The Competitive Effects of Entry: Evidence from Supercenter Expansion

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Abstract

Coupling weekly grocery transactions with the exact location and opening date of Walmarts over an eleven year period, we examine how entry affects prices and revenues at incumbent supermarkets. We find that Walmart Supercenter entry within one mile of an incumbent causes a sharp 16% drop in revenue, a competitive effect that decays quickly with distance. Surprisingly, despite large cross-sectional differences in supermarket prices by exposure to Walmart, our findings also indicate that Supercenter entry has no causal effect on incumbent prices. This result is robust across many dimensions including a lack of price response for individual products and across brands within a category. We argue that the null price response by incumbents is consistent with the widespread use of cost-plus pricing policies, a form of managerial inattention.

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1 Introduction

Economic frameworks differ in their predictions regarding how retail prices, which play an important role in allocating resources and affecting social welfare, respond to changes in market conditions. In standard models used by economists and government regulators, firms are assumed to set prices to equalize marginal revenue and marginal cost according to a static "Nash in prices" equilibrium where positive markups are supported via product differentiation (Ackerberg et al., 2007). In contrast, macroeconomists emphasize the role of cost-side frictions in setting prices, such as menu and monitoring costs, or long-term contracts that constrain the rate and frequency with which firms adjust prices. The recent widespread availability of high-frequency supermarket scanner data has yielded a rich empirical literature evaluating the source and scale of these adjustment costs, and exploring their role in determining the effects of monetary policy (Klenow and Malin, 2010; Eichenbaum et al., 2011). At the same time, there is also a long tradition, extending at least as far back as the influential case studies of Cyert and March (1963), that views price-setting by firms as "boundedly rational" (Simon, 1955, 1962).

While there exists work examining the degree to which firms react and pass costs through to consumers (Peltzman, 2000; Besanko et al., 2005), much less is known empirically about how firms react to changes in market structure or other "demand shocks" that impact marginal revenue. These kinds of changes are important for understanding the mechanism of price adjustment because, in contrast with changes in costs, they force firms to contend with potentially complex changes in their residual demand curves. From an empirical standpoint, however, identifying the casual impact of demand shocks is challenging since it requires a large number of sizable shocks to reliably infer a consequential impact on pricing, but any such changes are likely to be endogenous, threatening causal inference.

Our empirical strategy thus involves isolating and exploiting a particular set of shocks that are large in magnitude and for which the precise *timing* can be viewed as exogenous: entry by Walmart Supercenter outlets.[1] Walmart's everyday low price strategy and 15-25% price advantage present a sizable competitive advantage that is consistent across treatments (Hausman and Leibtag, 2007; Ellickson et al., 2012). Moreover, retail grocery presents a nearly ideal setting for

[1] Gagnon and Lopez-Salido (2014) pursue a similar approach by examining the price response of U.S. supermarkets to natural disasters, severe weather and work stoppages due to labor disputes and find small price effects. While these events certainly constitute significant, very likely exogenous, shocks, there are many institutional barriers in place that limit the ability of the firms to change prices in response to such events (e.g. laws and social norms that discourage price gouging, emphasis on "fair pricing" (Rotemberg, 2011)). Moreover, because they also consider only market-wide price responses, they do not capture the highly localized nature of retail competition. This is especially salient in groceries since consumers purchase groceries at least once a week (due to perishability) and are reluctant to travel large distances or purchase online.

quantifying price response by incumbents for at least three reasons: First, due to the presence of large sunk and fixed costs, supermarkets are well-known to have substantial price-cost markups, ensuring a wide latitude for competitive price response.[2] Second, supermarket firms were among the earliest adopters of computerized information technology (e.g. scanning registers, electronic data interchange), suggesting that they are as well positioned as any to implement sophisticated pricing strategies. Finally, grocery markets are highly localized and vertically differentiated, yielding many "local experiments" that impact both stores and products at different points in the quality spectrum. This bolsters statistical power and provides the variation necessary to rule out a variety of confounding explanations for our baseline results.

To measure the causal impact of Walmart's entry on incumbent pricing, we combine data on the exact geographic locations and opening dates for the universe of Walmart Supercenters with high-frequency transactions data for a representative sample of U.S. supermarkets. Importantly, the high resolution of these unique data allow us to make two contributions to inferring causality: First, we are able to use the confidential addresses of incumbents to examine how the effects depend on the driving distance between the supermarket and the entering Supercenter. Knowing the exact locations is important given the localized nature of retailing (Figurelli, 2012; Smith, 2006). Second, because we observe transactions data every week at the store level, we are able to exploit the timing of Supercenter openings. We observe incumbent revenue and prices immediately prior and just after a Supercenter opening, allowing us to pin down Walmart's causal impact by controlling for its endogenous choice of location.

To gauge the importance of these shocks, we first examine the revenue impacts of Walmart Supercenter exposure. We find declines in revenue on the order of 16% of sales on average at the stores most geographically proximate. These are large and disruptive events. In addition, reflecting the local nature of retail competition, we find that revenue effects do not statistically differ from zero beyond seven miles in exposure distance. At the same time, supporting our research design, we also do not find any evidence of pre-treatment trends in revenue, but rather drops that immediately follow the opening of a nearby Supercenter. The sizes and immediacy of the revenue impacts thus suggest a relevant setting to observe competitive price reactions.

Surprisingly, we find that prices at incumbent supermarkets do not react at all to Supercenter entry – either immediately, pre-emptively, or over the longer term. This result thus stands in sharp contrast to the prior literature examining Walmart entry, which finds considerable price reductions

[2] Due in part to its persistently high concentration, the grocery industry is a frequent target of anti-trust attention. A number of empirical studies, including several that include either internal cost information or economic census data, document price-cost markups in the range of 40-50% (Stroebel and Vavra, 2014). This ensures a wide latitude for downward adjustment, while upward adjustment – which may be the optimal response – is also clearly unconstrained.

(Basker and Noel, 2009; Hausman and Leibtag, 2007).[3] We show that this difference is explained by our empirical strategy of leveraging the timing of Supercenter openings, as opposed to cross-sectional variation in prices, via the inclusion of store fixed effects. Absent store fixed effects – and therefore not accounting for the selective nature of Walmart's entry decisions within a market – we estimate price reactions on the order of 2.5% to 3.5%, according closely with earlier findings.

Focusing first on possible confounds that threaten casual inference, we examine whether changes in the composition of *products* sold could be masking a measurable price response. For example, firms could adjust pack sizes or product assortment instead. To address this possibility, we extend our empirical approach to UPC-level data, allowing us to examine prices for the same product in the same store before and after Supercenter exposure, and find no evidence for price reactions. We then consider whether changes in the composition of *consumer types* could produce pressures on the direction of price response (e.g. the incentive to raise price to exploit the remaining captive consumers balances exactly the incentive to expand market share by lowering price). This tension, formalized in Chen and Riordan (2008), has been highlighted in several empirical settings.[4] To evaluate the possibility that these incentives offset on average, we examine competitive impacts across price tiers and find no price effects despite vertical differentiation of products within category (and large revenue drops at the bottom of the quality spectrum).

Turning to the interpretation of our results, some potential explanations for the lack of price response are effectively ruled out by the setting. Like DellaVigna and Gentzkow (2017), we believe that menu costs are not a factor here, as supermarkets frequently adjust prices to implement sales. Monitoring costs are also unlikely to play a role, since Supercenter entry nearby would be impossible not to notice. Similarly, the well-documented existence of large price-cost markups in grocery retail, even relative to Walmart's large price advantage, implies that firms are not precluded from cutting prices by a hard cost constraint. Upward adjustments of prices, which may be optimal should the incumbent become a monopolist on the residual demand curve, are also not constrained. We find it more plausible that firms could be constrained by long term or otherwise restrictive contracts with

[3] Though it is not the focus of either paper, Matsa (2011) and Ailawadi et al. (2010) also find limited price response to Walmart. In these studies, the null result is due to low precision of the point estimates, whereas the null result we find here is sharp. Furthermore, neither paper address the issue of selection in Walmart's choice of location or the role of distance in determining its impact. These aspects play a central role in our analysis.

[4] For example, in the context of air travel, incumbent air carriers reduce ticket prices in response to rival entry (Reiss and Spiller, 1989; Borenstein, 1989, 1992). The response is particularly pronounced for entry by low cost carriers like Southwest (Morrison, 2001), and may even take place in anticipation of entry (Goolsbee and Syverson, 2008). This is consistent with a very strong competitive price effect, likely reflecting the relative homogeneity of the underlying consumer product. On the other hand, upon entry by generic drugs, incumbent manufacturers of branded pharmaceuticals typically *raise* prices (Frank and Salkever, 1992). This is despite that fact that generic entrants are required to establish bio-equivalence by the FDA (meaning that "true" product differentiation is minimal). This behavior may be an optimal response to the shift in the distribution of consumer types towards those with higher willingness to pay for the branded products (Frank and Salkever, 1997), a mechanism that likely operates through access to insurance.

manufacturers (Villas-Boas, 2007), who have little incentive to respond to local retailer entry. To address this possibility, we therefore examine price response separately for branded products and for store brands, whose prices are entirely under their own control. For neither product type do we find evidence of price reactions.

Another plausible explanation concerns the multi-market nature of chain retailing. In particular, chains with many widely dispersed outlets might set prices regionally or centrally to economize on advertising expenses or to leverage other scale or scope economies (DellaVigna and Gentzkow, 2017; Adams and Williams, 2017), thereby blunting the response to competitive entry impacting local stores. However, our data reveal that even local chains (e.g. those with only a handful of stores) do not respond to Supercenter entry by adjusting prices, casting doubt on the empirical relevance of these factors as well.

We argue that the explanation most consistent with our findings is that supermarket firms routinely employ "rule of thumb," cost-plus pricing policies, a form of managerial inattention.[5] This practice is otherwise known as "margin maintenance." Since entry by Walmart does not impact costs, it does not trigger a price reaction from incumbents. While our data do not allow us to test this hypothesis directly, this interpretation is consistent with other recent empirical studies of supermarket pricing. In particular, Eichenbaum et al. (2011) exploit detailed information on both wholesale costs and retail markups for a very large supermarket chain operating in both the US and Canada to show that grocery prices rarely change unless triggered by an accompanying change in costs. Prices are set with a relatively long duration, aimed at keeping markups within a fairly narrow target range. McShane et al. (2016) provide similar evidence using data from another retailer.[6] The fact that incumbent firm size does not change our null result suggests that it is not simply a fixed (chain-level) adjustment cost, but rather a broad-based pattern of behavior.

Our findings contribute to several strands of literature. First, we contribute to prior work that studies the economics of supercenters and examines the implications of the competitive advantages enjoyed by Walmart.[7] Our analysis reveals aspects of how Walmart selects locations within a market, favoring areas near relatively high revenue and low-priced competitors (a selection rule

[5]Notably, such "rule of thumb" pricing was a key motivation in developing the bounded rationality framework. It was a central feature of Cyert and March's influential study, leading Simon (1962) to conclude: "Price setting involves an enormous burden of information gathering and computation that precludes the use of any but simple rules of thumb as guiding principles."

[6]There is also a large volume of both anecdotal and survey-based evidence documenting the widespread use of cost-plus pricing in both industrial and retail settings (Blinder et al., 1998; Noble and Gruca, 1999; Phillips, 2005; Watson et al., 2015).

[7]See e.g. Basker (2007); Holmes (2011); Jindal et al. (2015) and papers examining Walmart's impact on a variety of market outcomes, including wages and employment (Basker, 2005; Neumark et al., 2008), market structure (Foster et al., 2006; Jia, 2008; Zhu et al., 2009; Ellickson et al., 2013), rival responses (Matsa, 2011; Ailawadi et al., 2010) and consumer welfare (Hausman and Leibtag, 2007; Atkin et al., 2018).

that we show biases prior estimates of competitive effects of Walmart). Our findings also have important implications for the competitive welfare gains from Walmart Supercenter expansion. Hausman and Leibtag (2007) argue that fully one fifth of the consumer benefits of Supercenter expansion is due to price reductions at rival stores. In contrast, our results indicate no such competitive response, implying that the actual welfare increase is substantially smaller. While we do not rule out responses on quality dimensions (Matsa, 2011), our null results suggest that a primary impact of entry is not lower incumbent prices, but rather lower sales volume at incumbent stores. This is likely to lead to an increased likelihood of store failure, consistent with Ellickson and Grieco (2013), suggesting that the competitive reaction may primarily occur along the extensive, rather than intensive, margin.

Our results also contribute to a small, but growing literature on behavioral aspects of firm decision-making and their implications for market efficiency. For example, DellaVigna and Gentzkow (2017) document that price variation within grocery chains across markets is far more muted than would be predicted by local market conditions, while Blake et al. (2015) find vast overspending by eBay on search advertising. Shapiro (2016) also concludes that pharmaceutical firms over-advertise.[8] Our results suggest that the commonly applied pricing assumptions at the core of many empirical models of entry and competitor response may be mispecified in important contexts. For example, to the extent that firms focus on changes in costs over changes in demand or the competitive environment, welfare conclusions and market simulations from models predicated on these latter factors are likely to be misstated. Finally, our results contribute to recent empirical work in macroeconomics focused on understanding the sources of nominal rigidities and the stickiness of price adjustment (Blinder et al., 1998; Bils and Klenow, 2004; Klenow and Malin, 2010). Our contribution lies in highlighting the relative importance of demand versus cost shocks in determining price adjustment in retail settings.

2 Data Description

Our analysis combines two primary data sources. The first dataset, provided by the retail consulting firm Trend Results (www.trendresults.com), contains the exact opening date and address of every Walmart in operation through 2011. We restrict our attention to the 3,150 Walmart stores designated as Supercenters that carry a full grocery line.[9] These records are used to link the

[8]Papers that examine the role of managerial ability in driving departures from optimizing behavior also include Bloom and Van Reenen (2007), Hortacsu and Puller (2008), Goldfarb and Xiao (2011), and Ellison et al. (2016).

[9]While these records provide the universe of Walmart store openings since 1962, they do not identify Walmarts that were expanded into Supercenters or when such an expansion took place. 543 traditional Walmarts remained at the time our data were gathered (159 of which opened in 2001 or later).

timing of Supercenter openings with associated pricing and other outcomes at nearby incumbent supermarkets.

Our second data source is the IRI marketing dataset, which records weekly store-level sales at a nationally representative sample (roughly 10%) of supermarkets (Bronnenberg et al., 2008). The data cover the period from 2001 through 2011 (11 years in total). The data include the transaction records for 2,450 incumbent supermarkets during the 573 weeks (a median of 293 weeks per store) that span the sample period. About 60% of the IRI supermarkets represent national chains, another 6% do not belong to a chain at all, while the remaining supermarkets belong to regional or local chains. Geographically, the supermarkets are spread across 50 IRI markets, which are approximately equivalent to Metropolitan Statistical Areas (MSAs). We augment the transactions records with the physical address of each supermarket, obtained from IRI. Table 16 in the Appendix presents additional summaries of the incumbents, including local demographics.[10] Each record in the IRI data contains a UPC identifier, quantity purchased, and the purchase price of the item at a given supermarket in a given week. Transactions data for fifteen food product categories are used to construct our dependent variables, which are described next.[11]

For each IRI supermarket, we construct weekly revenue and price series by product category. Price series are constructed by dividing total weekly revenues across all Universal Product Codes (UPCs) sold in the category by the total category volume sold across those UPCs.[12] We use the definitions of volume equivalent units for each category (e.g. 1 unit = 16 oz. of coffee) provided by IRI. Thus, the price of product category c in week t at store s is the total revenue divided by the total sales volume in category c for that week:

$$P_{st}^{c} = \frac{\sum_i P_{ist}^{c} \times Q_{ist}^{c}}{\sum_i Q_{ist}^{c} \times V_{ist}^{c}} \tag{1}$$

In this equation, i indexes UPC, P_{ist}^{c} represents the real transaction price of i in store s during week t, V_{ist}^{c} the volume weight of that UPC, and Q_{ist}^{c} denotes the total unit sales of the UPC.[13]

Summary statistics (over stores and weeks) for the incumbent supermarkets' revenue and prices are provided in Table 1. In a given week, incumbent supermarkets generate nearly $45,000 (which annualizes to $2.3 million) in revenue on average across the fifteen food categories considered.[14]

[10] Demographic estimates for 2007 are provided by Applied Geographic Solutions via IRI for a two mile radius around 2,012 of the supermarkets.

[11] We exclude milk, a product category subject to substantial price regulations, and beer, which is not sold in all supermarkets due to varying regulatory environments.

[12] A similar price index and panel data approach was used by both sides to determine the extent to which Office Depot and Staples constrained each other's pricing in the U.S. Federal Trade Commission's challenge of the Staples/Office Depot merger (Ashenfelter et al., 2006).

[13] Note that all UPC prices are deflated to January 2001 dollars using the CPI.

[14] These product categories represent about 58% of all revenue recorded and released by IRI.

Notably, there is considerable variation in revenue, with the 90th percentile representing nearly twice the average. There is also large price variation. In the median store-week, 16 oz. of coffee costs \$4.23, but at the 90th percentile costs \$6.29 – around 50% more expensive. The high frequency variation in these series (week-to-week) allows us to isolate changes at incumbents immediately following a Supercenter opening.

Linking the Supercenter openings with the IRI supermarket data involves two steps. First, we create Supercenter-IRI store matches if the straight line ("crow's flight") distance between any pair is less than fifteen miles. Of the 1,055 Supercenters that Walmart opened in the United States during our sample period (between January 2001 and the end of 2011), this decision rule matches 481 Supercenters with at least one incumbent IRI supermarket.[15] Second, we compute the driving distance between the Supercenters and the incumbents' locations using Google's mapping software API. Google Maps obtains the driving distance by calculating the fastest route by car between two locations, providing an accurate measure of the navigable spatial distance between competing stores. Our final merged sample contains 756,097 store-week observations.

Merging these data sources provides cross-sectional and panel variation in Supercenter exposure. Incumbent supermarkets' exposure to Walmart Supercenters in our sample is summarized in Table 2. The variable #WM represents a count of all Supercenters operating within 11 miles driving distance of any supermarket in the IRI dataset, which we set as the maximum exposure distance.[16] The total count is then binned into driving distance bands centered around each incumbent supermarket. In the average store-week, an incumbent IRI store is exposed to 1.6 Supercenters. Additionally, counts of the exposures during our sample categorized by distance band and entry order (i.e. first ever exposure, second, etc.) are presented in Table 3. In the 1 to 3 mile driving distance band, for example, we observe 110 exposure events in our sample, 20 of which were the incumbents' first ever exposure to a Supercenter at any distance and 42 of which were their second. During the 11 year sample, 1,190 total exposure events are observed within the maximum 11 mile driving distance. Our empirical model leverages this variation in both timing and distance.

Our analysis aims to uncover the causal effects of Supercenter exposure on incumbent outcomes. As a prelude to the full analysis, however, we first examine the average differences in incumbent supermarket outcomes immediately before and after a Supercenter opening. Table 4 therefore reports revenues and prices for exposed incumbents by driving distance band for the eight weeks immediately prior to an opening and the eight weeks following. The summaries are restricted to the incumbents' nearest Supercenter exposure. The table reveals two main descriptive results: First, as a comparison of the Pre columns across the distance bands shows, there is a robust association

[15] 1,311 of the 3,150 Supercenters opened before 2012 are matched.

[16] Note that driving distance miles are greater than or equal to "crow's flight" miles by construction.

between lower average prices and closer treatment exposures. In other words, supermarkets located nearer to a Walmart Supercenter tend to be lower priced even in the weeks immediately leading up to a Supercenter opening. For instance, 16 oz. of coffee costs \$3.71 at stores exposed within 1 mile and \$4.25 (15% higher) at stores exposed between 7 to 9 miles driving distance. Importantly, this association may reflect the causal effect of Supercenter exposure or Walmart's selection of where to locate. The second finding in Table 4 is that the average within-store, pre-post differences in prices are small and almost always statistically insignificant. In other words, at least in the immediate eight week windows presented in the table, it is difficult to discern obvious price effects of Supercenter exposure. As an example, cereal prices are on average \$2.50 per 16 oz. before a Walmart opening and \$2.48 post-opening in the less than 1 mile driving distance band. This descriptive finding suggests little price response, though this may be confounded by dynamics not captured in the snapshot presented.[17] These within-store (post-pre exposure) differences by driving distance are a key element of our empirical model, described in detail in the next section.

3 Empirical Model

Our empirical model exploits the sample's unique spatial and temporal variation to estimate the causal effects of Supercenter exposure on incumbent outcomes. We apply the model to both logged revenue and logged prices of incumbent supermarkets. To simplify exposition, both are represented by y_{st} but it should be understood that the coefficients differ across the two outcome measures. Our estimating equation can be written generally as:

$$y_{st} = \sum_j \beta(D_{sj}) WM_{jt} + \epsilon_{st} \tag{2}$$

WM_{jt} is an indicator variable for the presence of the jth Supercenter at time t. The treatment effect of interest, $\beta(D_{sj})$, is written as a function of the driving distance, D_{sj}, between the incumbent supermarket and Supercenter j.[18] We assume that there is a distance $\overline{D}$ at which the effects of Walmart entry are zero. Finally, ϵ_{st} represents all other factors that influence y_{st}.

The identification of $\beta(D_{sj})$ is confounded by a potential correlation between ϵ_{st} and WM_{jt}. As Walmart deliberately selects where to locate, it is implausible that this correlation is zero. Taking advantage of the variation in the timing of Supercenter entry across incumbents, we specify ϵ_{st} as a function of store fixed effects, π_s, time dummies, λ_t, a market-specific time trend, and a residual

[17] It may be, for example, that incumbents anticipate Walmart's arrival by lowering prices in advance or, conversely, do not change prices until later.

[18] Note that equation (2) assumes that the effect of a particular Supercenter entry on the outcome of interest does not depend on the number of previous exposures.

error term, υ_{st}.[19] In particular,

$$\epsilon_{st} = \pi_s + \lambda_t + \gamma_{m(s)}(t) + \upsilon_{st} \tag{3}$$

where $m(s)$ denotes the market for store s. Our identifying assumption is that the timing and location of Walmart entry is uncorrelated with υ_{st} conditional on the store fixed effects, time dummies, and market trends. To formalize this notion, denote by μ_{st} the store fixed effect for s, the time dummy at t, and the market trends. Letting WM_{st} represent the set of Supercenters that incumbent s is exposed to at time t, our assumption is that υ_{st} is conditionally uncorrelated with Walmart entry:

$$E[\upsilon_{st}|\mu_{st}] = E[\upsilon_{st}|\mu_{st}, WM_{st}] = 0$$

We approximate $\beta(D_{sj})$ in equation (2) using discrete driving distance bands around incumbent supermarkets' locations. This specification is implemented with a set of indicator variables that take on a value of one when store s is exposed to Supercenter j within distance band b. The use of discrete driving bands lets the data determine the distance, $\overline{D}$, at which the effect of exposure on incumbent outcomes attenuates to zero. In practice, we set an upper bound of 11 miles in driving distance beyond which an incumbent is considered "not exposed" to a particular Supercenter opening. Denoting the B distance bands by D^b_{sj} and substituting in for ϵ_{st} using (3), (2) becomes:

$$y_{st} = \sum_{b=0}^{B} \beta_b \sum_j D^b_{sj} WM_{jt} + \pi_s + \lambda_t + \gamma_{m(s)}(t) + \upsilon_{st} \tag{4}$$

This empirical model can be understood as a generalization of a difference-in-differences approach where contemporaneous changes in outcomes are compared between supermarkets that are treated by a Supercenter and stores that are not. For a given Supercenter opening, the control stores include both stores never exposed and stores exposed earlier or later over the duration of the data. The distance band specification extends this logic to also compare stores treated at different driving distances.

4 Results

This section reports estimates from the incumbent revenue and price models. In addition to estimating (4), we compare the results with estimates that rely on cross-sectional variation and examine

[19] We also explore specifications that allow for separate trends for each level of total exposures to Supercenters by the end of our sample. We specify these trends to be quadratic.

robustness to different specifications of the trends. To check for pre-treatment trends that would confound causal inference, we also estimate "event study" specifications, described below. To help establish the relevance of our research design examining incumbent supermarkets' response to the "demand shock" of Supercenter entry, we examine revenue first before turning to competitive effects on prices.

4.1 Revenue

Using log revenue as the dependent variable in (4), Table 5 presents the estimates of the effect of Supercenter exposure on incumbent supermarkets' revenue. The first column uses cross-sectional differences (along with the panel variation) in revenue by exposure distances, reporting a negative association in some driving distance bands but no clear pattern overall. In column (3), we include IRI market and supermarket chain fixed effects to compare differentially exposed incumbents in the same chain and market. These results indicate large revenue effects that decay quickly with the exposure distance. At one mile, the effect is slightly under 12%.

By incorporating store fixed effects, column (5) then applies the empirical model's difference-in-differences approach of exploiting differential timing of Supercenter exposure. The results indicate that entry causes drops in supermarket revenue of over 16% when Walmart locates within one mile. As the estimated revenue effects at close distances increase significantly when store fixed effects are included, the difference suggests that Walmart locates next to high-revenue stores. Absent store fixed effects, the number of Walmarts within a one-mile distance band serves as a proxy for high-revenue stores. Revenue effects again attenuate sharply with distance, indicating considerable localization in the exposure impact. Within 1 to 3 miles driving distance, exposure depresses revenue by 7%, less than half of the effect at under 1 mile. At 3 to 5 miles, the effect falls to 5%. Beyond 5 miles, Walmart's effect on incumbent revenue cannot be rejected as different from zero.[20]

The final two columns add IRI market-specific and treatment group-specific trends in revenue respectively. The treatment group trends allow revenues to trend differently based on the total number of Supercenter exposures an incumbent experiences by the end of our sample.[21] Adding these controls has little effect on the coefficients on interest, suggesting that what is key here is to properly account for store fixed effects.

Causal inference for the estimates is justified under the assumption of conditionally exogenous entry timing. While the validity of this assumption cannot be tested directly, trends in exposed stores' revenue prior to a Supercenter exposure are informative in this regard. If the treated stores

[20]Note this decay is well short of the 11 mile upper bound we set for exposures.

[21]In other words, unexposed stores have their own trend, one time exposed stores have their own trend, and so forth.

and control stores have similar trends leading up to exposure, we fail to reject the "common trends" assumption. To implement this test, we estimate an "event study" specification by modifying our estimating equation to interact the treatment effect of a Supercenter with the time until or since its opening week:

$$y_{st} = \sum_{k=-13}^{13} \beta_k \sum_j \mathbf{1}\{W_{jt} = k\}\mathbf{1}\{D_{sj} \leq 7\} + \sum_{b=1}^{B} \beta_b \sum_j D_{sj}^b WM_{jt} + \mu_{st} + \upsilon_{st} \tag{5}$$

where W_{jt} indexes the number of eight week windows period t is from Supercenter j's opening date. We restrict the pre and post trends to exposures within 7 miles and bin weeks around the entry date into windows up to two years (13 windows) pre and post opening.[22] We choose 7 miles based on the prior results showing the revenue effects are not statistically different from 0 at this distance and beyond. We control for the driving distance of the exposure by continuing to include the exposure counts for all driving distance bands except less than 1 mile ($b = 0$) as regressors. The β_k estimates therefore can be interpreted as the revenue effect in a given window k for an exposure within 1 mile. Note, finally, that this estimation also uncovers how the magnitude of the treatment effect varies post-entry.

Appendix Table 18 presents the detailed results, finding neither trends leading up to opening nor appreciable changes in the magnitude of the treatment effect post-exposure. This is depicted visually in Figure 1 which plots the β_k point estimate and confidence intervals from estimating (5). Prior to entry (indicated by 0 on the horizontal axis), differences in revenue relative to more than two years prior to entry are not statistically different from zero. Thus, the estimates indicate that the revenue of treated and control stores do not trend differentially prior to treatment. After a Supercenter opening, however, treated incumbent supermarkets (within 1 mile driving distance) experience a 15% revenue drop on average that persists over time, with some small attenuation after a year and a half. In sum, the results highlight the significant causal, though spatially bounded, consequences of Supercenter exposure on the revenue of competitor supermarkets. An opening of a Supercenter thereby constitutes a significant shock to the local competitive environment. We now examine how these rivals respond in prices.

4.2 Prices

To examine the causal effect of Supercenter exposure on incumbent supermarkets' prices, we modify our estimating equation to estimate the effects across all categories by pooling the individual logged

[22] We include a "window" for 105 weeks *or more* post-entry and treat windows for prior to 104 weeks as the excluded category in the regression.

price series:

$$y^c_{st} = \sum_{b=0}^{B} \beta_b \sum_j D^b_{sj} WM_{jt} + \pi^c_s + \lambda^c_t + \gamma^c_{m(s)}(t) + \upsilon^c_{st} \tag{6}$$

Superscript c indexes the food product categories. Pooling the individual price series obviates the need to construct a store price index from the individual category series.

The results of estimating (6) are presented in Table 6. The baseline estimates in column (1), which leverage cross sectional differences in prices with exposure distances, indicate large and statistically significant price effects. For example, an exposure within 1 mile is associated with a massive 8% reduction in prices. Comparing incumbents in the same chain and market in column (3) attenuates the effect sizes some, with the results indicating about a 3% price reduction in response to a 1 mile exposure. These magnitudes fit closely with those in the existing literature showing price effects on the order of 1-3% (Hausman and Leibtag, 2007; Basker and Noel, 2009). Notably, the estimated magnitudes also display a monotonic pattern with the exposure distance.

Isolating within-store changes in prices by conditioning on store fixed effects changes the results dramatically, however. Column (5) indicates that the price effects are attenuated such that they are statistically indistinguishable from zero in most distance bands, including very nearby exposures. Columns (6) through (8), which incorporate various secular trends, find robust null effects. In our preferred specification (8), an estimated effect of Supercenter exposure on prices is not different from zero at any treatment distance and, further, the point estimates are very small in magnitude. Using the complete set of controls, column (9) pools exposures within 7 miles, the furthest distance at which we observe any revenue effects. The 95% confidence interval for this point estimate rules out even a modest 0.5% price decline due to Supercenter exposure, suggesting the null result is not a consequence of lack of power.

Walmart's choice of where to locate rationalizes the sharp differences we find between results that control for store fixed effects and results that do not. Walmart chooses to locate next to low-price stores, so absent the inclusion of store fixed effects, treatment within the one-mile distance band serves as a proxy for being low-priced stores rather than identifying the causal effect of Supercenter entry on prices. To illustrate this, we recover the incumbent supermarkets' estimated fixed effects from column (8) of Table 6. These fixed effects represent each incumbent's predicted prices absent the treatment effects of Supercenter exposure (and temporal factors). We decompose the fixed effects as a function of each incumbent's market, chain, local demographics, and nearest Supercenter exposure in Table 7. Column (1) shows that stores exposed at nearer distances have lower predicted prices. Subsequent columns reveal this association is robust to comparing incumbent supermarkets in the same chain and market. The estimates in column (6) indicate that supermarkets exposed within 1 mile have nearly 3% lower predicted prices, while stores exposed between 1 to 3 miles have around 2% lower prices. Thus, rather than Supercenter exposure causing incumbents to lower prices, our findings show that Walmart locates near low price competitors.

As with the revenue results, we check for differential pre-exposure trends and post-treatment effects on incumbent prices. The results from estimating our augmented, "event study" model interacting treatment with time to exposure for exposures within 7 miles driving distance are displayed in Appendix Table 19 and plotted in Figure 2.[23] Notably, there is neither evidence of pre-treatment trends, validating causal inference, nor evidence of deviations from the null effect after entry. Further, the standard errors of the treatment effects over time are able to rule out even a modest 1% drop in prices post-entry from the 95% confidence region. In other words, the finding of no post-treatment effect is reasonably precise and not simply due to lack of statistical power.[24]

5 Potential Confounds and Explanations

Our finding of no causal effect on incumbents' prices is surprising in light of the large revenue effect of Supercenter entry in an industry with significant margins (as well as the prior results in the Walmart literature). Accordingly, in this section we perform a number of robustness checks to examine potential confounds and then evaluate several potential explanations for the non-response. We begin by examining whether changes in the composition of either products or consumers could either mask a meaningful response or lead to offsetting effects.[25] Across all specifications, we find consistent evidence of no price response. We then turn to several potential explanations for why firms would fail to adjust prices, including restrictive vertical contracts, fixed adjustment costs, firm or zone-level pricing, and simple cost-plus "rules of thumb."

5.1 UPC Aggregation

We begin by shifting our focus from the aggregated category level to the individual product. The potential concern we seek to address is whether our choice of how to aggregate prices across products could obscure a measurable price response. For example, incumbents may respond to Supercenter entry by offering smaller package sizes (that are relatively more expensive on a volume basis). In such a case, even if prices are cut, this change in assortment would offset the price response

[23] We do not include any controls for distance in these specifications.

[24] We examine price trends for just first time exposures to Walmart in results not presented and also find no prior trends in prices or treatment effects of exposure.

[25] In Table 20 of the Appendix, we also check for a price effect corresponding to the *first* Supercenter to which a store is exposed and also find no response at either the 5 or 7 mile distance thresholds for treatment.

and be masked by our volume-weighted price index. More generally, stores' assortment choices or consumers' substitution decisions may be altered by Supercenter exposure.

To address this concern, we implement our empirical strategy at the UPC level on four subsamples of our purchase data. The causal effect of Supercenter exposure is then identified by comparing prices for the same UPC in the same incumbent supermarket before and after Supercenter openings. This analysis thus indirectly tests whether changes in the composition of UPCs purchased post-exposure possibly confound price changes, generating bias. We consider the top thirty UPCs by total revenue for each of carbonated beverage, margarine/butter, salty snack, and peanut butter categories for this item level analysis (120 individual UPCs in total).

The results are displayed in Tables 8 through 11 respectively and reveal no robust evidence of price response to Supercenter exposure. Further, each set of results exhibits the same key pattern from Table 6: estimates that use cross-sectional differences identify large associations between lower prices and Supercenter exposure. However, conditioning on store fixed effects to isolate the changes that occur within treated stores, the estimated price effects are not statistically different from zero. The lone exception, shown in Table 11, is a statistically significant price drop for peanut butter UPCs of about 1.6% for exposures within 1 mile.[26] These UPC-level results therefore support the conclusion drawn from the aggregated price series of a null effect.

5.2 Heterogeneity across Products

A second potential confound is that exposure to Supercenter entry might generate a null causal effect by affecting price dispersion across products. This dual response could follow from a Supercenter changing the distribution of consumers who shop at the incumbent in addition to changing the competitive environment. For instance, a Supercenter opening may incentivize the store to price-compete for price-sensitive shoppers and to raise prices for brands demanded by quality-sensitive shoppers, leading to an offsetting effect that zeroes out across products. Along these lines, in a study of shopper "home scan" data, Jindal et al. (2015) find that low priced "value" brands perform better at Walmart Supercenters while premium brands perform better at supermarkets. Moreover, consumers who shop at both types of outlets are more price sensitive than those who are loyal to a single one.

Similarly, a shifting consumer distribution may instead imply that the optimal incumbent response to a Supercenter opening is no response across all products. The distributional change, termed the "price sensitivity" effect by Chen and Riordan (2008), implies the incumbent should

[26] At all other distance bands, the effects are not different from zero nor are they significant when all exposures within 7 miles are pooled.

raise prices, while the competitive or "market share" effect implies a price cut. The estimated null causal effect of entry on prices would thus represent the net of these two effects.

With this motivation, we use frozen pizza sales to explore differential price effects across brands. As a category, frozen pizza is characterized by considerable differences in prices across brand, reflecting strong vertical differentiation. Prices by brand are summarized in Appendix Table 6. For example, California Pizza Kitchen is over three times as expensive on average as a Totino's pizza in volume terms. For this reason, the frozen pizza category is a natural candidate for observing heterogeneous response across price tiers. To implement this check, we extract the full universe of frozen pizza sales.[27]

We first examine the revenue effect of Supercenter exposure across frozen pizza brands to verify that this category provides a good test. The results obtained from applying our empirical model are presented in Table 12. Columns (1) and (2) pool all exposures within a 7 mile driving distance, while (3) and (4) focus only on exposures within 5 miles. In columns (2) and (4), the number of exposures is interacted with brand dummies to estimate a treatment effect for each brand. These estimates reveal that while some, generally lower priced, brands experience sharp revenue drops in response to a Supercenter opening, other brands experience no significant change in revenue at all. For instance, revenues for California Pizza Kitchen do not appear to change post-entry, whereas Totino's revenues decline between 5 and 8%.

Table 13 presents the corresponding results for the effects on frozen pizza prices by brand. As with the prior robustness check, this model is applied at the UPC level to avoid biases arising from aggregation.[28] Matching the results obtained with the aggregated price series and the UPC prices, the estimated overall effect of Supercenter exposure is not different from zero, as displayed in columns (1) and (3). Columns (2) and (4) further reveal that for no brand (in either specification) is the point estimate statistically different from zero. Thus, the findings show that not only are there no price effects across tiers, there are no effects despite some products experiencing large revenue declines from Supercenter exposure and others little to none. Together, Tables 12 and 13 indicate that demand shocks vary across products while price reactions do not differ significantly from zero for any product. This finding is inconsistent with "price sensitivity" and "market share" effects netting to zero as the tradeoff depends on how the distribution of consumer preferences changes in response to Supercenter entry.

[27]All UPCs that appear for at least 26 weeks and in 5 or more supermarkets (for non-private label items) are kept in the frozen pizza sample.

[28]Note that the large sample size precludes the estimation of parametric trends. Estimation instead uses an iterative estimator with store-UPC fixed effects and market-UPC-period fixed effects.

5.3 Heterogeneity across Private and Branded labels

Turning next to potential explanations, we assess the possibility that the null response is driven by the retailers not having full control of the pricing process. In particular, it is conceivable that incumbent supermarkets are constrained in their price-setting ability by vertical relationships with manufacturers. There is no clear consensus in the literature regarding who has the most power in setting prices, the retailer or the manufacturer. The previous literature has modeled this either as a non-cooperative game (Villas-Boas, 2007) or cooperative (Nash) bargaining problem (Draganska et al., 2010). If the manufacturer dominates the relationship, the price response at an individual store may be muted.

To address this concern, we split our analysis between those branded products for which there is a potential channel conflict, and private label "store brand" products over which the retailer has direct control. In other words, it might be the case that, although the prices of branded products are constrained by manufacturer relationships, incumbents can respond to a Supercenter opening by reducing the prices of private label products. The combined effect might appear as an overall null effect. To consider this possibility with our data, we construct category price series separately for all private label and branded UPCs using equation (1). For both branded and private labels, we then pool the logged category price series to estimate the price effect of Supercenter exposure. The results are displayed in Table 14.

The specifications estimated correspond to columns (8) and (9) of Table 6, which incorporate store-category fixed effects and multiple secular trends. In columns (1) and (3), estimates are reported for branded and private labels respectively by distance band. The results reveal that, for either branded or private products, at no distance band can the price effect be rejected as statistically different from zero at conventional thresholds. As an additional check, in columns (2) and (4), we group all Supercenter exposures within 7 miles driving distance. We again find a null effect, matching the findings for the overall UPC price series.

5.4 Heterogeneity across Supermarket Type

Next, we examine whether the non-response can be explained by retailer scale. Large chains may face incentives to mute their response to local entry to soften price competition, as in a model of multi-market contact. Similarly, chain supermarkets may set uniform retail prices across their stores within a given market or region, either to economize on firm-level adjustment costs or to mitigate price comparisons within their chain.[29] This multi-market feature of price-setting would

[29] In an analysis of AC Nielsen data on store-level prices at U.S. supermarkets, Nakamura (2008) finds that 65 percent of price variation is common to stores of a particular chain, while 17 percent is idiosyncratic to the store and

in turn limit the extent to which chains might optimally respond to Supercenter openings that only affect one or a few of their stores. Hence, we investigate whether price responses differ based on whether the incumbent is a national chain, a regional chain, a subregional or local chain, or an independent supermarket.

Using our pooled category price series, we interact incumbents' total Supercenter exposure with indicators for type to look for evidence of this form of heterogeneity. The results are displayed in Table 15. In column (1), we bin all exposures up to 7 miles driving distance together (not otherwise controlling for exposure distance), while in column (2) we shorten the distance threshold to just 5 miles. The results indicate no statistically significant price reactions for any incumbent type. These results are thus consistent with our main finding of no price response by incumbent supermarkets to Supercenter openings.

5.5 Cost-Plus Pricing

The last explanation we consider is that supermarkets follow simple, cost-plus pricing strategies that do not adjust to demand shocks. That many firms adopt simple pricing rules has been well known for quite some time, dating back at least as far as Cyert and March (1963). The strongest empirical evidence in this regard is provided by Eichenbaum et al. (2011), who obtained data from a very large (over 1000 store) supermarket firm operating in the US and Canada. Critically, they observe both shelf prices and wholesale costs, allowing them to connect price changes directly to input prices. Notably, they find that prices rarely change without an accompanying cost change, though prices are not always adjusted when costs move. Instead, they find that the firms adjust prices relatively infrequently, with the apparent goal of maintaining relatively stable "target" markups over cost. In particular, the periodic adjustments are used to keep the actual markups within about plus or minus 10% of their long-run target.[30] Analyzing similar data from a different retailer, McShane et al. (2016), also find that when shelf prices are adjusted, it is typically in response to an associated cost shock, with the resulting price change used to maintain the prior gross margin. There is also a body of survey evidence documenting the ubiquity of cost-plus pricing, particularly amongst retail

product (the remaining 16 percent is common across stores of different chains selling the same product). This suggests that while some price changes occur at the level of the store, the majority are chain-wide (however, many of these are likely responses to chain-wide shocks). DellaVigna and Gentzkow (2017) find even higher levels of "uniform pricing" in the Kilt's Nielsen data, concluding that firms face chain level decision-making costs. In a broad-ranging analysis of the same data, Hitsch et al. (2016) also find that chain factors explain a larger fraction of price dispersion than market factors, which they conclude is partly driven by the fact that, by segmenting the market, chains face relatively more homogeneous demand than the market as a whole. Gagnon and Lopez-Salido (2014) find similar patterns in the IRI Marketing dataset. Consistent with our focus, they also find very limited *chain-level* price response to several types of demand shocks, including natural disasters, severe weather and labor conflicts.

[30] Using same dataset, but focusing on stores close to the US/Canada border, Gopinath et al. (2011) find that almost all of the variation in relative retail prices, in response to exchange rate shocks, is explained by variation in relative costs and not by variation in relative markups.

firms.[31]

In our setting, we find robust evidence for no price response – either downward, upward, or pre-emptively – by incumbent retailers to Supercenter entry. This finding is consistent with margin maintenance: As Suprecenter entry does not change costs, it also does not trigger a change in the pricing rules used by incumbents. Further, our examination of price response across products provides two additional pieces of supporting evidence for this interpretation. First, we do not observe price reductions even for the lower tier products whose sales are most impacted by Supercenter entry. In terms of the framework in Chen and Riordan (2008), these are the products for which competitive incentives to lower prices are likely to dominate. At the same time, the opposing "price sensitivity" effect suggests that increasing prices for the upper tier products (for which we do not see significant revenue impacts) is the optimal response, which we also do not find evidence for. Although this evidence is not itself conclusive (cross-price elasticities must factor in and upward adjustment could be constrained by reputation considerations), cost-plus pricing provides a consistent rationalization. While our data, lacking information on costs, do not allow us to test for cost-plus pricing directly, the fact that we find that incumbent firm size does not change our null result suggests that it is not simply a fixed (chain-level) adjustment cost, but rather a broad-based pattern of behavior.

Our results suggest that such "cost-plus" thinking may influence how firms respond to even large-scale changes in their competitive environment. In the retail setting, simple rules of thumb might be an optimal response to an intractable optimization problem that involves monitoring the prices of thousands of products at numerous competitors, while managing one's own complex supply chain. The intractability of this problem is further augmented by the practical challenges in many settings of collecting and analyzing vast amounts of competitor and consumer data. While advances in information technology and data science have substantially lessened the burden of solving such problems, our findings suggest that even the most sophisticated retailers are still unable to quickly adapt.

[31] For example, Watson et al. (2015), who interview grocery pricing managers in the US and UK and find that minimum margin targets are the predominant practice in both countries. They find that competitive based pricing strategies (i.e. reacting to rival prices) are typically viewed by practitioners as being infeasible due to poor access to data for competing firms and the inherent challenge of tracking a vast array of prices across a large number of competitors with a limited staff and budget. In addition, Phillips (2005) summarizes a host of previous surveys on pricing practices, noting that cost-plus pricing remains a popular pricing strategy that is used by up to 70% of firms in some geographies. Additional survey evidence is provided in Blinder et al. (1998) and Noble and Gruca (1999).

6 Conclusion

We combine data on weekly grocery transactions with the exact locations and opening dates of Walmart Supercenters to examine competitive price reactions by incumbent supermarkets. The unique temporal and spatial variation in our data allow us to separate the causal effect of entry from Walmart's decision of where to locate. While we find large, but localized, impacts on revenues, we find no evidence that incumbent supermarkets adjust prices in response to Supercenter entry. This result is robust across many dimensions, including a lack of price response pre-emptively, for individual products, and across brands within a category. Our findings stand in sharp contrast to earlier studies that suggest sizable price reductions that imply considerable welfare gains to consumers via competitive mechanisms (Hausman and Leibtag, 2007; Basker and Noel, 2009).

We argue that this non-response is unlikely to be explained by menu or monitoring costs, vertical contracts with manufacturers, or by multi-market pricing, but is most consistent with widespread use of simple, "rule of thumb," cost-plus pricing strategies, a form of managerial inattention. Since entry by Walmart does not impact costs, it does not trigger a price reaction from incumbent supermarkets. While our data do not allow us to test this hypothesis directly, the fact that we find that incumbent firm size does not change our null result suggests that it is not simply a fixed (chain-level) adjustment cost, but rather a broad-based pattern of behavior. This conclusion raises the question of why such simple policies persist in competitive environments and how much profit is left on the table by not employing more sophisticated strategies. Assessing the implications of these practices on both profitability and consumer surplus (via a demand model or using data that provide information on costs or survival) and how more recent entrants, in particular competition with online grocery retailers, may influence strategies are promising areas for future research, as is understanding of how such rules may be initially formed and later updated.

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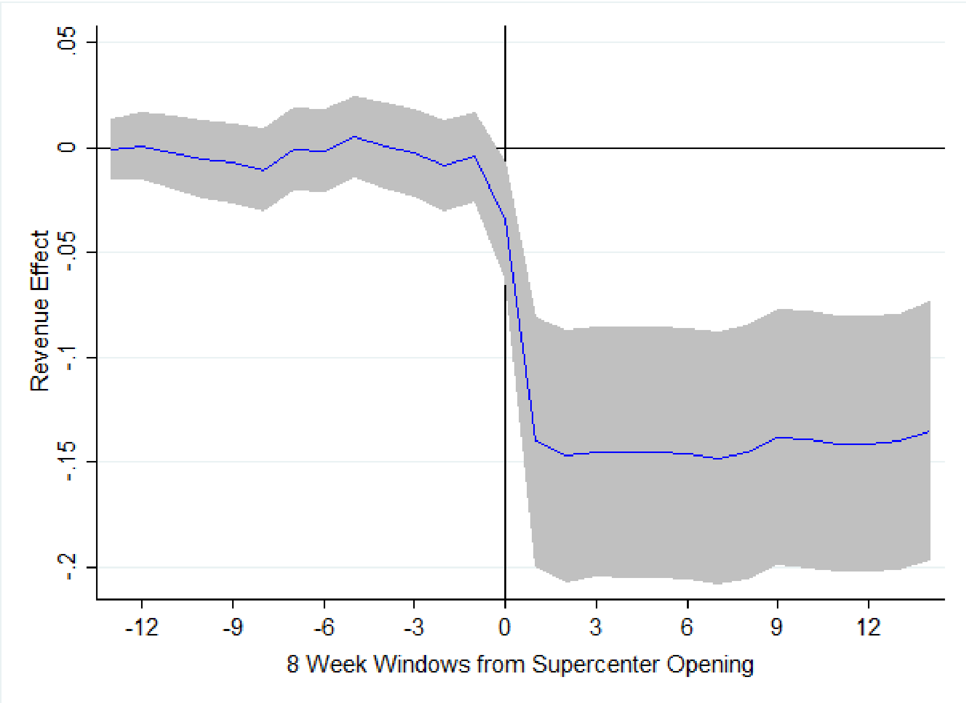
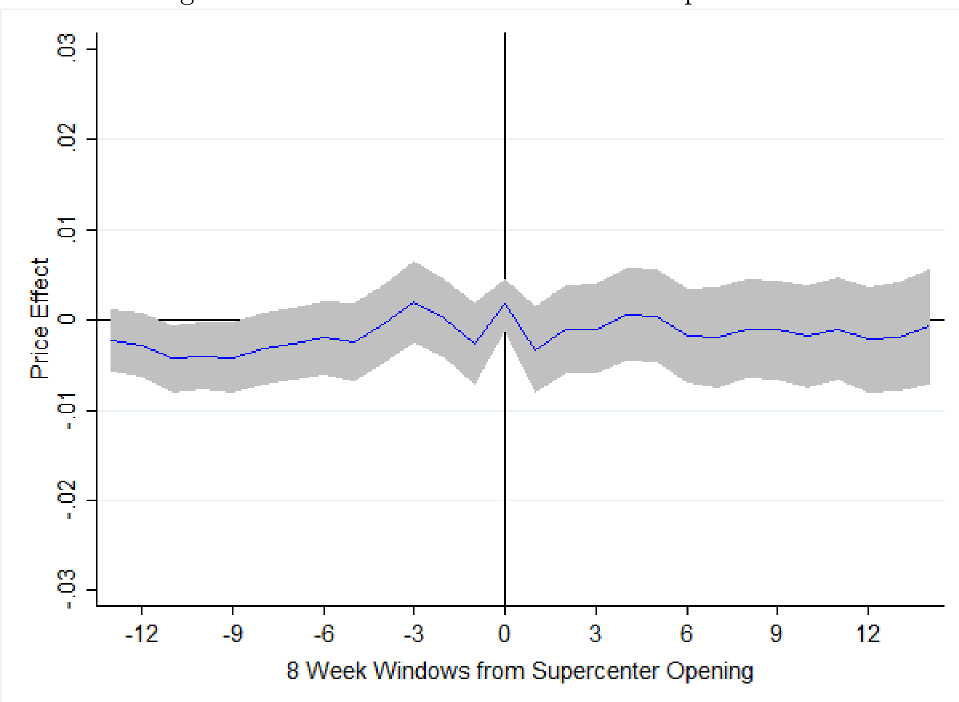
Figure 1: Trends in the Revenue Effect of Supercenters[a]



[a]Estimates correspond to column (5) of Table 18.

Figure 2: Trends in the Price Effect of Supercenters[a]



[a]Estimates correspond to column (5) of Table 19.

Table 1: Summaries of Incumbent Supermarket Outcomes

	Units	N	Mean	SD	p10	Median	p90
Revenue	Dollars	756097	44738	26949	18099	38378	79275
Carb Bev Price	$/192 oz	755078	3.69	0.56	3.07	3.62	4.40
Coffee Price	$/16 oz	755076	4.43	1.37	2.88	4.23	6.29
Cereal Price	$/16 oz	755282	2.64	0.37	2.22	2.61	3.08
Fz Dinners Price	$/16 oz	681853	2.91	0.52	2.29	2.88	3.59
Fz Pizza Price	$/16 oz	755002	2.78	0.53	2.17	2.72	3.44
Hotdog Price	$/16 oz	754935	2.27	0.59	1.56	2.24	3.02
Marg/Butr Price	$/16 oz	755107	1.36	0.43	0.87	1.28	1.94
Mayo Price	$/16 oz	755026	1.55	0.32	1.17	1.53	1.97
Must/Ketc Price	$/16 oz	755387	1.15	0.30	0.81	1.10	1.54
Pean Butr Price	$/16 oz	755383	1.74	0.27	1.43	1.72	2.08
Salty Snck Price	$/16 oz	754635	3.08	0.39	2.61	3.06	3.56
Soup Price	$/16 oz	755235	1.40	0.22	1.14	1.38	1.69
Spag Sauc Price	$/16 oz	755051	1.12	0.27	0.84	1.08	1.43
Sugar Sub Price	$/1 oz	755422	0.67	0.16	0.50	0.65	0.87
Yogurt Price	$/1 pint	754724	1.46	0.21	1.21	1.44	1.71

Notes: Revenue is for only the summarized categories. Dollars are in January 2001 terms per CPI.

Table 2: Summary of Walmart Supercenter Exposures

	Mean	SD	p10	p25	Median	p75	p90
# WM	1.60	1.63	0	0	1	2	4
# WM $<$ 1 Mi	0.04	0.20	0	0	0	0	0
1 Mi $\leq$ # WM $<$ 3 Mi	0.19	0.41	0	0	0	0	1
3 Mi $\leq$ # WM $<$ 5 Mi	0.26	0.51	0	0	0	0	1
5 Mi $\leq$ # WM $<$ 7 Mi	0.32	0.60	0	0	0	1	1
7 Mi $\leq$ # WM $<$ 9 Mi	0.37	0.67	0	0	0	1	1
9 Mi $\leq$ # WM $<$ 11 Mi	0.42	0.71	0	0	0	1	1

Notes: 756,097 incumbent store-week observations. Table summarizes exposure to Walmart Supercenters overall and by driving distance bands around incumbent supermarkets.

Table 3: Observed Supercenter-Incumbent Supermarket Exposures

Exposure	1st	2nd	3rd	4th	5th	6th	7th	Total
# WM $<$ 1 Mi	7	15	6	0	0	1	1	30
1 Mi $\leq$ # WM $<$ 3 Mi	20	42	25	12	6	5	0	110
3 Mi $\leq$ # WM $<$ 5 Mi	24	47	35	30	11	10	9	166
5 Mi $\leq$ # WM $<$ 7 Mi	30	64	54	42	19	18	7	234
7 Mi $\leq$ # WM $<$ 9 Mi	50	71	70	46	39	16	14	306
9 Mi $\leq$ # WM $<$ 11 Mi	55	81	79	64	28	21	16	344
Total	186	320	269	194	103	71	47	1190

Notes: Table summarizes Walmart Supercenters openings observed in the sample by driving distance band and order of exposure. For example, the first cell of the first column indicates that we observe during our sample 7 Supercenter openings within 1 mile that are the incumbent's 1st exposure.

Table 4: Incumbent Outcomes for 8 Weeks Pre and Post Nearest Supercenter Exposure

	Less than 1 Mi		1 to 3 Mi		3 to 5 Mi		5 to 7 Mi		7 to 9 Mi		9 to 11 Mi	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Revenue	55193	46494†	45305‡	42971	40800‡	39301	47166‡	45980	51797	49837	45451‡	43661
Prices:												
Carb Bev	3.66	3.71	3.66	3.67	3.61	3.63	3.69	3.70	3.55‡	3.60	3.61	3.62
Coffee	3.71	3.83	4.03‡	4.13	4.39‡	4.41	4.58‡	4.47	4.25‡	4.26	4.61‡	4.64
Cereal	2.50	2.48	2.57‡	2.56	2.63‡	2.64	2.70‡	2.71	2.65‡	2.65	2.76‡	2.76
Frozen Dinners	2.79	2.82	2.90‡	2.90	2.90‡	2.90	2.96‡	2.95	2.89‡	2.90	3.03‡	3.05
Frozen Pizza	2.64	2.58	2.68	2.67	2.80‡	2.81	2.90‡	2.89	2.84‡	2.83	2.94‡	2.92
Hotdogs	2.05	2.05	2.21‡	2.19	2.29‡	2.28	2.38‡	2.32	2.35‡	2.35	2.46‡	2.49
Marg/Butter	1.14	1.13	1.22‡	1.23	1.35‡	1.36	1.42‡	1.40	1.40‡	1.40	1.58‡	1.56
Mayonaisse	1.46	1.46	1.46	1.48	1.56‡	1.57	1.60‡	1.59	1.56‡	1.55	1.67‡	1.68
Mustard/Ketchup	1.05	1.03	1.10‡	1.10	1.15‡	1.16	1.20‡	1.18	1.17‡	1.17	1.25‡	1.24
Peanut Butter	1.64	1.61	1.68‡	1.70	1.77‡	1.76	1.80‡	1.81	1.73‡	1.72	1.79‡	1.81
Salty Snacks	2.89	2.90	2.97‡	2.99	3.02‡	3.05	3.13‡	3.12	3.02‡	3.05	3.11‡	3.11
Soup	1.34	1.34	1.38‡	1.36	1.46‡	1.43†	1.46‡	1.42†	1.42‡	1.37†	1.47‡	1.46
Spaghetti Sauce	1.05	1.02	1.08‡	1.08	1.13‡	1.12	1.17‡	1.15	1.13‡	1.12	1.23‡	1.20
Sugar Substitutes	0.62	0.62	0.63	0.63	0.69‡	0.68	0.69‡	0.69	0.70‡	0.69	0.72‡	0.72
Yogurt	1.37	1.37	1.41‡	1.41	1.46‡	1.46	1.51‡	1.50	1.47‡	1.48	1.56‡	1.56
N	235	248	792	793	697	712	444	450	417	414	264	265

Notes: † indicates Post differs from Pre with $p < .05$. ‡ indicates difference from Pre at less than 1 mile band with $p < .05$. N corresponds to store-week observations for revenue (first row).

Table 5: Competitive Revenue Effect of Supercenter Openings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
# WM < 1 Mi	-0.00966	0.0139	-0.115***	-0.134***	-0.162***	-0.160***	-0.154***
	(0.0697)	(0.0517)	(0.0367)	(0.0373)	(0.0328)	(0.0341)	(0.0338)
1 Mi $\leq$ # WM < 3 Mi	-0.0688**	-0.0111	-0.0615***	-0.0845***	-0.0674***	-0.0769***	-0.0716***
	(0.0300)	(0.0259)	(0.0178)	(0.0200)	(0.0259)	(0.0248)	(0.0255)
3 Mi $\leq$ # WM < 5 Mi	-0.0190	0.0530***	-0.00899	-0.0354**	-0.0497***	-0.0505***	-0.0417***
	(0.0222)	(0.0202)	(0.0141)	(0.0162)	(0.0161)	(0.0158)	(0.0146)
5 Mi $\leq$ # WM < 7 Mi	-0.0522***	-0.00100	-0.0183	-0.0455***	-0.0188	-0.0269*	-0.0253*
	(0.0198)	(0.0165)	(0.0121)	(0.0145)	(0.0141)	(0.0144)	(0.0150)
7 Mi $\leq$ # WM < 9 Mi	-0.0263	-0.00794	-0.0219*	-0.0479***	-0.0153	-0.0220*	-0.0176
	(0.0173)	(0.0156)	(0.0114)	(0.0141)	(0.0140)	(0.0133)	(0.0127)
9 Mi $\leq$ # WM < 11 Mi	-0.00855	-0.00332	-0.0110	-0.0371***	-0.0188	-0.0174	-0.0149
	(0.0169)	(0.0153)	(0.0113)	(0.0138)	(0.0122)	(0.0116)	(0.0112)
Period FE	Y	Y	Y	Y	Y	Y	Y
Market FE	N	Y	Y	Y	Y	Y	Y
Chain FE	N	N	Y	Y	Y	Y	Y
Treat Group FE	N	N	N	Y	Y	Y	Y
Store FE	N	N	N	N	Y	Y	Y
Market Trends	N	N	N	N	N	Y	Y
Treat Group Trends	N	N	N	N	N	N	Y

Notes: 756,097 store-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets. All trends are quadratic

Table 6: Competitive Price Effect of Walmart Supercenters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# WM $<$ 1 Mi	-0.0844***	-0.0352***	-0.0264***	-0.00402	-0.00385	-0.00379	0.00388	0.00366	
	(0.0118)	(0.0111)	(0.00534)	(0.00876)	(0.00878)	(0.00879)	(0.00706)	(0.00704)	
1 Mi $\leq$ # WM $<$ 3 Mi	-0.0582***	-0.0247***	-0.0155***	-0.00339	-0.00337	-0.00318	0.00281	0.00204	
	(0.00671)	(0.00599)	(0.00312)	(0.00604)	(0.00604)	(0.00604)	(0.00441)	(0.00440)	
3 Mi $\leq$ # WM $<$ 5 Mi	-0.0383***	-0.00886*	-0.00451*	-0.00853**	-0.00865**	-0.00861**	-0.00350	-0.00338	
	(0.00565)	(0.00530)	(0.00242)	(0.00413)	(0.00412)	(0.00412)	(0.00317)	(0.00320)	
5 Mi $\leq$ # WM $<$ 7 Mi	-0.0151***	0.000659	-0.00414*	-0.00900**	-0.00916**	-0.00911**	0.00127	0.00138	
	(0.00451)	(0.00427)	(0.00232)	(0.00357)	(0.00356)	(0.00356)	(0.00297)	(0.00291)	
7 Mi $\leq$ # WM $<$ 9 Mi	-0.00114	0.00937**	-0.00209	-0.00692**	-0.00702**	-0.00707**	-0.00169	-0.00128	
	(0.00422)	(0.00411)	(0.00208)	(0.00299)	(0.00300)	(0.00299)	(0.00235)	(0.00252)	
9 Mi $\leq$ # WM $<$ 11 Mi	-0.0111***	-0.00313	-0.00206	-0.00420	-0.00426	-0.00425	0.000621	0.000218	
	(0.00424)	(0.00385)	(0.00199)	(0.00288)	(0.00288)	(0.00288)	(0.00234)	(0.00238)	
# WM $<$ 7 Mi									0.000301
									(0.00191)
Period FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Category FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Market FE	N	Y	Y	Y	Y	Y	Y	Y	Y
Chain FE	N	N	Y	Y	Y	Y	Y	Y	Y
Store FE	N	N	N	Y	Y	Y	Y	Y	Y
Store-Category FE	N	N	N	N	Y	Y	Y	Y	Y
Category Trends	N	N	N	N	N	Y	Y	Y	Y
Market Trends	N	N	N	N	N	N	Y	Y	Y
Treat Group Trends	N	N	N	N	N	N	N	Y	Y

Notes: 11,253,196 store-category-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets and category refers to product category. All trends are quadratic.

Table 7: Predicted Prices Decomposition

	(1)	(2)	(3)	(4)	(5)	(6)
Closest WM < 1 Mi	-0.0866***	-0.0390***	-0.0469***	-0.0444***	-0.0428***	-0.0266***
	(0.0120)	(0.0107)	(0.0113)	(0.0105)	(0.0104)	(0.00577)
1 Mi ≤ Closest WM < 3 Mi	-0.0837***	-0.0333***	-0.0356***	-0.0343***	-0.0347***	-0.0176***
	(0.00757)	(0.00787)	(0.00805)	(0.00764)	(0.00748)	(0.00433)
3 Mi ≤ Closest WM < 5 Mi	-0.0760***	-0.0209***	-0.0261***	-0.0316***	-0.0309***	-0.0102**
	(0.00761)	(0.00792)	(0.00808)	(0.00763)	(0.00756)	(0.00425)
5 Mi ≤ Closest WM < 7 Mi	-0.0653***	-0.0187**	-0.0271***	-0.0290***	-0.0300***	-0.0195***
	(0.00849)	(0.00820)	(0.00813)	(0.00768)	(0.00755)	(0.00467)
7 Mi ≤ Closest WM < 9 Mi	-0.0409***	-0.00277	-0.0124	-0.0177*	-0.0186*	-0.0129**
	(0.0117)	(0.0109)	(0.0111)	(0.0105)	(0.0103)	(0.00502)
9 Mi ≤ Closest WM < 11 Mi	-0.0398***	-0.0133	-0.0218**	-0.0235**	-0.0225**	-0.00273
	(0.0111)	(0.0100)	(0.0105)	(0.00991)	(0.00961)	(0.00525)
2nd Income Quintile				0.0343***	0.0348***	0.0268***
				(0.00689)	(0.00690)	(0.00382)
3rd Income Quintile				0.0531***	0.0539***	0.0414***
				(0.00705)	(0.00705)	(0.00414)
4th Income Quintile				0.0906***	0.0889***	0.0620***
				(0.00760)	(0.00754)	(0.00461)
5th Income Quintile				0.140***	0.140***	0.0983***
				(0.00784)	(0.00777)	(0.00457)
2nd Density Tercile				0.0126**	0.0126**	0.00998***
				(0.00547)	(0.00534)	(0.00329)
3rd Density Tercile				0.0226***	0.0201***	0.0139***
				(0.00714)	(0.00696)	(0.00414)
Regional Chain					0.0390***	
					(0.00651)	
Subregional / Local Chain					0.0524***	
					(0.0100)	
Non-Chain Supermarket					0.00340	
					(0.0109)	
Constant	0.0498***	-0.0117	0.00759	-0.0897***	-0.100***	-0.0300
	(0.00519)	(0.0144)	(0.0155)	(0.0142)	(0.0159)	(0.0332)
Category FE	Y	Y	Y	Y	Y	Y
Market FE	N	Y	Y	Y	Y	Y
Chain FE	N	N	N	N	N	Y
N	36,486	36,486	30,061	30,061	30,061	30,061

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. Markets are IRI designated markets. National chain, 1st Income Quintile, and 1st Density Tercile stores are excluded group. Dependent variable is demeaned store-category fixed effect from column (8) of Table 6.

Table 8: Competitive Price Effect of Walmart Supercenters: Top 30 Carbonated Beverage UPCs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# WM < 1 Mi	-0.0304***	-0.0153***	-0.00866***	-0.00628	-0.0101	-0.00780	0.00709	0.00716	
	(0.00646)	(0.00519)	(0.00329)	(0.0105)	(0.0108)	(0.0109)	(0.0102)	(0.0103)	
1 Mi ≤ # WM < 3 Mi	-0.0150***	-0.00866***	-0.00311**	-0.00931	-0.00949	-0.0103	-0.00275	-0.00202	
	(0.00336)	(0.00269)	(0.00151)	(0.00863)	(0.00807)	(0.00813)	(0.00698)	(0.00679)	
3 Mi ≤ # WM < 5 Mi	-0.0126***	-0.00505**	-0.00122	0.00479	0.00234	0.00288	-0.00119	-0.000775	
	(0.00255)	(0.00212)	(0.00109)	(0.00564)	(0.00543)	(0.00537)	(0.00512)	(0.00499)	
5 Mi ≤ # WM < 7 Mi	-0.0124***	-0.00468**	-0.00169	-0.00551	-0.00507	-0.00487	-0.00188	-0.00192	
	(0.00230)	(0.00190)	(0.00114)	(0.00467)	(0.00448)	(0.00448)	(0.00387)	(0.00368)	
7 Mi ≤ # WM < 9 Mi	-0.00590***	0.00153	8.72e-05	-0.00303	-0.00353	-0.00319	-0.00102	-4.71e-05	
	(0.00201)	(0.00160)	(0.000958)	(0.00387)	(0.00365)	(0.00360)	(0.00333)	(0.00344)	
9 Mi ≤ # WM < 11 Mi	-0.00800***	-0.00111	-0.000859	-0.00904**	-0.00817**	-0.00790**	-0.00519	-0.00502	
	(0.00199)	(0.00152)	(0.000842)	(0.00413)	(0.00405)	(0.00402)	(0.00338)	(0.00342)	
# WM < 7 Mi									-0.000573
									(0.00281)
Period FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
UPC FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Market FE	N	Y	Y	Y	Y	Y	Y	Y	Y
Chain FE	N	N	Y	Y	Y	Y	Y	Y	Y
Store FE	N	N	N	Y	Y	Y	Y	Y	Y
Store-UPC FE	N	N	N	N	Y	Y	Y	Y	Y
UPC Trends	N	N	N	N	N	Y	Y	Y	Y
Market Trends	N	N	N	N	N	N	Y	Y	Y
Treat Group Trends	N	N	N	N	N	N	N	Y	Y

Notes: 15,626,919 store-UPC-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets. All trends are quadratic. Top 30 UPCs defined by total real sales revenue during the sample period.

Table 9: Competitive Price Effect of Walmart Supercenters: Top 30 Margarine/Butter UPCs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# WM < 1 Mi	-0.0581***	-0.0213**	-0.0130***	-0.0114	-0.00837	-0.00478	-0.00190	-0.00127	
	(0.0116)	(0.00884)	(0.00347)	(0.0122)	(0.0114)	(0.0115)	(0.00810)	(0.00829)	
1 Mi ≤ # WM < 3 Mi	-0.0399***	-0.0134***	-0.00669***	-0.00904	-0.0122*	-0.0116*	-0.00470	-0.00489	
	(0.00569)	(0.00359)	(0.00170)	(0.00711)	(0.00669)	(0.00641)	(0.00455)	(0.00457)	
3 Mi ≤ # WM < 5 Mi	-0.0354***	-0.00808***	-0.00302**	-0.0109*	-0.0124**	-0.0134**	-0.00438	-0.00437	
	(0.00423)	(0.00294)	(0.00118)	(0.00598)	(0.00583)	(0.00557)	(0.00359)	(0.00369)	
5 Mi ≤ # WM < 7 Mi	-0.0203***	-0.00448*	-0.00338***	-0.00399	-0.00769*	-0.00772*	-0.000471	0.000127	
	(0.00373)	(0.00238)	(0.00105)	(0.00412)	(0.00403)	(0.00397)	(0.00302)	(0.00302)	
7 Mi ≤ # WM < 9 Mi	-0.00438	0.00420**	-0.000183	-0.00542	-0.00618*	-0.00746**	-0.00181	-0.00122	
	(0.00319)	(0.00209)	(0.000894)	(0.00361)	(0.00345)	(0.00344)	(0.00260)	(0.00262)	
9 Mi ≤ # WM < 11 Mi	-0.0109***	0.000569	7.62e-05	-0.00554	-0.00576*	-0.00566*	-0.000307	0.000252	
	(0.00329)	(0.00209)	(0.000935)	(0.00338)	(0.00333)	(0.00325)	(0.00248)	(0.00261)	
# WM < 7 Mi									-0.00224
									(0.00211)
Period FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
UPC FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Market FE	N	Y	Y	Y	Y	Y	Y	Y	Y
Chain FE	N	N	Y	Y	Y	Y	Y	Y	Y
Store FE	N	N	N	Y	Y	Y	Y	Y	Y
Store-UPC FE	N	N	N	N	Y	Y	Y	Y	Y
UPC Trends	N	N	N	N	N	Y	Y	Y	Y
Market Trends	N	N	N	N	N	N	Y	Y	Y
Treat Group Trends	N	N	N	N	N	N	N	Y	Y

Notes: 13,767,512 store-UPC-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets. All trends are quadratic. Top 30 UPCs defined by total real sales revenue during the sample period.

Table 10: Competitive Price Effect of Walmart Supercenters: Top 30 Salty Snack UPCs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# WM < 1 Mi	-0.0181***	-0.0161***	-0.00674***	0.000646	-0.00117	-0.00114	0.000362	0.000653	
	(0.00596)	(0.00493)	(0.00228)	(0.00816)	(0.00753)	(0.00755)	(0.00617)	(0.00622)	
1 Mi ≤ # WM < 3 Mi	-0.00621*	-0.00789***	-0.00202**	0.000555	-0.00374	-0.00329	-0.000706	-0.000370	
	(0.00320)	(0.00260)	(0.000990)	(0.00502)	(0.00459)	(0.00470)	(0.00377)	(0.00385)	
3 Mi ≤ # WM < 5 Mi	-0.00661***	-0.00652***	-0.000937	-0.00465	-0.00482*	-0.00503*	0.000366	0.00156	
	(0.00244)	(0.00212)	(0.000672)	(0.00331)	(0.00286)	(0.00289)	(0.00241)	(0.00240)	
5 Mi ≤ # WM < 7 Mi	-0.00658***	-0.00473***	-0.00114	-0.00837***	-0.00819***	-0.00848***	-0.00135	-0.000655	
	(0.00215)	(0.00183)	(0.000901)	(0.00294)	(0.00280)	(0.00286)	(0.00242)	(0.00242)	
7 Mi ≤ # WM < 9 Mi	-0.00244	0.000163	-0.000524	-0.00321	-0.00272	-0.00297	0.000845	0.00175	
	(0.00195)	(0.00159)	(0.000610)	(0.00237)	(0.00211)	(0.00213)	(0.00199)	(0.00197)	
9 Mi ≤ # WM < 11 Mi	-0.00322*	-5.70e-05	9.83e-05	-0.00172	1.84e-05	-0.000171	0.00228	0.00283	
	(0.00179)	(0.00150)	(0.000521)	(0.00214)	(0.00212)	(0.00213)	(0.00182)	(0.00186)	
# WM < 7 Mi									-9.35e-05
									(0.00148)
Period FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
UPC FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Market FE	N	Y	Y	Y	Y	Y	Y	Y	Y
Chain FE	N	N	Y	Y	Y	Y	Y	Y	Y
Store FE	N	N	N	Y	Y	Y	Y	Y	Y
Store-UPC FE	N	N	N	N	Y	Y	Y	Y	Y
UPC Trends	N	N	N	N	N	Y	Y	Y	Y
Market Trends	N	N	N	N	N	N	Y	Y	Y
Treat Group Trends	N	N	N	N	N	N	N	Y	Y

Notes: 7,723,576 store-UPC-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets. All trends are quadratic. Top 30 UPCs defined by total real sales revenue during the sample period.

Table 11: Competitive Price Effect of Walmart Supercenters: Top 30 Peanut Butter UPCs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# WM < 1 Mi	-0.0533***	-0.0250***	-0.0126***	-0.0250**	-0.0176	-0.0180	-0.0159**	-0.0166**	
	(0.0104)	(0.00584)	(0.00289)	(0.0120)	(0.0110)	(0.0110)	(0.00808)	(0.00815)	
1 Mi ≤ # WM < 3 Mi	-0.0275***	-0.0139***	-0.00619***	0.00490	0.00196	0.00203	0.00552	0.00509	
	(0.00562)	(0.00257)	(0.00144)	(0.00561)	(0.00545)	(0.00540)	(0.00433)	(0.00443)	
3 Mi ≤ # WM < 5 Mi	-0.0212***	-0.00563***	-0.00272***	-0.00516	-0.00567*	-0.00569*	-0.00323	-0.00365	
	(0.00427)	(0.00207)	(0.00103)	(0.00389)	(0.00324)	(0.00321)	(0.00242)	(0.00262)	
5 Mi ≤ # WM < 7 Mi	0.00193	-0.000398	-0.00203**	0.00128	-0.000650	-0.000377	0.00256	0.00227	
	(0.00386)	(0.00176)	(0.000876)	(0.00334)	(0.00305)	(0.00304)	(0.00247)	(0.00249)	
7 Mi ≤ # WM < 9 Mi	0.00494	0.00433***	0.000318	-0.000746	-0.000661	-0.000773	0.00246	0.00151	
	(0.00333)	(0.00154)	(0.000828)	(0.00283)	(0.00251)	(0.00251)	(0.00197)	(0.00220)	
9 Mi ≤ # WM < 11 Mi	-0.00662**	-0.00125	-3.40e-05	0.00117	0.00293	0.00341	0.00380*	0.00334	
	(0.00325)	(0.00161)	(0.000810)	(0.00322)	(0.00289)	(0.00287)	(0.00219)	(0.00233)	
# WM < 7 Mi									-0.000505
									(0.00177)
Period FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
UPC FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Market FE	N	Y	Y	Y	Y	Y	Y	Y	Y
Chain FE	N	N	Y	Y	Y	Y	Y	Y	Y
Store FE	N	N	N	Y	Y	Y	Y	Y	Y
Store-UPC FE	N	N	N	N	Y	Y	Y	Y	Y
UPC Trends	N	N	N	N	N	Y	Y	Y	Y
Market Trends	N	N	N	N	N	N	Y	Y	Y
Treat Group Trends	N	N	N	N	N	N	N	Y	Y

Notes: 11,032,410 store-UPC-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets. All trends are quadratic. Top 30 UPCs defined by total real sales revenue during the sample period.

Table 12: Competitive Revenue Effect of Walmart Supercenters by Brand: Frozen Pizza

	(1)	(2)	(3)	(4)
# WM	-0.0509***		-0.0603***	
	(0.0111)		(0.0152)	
# WM * Amy's Kitchen		-0.0494*		-0.0250
		(0.0267)		(0.0350)
# WM * CA Pizza Kitchen		-0.0230		-0.00131
		(0.0244)		(0.0368)
# WM * Stouffer's		-0.0347		-0.0572**
		(0.0223)		(0.0292)
# WM * Other		-0.0840***		-0.0843**
		(0.0282)		(0.0380)
# WM * Freschetta		-0.0591***		-0.0600**
		(0.0170)		(0.0239)
# WM * Celeste		-0.0783**		-0.0622
		(0.0318)		(0.0468)
# WM * DiGiorno		-0.0554***		-0.0643***
		(0.0141)		(0.0191)
# WM * Red Baron		-0.0560***		-0.0725***
		(0.0158)		(0.0208)
# WM * Tony's		-0.0171		-0.0549*
		(0.0240)		(0.0308)
# WM * Tombstone		-0.0131		-0.0303
		(0.0237)		(0.0316)
# WM * Jack's		-0.128***		-0.213***
		(0.0404)		(0.0741)
# WM * Private Label		-0.0852***		-0.0755*
		(0.0304)		(0.0411)
# WM * Totino's		-0.0476**		-0.0756***
		(0.0201)		(0.0279)
Distance Threshold	7 Miles		5 Miles	
Period FE	Y	Y	Y	Y
Store-Brand FE	Y	Y	Y	Y
Brand Trends	Y	Y	Y	Y
Market Trends	Y	Y	Y	Y
Treat Group Trends	Y	Y	Y	Y

Notes: 7,751,801 store-brand-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Markets are IRI designated markets.

Table 13: Competitive Price Effect of Walmart Supercenters by Brand: Frozen Pizza

	(1)	(2)	(3)	(4)
# WM	-0.00143		-0.00216	
	(0.00171)		(0.00212)	
# WM * Amy's Kitchen		-0.00640		-0.00535
		(0.00406)		(0.00577)
# WM * CA Pizza Kitchen		0.000750		0.00267
		(0.00223)		(0.00280)
# WM * Stouffer's		-0.00206		-0.00352
		(0.00223)		(0.00320)
# WM * Other		0.00144		0.000712
		(0.00207)		(0.00245)
# WM * Freschetta		0.000594		3.12e-05
		(0.00267)		(0.00335)
# WM * Celeste		0.00662		0.00332
		(0.0113)		(0.0133)
# WM * DiGiorno		-0.00141		-0.00100
		(0.00166)		(0.00207)
# WM * Red Baron		-0.000676		-0.00272
		(0.00261)		(0.00339)
# WM * Tony's		-0.000376		-0.00212
		(0.00309)		(0.00401)
# WM * Tombstone		-0.00400		-0.00305
		(0.00324)		(0.00437)
# WM * Jack's		-0.00291		-0.00497
		(0.00617)		(0.00734)
# WM * Private Label		0.000387		-0.000428
		(0.00108)		(0.00162)
# WM * Totino's		-0.00824*		-0.00909
		(0.00494)		(0.00632)
Distance Threshold	7 Miles		5 Miles	
Store-UPC FE	Y	Y	Y	Y
Market-UPC-Period FE	Y	Y	Y	Y

Notes: 75,467,137 store-UPC-week observations. *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors clustered by store in parentheses. Markets are IRI designated markets.

Table 14: Competitive Price Effect of Walmart Supercenters by Branded and Private Labels

	Branded		Private	
	(1)	(2)	(3)	(4)
# WM < 1 Mi	0.000428		0.00741	
	(0.00648)		(0.00800)	
1 Mi ≤ # WM < 3 Mi	0.000861		-0.00521	
	(0.00404)		(0.00583)	
3 Mi ≤ # WM < 5 Mi	-0.00230		-0.00577	
	(0.00277)		(0.00501)	
5 Mi ≤ # WM < 7 Mi	0.00161		0.000110	
	(0.00245)		(0.00449)	
7 Mi ≤ # WM < 9 Mi	-0.00121		-0.000867	
	(0.00210)		(0.00378)	
9 Mi ≤ # WM < 11 Mi	-0.00131		0.00667*	
	(0.00206)		(0.00380)	
# WM < 7 Mi		0.000473		-0.00297
		(0.00164)		(0.00308)
Period FE	Y	Y	Y	Y
Store-Category FE	Y	Y	Y	Y
Category Trends	Y	Y	Y	Y
Market Trends	Y	Y	Y	Y
Treat Group Trends	Y	Y	Y	Y
N	11,253,014		10,564,592	

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets. All trends are quadratic.

Table 15: Competitive Price Effect of Walmart Supercenters by Incumbent Supermarket Type

	(1)	(2)
# WM * National Chain	-7.42e-05	-0.000696
	(0.00224)	(0.00290)
# WM * Regional Chain	-0.00359	-0.00682
	(0.00426)	(0.00610)
# WM * Subregional/Local Chain	0.00538	0.00599
	(0.00520)	(0.00686)
# WM * Non-Chain	0.00325	-0.00568
	(0.00731)	(0.00703)
Distance Threshold	7 Miles	5 Miles
Period FE	Y	Y
Store-Category FE	Y	Y
Category Trends	Y	Y
Market Trends	Y	Y
Treat Group Trends	Y	Y

Notes: 11,112,139 store-category-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets. All trends are quadratic.

Appendix

Table 16: Incumbent Supermarket Characteristics

	N	Mean	SD	p10	p25	Median	p75	p90
Initial Exposures to WM	2450	1.31	1.36	0	0	1	2	3
Total Exposures to WM	2450	1.81	1.75	0	1	1	3	4
National Chain	2450	0.60	0.49	0	0	1	1	1
Regional Chain	2450	0.16	0.36	0	0	0	0	1
Subregional / Local Chain	2450	0.12	0.32	0	0	0	0	1
Non-Chain Supermarket	2450	0.06	0.24	0	0	0	0	0
Household Median Income	2012	58499	20308	36570	44505	54577	69066	85154
Population Density	2014	3473	3993	685	1381	2530	4265	6669

Notes: Table presents across incumbent store summary statistics. Each observation represents an incumbent store. Household median income and population density represent 2007 estimates for 2 mile radii around each store.

Table 17: Frozen Pizza UPC Price Summaries

Brand	N	Mean	SD	p10	p25	Median	p75	p90
Amy's Kitchen	1,362,665	6.89	1.58	5.23	5.89	6.65	7.64	8.81
CA Pizza Kitchen	3,179,862	6.12	1.09	4.75	5.49	6.13	6.77	7.40
Stouffer's	6,772,889	5.22	1.75	3.14	3.79	4.94	6.57	7.59
Other	10,456,064	4.23	2.06	1.90	2.51	3.93	5.64	6.96
Freschetta	5,756,212	3.90	1.29	2.51	2.95	3.64	4.68	5.67
Celeste	2,107,573	3.48	1.28	2.16	2.48	3.10	4.22	5.48
DiGiorno	12,318,844	3.48	1.01	2.35	2.74	3.29	4.09	4.88
Red Baron	10,780,356	3.45	1.09	2.11	2.65	3.33	4.12	4.85
Tony's	4,186,047	2.80	0.88	1.78	2.12	2.63	3.40	4.00
Tombstone	5,648,785	2.79	0.77	1.87	2.22	2.70	3.32	3.79
Jack's	1,606,151	2.47	0.50	1.84	2.13	2.44	2.79	3.11
Private Label	7,696,518	2.41	1.07	1.53	1.72	2.05	2.68	4.07
Totino's	3,595,171	1.90	0.58	1.33	1.50	1.79	2.16	2.58

Notes: Table presents summary statistics for frozen pizza UPC prices (in January 2001 dollars) by brand. Each observation represents a store-UPC-week.

Table 18: Trends in the Revenue Effect of Supercenters

	(1)	(2)	(3)	(4)	(5)
97 to 104 weeks prior			-0.00401	-0.00180	-0.000858
			(0.00758)	(0.00707)	(0.00714)
89 to 96 weeks prior			-0.00288	-0.000633	0.000797
			(0.00844)	(0.00792)	(0.00807)
81 to 88 weeks prior			-0.00510	-0.00407	-0.00227
			(0.00916)	(0.00859)	(0.00885)

73 to 80 weeks prior			-0.00829	-0.00793	-0.00562
			(0.00953)	(0.00892)	(0.00917)
65 to 72 weeks prior			-0.0114	-0.0100	-0.00746
			(0.00973)	(0.00929)	(0.00951)
57 to 64 weeks prior			-0.0154	-0.0135	-0.0106
			(0.0102)	(0.00975)	(0.00999)
49 to 56 weeks prior			-0.00695	-0.00382	-0.000854
			(0.00996)	(0.00955)	(0.00987)
41 to 48 weeks prior			-0.00845	-0.00469	-0.00158
			(0.0101)	(0.00970)	(0.0100)
33 to 40 weeks prior			-0.00133	0.00165	0.00502
			(0.00965)	(0.00944)	(0.00979)
25 to 32 weeks prior			-0.00476	-0.00283	0.000834
			(0.0101)	(0.0100)	(0.0103)
17 to 24 weeks prior			-0.00866	-0.00634	-0.00244
			(0.0104)	(0.0103)	(0.0106)
9 to 16 weeks prior			-0.0137	-0.0127	-0.00856
			(0.0106)	(0.0105)	(0.0108)
1 to 8 weeks prior		-0.00253	-0.00630	-0.00818	-0.00434
		(0.00770)	(0.0105)	(0.0105)	(0.0108)
Week of entry	-0.0371***	-0.0371***	-0.0388***	-0.0354**	-0.0346**
	(0.0138)	(0.0138)	(0.0141)	(0.0144)	(0.0140)
1 to 8 weeks post	-0.146***	-0.146***	-0.149***	-0.144***	-0.140***
	(0.0291)	(0.0292)	(0.0296)	(0.0304)	(0.0301)
9 to 16 weeks post	-0.152***	-0.152***	-0.156***	-0.152***	-0.147***
	(0.0294)	(0.0294)	(0.0299)	(0.0307)	(0.0304)
17 to 24 weeks post	-0.150***	-0.150***	-0.153***	-0.150***	-0.145***
	(0.0292)	(0.0292)	(0.0297)	(0.0305)	(0.0302)
25 to 32 weeks post	-0.150***	-0.150***	-0.154***	-0.150***	-0.145***
	(0.0292)	(0.0293)	(0.0298)	(0.0306)	(0.0303)
33 to 40 weeks post	-0.151***	-0.151***	-0.155***	-0.151***	-0.145***
	(0.0292)	(0.0292)	(0.0297)	(0.0306)	(0.0303)
41 to 48 weeks post	-0.152***	-0.152***	-0.156***	-0.152***	-0.146***
	(0.0293)	(0.0293)	(0.0299)	(0.0307)	(0.0304)
49 to 56 weeks post	-0.156***	-0.156***	-0.160***	-0.155***	-0.148***
	(0.0294)	(0.0295)	(0.0300)	(0.0309)	(0.0306)
57 to 64 weeks post	-0.152***	-0.152***	-0.156***	-0.152***	-0.145***
	(0.0295)	(0.0296)	(0.0301)	(0.0311)	(0.0308)
65 to 72 weeks post	-0.144***	-0.145***	-0.148***	-0.145***	-0.138***
	(0.0297)	(0.0297)	(0.0303)	(0.0313)	(0.0310)
73 to 80 weeks post	-0.147***	-0.147***	-0.151***	-0.147***	-0.139***
	(0.0297)	(0.0298)	(0.0304)	(0.0313)	(0.0311)

81 to 88 weeks post	-0.148***	-0.148***	-0.152***	-0.148***	-0.141***
	(0.0296)	(0.0297)	(0.0303)	(0.0311)	(0.0309)
89 to 96 weeks post	-0.149***	-0.150***	-0.153***	-0.149***	-0.141***
	(0.0296)	(0.0296)	(0.0302)	(0.0310)	(0.0309)
97 to 104 weeks post	-0.149***	-0.149***	-0.153***	-0.148***	-0.140***
	(0.0296)	(0.0296)	(0.0302)	(0.0310)	(0.0309)
105 weeks or more post	-0.143***	-0.143***	-0.147***	-0.146***	-0.135***
	(0.0296)	(0.0297)	(0.0302)	(0.0313)	(0.0313)
1 Mi $\leq$ # WM < 3 Mi	0.0783**	0.0783**	0.0780**	0.0671*	0.0664*
	(0.0386)	(0.0386)	(0.0386)	(0.0386)	(0.0385)
3 Mi $\leq$ # WM < 5 Mi	0.0962***	0.0962***	0.0957***	0.0934***	0.0968***
	(0.0326)	(0.0326)	(0.0327)	(0.0329)	(0.0318)
5 Mi $\leq$ # WM < 7 Mi	0.126***	0.126***	0.126***	0.117***	0.112***
	(0.0316)	(0.0316)	(0.0317)	(0.0329)	(0.0332)
7 Mi $\leq$ # WM < 9 Mi	-0.0155	-0.0154	-0.0152	-0.0216	-0.0166
	(0.0140)	(0.0140)	(0.0140)	(0.0133)	(0.0127)
9 Mi $\leq$ # WM < 11 Mi	-0.0188	-0.0188	-0.0188	-0.0171	-0.0140
	(0.0122)	(0.0122)	(0.0122)	(0.0115)	(0.0111)
Period FE	Y	Y	Y	Y	Y
Store FE	Y	Y	Y	Y	Y
Market Trends	N	N	N	Y	Y
Treat Group Trends	N	N	N	N	Y

Notes: 756,097 store-week observations. *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets. All trends are quadratic. Less than 1 mile is excluded driving distance exposure category.

Table 19: Trends in the Price Effect of Supercenters

	(1)	(2)	(3)	(4)	(5)
97 to 104 weeks prior			-0.00419**	-0.00217	-0.00225
			(0.00192)	(0.00171)	(0.00170)
89 to 96 weeks prior			-0.00432**	-0.00264	-0.00275
			(0.00203)	(0.00180)	(0.00179)
81 to 88 weeks prior			-0.00488**	-0.00419**	-0.00428**
			(0.00206)	(0.00184)	(0.00183)
73 to 80 weeks prior			-0.00437**	-0.00389**	-0.00400**
			(0.00215)	(0.00187)	(0.00186)
65 to 72 weeks prior			-0.00456**	-0.00400**	-0.00415**

			(0.00219)	(0.00194)	(0.00195)
57 to 64 weeks prior			-0.00367*	-0.00297	-0.00317
			(0.00222)	(0.00196)	(0.00196)
49 to 56 weeks prior			-0.00327	-0.00247	-0.00267
			(0.00230)	(0.00200)	(0.00201)
41 to 48 weeks prior			-0.00253	-0.00176	-0.00195
			(0.00239)	(0.00202)	(0.00204)
33 to 40 weeks prior			-0.00324	-0.00230	-0.00245
			(0.00245)	(0.00208)	(0.00213)
25 to 32 weeks prior			-0.00109	-0.000227	-0.000381
			(0.00250)	(0.00213)	(0.00218)
17 to 24 weeks prior			0.000875	0.00212	0.00197
			(0.00257)	(0.00217)	(0.00223)
9 to 16 weeks prior			-0.00153	0.000325	0.000177
			(0.00262)	(0.00213)	(0.00219)
1 to 8 weeks prior		-0.00313	-0.00452*	-0.00245	-0.00261
		(0.00191)	(0.00272)	(0.00220)	(0.00227)
Week of entry	0.00244*	0.00237*	0.00171	0.00198	0.00173
	(0.00140)	(0.00143)	(0.00167)	(0.00143)	(0.00144)
1 to 8 weeks post	-0.00365*	-0.00383*	-0.00526*	-0.00303	-0.00325
	(0.00198)	(0.00207)	(0.00285)	(0.00229)	(0.00236)
9 to 16 weeks post	-0.00192	-0.00209	-0.00355	-0.000828	-0.00102
	(0.00207)	(0.00216)	(0.00293)	(0.00234)	(0.00241)
17 to 24 weeks post	-0.00193	-0.00211	-0.00362	-0.000746	-0.000957
	(0.00215)	(0.00224)	(0.00299)	(0.00241)	(0.00250)
25 to 32 weeks post	-0.000343	-0.000505	-0.00203	0.000854	0.000626
	(0.00216)	(0.00224)	(0.00299)	(0.00247)	(0.00258)
33 to 40 weeks post	-0.00130	-0.00146	-0.00297	0.000722	0.000478
	(0.00218)	(0.00225)	(0.00300)	(0.00245)	(0.00255)
41 to 48 weeks post	-0.00362	-0.00377*	-0.00527*	-0.00141	-0.00170
	(0.00222)	(0.00228)	(0.00303)	(0.00249)	(0.00260)
49 to 56 weeks post	-0.00422*	-0.00441*	-0.00592*	-0.00170	-0.00193
	(0.00235)	(0.00242)	(0.00314)	(0.00266)	(0.00277)
57 to 64 weeks post	-0.00366	-0.00386	-0.00536*	-0.000683	-0.000936
	(0.00237)	(0.00244)	(0.00314)	(0.00260)	(0.00273)
65 to 72 weeks post	-0.00408*	-0.00425*	-0.00576*	-0.000770	-0.00103
	(0.00242)	(0.00248)	(0.00321)	(0.00262)	(0.00276)
73 to 80 weeks post	-0.00539**	-0.00556**	-0.00708**	-0.00163	-0.00181
	(0.00253)	(0.00260)	(0.00330)	(0.00268)	(0.00284)
81 to 88 weeks post	-0.00472*	-0.00491*	-0.00646**	-0.000794	-0.000947
	(0.00254)	(0.00261)	(0.00329)	(0.00272)	(0.00289)
89 to 96 weeks post	-0.00622**	-0.00641**	-0.00793**	-0.00203	-0.00217

	(0.00264)	(0.00272)	(0.00338)	(0.00277)	(0.00294)
97 to 104 weeks post	-0.00634**	-0.00653**	-0.00802**	-0.00169	-0.00184
	(0.00274)	(0.00281)	(0.00345)	(0.00284)	(0.00304)
105 weeks or more post	-0.0121***	-0.0123***	-0.0139***	-0.000911	-0.000705
	(0.00294)	(0.00299)	(0.00353)	(0.00296)	(0.00323)
Period FE	Y	Y	Y	Y	Y
Store-Category FE	Y	Y	Y	Y	Y
Market Trends	N	N	N	Y	Y
Treat Group Trends	N	N	N	N	Y

Notes: 11,253,196 store-category-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets. All trends are quadratic.

Table 20: Competitive Price Effect of Walmart Supercenters by Order of Entry

	(1)	(2)	(3)	(4)
# WM	0.000301		-0.000744	
	(0.00191)		(0.00241)	
1st WM		-0.000339		-0.000307
		(0.00311)		(0.00317)
2nd WM		0.000471		0.000498
		(0.00425)		(0.00533)
3rd+ WM		-0.00358		-0.0140
		(0.00614)		(0.00861)
Distance Threshold	7 Miles		5 Miles	
Period FE	Y	Y	Y	Y
Store-Category FE	Y	Y	Y	Y
Category Trends	Y	Y	Y	Y
Market Trends	Y	Y	Y	Y
Treat Group Trends	Y	Y	Y	Y

Notes: 11,253,196 store-category-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets and category refers to product category. All trends are quadratic.