The Competitive Effects of Entry: Evidence from Supercenter Expansion

Peter Arcidiacono, Paul B. Ellickson, Carl F. Mela, and John D. Singleton*

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Abstract

Coupling weekly grocery transaction records with the exact location and opening date of entering Walmarts over an eleven year period, we examine how their 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, an effect that decays quickly with distance. Surprisingly, despite large cross store differences in prices of supermarkets by exposure to Walmart, our findings also indicate that Supercenter entry has no causal effect on incumbent prices. This lack of a price response is robust across many dimensions including, but not limited to, a lack of response for individual categories and brands within a category.

*Arcidiacono: Department of Economics, Duke University & NBER (psarcidi@econ.duke.edu); Ellickson: Simon Business School, University of Rochester (paul.ellickson@simon.rochester.edu); Mela: Fuqua School of Business, Duke University (mela@duke.edu); Singleton: Department of Economics, Duke University (john.singleton@duke.edu). We thank Emek Basker, Bart Bronnenberg, Allan Collard-Wexler, Paul Eliason, Olga Kozlova, and seminar participants at the Federal Trade Commission for helpful comments and Nikhil Gavai for excellent research assistance. We also would like to thank IRI for making the data available. All estimates and analysis in this paper based on data provided by IRI are by the authors and not by IRI.

1 Introduction

Most macroeconomists agree that firms adjust prices quite slowly, a phenomenon that plays an important role in understanding the design and impact of monetary policy. Across many sectors of the U.S. economy, prices are apparently adjusted on the order of once or twice per year. Identifying the frequency with prices adjust is critical for understanding whether a "contract multiplier" is needed to "explain why real effects of nominal shocks appear to last several years" (Klenow & Malin, 2010). Macroeconomics offers a variety of explanations for this price stickiness, including menu costs, consumer antagonism, cost-plus pricing and the fear of competitive reactions, though there is little consensus regarding which is most relevant (Blinder *et al.* , 1998). Prices are clearly sticky, but how sticky and, more importantly, why they are sticky, remains unclear.

At the other end of the spectrum, IO economists assume (tacitly, for the most part) that firms adjust prices very quickly. The workhorse model for analyzing strategic responses to structural changes in market conditions, including the market simulations used by academics and government agencies to assess policy changes and potential mergers, has firms setting prices according to a static "Nash in prices" equilibrium in which positive markups (price-cost margins) are supported via product differentiation (Ackerberg *et al.* , 2007). In practice, most counterfactual merger analyses and dynamic models of industry evolution assume that prices instantly adjust to their new equilibrium levels.[1] For example, to compute welfare gains for a new product introduction, new prices (reflecting consumer preference estimates recovered from a suitably flexible demand system) are computed from the first order conditions of a static pricing equilibrium and compensating variation is calculated relative to the set of products (and prices) observed before the proposed change occurs (Nevo, 2000). The merger simulations used in modern competition policy are computed similarly, implicitly assuming an immediate reaction and placing the focus squarely on price.[2] However, if prices adjust quite slowly (or worse, *not at all*), then effective merger policy will also be constrained by the time it takes to adjust to the new pricing equilibrium, just as the impact of monetary policy depends on the frequency with which firms adjust prices.

Although there exists a rich literature examining the degree to which firms pass cost shocks

[1] As noted above, most merger simulations assume prices are set in static equilibrium, meaning that there is no direct role for a "speed of adjustment" to a new pricing equilibrium. Instead, authors simply compute what is effectively the long run equilibrium and ignore the transition dynamics that lead to it. Although there is a growing theoretical and empirical literature examining dynamic competition (emphasizing Markov perfect equilibrium), the majority of the papers in this literature emphasize dynamics in investment and entry/exit decisions only. Prices are still assumed to follow a static Nash equilibrium. This "static-dynamic breakdown" is mainly due to the increased computational burden associated with incorporating pricing dynamics (Doraszelski & Pakes, 2007).

[2] As Werden & Froeb (2008) note, "at the current state of the art, merger simulation also predicts only the immediate price and output effects of mergers. Issues relating to the longer-term evolution of the industry, such as entry, product repositioning, and other changes in marketing strategy are assumed away in merger simulation and hence must be separately considered."

through to consumers (Peltzman, 2000; Besanko *et al.* , 2005), much less is known about how firms react to changes in market structure or other "demand shocks."[3] Quantifying such reactions is challenging because 1) it requires a large number of sizable shocks to reliably infer a consequential impact on pricing and 2) any such changes are likely to be endogenous, complicating causal inference.[4] In this paper, we exploit a particular set of shocks which are large in magnitude, and for which the precise *timing* is arguably exogenous.

Our empirical strategy is to examine the reaction by incumbent supermarkets to the entry of Walmart Supercenters, the largest disruption to the structure of this relatively stable industry over the preceding fifty years (Matsa, 2011). Walmart's everyday low price strategy and 15-25% price advantage present a sizable competitive advantage that is consistent across treatments (Hausman & Leibtag, 2007; Ellickson *et al.* , 2012). Retail grocery provides particularly relevant setting, as many of the products studied by IO economists and quantitative marketing researchers are consumer packaged goods sold primarily through supermarkets and, according to the 2012 Consumer Expenditure Survey, Americans spend 12.8 percent of their income on food at home. The research to date on Walmart entry suggests that price reactions to entry are quick and extensive, in contrast to the standard macroeconomic phenomenon of price stickiness, but in line with the IO literature. However, prior work, by relying on market and temporally aggregated data, has been limited in its ability to separate the causal effect of Walmart exposure from Walmart's endogenous selection of where to locate.

Accordingly, we combine data on the exact geographic locations and opening date of all Walmart Supercenter openings with high frequency transactions records for a representative sample of U.S. supermarkets to estimate the causal impact of Supercenter entry on incumbent revenues and prices. Since we observe incumbent revenue and prices immediately before and after Walmart Supercenter exposure, and over a large number of years, markets, and stores, we are able examine how the effects depend on the distance between the supermarket and the entering Supercenter, while also controlling for Walmart's endogenous choice of location. Knowing the exact locations is critical, as

[3]We also contribute to a large and growing literature examining the competitive advantages enjoyed by Walmart (Basker, 2007; Holmes, 2011; Jindal *et al.* , 2015) and its 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 & Leibtag, 2007; Atkin *et al.* , 2015).

[4]Gagnon & Lopez-Salido (2014) examine 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 cannot 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.

retail competition is well-known to be extremely localized (Figurelli, 2012; Smith, 2006), a stylized fact which is re-enforced by our results.

Reflecting the huge magnitude of this demand shock, we find large revenue declines (on the order of 16% of sales, on average) at the stores most geographically proximate to a Supercenter opening. Thus, if firms are ever likely to respond to a change in their competitive environment, this presents an ideal context in which to observe price reactions. Surprisingly, we find that incumbent firms do not react *at all* to entry, either immediately, preemptively, or over the longer term. This stands in sharp contrast to the previous literature examining Walmart entry, which finds considerable price reactions (Basker & Noel, 2009; Hausman & Leibtag, 2007).[5]

The large difference in revenue and price effects upon the inclusion of store fixed effects is indicative of Walmart's decisions to locate near low price, high revenue stores. Absent store fixed effects, the coefficient on Walmart entry picks up the higher revenue and lower prices of stores within these bands relative to other stores in the overall market. Controlling for store fixed effects results in lower revenue effects and no price effects. However, absent store fixed effects – and therefore not accounting for the selective nature of Walmart's entry decisions within a market – estimated price reactions are on the order of 2.5% to 3.5%, which accords closely with earlier findings.

Given the surprising nature of these results, we consider several possible explanations for the lack of incumbent price response. First, note that the *direction* of the optimal price response is ambiguous ex ante, as it depends on the relative strength of price competition and the distribution of consumer types, such as willingness to pay (Chen & Riordan, 2008). For example, in the context of air travel, incumbent air carriers reduce ticket prices in response to rival entry (Reiss & Spiller, 1989; Borenstein, 1989, 1992). The response is particularly pronounced for entry by low cost carriers like Southwest (Morrison, 2001), in which case it may actually take place in anticipation of entry (Goolsbee & 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 & Salkever, 1992).[6] 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 & Salkever, 1997), a mechanism that likely operates through access to insurance. Either (or both) cases could be in play in the context of grocery competition, and the two effects may offset exactly,

[5]Though it is not the focus of either paper, Matsa (2011) and Ailawadi *et al.* (2010) also find limited price response to Walmart entry. 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. In contrast, these aspects play a central role in our analysis.

[6]This is despite that fact that generic entrants are required to establish bio-equivalence by the FDA (meaning that "true" product differentiation is minimal).

leading to no price response at all. While Walmart is a clear "low-cost" entrant to an industry that offers relatively standardized consumer products, they also enter towards the bottom of the perceived quality distribution (in terms of product selection and service), not unlike a generic drug manufacturer. However, we find no competitive price effects across product price tiers, despite vertical differentiation of products within category, suggesting this knife's edge balance is not the mechanism behind our results.

A second possible explanation for the results is that price changes may anticipate entry (as in the Southwest airlines example) or that it takes a long time for firms to respond. However, we observe that prices are stable long before and after entry. We also consider multi-market effects. Specifically, 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, thereby blunting the response to competitive entry impacting local stores. Yet our data suggest that even local grocers (e.g. those with only a handful of stores) do not respond by cutting prices. A fourth explanation that we examine is whether the reactions of retailers are constrained by their vertical relationships with manufacturers (Villas-Boas, 2007), who have little incentive to respond to local retailer entry. However, we find that supermarkets do not even respond for products whose prices are entirely under their own control (store brands). Fifth, it is possible that that retailers' slim margins make it difficult for them to cut prices because they are already near costs. Working against this hypothesis is the likelihood that, for many incumbent supermarkets, the optimal response would arguably have been to raise prices for at least a subset of brands and categories, and this action is not constrained by cost. Yet we find price response to be negligible across retailers, categories and products.

Finally, there is a small but growing empirical literature aimed at quantifying the extent to which firms (and retailer firms in particular) simply set prices according to fairly rigid "cost plus" rules of thumb. Empirical evidence consistent with this practice is provided by McShane *et al.* (2016), who also find that when retailer prices *are* adjusted, it is typically in response to an associated cost shock; the resulting price change is used to maintain the prior gross margin. Consistent with this mechanism, Eichenbaum *et al.* (2011) also find that prices rarely change absent a corresponding change in cost. More anecdotal evidence regarding the ubiquity of "cost plus" pricing is documented by 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. [7] As the "demand shock" of Walmart entry leaves costs unchanged, our findings of no competitive price reaction across stores

[7] They also 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.

or items are consistent with the widespread practice of such "rule of thumb" pricing.

Our findings have implications for the competitive welfare gains to Walmart entry. Consumer welfare gains from Walmart entry are likely not a result of decreased market power by incumbent stores, but simply due to the addition of a new, low priced alternative. In particular, a primary impact of entry is not lower incumbent prices, but rather lower sales volume at incumbent stores, which then leads to an increased likelihood of store failure, as shown in Ellickson & Grieco (2013). This suggests that the competitive reaction primarily occurs along the extensive, rather than intensive margin. Such blunt reactions likely take some time to play out. Our findings have further implications for the commonly applied pricing assumptions in IO models of entry and incumbent response, at least in the short-term. To the extent firms are focusing on costs over demand or competition, welfare conclusions from models predicated on these latter factors could be misstated.

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.[8] These records are used to link the 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). These 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.[9] Each record in the IRI data contains a UPC identifier, quantity purchased, and the purchase price of the item at a sampled

[8]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).

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

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.

supermarket in a given week. Transactions data for fifteen food product categories are used to construct our dependent variables, which are described next.[10]

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.[11] We use IRI's definitions of volume equivalent units for each category (e.g. 1 unit = 16 oz. of coffee). 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.[12]

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.[13]

[10] 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.

[11] 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).

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

[13] 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 between January 2001 and the end of 2011 (i.e. during our sample period), this decision rule matches 481 Supercenters with at least one incumbent IRI supermarket.[14] 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. The 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.[15] 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 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

[14] 1,311 of the 3,150 Supercenters opened before 2012 are also matched.

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

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.

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.[16] 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.[17] 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

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

[17] 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.

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

	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).

error term, υ_{st}.[18] 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 $\beta(D_{sj})$ 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 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_{sj}^b and substituting in for ϵ_{st} using (3), (2) becomes:

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

This empirical model can be understood as a generalization of a difference-in-differences approach where contemporaneous changes in outcomes are compared between supermarkets treated by a Supercenter and control stores. 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

[18]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. We also estimate "event study" specifications, described below, to check for pre-treatment trends that would confound causal inference. We examine revenues first, before turning to 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.[19]

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.[20] 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 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

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

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

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 ≤ # 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 ≤ # 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 ≤ # 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 ≤ # 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 ≤ # 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

estimating equation to interact the treatment effect of a Supercenter with the time until or since its opening week:

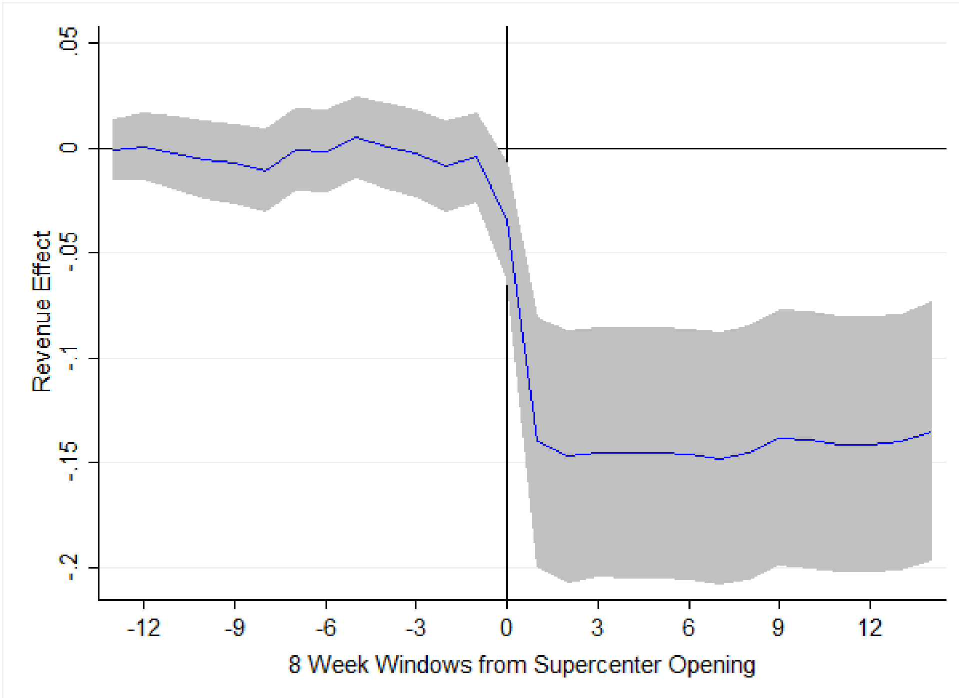
$$y_{st} = \sum_{k=-13}^{13} \beta_k \sum_j \mathbf{1}\{W_{jt} = k\}\mathbf{1}\{D_{sj} \leq 7\} + \sum_{b=1}^{B} \beta_b \sum_j D_{sj}^b WM_{jt} + \mu_{st} + \upsilon_{st} \tag{5}$$

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.[21] 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

[21] 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.

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



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

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 competitive environment, at least for those stores located nearby. 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 price series:

$$y_{st}^{c} = \sum_{b=0}^{B} \beta_b \sum_{j} D_{sj}^{b} WM_{jt} + \pi_s^c + \lambda_t^c + \gamma_{m(s)}^{c}(t) + \upsilon_{st}^{c} \tag{6}$$

Superscript c indexes the food product categories. Pooling the individual price series obviates the need to construct a store price index from the 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 & Leibtag, 2007; Basker & 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. Namely, Walmart choses to locate next to low-price stores: stores within a one-mile distance band of a Walmart have lower prices both before and after Walmart entry. Hence, absent the inclusion of store fixed effects, Walmart interacted with the one-mile distance band serves as a proxy for low-price stores rather than picking up the causal effect of Walmart on prices.

To illustrate this selection effect, 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.

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 ≤ # 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 ≤ # 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 ≤ # 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 ≤ # 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 ≤ # 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

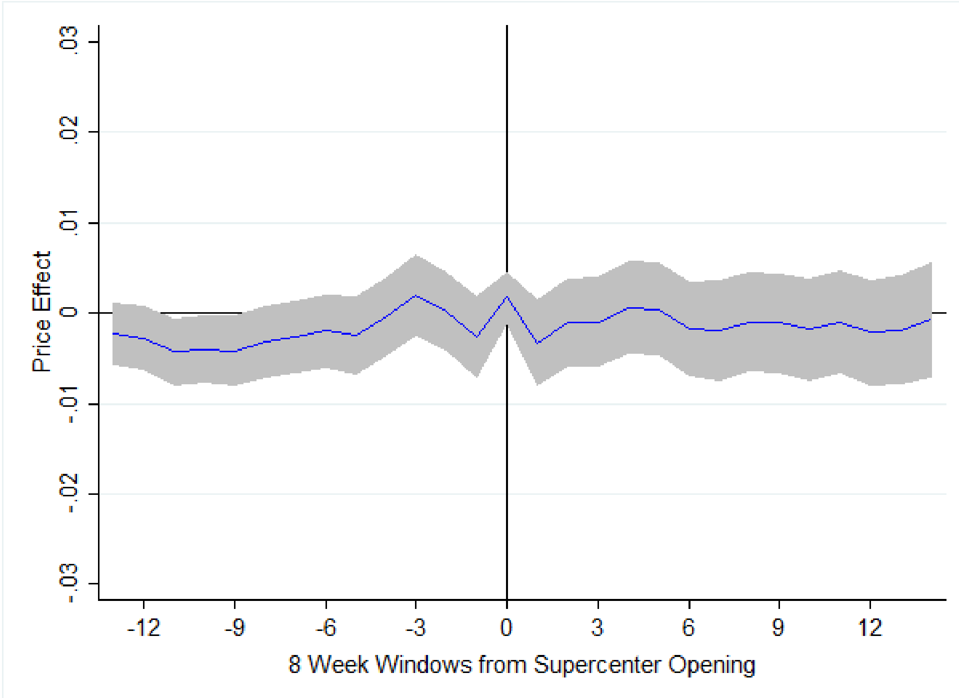
Notes: 11,253,196 store-category-week observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered by store in parentheses. Treatment groups are defined by total Supercenter exposures. Markets are IRI designated markets and category refers to product category. All trends are quadratic.

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.

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



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

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.[22] 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.[23]

5 Robustness of the Price Effect Estimates

In light of the large revenue effect of Supercenter exposure that we obtain and prior results in the literature, our finding of no causal effect of Supercenter competition on incumbents' prices is surprising. Accordingly, we perform a number of additional robustness checks to evaluate potential confounds. First, we examine sensitivity to our aggregated construction of category price series.

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

[23]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.

Second, guided by theory and the related literature, we check whether there are subsets of products or incumbents where price responses are observed. Remarkably, across all specifications, we find consistent evidence of no price response.[24]

5.1 UPC Aggregation

Our first robustness check examines pricing at the individual item level rather than the aggregated category level. The potential concern is that our choice of how to aggregate prices across products obscures a measurable price response. For example, firms may respond 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 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 opening. 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.[25] These UPC level results therefore support the conclusion drawn from the aggregated price series of a null effect.

5.2 Heterogeneity across Products

Supercenter exposure 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

[24] In results not presented, we also check for a price effect corresponding to only the *first* Supercenter to which a store is exposed and still find no response.

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

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.

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 & Riordan (2008), implies the incumbent should *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.[26]

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 low 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.[27] Matching the results obtained with the aggregated price series and the UPC prices,

[26]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.

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

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.

the estimated overall effect of Supercenter exposure is not different from zero, as displayed in (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 changes do not differ significantly from zero. This finding is not consistent with "price sensitivity" and "market share" effects netting to zero as the tradeoff between these two factors depends on how the distribution of consumer preferences changes in response to Supercenter entry.

5.3 Heterogeneity across Private and Branded labels

Another possible confound is that incumbent supermarkets may be 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, retailer or manufacturer. While the over-arching goal is clearly to maximize overall "channel" profits, there is an obvious conflict over how to split the pie. 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 price of branded products are unresponsive, 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 cateogry 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.

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.

5.4 Heterogeneity across Supermarket Type

Finally, the ability to respond to Supercenter exposure may vary by the type of incumbent supermarket. For example, chain supermarkets may set uniform retail prices across their stores within a given market or region.[28] This multimarket feature of price-setting would 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.

6 Conclusion

Combining data on weekly grocery transactions with the exact locations and opening dates of Walmart Supercenters, we examine the impact of entry on prices and revenues at incumbent supermarkets. The temporal and spatial variation in our data allow us to separate the causal effect of entry from Walmart's decision of where to locate. We find large, but very localized impacts on revenues, but no impact on price. The latter result stands in sharp contrast to earlier studies that suggested quick and sizable reductions, in turn implying considerable welfare gains to consumers via competitive mechanisms. In their analysis of the U.S. grocery industry, Hausman & Leibtag (2007) conclude that entry by Walmart supercenters led to short-term consumer benefits on the order of 25% of household expenditures. Moreover, they argue that fully one fifth of this increase comes from price reductions at rival stores. In contrast, our results indicate there is no such competitive response at all, implying that the actual welfare increase is substantially smaller. We considered, and

[28] 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 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). In a broad-ranging analysis of the Kilt's Nielsen 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 & 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.

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.

eliminated, several potential confounds. While we do not rule out responses on quality dimensions directly (Matsa, 2011), these null results suggest that firms are either unwilling or unable to respond in price to large changes in their competitive environment – a finding that calls into question the basic assumptions underlying the standard methods by which merger simulations and quantitative industry analyses are conducted. Firms may be much less responsive to demand shocks (at least in prices) than we typically assume.

A fruitful area for future research lies in rationalizing these surprising results. While we rule out some explanations with our data (e.g, ex-ante price reactions and constraints on pricing across stores within a chain), others remain. For example, operational and/or cognitive limitations may lead firms to follow simple cost-based pricing rules that are not easily adapted to changes in market conditions. This is consistent with empirical evidence presented in McShane *et al.* (2016), who find pricing strategies geared toward maintaining fixed margins. Our results suggest that such "cost plus" thinking may influence how firms respond to even large-scale changes in their 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 hundreds of competing stores, while managing one's own complex supply chain. The intractability of this problem is further augmented by the practical challenges in many setting 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 results suggest that even the most sophisticated retailers are still unable to quickly adapt. However, the growing availability of 'big data' can and should be leveraged to yield pricing models that better match the empirical realities. Doing so may substantially alter competition policy, such as the standards by which mergers are evaluated.

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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.