Group	Mean	SD	Mean	SD
Treatment	9.98	3.74	2.37	1.17
Control	10.67	3.79	2.55	1.3

Notes. In the panel data, *income* is recorded as an ordinal variable with 16 categories with near-equal intervals: 1 represents under $5,000, 2 represents $5,000–$7,999, and so on. The highest income level, 16, represents $100,000 and over. We treat the ordinal variable as a continuous variable and report means and standard deviations here.

3. Analysis and Results

3.1. Empirical Approach: Difference-in-Difference

We use a difference-in-difference approach to estimate the impact of Walmart supercenter conversions on three aspects of consumer shopping behavior: weekly spending, weekly count of visits, and weekly average per-visit expenditure. Weekly average per-visit expenditures are the weekly spending divided by the weekly count of visits. This quantity is defined only when any purchase is made at the given retail channel during a given week. We assign a value of 0 for weekly spending and weekly count of visits if a household makes no trips (or purchases at) a given channel in a given week.

After aggregating the relevant trip data to the weekly level, we analyze the sample households' shopping behavior at (1) all Walmart stores, (2) the focal Walmart store, (3) existing Walmart supercenters, (4) grocery stores, (5) drugstores, (6) mass merchandisers, and (7) warehouse clubs. The focal Walmart, the nearest Walmart store to a sample household, indicates the treatment Walmart store to the treatment households and the control Walmart store to the control households. Existing Walmart supercenters are located more than 15 miles away from the households. We do not separately analyze existing Walmart discount stores because shopping at those stores is less than 1% of total Walmart spending.[6] Because the identities and stores of competing retailers around Walmart supercenter conversions change across locations, we analyze the data at the channel level, instead of at the chain or store level, except for Walmart stores.

We take the three aspects of shopping behavior as dependent variables and estimate separate regressions for each of the dependent variables:

$$S_{it} = \alpha_{S,i} + \beta_{S,t} + \sum_{l=1}^{10} BC_{l,it} \cdot \gamma_{S,l} + \sum_{m=1}^{11} AC_{m,it} \cdot \delta_{S,m} + \varepsilon_{S,it}, \tag{1}$$

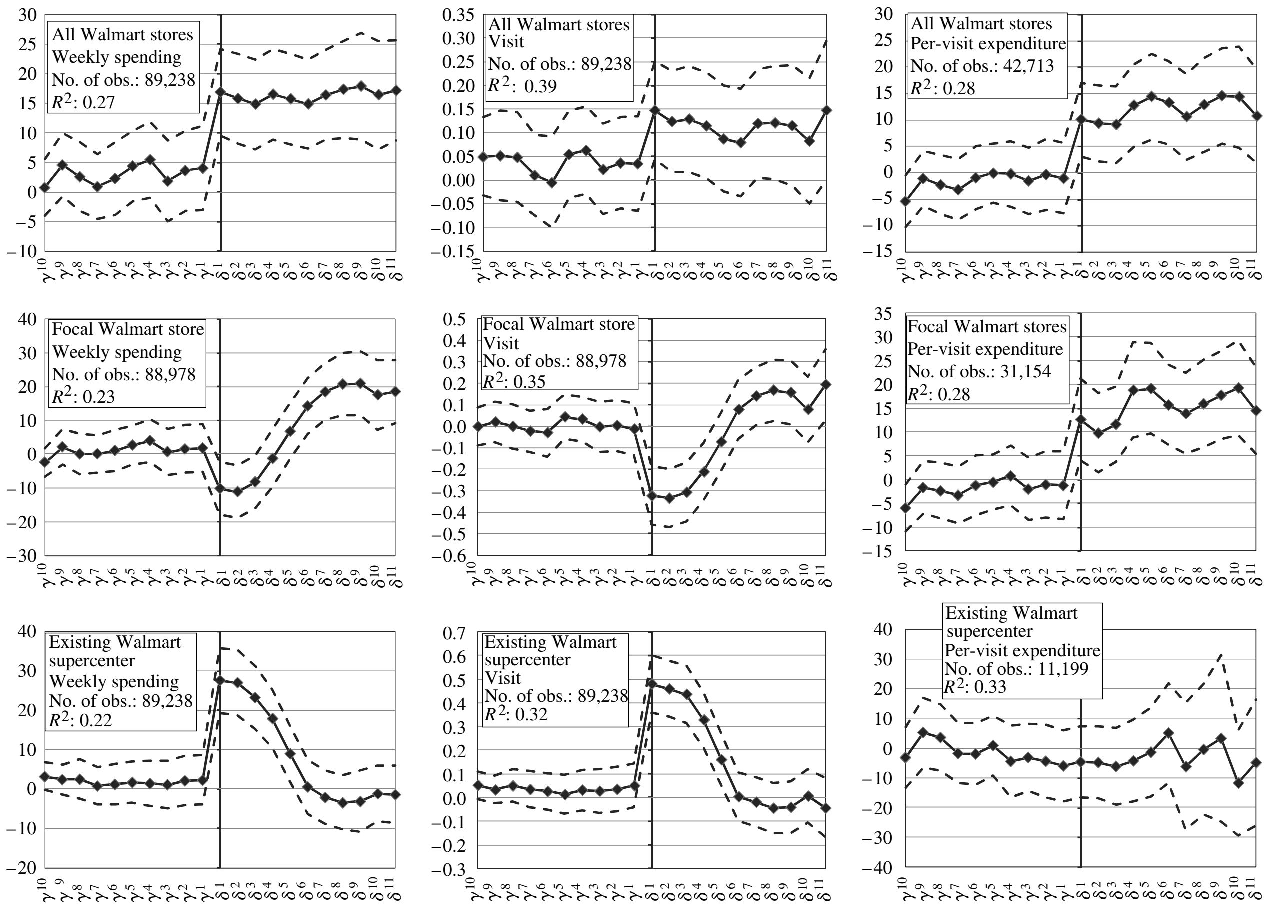
$$V_{it} = \alpha_{V,i} + \beta_{V,t} + \sum_{l=1}^{10} BC_{l,it} \cdot \gamma_{V,l} + \sum_{m=1}^{11} AC_{m,it} \cdot \delta_{V,m} + \varepsilon_{V,it}, \tag{2}$$

$$E_{it} = \alpha_{E,i} + \beta_{E,t} + \sum_{l=1}^{10} BC_{l,it} \cdot \gamma_{E,l} + \sum_{m=1}^{11} AC_{m,it} \cdot \delta_{E,m} + \varepsilon_{E,it}, \tag{3}$$

where S_{it} represents the weekly spending (in dollars) of household i at week t, V_{it} represents the weekly count of visits of household i at week t, E_{it} represents the weekly average per-visit expenditures of household i at week t, α represents household fixed effects to control household heterogeneity, and β represents weekly fixed effects to control temporal shocks or seasonality. The terms $BC_{l,it}$ and $AC_{m,it}$ are treatment household-specific 10-week time dummies that capture treatment household-specific time trends before and after the Walmart supercenter conversion. For example, $AC_{1,it}$ is equal to 1 if i is a treatment household and t belongs to the first 10-week period after the

[6] Therefore, all Walmart stores are almost equal to the focal Walmart store plus existing Walmart supercenters.

Figure 2 Estimation Results: All Walmart Stores, Focal Walmart Stores, and Existing Walmart Supercenters



Notes. A vertical line in the graph denotes the timing of the conversion.

conversion and is equal to 0 otherwise. This allows us to estimate the changes in the shopping behavior as a result of conversion compared with changes in the shopping behavior of the control households. Note that $AC_{11,\,it}$ covers 100 or more weeks post conversion. For identification, 100 or more weeks prior to conversion is not included in (1)–(3). The terms $\varepsilon_{S,\,it}$, $\varepsilon_{V,\,it}$, and $\varepsilon_{E,\,it}$ represent independent and identically distributed Gaussian random shocks. For robust inferences, we use White's heteroskedasticity-robust standard errors.

3.2. Impact of Supercenter Conversion on Walmart Shopping Behavior

Figure 2 reports the estimation results of models (1)–(3) for conversion effects at all Walmart stores, the focal Walmart store, and existing Walmart supercenters. For ease of interpretation, we show the estimates of γ's (i.e., coefficients of $BC_{l,\,it}$'s) and δ's (i.e., coefficients of $AC_{m,\,it}$'s) with 0.05-level standard error bands. The three panels in the first row show the changes in shopping behavior at all Walmart stores. Weekly spending substantially increases after conversion. The difference between the average of estimated γ's and the average of estimated δ's is equal to \$13.33. If we use the treatment households' average spending before supercenter conversions reported in Table 2 as a baseline, this translates to a 41% (= 13.33/32.54) increase in weekly spending. Visits slightly increase (the average of estimated δ's − the average of estimated γ's = 0.08), which translates to a 10% increase (= 0.08/0.76) compared with the baseline. However, per-visit expenditure increases considerably (the average of estimated δ's − the average of estimated γ's = \$13.62), which amounts to 31% (= 13.62/43.59) compared with the baseline. Note that all these findings echo what we found in §2.3.

The three panels in the second row of Figure 2 show the changes in shopping behavior at the treatment Walmart stores.[7] Compared with the control households' weekly spending at the control Walmart stores,

[7] In some conversions, the store may be closed for a few days or weeks to facilitate final preparation for customers. We examine this by looking at our panel data. To be more specific, we regard that the converted Walmart store is closed for short period of time if any purchase from the panel members is not reported for 10 or more days near the conversion date. Using this approach, we identify 36 conversions with such "short-term closures" out of total

the weekly spending of treatment households at the treatment stores abruptly decreases by approximately \$12 with the supercenter conversion and then begins to catch up right after. The weekly spending hits the before-conversion level about a year after the conversion and then increases by approximately \$18 from the before-conversion level. The change in weekly visits shows a similar pattern. By contrast, per-visit expenditure shows a step change with the conversion (the average of estimated δ's − the average of estimated γ's = \$17.22).

The three panels in the third row of Figure 2 show the changes in shopping behavior at the existing Walmart supercenters. The changes in weekly spending and visits show the opposite patterns from those of the treatment Walmart store. Per-visit spending remains unchanged in the existing supercenters with the conversion. Taken together, this suggests that some consumers shift their Walmart purchases from the treatment stores to nearby supercenters temporarily after the conversion but come back to the treatment stores about a year after the conversion. Given that we excluded stores that were shut down during conversion in our sampling (as described in Footnote 7), store closure is not likely to be responsible for the short-term decline in visits. We speculate that this could be due to inconveniences associated with the conversion. For example, extended periods of ongoing construction during the conversion could have caused some customers to switch to other Walmart stores, and they may have continued this behavior for a while even after completion of the conversion. Indeed, a previous study reports a similar dip in store traffic after store remodeling (Brüggen et al. 2011). A search of Yelp reviews around the time of a Walmart supercenter conversion shows ample evidence of consumer inconvenience, with reviews using terms such as "crowded," "difficult to navigate," and "such a mess." Finally, the store's floor plan might have changed with the conversion, and this unfamiliarity generates inconvenience to the shoppers, leading them to patronize familiar nearby supercenters for the short term.[8] However, this inconvenience is overcome within a year, and the converted stores eventually end up generating more customer traffic and revenue than prior to the conversion.

3.3. Impact of Supercenter Conversion on Competing Retailers in Other Channels

Figure 3 reports the estimation results of the impact of Walmart supercenter conversions on competing retailers in other channels for models (1)–(3). We examine the influence of the conversions on four different channels: grocery stores (e.g., Safeway, Kroger), drugstores (e.g., CVS, Walgreens), mass merchandisers (e.g., Target, Kmart), and warehouse clubs (e.g., Costco, Sam's Club).[9]

The first row in Figure 3 shows that grocery stores experience a significant loss (the average of estimated δ's − the average of estimated γ's = −\$9.73) in weekly spending after Walmart supercenter conversions, which translates to a 20% (= 9.73/49.10) decrease in weekly spending compared with the baseline. Decomposing the revenue loss into components attributed to counts of store visits and per-visit expenditure shows that weekly counts of visits to grocery stores decrease by 0.32 per week (equal to the average of estimated δ's − the average of estimated γ's) and that per-visit expenditures at grocery stores decrease by \$1.97 (equal to the average of estimated δ's − the average of estimated γ's) after Walmart supercenter conversions. Using the treatment households' average weekly number of visits in Table 3 as a baseline, the reduction in store visits corresponds to a 18% decrease (= 0.32/1.73). By contrast, the reduction in per-visit expenditure is smaller (1.97/33.26 = 6%). Thus, the decrease in weekly spending at grocery stores after Walmart supercenter conversions is primarily due to the decrease in the number of store visits, with smaller impacts from per-visit expenditure. Both the magnitude of revenue impacts at grocery stores and the qualitative findings in revenue decomposition correspond well to the findings of Singh et al. (2006).

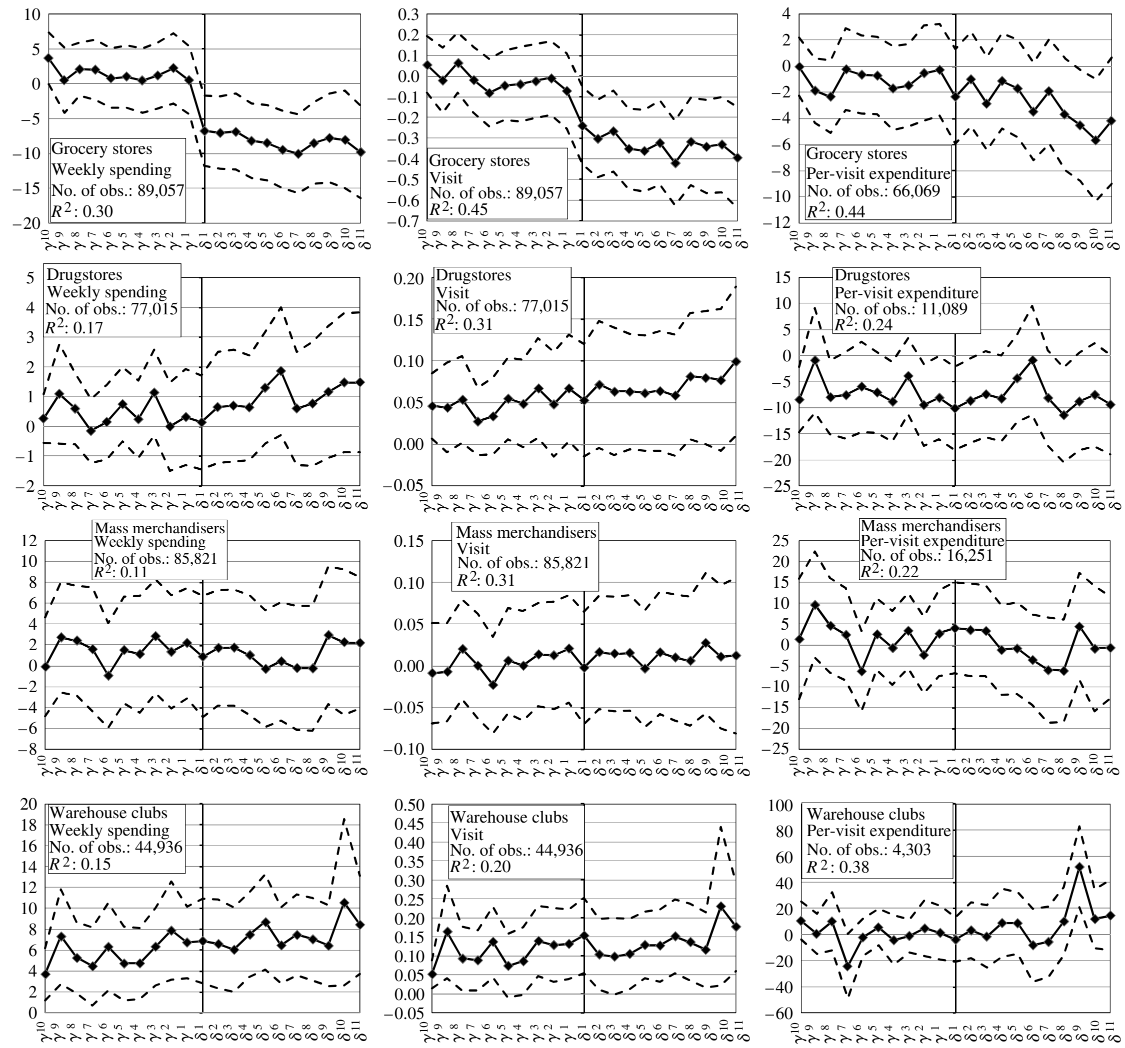
The estimation results for drug stores (second row in Figure 3), mass merchandisers (third row in Figure 3), and warehouse clubs (fourth row in Figure 3) show no trend, indicating that the competitive impact of supercenter conversions is not significant. These results suggest that Walmart supercenter conversions do not affect drugstores, mass merchandisers, and warehouse clubs. This is plausible because the product categories that compete directly with these channels already exist in the traditional discount format of Walmart stores.

213 observed conversions. The average span of store closure is 16.5 days (SD, 7.02 days; min, 10 days; max, 45 days). We exclude these short-term closures in our analysis of treatment stores. As a result, 260 of total 89,238 household-by-week observations are removed. We thank an anonymous reviewer for suggesting this point.

[8] Target recently developed the "PFresh" format, which introduces a limited selection of produce and meat into its discount stores. As in the Walmart conversion, the floor plan is changed with this new strategy. A review of the PFresh Target appeared in the *San Francisco Chronicle* (see Hartlaub 2010) and indicated that the floor plan change results in substantial inconvenience to shoppers. According to the author, "I couldn't have been more disturbed if I came home one day, and someone had removed all my bedroom furniture and replaced it with freezers full of chicken nuggets. . . . Would I rather have the old Target back? Totally."

[9] The number of households used for estimation varies slightly across channels because we exclude from the analyses households that never shopped in the given channel.

Figure 3 **Estimation Results: Grocery Stores, Drugstores, Mass Merchandisers, and Warehouse Clubs**



Note. A vertical line in the graph denotes the timing of the conversion.

3.4. Robustness Check Using Alternative Model Specification

The analyses in §§3.2 and 3.3 rely on linear regression models (1)–(3). This approach has several advantages. First, it is simple and free from restrictive distributional assumptions. Second, the interpretation of the estimation result is straightforward. However, alternative specifications can also be considered, given that the weekly spending contains many zero observations and a few large values, and weekly visits are discrete counts. As a robustness check, we construct a joint model of visit and expenditure, considering the potential correlation between two decisions, and reexamine the effects of Walmart supercenter conversions on consumers' shopping at Walmart and other retail channels.[10]

[10] We do not separately model weekly spending (S_{it}) here because $S_{it} = V_{it} \times E_{it}$.

We specify a zero-inflated Poisson process to model weekly visits:

$$\mathrm{Pois}(V_{it}) = \exp(\mu_{it}) \cdot \mu_{it}^{V_{it}} / V_{it}!, \tag{4}$$

$$\mu_{it} = \exp\bigg(\alpha_{V,i} + \beta_{V,t} + \sum_{l=1}^{10} BC_{l,it} \cdot \gamma_{V,l} + \sum_{m=1}^{11} AC_{m,it} \cdot \delta_{V,m}\bigg), \tag{5}$$

$$\Pr(V_{it} = k) = \begin{cases} (1-\phi) + \phi \cdot \mathrm{Pois}(V_{it} = 0) & \text{if } k = 0, \\ \phi \cdot \mathrm{Pois}(V_{it} = k) & \text{if } k = 1, 2, 3, \ldots, \end{cases} \tag{6}$$

where ϕ $(0 \le \phi \le 1)$ is a zero-inflation parameter. Note that the specification for the Poisson mean (μ_{it}) is the same as (2). We model the per-visit expenditure as follows:

$$\ln(E_{it}) = \alpha_{E,i} + \beta_{E,t} + \sum_{l=1}^{10} BC_{l,it} \cdot \gamma_{E,l} + \sum_{m=1}^{11} AC_{m,it} \cdot \delta_{E,m} + v_{it}. \quad (7)$$

This specification follows (3), except for the log transformation to handle extreme values. The random shock v_{it} represents the unobserved factors, which influence consumers' spending decisions. The visit decision might be correlated with the decision on how much to spend because of common factors (e.g., retailer's marketing activity). To capture this potential correlation between two decisions, we link the discrete outcome of the visit to the continuous unobserved random shock in expenditure via the Gaussian copula, which is known to be general and robust for most applications and has many desirable properties (see Danaher and Smith 2011). The results show a very similar pattern to those found from linear regression models, adding robustness to our findings regarding the influences of Walmart conversion.[11]

3.5. Demand Externality in Preexisting Categories from Supercenter Conversion

Newly added categories with supercenter conversions would clearly contribute to the increase in per-visit expenditures at Walmart. However, it is unclear whether per-visit expenditures for preexisting categories also increase. We investigate whether there is demand externality to preexisting categories from the addition of new produce, fresh food, and frozen food sections with supercenter conversions by analyzing how weekly category spending changes after supercenter conversions. We analyze nine product categories grouped into two overall categories: four food categories—RTE cereal, mayonnaise, coffee (ground coffee and whole bean), and cola—and five nonfood categories—batteries, toothpaste, vitamin and mineral supplements, cold/sinus/allergy medicine, and linen and window furniture coverings. A comparison of these two groups allows us to detect systematic patterns if differences exist across them. We use the following linear regression model for this analysis:

$$C_{it} = \alpha_{C,i} + \beta_{C,t} + \sum_{l=1}^{10} BC_{l,it} \cdot \gamma_{C,l} + \sum_{m=1}^{11} AC_{m,it} \cdot \delta_{C,m} + \varepsilon_{C,it}, \quad (8)$$

where the dependent variable C_{it} is household i's weekly category spending at Walmart stores in week t.

Figure 4 shows the estimation results for conversion effects on weekly category spending.[12] In the four food categories, we observe that the estimated $\gamma_{C,l}$'s are not significantly different from zero but that the estimated $\delta_{C,m}$'s are significant and positive in most cases. This result indicates that significant sales increases from supercenter conversions occur in the four food categories. By contrast, both the estimated $\gamma_{C,l}$'s and $\delta_{C,m}$'s are not significantly different from zero, indicating a nonsignificant demand effect in the five nonfood categories. Taking these findings together, Figure 4 suggests that the positive demand increase from supercenter conversions is localized to food categories. The average of estimated δ's is larger than the average of estimated γ's by \$0.05, \$0.20, \$0.16, and \$0.21 for mayonnaise, RTE cereal, coffee, and cola, respectively. The average weekly spending on these four categories at Walmart is \$0.07, \$0.32, \$0.25, and \$0.35 in our data. The increases in the weekly category spending translate to 64%, 62%, 64%, and 59%, respectively.

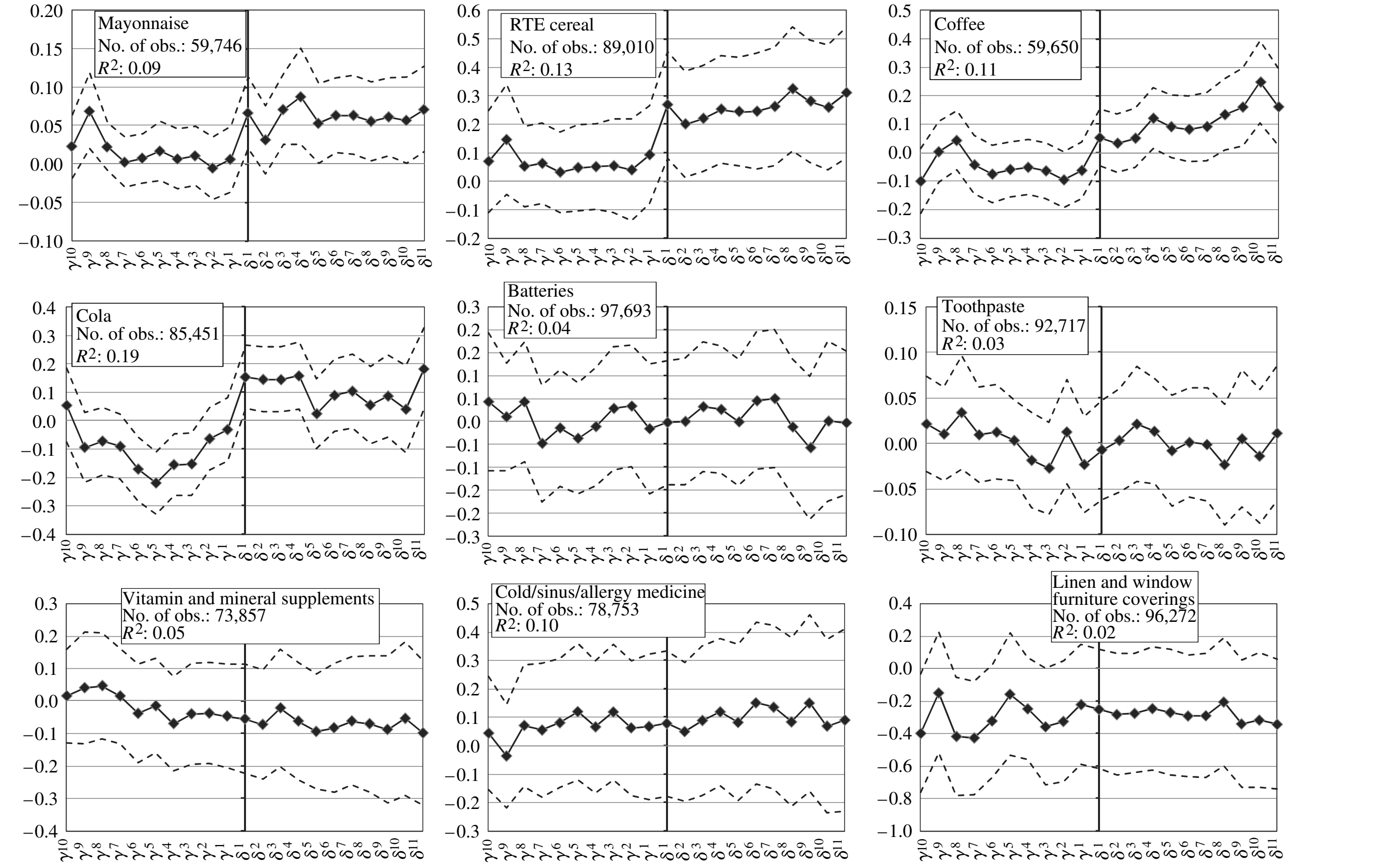
Given the increase in food category spending after conversion, a subsequent question arises: Is the increase in weekly spending on food categories mainly the result of an increase in purchase incidence or an increase in category expenditure per incidence? To answer this question, we estimate linear regression models similar to (8) using the weekly count of category purchase incidence and category expenditure per incidence as dependent variables. Figure 5 shows that purchase incidence of food categories increases after Walmart supercenter conversion. This is statistically significant in RTE cereal and mayonnaise categories. By contrast, we cannot find any noticeable change in category expenditure per incidence. To summarize, more Walmart trips are associated with food category purchases after supercenter conversion, and this increase in purchase incidence is responsible for the increase in weekly spending in food categories after Walmart supercenter conversion. However, both purchase incidence and category expenditure in nonfood categories remain unchanged after Walmart supercenter conversion.

To provide additional robustness checks to the asymmetric demand externality between food and nonfood categories found above, we analyze department-level data from a Target discount store (from Nielsen) that went through supercenter conversion in October 2004. Specifically, we compare the yearly average department revenue before and after

[11] Our approach can be regarded as an extension of Heckman's (1979) or Lee's (1983) selection model to a zero-inflated Poisson case. To preserve space, we do not report specific estimation results here, but interested readers can find them in the online appendix (available as supplemental material at http://dx.doi.org/10.1287/mnsc.2014.2143).

[12] The estimates for household dummies and weekly dummies are available upon request from the authors.

Figure 4 **Estimation Results for Weekly Category Spending at Walmart Stores**

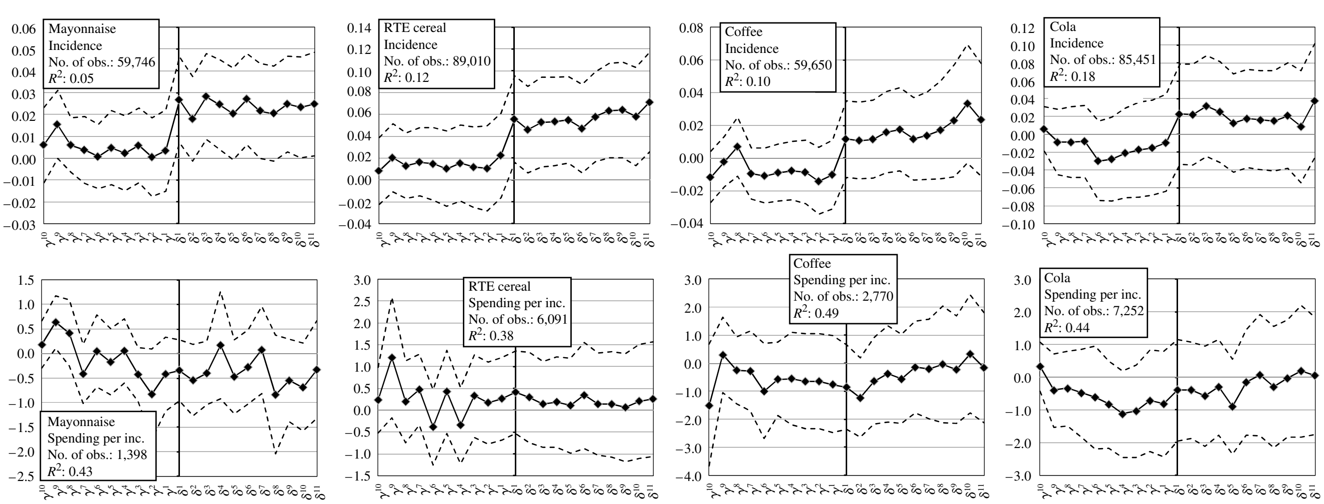


Note. A vertical line in the graph denotes the timing of the conversion.

conversion at the Target discount store, which was converted to a supercenter. Table 5 shows a similar pattern of asymmetric demand externality between food and nonfood categories from supercenter conversion. This ensures the robustness of our findings since a similar pattern is replicated in another retailer (i.e., Target) and a larger number of categories (i.e., department-level data).

Finally, retailers may increase assortment sizes in certain product categories with supercenter conversion, which may also cause a demand increase in preexisting categories. We analyze store-level data

Figure 5 **Estimation Results for Food Category Weekly Count of Purchase Incidence and Category Expenditure per Incidence at Walmart Stores**



Note. A vertical line in the graph denotes the timing of the conversion.

Table 5 **Percent Change in Revenue: Before vs. After SuperTarget Conversion**

Group	Department	% increase
Nonfood	Nonfood grocery	28.4
	General merchandise	32.3
	Health and beauty aids	26.0
Food	Prepared food	106.0
	Unprepared food	330.5
	Direct store delivery food	160.3
	Dairy	2,033.9
Total revenue		77.4

Table 6 **Assortment Sizes Before and After SuperTarget Conversion**

	Food categories		Nonfood categories	
	Cola	RTE cereal	Toothpaste	Cold/sinus/allergy medicine
Assortment size (preconversion)	31.70	59.96	60.12	42.00
Assortment size (postconversion)	42.83	187.80	58.67	47.78
Assortment size difference	11.1345***	127.9***	1.4423*	5.78***
SD	2.88	9.58	6.03	12.09
p-value	0.00	0.00	0.09	0.00
% change	35	213	−2	14
Sample size	52	52	52	52

*Significant at the 0.10 level; **significant at the 0.05 level; ***significant at the 0.01 level.

from the same Target store to investigate the change of assortment sizes in four categories—cola, RTE cereal, toothpaste, and cold/sinus/allergy medicine. In Table 6, we find significant increases in the size of assortment in food categories (i.e., cola and RTE cereal) but small or nonsignificant increases in the size of assortment in nonfood categories (i.e., toothpaste and cold/sinus/allergy medicine). Therefore, an increase in assortment size in food categories can be partially responsible for the observed increase in weekly spending in food categories.

4. Discussion and Conclusion

This study examines how Walmart supercenter conversion affects consumers' shopping behavior at Walmart stores and competing retailers. In particular, we show that there are significant revenue gains at Walmart stores that undergo conversion as a result of larger per-visit expenditures, with a much smaller impact from store visits. This implies that the increase in basket sizes, which industry analysts have largely ignored, is critical to understanding the source of revenue gains at Walmart supercenters. Our results also indicate that sequential Walmart supercenter expansion is one of the major drivers of the overall reduction in the number of shopping trips (i.e., trip compression) over time observed by industry groups such as IRI and Nielsen (e.g., IRI 2006).

We also found that Walmart supercenter conversion has a nonsignificant or marginal effect on competing mass merchandisers, drugstores, and warehouse clubs. In contrast with the case of Walmart supercenter entries, managers at mass merchandisers, drugstores, and warehouse clubs do not need to worry about Walmart supercenter conversion. This is likely because the categories that compete directly with these channels are already in place in the traditional discount format Walmart stores before conversion. However, grocery stores experience the most significant loss in weekly revenue mostly from fewer store visits, with smaller impacts from per-visit expenditure. This implies that grocery store managers should focus on promotion or assortment tactics to win back the lost trips rather than promotions aimed at increasing basket sizes.

Finally, localized demand externality in food categories in the case of supercenter conversion has important implications on how retailers can benefit from store scope expansion. Two factors are likely to be the cause of localized demand increases in food categories only: compared with nonfood categories, food categories are (1) closely located to the newly added sections in terms of physical distance and (2) closely associated with newly added sections in terms of category association (Inman et al. 2004). Retailers can potentially exploit store layouts (physical distance) and category association to maximize positive demand spillover from retail scope expansion. We leave to future research the identification of the exact roles of physical distance and category association in demand spillover to existing categories.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.2143.

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