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Sales and Firm Entry: The Case of Wal-Mart

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Abstract

Temporary price reductions or "sales" have become increasingly important in the evolution of
the price level. We present a model of repeated price competition to illustrate how entry causes
incumbents to alternate between high and low prices. Using a six year panel of weekly
observations from a grocery chain, we find that individual stores employ more sales as the
distance to Wal-Mart falls. Moreover, the increase in the frequency of sales was concentrated on
the most popular products, suggesting the use of a loss-leader strategy.

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1. Introduction

Nakamura and Steinsson (2008) found that the fraction of price quotes that are "sales" (i.e. temporary price reductions) has increased substantially over the last two decades. Certain product categories, such as breakfast cereal or potato chips, are now "on sale" twice as often as they were in the late 1980's. Determining the cause of this trend is important not only for understanding why firms have sales, but also for the ongoing debate about the role that sales play in aggregate price adjustment.[2] We examine one possible explanation for the rise in the frequency of sales: the diffusion of Wal-Mart stores. We show that frequent but temporary price reductions can be a rational response to firm entry and then show that a representative grocery chain appears to have responded this way to Wal-Mart's entry.[3]

The expansion of Wal-Mart dramatically altered the retail landscape. Since 1980, Wal-Mart has grown from 300 stores located in 11 states to over 4,400 stores with locations in every state. The chain's revenue is now over 8 percent of U.S. consumption expenditure on goods, and 80% of grocery stores cited Wal-Mart-type stores as their biggest concern.[4] Unlike traditional retailers who have periodic price reductions (i.e. sales), Wal-Mart attracts customers through "everyday low prices". Capps Jr and Griffin (1998) estimated that competition with this strategy was responsible for a 21% reduction in purchases at incumbent stores.

Many empirical studies have examined Wal-Mart's effect on the prices and revenue of incumbent retailers. Basker (2005) and Basker and Noel (2009) find that incumbents lower their average quarterly price over time, whereas Volpe and Lavoie (2008) find that the monthly prices of national brands are lowered further than those of private-label brands. Singh, Hansen, and

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[2] See for example, Chevalier and Kashyap (2011), Eichenbaum, Jaimovich, and Rebelo (2011), Kehoe and Midrigan (2010), and Guimaraes and Sheedy (2011).
[3] Throughout the rest of the paper, the term "sales" will only refer to temporary price reductions. We use the term revenue when we address the price times quantity sold.
[4] National Grocers Association (2003)

Blattberg (2006) find that the majority of revenue lost to Wal-Mart is due to decreased customers rather than decreased baskets. More importantly, they argue that incumbents can significantly mitigate revenue losses by keeping just a few of their best customers.

To the best of our knowledge, only Ailawadi, et al. (2010) has addressed Wal-Mart's effect on sales behavior using high frequency data. They find that the number of weekly sale prices decreases for supermarkets and increases for drug stores and mass format stores in response to Wal-Mart, but overall find that the responses were low in most cases. The limited response to Wal-Mart could be due to several limitations with their data. First, they examine the entry of Wal-Mart supercenters even though many of the locations were already served by a Wal-Mart discount store. As stores might have already adjusted to Wal-Mart, any additional entry might not have received a large response. Second, they focus on category-level data, while we find that changes to pricing strategy following Wal-Mart's entry depend on product specific characteristics.

We begin by showing that an increase in sales could be an optimal response to Wal-Mart by recasting the repeated price competition model in Lal (1990). In the model, two incumbent firms sell to loyal customers and customers who only buy from the lowest priced firm. Both firms charge a high price in duopoly and split the market. When a third firm with a lower marginal cost and no loyal customers enters, the incumbent's high prices are no longer optimal and they will do better by taking turns setting a low price. Similar to Wal-Mart, the entrant chooses a constant but low price strategy in order to capitalize on its low cost structure.

Next, we use scanner data from the Dominick's Finer Foods database to test whether the stores in the grocery chain responded to Wal-Mart entry with more frequent sales. The data span six years and consist of 2,874 products allowing us to control for unobserved heterogeneity at

very fine levels (e.g. the UPC-store). The data contains each store's location, allowing us to isolate Wal-Mart's effect on individual stores, and the sample period corresponds to the initial entry of Wal-Mart. We find that stores significantly increased their sales frequency as their distance to Wal-Mart declined. Consistent with a "loss-leader" strategy, the increases in sales frequency were concentrated on the most popular products. The adjustment of sales thus seems to be a competitive response to Wal-Mart and not a secular trend.

2. A Repeated Game of Retail Price Competition with Firm Entry

The Industrial Organization literature presents several reasons for the existence of temporary low prices or sales, but many of these models are unsuited for studying the frequency of sales. In Varian (1990), firms keep consumers (rationally) uninformed over time by choosing price randomly from a continuous distribution. However, the only unambiguous definition of a sale price in this model is that the lowest observed price is the sale price. This definition leaves no room for variation in the frequency of sales. In Conlisk, Gerstner, and Sobel (1984), a monopolist generally charges a high regular price but is occasionally induced into charging a temporarily low price when enough low reservation price consumers accumulate in the market. The model provides clear predictions about the frequency of sales, but the assumptions do not approximate the market for consumer packaged goods which we wish to study.

The most compelling model for studying the frequency of sales in the context of firm entry is Lal (1990). He seeks to explain the peculiar fact that on any given week, either brand A or brand B could be found on sale in a single store, but never both. We recast this model to represent retailers who face the entry of a low cost competitor.[5] We use the model to show that

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[5] Due to our context, we take a different approach to proving the existence of the primary equilibrium.

firm entry may cause two incumbent firms to switch from charging the same price every period to a strategy of alternating between a high and a low price.

2.1 Model Setup

The model consists of a retail market in which there are initially two firms, A and B, (called "incumbents") engaged in repeated Bertrand price competition. A third firm, C, (called the "entrant") unexpectedly enters the market. Each firm maximizes discounted profits using a common discount rate of $\delta \in (0,1)$. Firms A and B have a marginal cost of $c > 0$ and firm C's marginal cost is normalized to zero.

There are two types of customers who purchase a homogeneous basket of goods from one of the firms in each period as long as the price is less than or equal to r.[6] The first type of customer is loyal to one of the incumbent firms and will only purchase the basket from that firm. The second type of customer is a "switcher" who considers A and B to be perfect substitutes, but prefers them to C with varying intensity. The number of switchers is normalized to 1 and the number of loyal customers per incumbent is $\alpha > 0$.

Because switchers prefer the incumbents, firm C must charge a price lower than the minimum of the incumbents' prices to attract any customers.[7] The lower $C's$ price is relative to $\min\{p_A, p_B\}$, the more units C will sell. Assuming without loss of generality that $p_A \geq p_B$, the fraction of switchers that will buy from firm C is characterized the following way:

$$C\text{'s share of switchers} = \begin{cases} 0 & \text{if } p_C \geq p_B \\ \dfrac{p_B - p_C}{d} & \text{if } p_B \geq p_C \geq p_B - d \\ 1 & p_B - d \geq p_C \end{cases} \qquad (1)$$

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[6] We assume that $r > c$.

[7] The fraction of switchers that buy from firm C arises from a Hotelling model. See Appendix A for details.

Here d is a demand parameter that reflects the opportunity cost of visiting firm C instead of A or B (e.g. the cost per unit of distance to get to C). Firms A and B will sell α baskets to their loyal consumers and the incumbent with the lower price of the two sill sell to the switchers who do not buy from firm C.[8]

2.2 Model Results

To understand how firm C's entry changes the pricing strategies of A and B, we first analyze how they behave *before* C's arrival. The maximum total profit in this duopoly occurs when both firms charge r every period and threaten to punish deviations with a finite period Nash reversion strategy. Proposition 1 describes this equilibrium and states the conditions under which the price of r can be supported.

Proposition 1: If $\delta \geq \frac{\alpha-1}{\alpha+1}$, then the following symmetric strategy profile is a pareto-dominant sub-game perfect Nash equilibrium: Both firms charge a price of r in every period as long as both firms charged r in the previous period. If a firm deviates, both firms charge a price of c for the next $t - 1$ periods where t is the largest positive integer such that $\delta^t \geq \frac{2\alpha}{2\alpha+1}$. In the tth period following the deviation, firms resume charging a price of r. If either firm deviates, then the punishment restarts.

Proof: See Appendix B.

Once firm C enters the market, the game has several equilibria. We focus our attention on the *pure strategy* equilibria in which firm C plays a best response in each stage game.[9] We argue

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[8] For example, if $p_A > p_B \geq p_C$, then the revenue of $A, B,$ and C will be $p_A \alpha$, $p_B \left(\alpha + 1 - \frac{p_A - p_C}{d} \right)$, and $p_C \left(\frac{p_B - p_C}{d} \right)$ respectively. This assumes that $p_C + d \geq p_B \geq p_C$. If this is violated, then B gets either none or all of the switchers.
[9] This does not imply that firm C is passive. It cannot force either of the incumbents out of the market because of the loyal customers and only competes with the lowest priced incumbent because of the switchers.

that Pure strategy equalibria are more plausible because they do not require firms to have a randomizing device or a mechanism for detecting deviations. Requiring the entrant to play a best response provides a simple equilibrium in which only the incumbents need punishments to support the equilibrium path.[10] From this set of pure strategy equilibria, we focus on the one that maximizes the discounted profits of the incumbents.

Once the entrant arrives, the equilibrium strategy that maximizes the incumbents' joint profits involves the incumbents staggering and alternating prices between the monopoly price, r, and a lower price, $\bar{r}$.[11] That is to say that in any given period, one incumbent charges r and the other $\bar{r}$ and the in the following period they switch. This strategy can be supported without explicit collusion using a credible and effective punishment.[12] The equations in (2) specify the punishment prices that A and B charge in the tth period following a deviation from the equilibrium path:

$$
\begin{aligned}
p_A = p_B = c \quad & for \quad t \leq t^* - 1 \\
p_A = r, \ p_B = p \quad & for \quad t = t^* \\
p_A = \bar{r}, \ p_B = r \quad & for \quad t = t^* + 1
\end{aligned}
$$

$$
\left.\begin{aligned}
p_A(t) = p_B(t-1) \\
p_B(t) = p_A(t-1)
\end{aligned}\right\} for \ t \geq t^* + 2
$$

(2)

On the equilibrium path, incumbent firms take turns charging r and $\bar{r} < r$. If either deviates, they punish each other by charging a price of c for the next $t^* - 1$ periods. In period t^*, firm A only sells to its loyal customers at a price of r whereas firm B sells to some switchers by charging p.[13] After period t^*, the incumbents return to alternating prices of r and $\bar{r}$. If either of incumbent deviates, the punishment phase begins again. Proposition 2 states that the strategy

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[10] This type of strategy is also consistent with Wal-Mart's slogan at the time: "Always low prices. Always."
[11] See Appendix B for more detail.
[12] The punishment must be finite because the incumbents have the option to charge r to α loyal consumers.
[13] For convenience, the price p is set to equalize firm A and $B's$ discounted future profits following a deviation.

profile described above is a sub-game perfect Nash Equilibrium as long as the discount rate is large enough.

Proposition 2: As long as δ is large enough[14], there exists a sub-game perfect Nash Equilibrium strategy profile in which:

1) Firm C charges a price of $\frac{\bar{r}}{2}$ in every period

2) On the equilibrium path, firms A and B alternate between a price of r and

$$\bar{r} = \frac{2}{3}(\alpha(1+d) + c) < r$$

3) Firms A and B punish each other as described in (2) for deviations from the equilibrium path.

Proof: See Appendix B.

Most models of imperfect competition predict a reduction in average price when a competitor enters a market.[15] This model's contribution is thus to suggest that firms have periodic sales instead of permanently lowering price. In this way, they are still able to keep some price sensitive shoppers, while continuing to profit on their loyal weekly customers.

3. Empirical Analysis

The model in Section 2 suggests that incumbent firms may use temporarily low prices to keep some price sensitive consumers from shopping at a new firm. However, there are many other reasons to have sales. For instance, firms could use sale prices to manage inventory, incentivize consumers to try new products, or price discriminate among shoppers already in the stores. In order to isolate the effect of entry on sale prices, we examine weekly scanner data at 85

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[14] The minimum size of δ depends on the model parameters. See Table B1 of Appendix B.3.
[15] We focus on Wal-Mart, but this result applies to any "big box" retailer that enters a market where incumbents have loyal customers as well as switchers.

Dominick's Finer Foods (DFF) grocery stores before and after Wal-Mart's entry.[16] Summarized in Table 1, the data contain 2,874 products in 12 categories between 1989 and 1996. The sheer size of the data allows us to test not only whether stores responded to Wal-Mart, but also whether they focused their response on certain items.

The DFF data are particularly well-suited for testing our hypotheses. First, the data begin when Wal-Mart's presence in the Chicago-area was limited to a single store and continues through the opening of 26 additional stores. The near absence of Wal-Mart prior to the sample period allows us to view each store's initial reaction to Wal-Mart rather than the later introduction of a larger supercenter.[17] Second, having weekly observations of the same stores and products allows us to control for unobserved heterogeneity that is constant over time. For example, customer demographics vary from place to place but are unlikely to change enough during the sample period to affect the pricing strategy of a particular store. Third, the data contain the specific location of each store, allowing us to measure the driving distance to the nearest Wal-Mart for each week.

The Dominick's data have been widely used to examine pricing behavior. And while no study has examined Wal-Mart's entry on Dominick's behavior, Hoch, Kim, and Montgomery (1995) imply that the chain would have needed to adjust its pricing behavior following the entry of Wal-Mart. They demonstrate that a Dominick's store's distance and comparative size to the nearest low price warehouse store is a significant determinant of store-level price elasticity.

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[16] The DFF data are a joint venture between the chain and the James M. Kilts Center, University of Chicago Booth School of Business. The selection process is outlined in Appendix C.

[17] Because the sample period is early in the chain's expansion, the Wal-Mart stores which entered Chicago before 1996 were discount stores rather than supercenters. This distinction is important because Wal-Mart's discount stores do not sell fresh grocery products. Nevertheless, there is substantial overlap between the products in at Dominick's and those sold by Wal-Mart discount stores. Based on current stores, Dominick's stores directly competed with Wal-Mart discount stores on most of its products, and all of the products in the DFF sample used in this paper. As we will show, the demand at Dominick's stores is heavily influenced by Wal-Mart's entry, and if anything, the slight difference in products would only reduce the effect that we estimate.

Moreover, Hoch, Drèze, and Purk's (1994) work with the data suggests that stores would not have been able to simply lower their prices. They show that Dominick's profit would be significantly reduced if the chain used a low price strategy rather than a Hi-Lo pricing strategy.

We begin our empirical examination of Dominick's response to Wal-Mart entry by showing that the timing and location of Wal-Mart's entry does not seem to have been influenced by Dominick's stores. Second, we show that individual stores appear to deviate from the chain's pricing structure by having sales rather than lowering regular prices. Next, we analyze whether the introduction of Wal-Mart significantly affected the number of customers that visited Dominick's stores. Finally, we estimate the effect of Wal-Mart's entry on Dominick's frequency of sales across the entire store, across each product category, and across popular products within each category.

3.1 Defining Entry and Competition With Wal-Mart

Few Wal-Marts entered immediately next to an existing Dominick's store, but other stores would also have competed with Wal-Mart. In general, stores in a geographic area fight over the same set of customers, but the size of that area depends on roads, traffic patterns, and other location characteristics. Therefore, rather than selecting a binary measure of competition, we use the driving distance to the nearest Wal-Mart as a proxy for the intensity of competition with Wal-Mart.[18] Using Thomas Holmes' Wal-Mart location data (2011), we compute $Dist_{j,t}$, the shortest driving distance to a Wal-Mart from store j during week t.

Figure 1 illustrates Wal-Mart's growth by mapping the location and approximate entry date of every store in the Chicago-area prior to 1996. Expanding towards the city-center, Wal-

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[18] Hoch et al. (1995) also measure competition using driving distance. In the Data Appendix, we show that the empirical results are qualitatively similar if we replace the continuous variable with mileage cutoffs.

Mart stores opened in waves. Early stores were located in the suburbs, whereas each succeeding wave was located about 15 miles nearer to the city center than the previous wave. Holmes argues that this pattern of entry allowed the chain to sustain distributional efficiency during expansion.[19] Wal-Mart's entry location and timing thus seems to be determined by logistical efficiency rather than the time-varying unobserved factors that affect Dominick's frequency of sales.

Given the pattern discussed above, Wal-Mart's entry was somewhat predictable. Nearby Dominick's stores would have certainly known that Wal-Mart was coming once construction started, and maybe even before that given the public procedures involved in obtaining building permits. Because we do not have precise dates at which the plans for a new Wal-Mart store were made known to incumbent retailers, we measure competition with Wal-Mart on the basis of the date in which the store opened for business. We, therefore, will be roughly comparing the frequency of sales before and after Wal-Mart opened. Thus, if Dominick's preemptively increased the frequency of sales, then our estimates of the effect of Wal-Mart's entry would be biased towards zero.[20]

3.2 Chain Structure of Pricing

One of the primary drawbacks with using the Dominick's data is the possibility that prices were set at the chain level. If this were the case, then we would not expect to see store-specific responses to Wal-Mart, but rather a coordinated response across the entire chain. Instead, we would either see a delayed response (when a store was not allowed to act when it needed to) or an accelerated response (i.e. as a store was forced to act before it needed to) in the store-level data as the chain might only take action when a critical number of stores were close to

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[19] This interpretation is also consistent with Dube, Lester, and Eidlin (2007) and Neumark et al. (2008).
[20] We show in the Data Appendix that the high frequency data is not leading to spurious results.

Wal-Mart. The existence of chain-wide prices does not rule out the possibility of any response, but would change the level of aggregation appropriate for this analysis.

Dominick's reportedly made pricing decisions based on geographic areas. As stated by the data's documentation, "DFF priced products by 16 zones. Within each zone, there was supposed to be a uniform regular price (promoted prices are the same, chainwide)". Note that the quote states that regular prices would be the same within a zone and publically advertised sale prices would be the same across the entire chain. The statement suggests that an individual store's regular price response to Wal-Mart would be limited, but does not rule out the potential for store-specific sale prices. Indeed, the data contain very few store-specific regular prices within a zone. With the exception of a few weeks, over 90 percent of regular prices were the same within a zone. Therefore before we use the store-level data, we must examine the extent to which sale prices varied across stores within a zone.[21]

Looking the three largest zones, Figure 2 illustrates the fraction of stores participating in sales.[22] While it was common for an item to be on sale at all stores, many more stores opted out of a sale occurring in the zone than opted out of the zone's regular price. In an average week, 31% of stores did not have sales on items that were on sale in at least one other store in Zone 1, 34% in Zone 2, and 25% in Zone 12. Stores thus seem to have been able to set their own sale prices, and could have individually responded to Wal-Mart entry.

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[21] In the Data Appendix, we show that there is a negative relationship between competition with Wal-Mart and regular prices for 8 of the 12 categories, but the size of the effects are relatively small. The effect is also larger at the zone-level.

[22] The DFF data contain flags indicating whether UPC i was on sale at a store j during week t. While a flag correctly indicates when there was a deal, the documentation suggests that some deals may have gone unflagged. To capture these missing sales, we separately flag any price that declined and returned back to its original price or higher within two weeks. This technique has also been used by Campbell and Eden (2005) and Eden and Jaremski (2010). Using only the original sale indicator does not qualitatively change the results. Our final sale dummy variable, $Sale_{i,j,t}$, is the union of the two measures.

An interesting pattern emerges when we compare the fraction to the change in each zone's average driving distance to Wal-Mart. First, a store's sale price behavior was more likely to deviate from their zone's as Wal-Mart entered their area. The fraction of stores not participating in a sale falls from around 80% to 60% as the distance to Wal-Mart declined for each zone. This is consistent with individual stores located nearest to a new Wal-Mart selecting more things to put on sale than the rest of the stores in the zone. Second, while there were fewer zone-wide sales at the end of the sample than the beginning, sale behavior converges within the zone slightly when the distance to Wal-Mart was constant for a year or two. For instance, the fraction of stores not participating in a sale rises back about 10% from its lowest price by the end of the period. In this way, individual stores might have needed to respond to Wal-Mart's entry until the zone decided to take action.

While Dominick's could have responded to Wal-Mart by lowering the regular price or increasing their frequency of sales, the data show that any regular price response would largely only exist at the zone-level. However, because we are more interested in sale prices, we examine Dominick's response both at the store and zone level in order to capture the full effect of Wal-Mart's entry on Dominick's.

3.3 Wal-Mart and Shopper Visits to Dominick's

Dominick's sells many products that Wal-Mart did not sell so it is possible that the chain would not have been dramatically affected by the introduction of Wal-Mart. Therefore, we start by testing whether Wal-Mart's entry had a negative effect on a store's customer base. Specifically, we examine whether Wal-Mart entry affected the number of customers that make a purchase from each Dominick's stores each week.

The DFF database contains a customer count file that indicates the number of visits per store during each day in the sample. We estimate the effect of Wal-Mart entry using the fixed effects panel estimator. The dependent variable ($\Delta Y_{j,t}$) is the first difference of the logarithm of shoppers visiting store j during week t. The independent variable ($\Delta Dist_{j,t}$) is the change in driving distance in miles from store j to the nearest Wal-Mart in week t. The regression is:

$$\Delta Y_{j,t} = \alpha_1 Dist_{j,t} + Q_t + c_j + e_{i,j,t} \tag{3}$$

where Q_t is a vector of quarter dummies to control for seasonal variation in the growth rate of customer visits, c_j is the unobserved store heterogeneity that is fixed over time, and $e_{i,j,t}$ is the error term. In this specification, the unobserved heterogeneity can be interpreted as the store specific growth rate in customer visits.

The regression results from Table 2 indicate that Dominick's lost about 5% of shopper visits due to Wal-Mart entry. The distance to the nearest Wal-Mart fell by an average of about 200 log points and the point estimate from the regression above is 0.024. The results are also similar when total revenue is used as the dependent variable. We conclude that although there were substantial differences in the products offered by Dominick's and Wal-Mart, Dominick's would have competed with Wal-Mart on some level for certain types of customers.

3.4 Wal-Mart and the Store-Wide Frequency of Sales

We start to examine Dominick's sale price behavior by plotting the average driving distance to Wal-Mart and DFF's sales frequency for selected categories.[23] In Figure 3, the fraction of products on sale rises as driving distance falls. For example, during October of 1991, a 45 percent drop in the average distance to Wal-Mart (from 20 to 11 miles) corresponds with a

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[23] Displayed categories are Bathroom Tissue, Bottled Juices, Cereals, Soft Drinks, and Tuna.

50 percent increase in the trend component of the sales (from 12 to 18 percent). This graph indicates that the chain-wide frequency of sales increased rapidly following Wal-Mart entry.

Two additional conclusions are visible in Figure 3. First, and consistent with the results in Singh, Hansen, and Blattberg (2006), the incumbent pricing response does not begin until Wal-Mart moves into a reasonable competitive distance. Movements in Wal-Mart prior to that cutoff do not seem to affect Dominick's behavior in any visible way. Second, the increased frequency of sales begins to slightly dissipate after three years. The results are similar to Franklin (2001) who finds that Wal-Mart's market share grows over time. This growth is likely due to customers adjusting to Wal-Mart's presence and becoming less responsive to sales on individual items. Nevertheless, the frequency of sales remains at least 7 percentage points higher than its initial value.

Building on the aggregate picture, we proceed with Store-Week and Zone-Week linear regressions that control for unobserved heterogeneity. The dependent variable ($\%Sale_{j,t}$) is the percentage of products on sale in store j during week t, and the independent variable ($Dist_{j,t}$) is the driving distance in miles from store/zone j to the nearest Wal-Mart in week t. The model we estimate is given in equation (4). [24]:

$$\%Sale_{j,t} = \alpha_1 Dist_{j,t} + Q_t + Trend_t + c_j + e_{j,t} \qquad (4)$$

Reported in Table 3, the frequency of sales is negatively correlated with a store's and a zone's distance to the nearest Wal-Mart. A 35 mile reduction in the distance to Wal-Mart is associated with about a 1 percentage point increase in the fraction of products on sale in a store, and a 0.9 percentage point increase in the fraction of products on sale across a zone. Relative to

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[24] A Hausman test finds that a fixed effect estimator is appropriate (rather than a random effects estimator). We also test the assumption that $e_{j,t}$ is strictly exogenous by estimating the following model using the fixed effects estimator:
$$Y_{j,t} = \alpha_1 Dist_{j,t} + \delta Dist_{j,t+1} + \alpha_2 Quarter_t + c_j + e_{j,t}$$
The Wald test fails to reject the strict exogeneity hypothesis ($\delta = 0$) so we conclude that the assumption is valid.

the average frequency of sales (around 12.5%), these effects are both statistically and economically significant. Moreover, the coefficients generally increase when we control for the liner trend or disaggregate to the category level.

3.5 Product-Level Effect of Wal-Mart Entry on Frequency of Sales

The results indicate that Dominick's increased their average sale frequency in response to Wal-Mart's entry. If these additional sales were intended to induce certain customer groups to make a trip to the store, then we would expect the additional sales to be focused on key products or categories rather than all products. Therefore, we look at the product-level data and we estimate linear probability regressions for each category.[25] Each observation is a UPC-Store-Week, and the dependent variable $Sale_{i,j,t}$ is a binary indicator of whether product i was on sale in store j during week t. We measure an individual product's popularity as its share of category revenue over its life and across all stores.[26]

We begin with a simple model that averages Wal-Mart's effect across all products:

$$Sale_{i,j,t} = \beta_1 Dist_{j,t} + Q_t + c_{i,j} + e_{i,j,t} \qquad (5)$$

where $c_{i,j}$ is unobserved UPC-Store heterogeneity that is fixed over time. A negative β_1 coefficient implies that the average frequency of sales across the category rose in response to Wal-Mart. Next, we add the interaction of $Share_i$ and $Dist_{j,t}$ to evaluate whether stores selected popular products to discount. The model becomes:

$$Sale_{i,j,t} = \beta_1 Dist_{j,t} + \beta_2 Dist_{j,t} \times Share_i + Q_t + c_{i,j} + e_{i,j,t} \qquad (6)$$

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[25] The separate category regressions are necessary due to the large number of observations. However, estimating separate regressions for each category does not lead to different results than aggregating. Results from probit or logit models are qualitatively similar to those found in our linear probability model.

[26] Our contention is that $Share_i$ is determined by consumer preference rather than by store-level weekly promotion fluctuations. However, to make sure that the variable exogenous to store-activity, we do not include a product's own revenue in the total. Hosken and Reiffen (2004) use a similar procedure.

Here, the effect of competition with Wal-Mart depends on the category (through β_1) as well as the product's popularity (through β_2).

Table 4 shows the results of the model in equation (5). In total, four out of 12 categories have a significantly negative coefficient on $Dist_{j,t}$, whereas 6 had a statistically significant and positive coefficient. The results thus indicate that Dominick's did not lower the frequency of sales for all of its products in response to Wal-Mart, but might have targeted specific categories. Looking at Table 5, those categories with a significantly negative estimate for β_1 tended to be higher revenue categories (and higher purchase frequency categories). This indicates that Dominick's focused its response on certain key categories and characteristics.

When the interaction with share of revenue is added to the model as in Table 6, the negative and significant category-level effects all but disappear. β_1 remains significantly negative for only 2 categories (Toilet Tissue and Bottled Juice), while β_2 is significantly negative for 11 of the 12 categories. This means that the effect of Wal-Mart entry at the product level depends on the product's popularity rather than the type of product. The frequency of sales increased for popular products, but stayed the same or declined for less popular items.

The coefficient estimates of equation (6) are summarized in Figure 4, which displays the average effect of a 35 mile reduction in the distance to Wal-Mart for the 5th, 50th, and 95th percentiles of $Share_i$. The median response is generally close to zero, but the frequency of sales of products at the 95th percentile was generally 5 to 10 percent higher after Wal-Mart's entry. The UPC-level approach, therefore, provides additional evidence that the rise in sales across DFF stores was the result of competitive behavior rather than a general increase in sales.

The results are consistent with "loss-leader" models that suggest firms advertise low prices on only a few products (often below marginal cost) to attract shoppers who purchase other

profitable products.[27] For example, DeGraba (2006) illustrates how a low price on turkeys during Thanksgiving will attract a Thanksgiving dinner host who will also purchase a long list of other products needed for the dinner. Not every loss-leader can be so creatively selected, but the marketing literature has proposed several sets of loss-leader characteristics. Hosken and Reiffen (2004) argue that "loss-leader" products had to be popular in order to attract enough demand, whereas Lal and Matutes (1994) argue that "loss-leaders" products should be purchased often and costly to store. In this way, the increase in the frequency of sales at Dominick's is likely a "loss-leader" response to Wal-Mart's entry.

4. Conclusion

Drawing from related strands of research in the marketing and economics literature, we find that an increase in the frequency of sales can be a rational response to competition with a low cost retailer. The data from a representative chain of grocery stores support this strategy: individual stores which came into competition with Wal-Mart significantly increased their average frequency of sales. Moreover, the increased price promotion activity was focused on "loss-leader" products, providing additional evidence that the behavior was a strategic response to Wal-Mart entry rather than a coincident change in some other factor (e.g. promotion activity initiated by manufacturers).

This study has implications for two other areas of research. First, there have been several macroeconomic studies that evaluate the role of sales in price adjustment. The topic was initiated with the observation that prices change frequently, but that many of these changes are the result of sales (Bils and Klenow 2004). Recent studies such as Chevalier and Kashyap (2010), Kehoe

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[27] Loss-leading could suggest a permanently low price or a temporarily low price depending on the model, but traditionally it is explained using the later.

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and Midrigan (2010), Eichenbaum, Jaimovich, and Rebelo (2011), and Guimaraes and Sheedy (2011) attempt to reconcile the frequent adjustment of prices, that is largely due to sales, with the cornerstone assumption of price stickiness embedded in New Keynesian macroeconomic models. These studies tend to find that nominal rigidities are still important in spite of the frequent price adjustments associated with sales. Our results, however, caution against concluding that sales are unimportant for aggregate price adjustment because we show that temporary price reductions may be used in response as a persistent shock.

Second, Nakamura and Steinsson (2008) find that the fraction of price quotes that are sales has increased substantially over the last two decades. Certain product categories, such as breakfast cereal or potato chips, are now "on sale" twice as often as they were in the late 1980's. As the expansion of Wal-Mart took place over the same period, our results suggest that Wal-Mart could be at least partially responsible for the rise in sales.

References

Ailawadi, K. L, J. Zhang, A. Krishna, and M. W Kruger. "When Wal-Mart Enters: how incumbent retailers react and how this affects their sales outcomes." *Journal of Marketing Research*, 47(4), 2010, 577–593.

Basker, Emek. "Selling a Cheaper Mousetrap: Wal-Mart's Effect on Retail Prices." *Journal of Urban Economics*, 58(2), 2005, 203-229.

Basker, Emek, and Michael Noel. "The Evolving Food Chain: Competitive Effects of Wal-Mart's Entry into the Supermarket Industry." *Journal of Economics and Management Strategy*, 18(4), 2009, 977-1009.

Bils, Mark, and Peter J. Klenow. "Some Evidence on the Importance of Sticky Prices." *Journal of Political Economy*, 112(5), 2004, 947-985.

Campbell, Jeffrey R., and Benjamin Eden. "Rigid prices: evidence from U.S. scanner data." Federal Reserve Bank of Chicago, Working Paper Series: WP-05-08, 2005.

Capps Jr, O., and J. M Griffin. "Effect of a mass Merchandiser on traditional Food Retailers." *Journal of Food Distribution Research*, 29(1), 1998.

Chevalier, Judith A., and Anil K. Kashyap. "Best Prices." National Bureau of Economic Research, Inc, NBER Working Papers: 16680, 2011.

Conlisk, John, Eitan Gerstner, and Joel Sobel. "Cyclic Pricing by a Durable Goods Monopolist." *Quarterly Journal of Economics*, 99(3), 1984, 489-505.

DeGraba, Patrick. "The Loss Leader Is a Turkey: Targeted Discounts from Multi-product Competitors." *International Journal of Industrial Organization*, 24(3), 2006, 613-628.

Dube, Arindrajit, T. William Lester, and Barry Eidlin. "Firm Entry and Wages: Impact of Wal-Mart Growth on Earnings Throughout the Retail Sector." *SSRN eLibrary*, 2007.

Eden, B., and M. Jaremski. "Rigidity, Dispersion and Discreteness in Chain Prices." Working Papers, Vanderbilt University, 2010.

Eichenbaum, Martin, Nir Jaimovich, and Sergio Rebelo. "Reference Prices, Costs, and Nominal Rigidities." *American Economic Review*, 101(1), 2011, 234-262.

Franklin, A. W. "The impact of Wal-Mart supercenters on supermarket concentration in US metropolitan areas." *Agribusiness*, 17(1), 2001, 105–114.

Guimaraes, Bernardo, and Kevin D. Sheedy. "Sales and Monetary Policy." *American Economic Review*, 101(2), 2011, 844-876.

Hoch, Stephen J., Xavier Drèze, and Mary E. Purk. "EDLP, Hi-Lo, and Margin Arithmetic." *The Journal of Marketing*, 58(4), 1994, 16-27.

Hoch, Stephen J., Byung-Do Kim, Alan L. Montgomery, and Peter E. Rossi. "Determinants of Store-Level Price Elasticity." *Journal of Marketing Research*, 32(1), 1995, 17-29.

Holmes, T. J. "The Diffusion of Wal-Mart and Economies of Density." *Econometrica*, 79(1), 2011, 253–302.

Hosken, Daniel, and David Reiffen. "How Retailers Determine Which Products Should Go on Sale: Evidence from Store-Level Data." *Journal of Consumer Policy*, 27(2), 2004, 141-177.

Kehoe, Patrick, and Virgiliu Midrigan. "Prices Are Sticky After All." *NBER Working Paper No. w16364*, 2010.

Lal, Rajiv. "Price Promotions: Limiting Competitive Encroachment." *Marketing Science*, 9(3), 1990, 247-262.

Lal, Rajiv, and Carmen Matutes. "Retail Pricing and Advertising Strategies." *Journal of Business*, 67(3), 1994, 345-370.

Nakamura, Emi, and Jon Steinsson. "Five Facts about Prices: A Reevaluation of Menu Cost Models." *Quarterly Journal of Economics*, 123(4), 2008, 1415-1464.

Neumark, David, Junfu Zhang, and Stephen Ciccarella. "The effects of Wal-Mart on local labor markets." *Journal of Urban Economics*, 63(2), 2008, 405-430.

Peltzman, Sam. "Prices Rise Faster Than They Fall." *Journal of Political Economy*, 108(3), 2000, 466-502.

Singh, V. P, K. T Hansen, and R. C Blattberg. "Market entry and consumer behavior: An investigation of a Wal-Mart supercenter." *Marketing Science*, 25(5), 2006, 457.

Volpe, R. J, and N. Lavoie. "The effect of Wal-Mart supercenters on grocery prices in New England." *Applied Economic Perspectives and Policy*, 30(1), 2008, 4.

Appendix A: Demand in a Hotelling Model

Suppose there is a measure 1 of switchers who are distributed uniformly across the unit interval and differ only in their cost of visiting the entrant. Denote a switcher's type as $i \in [0,1]$. Switchers of type i face a cost of visiting the entrant of $d(i) = i\bar{d}$ where $\bar{d}$ is the highest cost any switcher incurs to visit the new store (but no cost to visit an incumbent). The marginal type who would be indifferent between visiting the new store or not is $\tilde{i} = \frac{p_B - p_C}{\bar{d}}$. All switchers of type $i < \frac{p_B - p_C}{\bar{d}}$ purchase from the entrant, and the rest purchase from the lowest priced incumbent.

Appendix B: Proofs of All Propositions

Proof of Proposition 1

To prove that choosing a price of r in every period is part of an SPNE in pure strategies, we propose a punishment for deviating and then check to make sure it is credible and effective. Because there is no pure strategy equilibrium in the stage game (except in very special cases), the punishment cannot involve reverting to a pure strategy Nash equilibrium forever. Suppose the punishment for deviating is to charge a price equal to marginal cost, c, for t periods. In period $t + 1$, both firms resume charging a price of r unless another deviation occurs. If either firm deviates during the punishment, the punishment starts over from the beginning. The duration of the punishment, t, is chosen to be as large as possible such that:

$$\frac{\delta^t \left(\alpha + \frac{1}{2} \right)(r - c)}{1 - \delta} \geq \frac{\alpha(r - c)}{1 - \delta}$$

This inequality ensures that the punishment is credible. The RHS is the continuation value of charging r forever assuming that the opponent charges something less than r. The LHS is the present value of profits assuming that after the punishment, both players go back to charging

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r every period. Rearranging terms, we can see that the most severe punishment that is credible would be to choose the largest t such that:

$$\delta^t \geq \frac{2\alpha}{2\alpha + 1} \tag{B.1}$$

For this threat to deter deviations, we must ensure that a one shot deviation is unprofitable. Therefore, the punishment will prevent deviations if:

$$\frac{\left(\alpha + \frac{1}{2}\right)(r - c)}{1 - \delta} \geq (\alpha + 1)(r - c) + \frac{\delta^t \left(\alpha + \frac{1}{2}\right)(r - c)}{1 - \delta}$$

Which will be satisfied as long as

$$\frac{1 - \delta^t}{1 - \delta} \geq \frac{\alpha + 1}{\alpha + \frac{1}{2}} \tag{B.2}$$

Which implies that the lower bound for δ is $\frac{1}{2}$ for the SPNE to exist. Combining (B.1) and (B.2):

$$\delta \geq \frac{\alpha - 1}{\alpha + 1} \tag{B.3}$$

To be clear, (B.3) shows the conditions under which the SPNE exists. The RHS of (B.3) is bounded above by 1 and increasing when $\alpha \geq 0$. Because we assume that the discount factor, $\delta \in (0,1]$, the larger is α, the larger δ must be. This means that the larger the relative size of the switchers, the more likely the equilibrium exists. Because total payoffs are maximized by charging the highest willingness to pay each period, the equilibrium is Pareto-dominant.

Maximum Profits Attainable by Incumbents

We claim that having a single incumbent charge a low price while the other charges the monopoly price results in the highest possible joint profit level for the incumbents. We prove this claim by contradiction. Suppose the cartel found it optimal to set both prices to $p < r$. Let

$\epsilon = r - p$. The cartel's profits in this case would be $2p\alpha + p\left(1 - \frac{p - p_C}{d}\right)$. If instead the cartel

had one firm charge $p < r$ and the other charge r, its profits would be:

$$r\alpha + p\alpha + p\left(1 - \frac{p - p_C}{d}\right) = \epsilon\alpha + 2p\alpha + p\left(1 - \frac{p - p_C}{d}\right)$$

which is $\epsilon\alpha$ more than if the cartel set both prices to p. Therefore setting both prices below r

cannot be optimal.

Proof of Proposition 2

We prove Proposition 2 in two sections. First, we establish the prices charged by all firms in the

equilibrium proposed in section 2.2. Next we show that the punishment strategy is both credible

and effective.

Equilibrium Prices

Below we establish the price that C will charge in every period as well as the "sale" price that A

and B will alternate with the monopoly price r. Recall that we assume C plays a best response to

the lowest priced incumbent and the "sale" price is assumed to maximize the single period

profits of the firm having a sale, given the price that C.

Without loss of generality, we begin by assuming that $p_A \geq p_B$. Because firm C will

always choose a price $p_C \in [p_B - d, p_B]$, its profits are:

$$\pi_C = p_C\left(\frac{p_B - p_C}{d}\right) \quad if \quad p_C \in [p_B - d, p_B]$$

π_C is maximized as long as one of the following conditions hold:

$$\frac{d\pi_C}{dp_C} = \begin{cases} \dfrac{p_B - 2p_C}{d} \leq 0 & \text{iff} \quad p_C = p_B - d \\ \dfrac{p_B - 2p_C}{d} = 0 & \text{iff} \quad p_C > p_B - d \end{cases}$$

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which implies that firm C's optimal response function is:

$$p_C = p_B - d \quad \text{iff} \quad p_B \geq 2d \tag{B.4}$$
$$p_C = \frac{p_B}{2} \quad \text{iff} \quad p_B < 2d \tag{B.5}$$

We have already shown that no more than one of the incumbent's products will be priced below

r. Without loss of generality, suppose $r = p_C \geq p_B$. The profits earned by firm B are:

$$\pi_B = \begin{cases} (p_B - c)\left(\alpha + \left(1 - \dfrac{p_B - p_C}{d}\right)\right) & \text{iff} \quad p_C \leq p_B \leq p_C + d \text{ and } p_B \leq r \\ (p_B - c)(\alpha + 1) & \text{iff} \quad 0 \leq p_B \leq p_C \\ (p_B - c)\alpha & \text{iff} \quad p_C + d \leq p_B \leq r \end{cases}$$

We can disregard the second case because we have already argued that C would never allow

$p_B < p_C$. Thus the relevant best response function for firm B is characterized by:

$$p_B = \frac{d(1 + \alpha) + p_C + c}{2} \quad \text{iff} \quad d(\alpha - 1) \leq p_C \leq \min\{d(\alpha - 1) + c, 2r - c - d(\alpha + 1)\} \tag{B.6}$$
$$p_B = r \quad \text{iff} \quad p_C < r - d \tag{B.7}$$

Now we proceed to identify the prices p_B^* and p_C^* that are mutually best responses. These

equilibrium prices will depend on the parameters $r, d, c,$ and α. We are interested in the case in

which $p_B < r$ which is only possible when condition (B.6) holds. There are two possible

scenarios to consider. The first is when (B.4) also holds, which implies:

$$p_B^* = d\alpha - c, \qquad p_C^* = d(\alpha - 1) - c$$

If this were an equilibrium then C's share would be $\frac{p_B^* - p_C^*}{d} = 1$ which implies that the

cartel would sell to none of the switchers. This is only optimal if $p_B^* = r$ because the cartel

would only charge a price less than r if they could sell to some of the switchers by doing so.

Thus, the combination of (B.4) and (B.6) cannot represent an equilibrium where $p_B^* < r$.

The second scenario involving $p_B^* < r$ occurs when (B.5) and (B.6) hold:

$$p_B = \frac{d(1 + \alpha) + \frac{p_B}{2} + c}{2} \text{ and } p_B < 2d$$

This implies that

$$p_B^* = \frac{2}{3}[d(1 + \alpha) + c] \; p_C^* = \frac{1}{3}[d(1 + \alpha) + c]$$

Next we ensure that the inequalities are satisfied:

(B.5) requires that $p_B^* = \frac{2}{3}[d(1 + \alpha) + c] < 2d \Rightarrow 2 - \frac{c}{d} > \alpha$

(B.6) requires $p_C^* = \frac{1}{3}[d(1 + \alpha) + c] \le 2r - c - d(\alpha + 1) \Rightarrow \frac{3r}{2d} - \frac{c}{d} - 1 \ge \alpha$

and $\frac{1}{3}(d(1 + \alpha) + c) \le d(\alpha - 1) + c \Rightarrow 2 - \frac{c}{d} \ge \alpha$

The equilibrium price and the parameter space for which they apply are summarized in (B.8):

$$p_B^* = \frac{2}{3}[d(1 + \alpha) + c] \; p_C^* = \frac{1}{3}[d(1 + \alpha) + c] \tag{B.8}$$
$$\text{if and only if } \alpha \le \min\left\{\left(2 - \frac{c}{d}\right), \left(\frac{3r}{2d} - \frac{c}{d} - 1\right)\right\}$$

Proof that the punishment is credible and effective

   To complete the proof of Proposition 2, we must show that the punishment outlined in Section 2 is credible and harsh enough to deter firms from deviating. In the analysis below, we take a different approach than Lal (1990) in order add in marginal costs and address some technical issues. To compress the notation, we define the following additional variables:

   Δ_p, Δ_r = profit to an incumbent charging $\bar{r}$ when the other charges p, r respectively

   $\delta_p, \delta_{\bar{r}}$ = profits to a defecting firm when the other firm charges p, r respectively

$$\Pi = \sum_{t=0}^{\infty} \delta^t r\alpha = \frac{r\alpha}{1 - \delta} = \text{ discounted profits of selling only to your loyal customers forever}$$

The punishment strategies given in equation (2) are credible ((i) and (ii)) and effective ((iii), (iv), (v)) under the following conditions:

(i) $\pi_A = r\alpha\delta^{t^*-1} + \Delta_r\delta^{t^*} + r\alpha\delta^{t^*+1} + \cdots = \dfrac{\delta^{t^*-1}}{1-\delta^2}(r\alpha + \delta\Delta_r) \geq \Pi$

(ii) $\pi_B = \Delta_p\delta^{t^*-1} + r\alpha\delta^{t^*} + \Delta_r\delta^{t^*+1} + \cdots = \pi_A \geq \Pi$

(iii) $\delta_p\delta^{t^*-1} + \delta^{t^*}\pi_A \leq \pi_B \Rightarrow A$ will not deviate in period t^*

(iv) $r\alpha\delta^{t^*-1} + \Delta_r\delta^{t^*} + \delta_{\bar{r}}\delta^{t^*+1} + \delta^{t^*+2}\pi_A \leq \pi_A \Rightarrow A$ will not deviate in period $t^* + 2$

(v) $\Delta_r\delta^{t^*-1} + \delta^{t^*}\pi_B \leq \pi_B \Rightarrow B$ will not deviate in period t^*

Conditions (i) and (ii) state that the continuation value of the punishment sequence for the two incumbents (π_A and π_B) must be at least as large as the discounted profits from serving only loyal customers, Π. Conditions (i) and (ii) also indicate how t^* and p are selected. t^* is chosen so that it is as large as possible without violating inequality (i), ensuring that the threat is as severe as it can be and still be credible. The price p is chosen to satisfy (ii), that $\pi_B = \pi_A$.

Condition (iii) is required so that A will not deviate in period t^*. Condition (iv) ensures that A will not deviate in period $t^* + 2$. Finally, (v) ensures that B will not deviate in period t^*.

We now analyze when it is possible for conditions (i) – (v) hold. First notice that (iii) always holds when (v) holds. This is simply because $\delta_p < \Delta_r$. Δ_r is the profit one incumbent makes when the other charges a price of r. The quantity δ_p is the profit that an incumbent could make if it were to deviate when the other is charging a price $p < r$. Since Δ_r is the best a firm can do when the other charges r, we know that $\delta_p < \Delta_r$. Therefore if (v) holds, so does (iii). .

Because (iii) is redundant, we analyze conditions (i) (ii) (iv) and (v) to find the parameter values for which they can be satisfied. Rearranging terms in (i) we can see that the duration of the punishment, t^* depends on $\frac{\Delta_r}{r\alpha}$. Specifically, t^* will be the largest integer that satisfies:

$$\frac{\Delta_r}{r\alpha} \geq \left(\frac{1 + \delta - \delta^{t^*-1}}{\delta^{t^*}}\right) \tag{B.9}$$

To interpret this condition, notice that the RHS is increasing in t^* (because $\delta \in (0,1)$). Secondly, the ratio $\frac{\Delta_r}{r\alpha} > 1$ can be interpreted as a measure of the temptation to cheat when the firm is supposed to be charging r, the high price. The larger the temptation, the harsher the punishment must be.

The next step is to use inequalities (iv) and (v) to determine what values of δ make the threat severe enough. It turns out that the lower bound on δ also depends on the ratio $\frac{\Delta_r}{r\alpha}$. First, notice that $\delta_{\bar{r}}$ will be less than but arbitrarily close to Δ_r. If the incumbent deviates when her opponent charges $\bar{r}$, then the best she can do is to slightly undercut her opponent's price and obtain a profit slightly less than Δ_r. Because Δ_r is the upper bound on the single period profits earned by A if she deviates, then we can substitute Δ_r for $\delta_{\bar{r}}$ in (iv) and still be certain that A will be deterred from deviating in period $t^* + 2$. After the substitution, (iv) and (v) can be written as:

$$\frac{\Delta_r}{r\alpha} \leq \frac{1 - \delta^{t^*}}{1 - \delta - \delta^2 + \delta^{t^*+1}} \quad if \ 1 > \delta + \delta^2 - \delta^{t^*+1} \tag{B.10}$$

This is a bit tricky to interpret. When the RHS of the inequality is positive, then it must be larger than $\frac{\Delta_r}{r\alpha}$. When the RHS is negative, conditions (iv) and (v) are always satisfied. The existence of an SPNE of the form described above depends on the magnitude of $\frac{\Delta_r}{r\alpha}$ which we know is larger than 1. In Table B1, we provide different levels of $\frac{\Delta_r}{r\alpha}$ with the corresponding t^* for the minimum level of δ that make the strategy a credible and effective threat.

Table B1					
$\frac{\Delta_r}{r\alpha}$	1.1	1.5	2	5	10
$\min \delta$	.96	.82	.83	.74	.69
$t^*(\min \delta)$	2	2	3	3	4

These results differ from those reported in Lal (1990). He claims that the strategy profile given in (2) is an SPNE for all values of $\delta > .62$, *regardless of the level of* $\frac{\Delta_r}{r\alpha}$. We show here that the minimum possible discount factor depends on the size of the gains from alternating sales relative to the "outside option". Nevertheless, even small levels of profits gained by selling to the switchers will result in alternating sales if the interest rate is low enough.

The final step is to show that charging a price of r and $\bar{r}$ in alternating periods using the proposed punishment strategies is a Nash equilibrium. Said differently, a one shot deviation cannot be profitable. This will be true if:

$$\left(\frac{1}{1-\delta^2}\right)(r\alpha + \Delta_r\delta) \geq \delta_{\bar{r}} + \delta\pi_a \qquad (B.11)$$

It is easy to show that (B.11) is satisfied if (v) is satisfied. Thus, the strategy profile in (2) constitutes a sub-game perfect Nash equilibrium as long as δ is large enough given $\frac{\Delta_r}{r\alpha}$.

Appendix C: Dominick's Finer Foods Sample Selection

The DFF sample offers a large number of products and stores, but there are several stores, UPCs, and store-UPC cells with very few observations. The main concern is that we cannot be sure of the reason for sparsely populated data. For instance, a UPC-Store cell with only one year (out of a possible seven) may represent a product deletion or incomplete data records. We want to make sure that the variation in the fraction of products on sale at a particular store is

not affected by changes in the mix of available data. In response to comments on this paper, we have also eliminated categories that we suspect were not sold at Wal-Mart stores at the time. Attempting to balance this objective with the desire to use as much data as possible, we implemented the following selection mechanism:

1) Drop any categories that we suspect were not sold at Wal-Mart.

2) Drop the final 18 weeks of the sample because represents only a partial-year of data.

3) Drop any category that does not span the entire sample period.

4) Next, we break up categories based on the relative number of products.

    a. For smaller categories (Bathroom Tissue, Bottled Juices, Cereals, Dish Detergent, Fabric Softeners, Laundry Detergent, Paper Towels, Snack Crackers, and Toothpaste),

        i. Drop all UPC-Store cells with less than 165 observations

        ii. Drop any store with less than 40 products in a category

    b. For large categories (Analgesics, Cookies, and Soft Drinks)

        i. Drop all UPC-Store cells with less than 180 observations

        ii. Drop any store with less than 50 products in a category

To illustrate how much of the data is excluded, Table C1 presents the summary statistics before and after the sample selection is taken. Although we delete two-thirds of the UPC-Store cells, our sample still accounts around 80% of the raw sample's revenue.

Figure 1: Location and Entry Year of Wal-Mart Stores in the Chicago Area
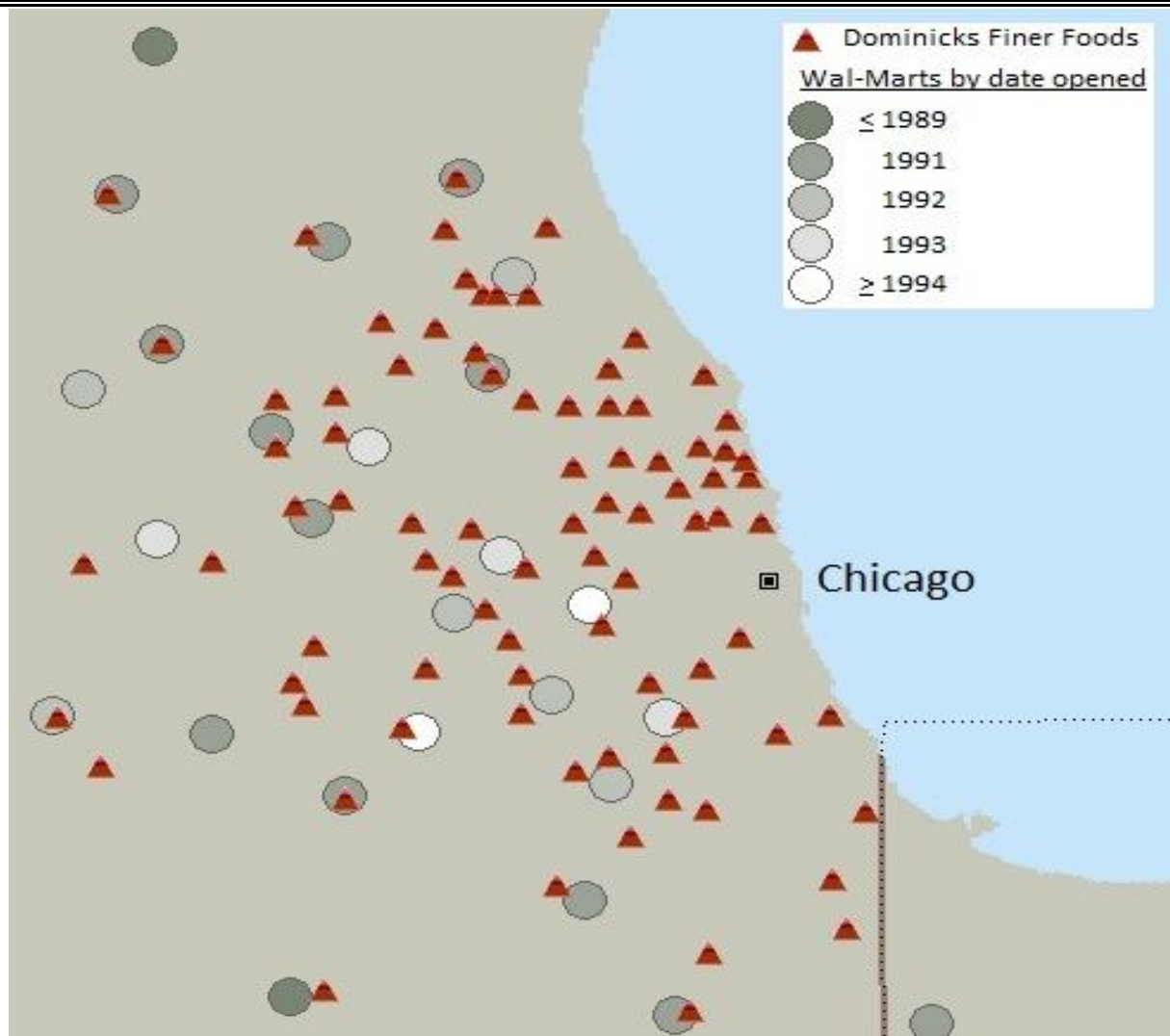
Note: Wal-Mart locations and entry dates were obtained from Holmes (2011). Dominick's locations come from the online documentation of the DFF database.

Figure 2: Fraction of Stores Participating in a Sale
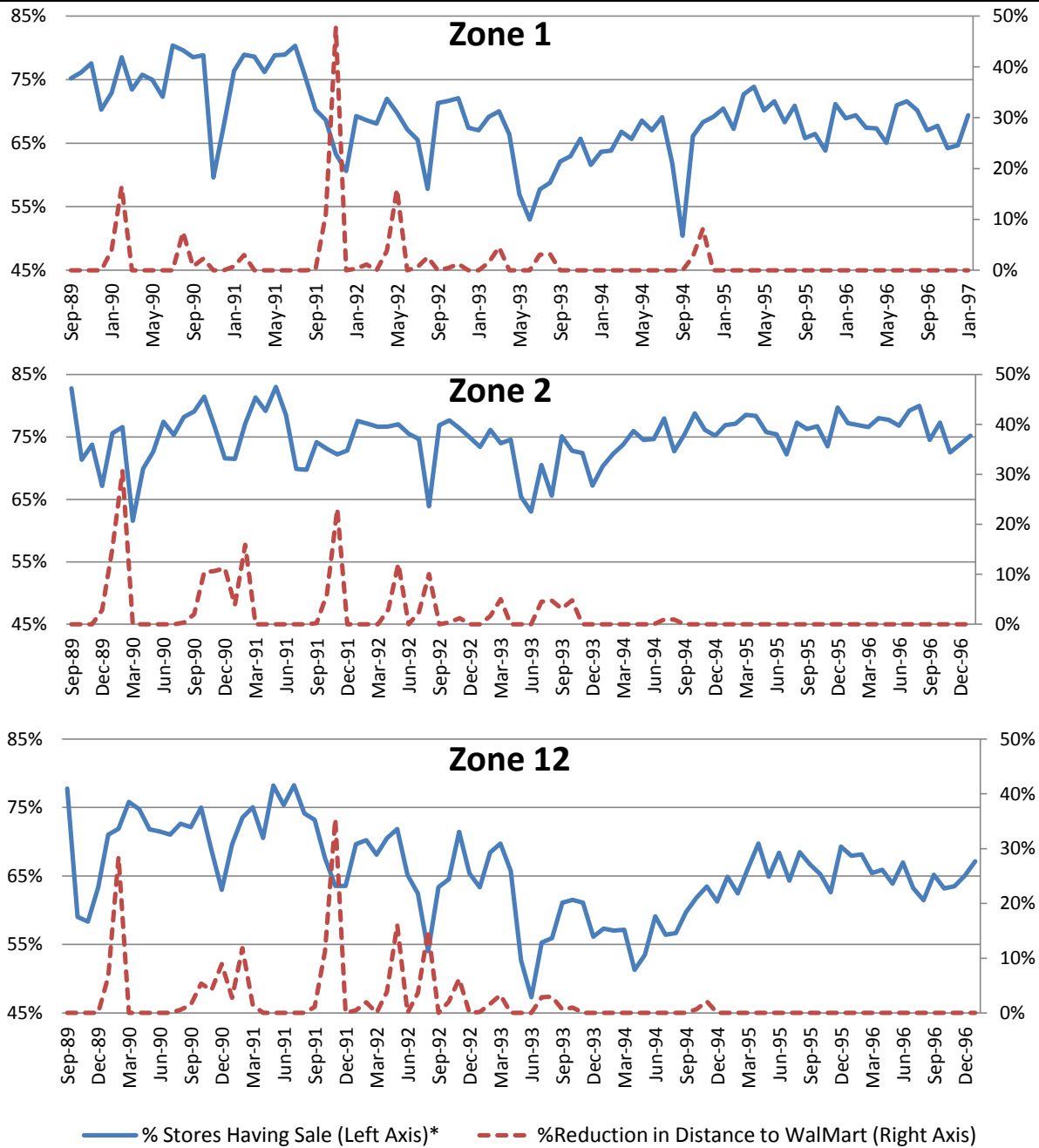
Notes: The figures plot the percent of stores having a sale on a product conditional on the product being on sale in at least one other store in the zone. This measure is averaged across UPCs. We show only zones with more than 7 stores and include UPCs that were sold in at least 7 stores. *The lower the value, the more autonomy individual stores exercised in their promotion decisions within the zone. The dotted line is the percent change in the average distance to the nearest Wal-Mart for stores in the zone.

Figure 3: Average Distance to Wal-Mart and Seasonally Adjusted Frequency of Sales
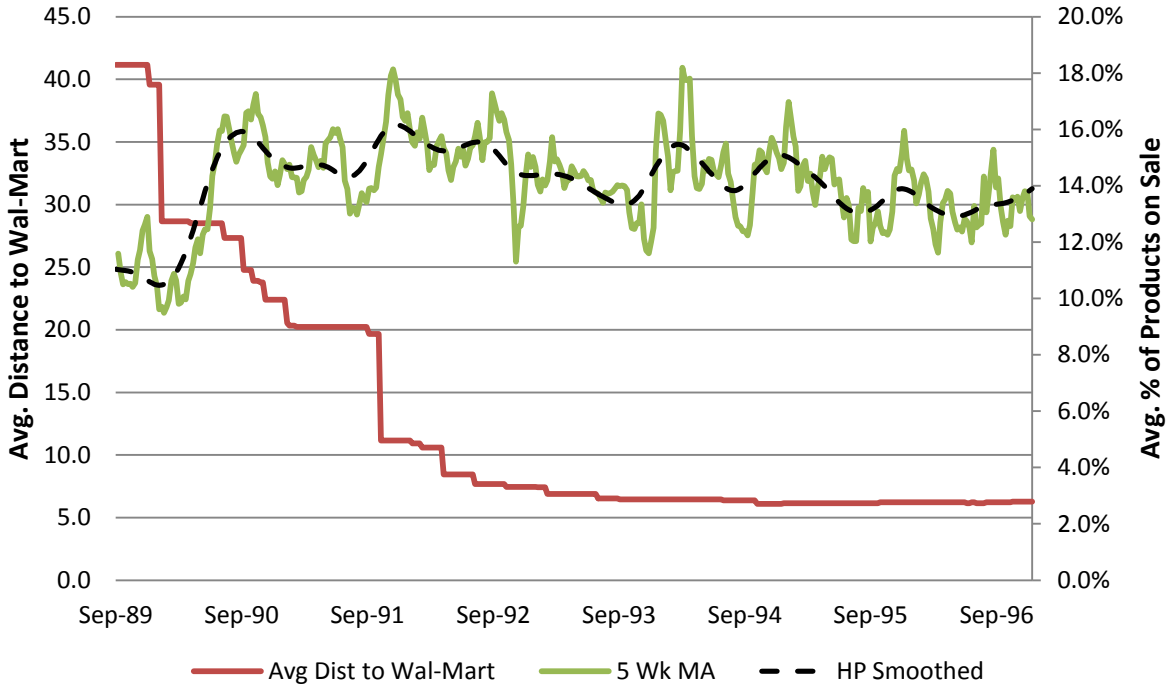
Notes: Average distance is the simple average across stores of the driving distance to the closest Wal-Mart. The other two series use two different smoothing techniques (moving average and HP-filter) to plot the fraction of products on sale.

Figure 4: Estimated Change in Frequency of Sales Following a 35 mile drop in *dist* for 95th , 50th, and 5th percentiles of share of category revenue
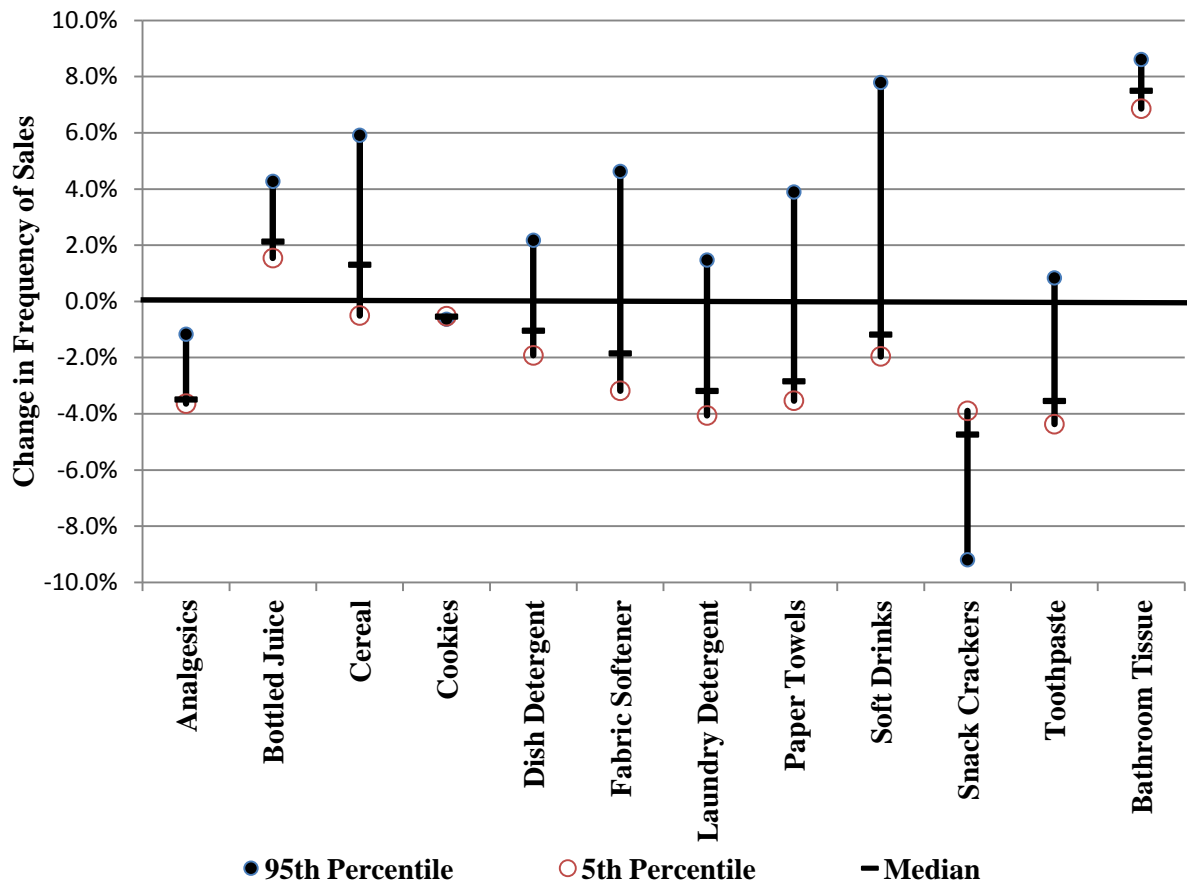
Notes: This figure plots the estimated effect of a 35 mile decline in distance to Wal-Mart (approximately the sample average) on the frequency of sales for each of three share percentiles, by category. The values are calculated by evaluating Equation (6) at different revenue share percentiles (5%, median, and 95%) for each category. Stars denote categories that have a negative and significant coefficient on share. The underlying

Table 1: Summary of Dominick's Sample

Category	# of UPCs	# of Stores	% of Sale Obs.	Profit Margin (%)	Avg. Quantity Sold	Avg. Price ($)
Analgesic	320	85	3.9	31.3	1.4	5.4
Bathroom Tissue	57	81	15.4	16.9	13.9	1.9
Bottled Juices	217	85	6	29.2	72.7	1.8
Cereals	227	85	10.7	16.6	9.5	2.2
Cookies	428	85	9.3	27.7	16.7	3.1
Dish Detergent	125	85	7.6	22.1	6.1	2.1
Fabric Softeners	156	85	13.5	24.9	9	2.3
Laundry Detergent	236	85	14.2	18	23	1.4
Paper Towels	76	80	21.2	22.1	5.6	5.4
Snack Crackers	180	85	17	27.1	7.6	2.2
Soft Drinks	564	85	13.3	16.5	33.1	2.3
Toothpaste	288	85	7.9	23.7	2.8	2.3
All Products	2,874	85	11.7	23	16.8	2.7

Notes: The selection of the sample is described in Appendix C. We visited modern stores to determine whether a product category was sold in Wal-Mart.

Table 2: Linear Panel Regressions of the Change in Customer Trips on Distance to Wal-Mart

	ΔLn(Number of Customer Trips)
Distance to Wal-Mart	.0241***
	[.0071]
Seasonal Dummies	Yes
Observations	26,605
Groups	86
R^2	0.001

Notes: T-Statistics are in brackets. Standard errors are clustered by store, and regressions are weighted by Revenue Share of Cell. * denotes significance at 10%; ** at 5% level and *** at 1% level.

Table 3: Linear Panel Regressions of *%Sale* on Distance to Wal-Mart

	% of UPCs on Sale During Week							
	Store		**Store-Category**		**Zone**		**Zone-Category**	
Distance	-0.034***	-0.074***	-0.037***	-0.122***	-0.0260***	-0.133***	-0.0347***	-0.143***
to Wal-Mart	[0.008]	[0.009]	[0.008]	[0.009]	[0.0077]	[0.0175]	[0.008]	[0.016]
Linear Trend		-0.006***		-0.013***		-0.0147***		-0.0149***
		[0.002]		[0.001]		[0.0019]		[0.0018]
Observations	31,833	31,833	542,758	542,758	5,655	5,655	74,805	74,805
Groups	85	85	1,519	1,519	15	15	210	210
R^2	0.055	0.073	0.01	0.027	0.065	0.197	0.038	0.062

Notes: The first two columns report results of a fixed effects panel estimate of two different models that use the store as the unit of analysis. The second column controls for a linear trend while the first column does not. The second two columns report analogous results from a random effects estimate of two models in which a category-store is the unit of analysis. The last four columns repeat the exercise with data aggregated to the zone level. The store and zone level models includes a vector of quarter dummies and the store-category and zone-category models include a vector of category x quarter dummies to control for seasonal effects for the chain and category respectively. The Distance coefficients are reported in percentage points per mile. T-Statistics are in brackets. Standard errors are clustered by store, and regressions are weighted by Revenue Share of Cell. * denotes significance at 10%; ** at 5% level and *** at 1% level.

Table 4: UPC Panel Regression of Sale Indicator (times 100) on dist

	Analgesics				Bottled Juice				Cereal			
	Store-Week		Zone-Week		Store-Week		Zone-Week		Store-Week		Zone-Week	
	(N=4,522,140)		(N=1,095,181)		(N=4,095,872)		(N=777,736)		(N=4,704,742)		(N=885,996)	
Distance to Wal-Mart	0.071***	0.087***	0.056***	0.075***	-0.084***	-0.338***	-0.103***	-0.403***	-0.074***	-0.092***	-0.087***	-0.115***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.009)	(0.014)	(0.002)	(0.002)	(0.004)	(0.005)
Linear Trend		0.003***		0.003***		-0.044***		-0.045***		-0.003***		-0.004***
		(0.000)		(0.000)		(0.001)		(0.002)		(0.000)		(0.001)
R^2	0.002	0.002	0.002	0.002	0.002	0.009	0.002	0.010	0.002	0.002	0.003	0.003

	Cookies				Dish Detergent				Fabric Softener			
	Store-Week		Zone-Week		Store-Week		Zone-Week		Store-Week		Zone-Week	
	(N=7,968,211)		(N=1,522,596)		(N=2,367,874)		(N=462,489)		(N=2,674,779)		(N=512,926)	
Distance to Wal-Mart	0.017***	-0.052***	0.008	-0.058***	-0.005	-0.118***	-0.005	-0.132***	0.009**	-0.163***	0.013	-0.204***
	(0.002)	(0.003)	(0.005)	(0.007)	(0.004)	(0.006)	(0.010)	(0.015)	(0.004)	(0.006)	(0.011)	(0.014)
Linear Trend		-0.012***		-0.010***		-0.020***		-0.019***		-0.032***		-0.034***
		(0.000)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
R^2	0.001	0.001	0.000	0.001	0.001	0.004	0.001	0.004	0.001	0.007	0.001	0.008

	Laundry Detergent				Paper Towels				Soft Drinks			
	Store-Week		Zone-Week		Store-Week		Zone-Week		Store-Week		Zone-Week	
	(N=3,354,941)		(N=645,351)		(N=1,110,969)		(N=243,761)		(N=10,900,000)		(N=2,085,206)	
Distance to Wal-Mart	0.049***	-0.219***	0.072***	-0.243***	-0.015	-0.363***	-0.016	-0.388***	-0.038***	-0.090***	-0.048***	-0.082***
	(0.003)	(0.005)	(0.008)	(0.013)	(0.011)	(0.014)	(0.027)	(0.034)	(0.004)	(0.004)	(0.009)	(0.010)
Linear Trend		-0.055***		-0.055***		-0.061***		-0.055***		-0.009***		-0.005***
		(0.001)		(0.001)		(0.002)		(0.004)		(0.001)		(0.001)
R^2	0.001	0.016	0.002	0.018	0.002	0.017	0.001	0.017	0.002	0.002	0.002	0.002

	Snack Crackers				Toothpaste				Toilet Tissue			
	Store-Week		Zone-Week		Store-Week		Zone-Week		Store-Week		Zone-Week	
	(N=3,523,478)		(N=661,460)		(N=3,831,736)		(N=819,487)		(N=1,032,093)		(N=199,385)	
Distance to Wal-Mart	0.167***	-0.113***	0.172***	-0.134***	0.044***	0.056***	0.044***	0.062***	-0.226***	-0.586***	-0.263***	-0.729***
	(0.004)	(0.005)	(0.010)	(0.014)	(0.003)	(0.003)	(0.007)	(0.007)	(0.010)	(0.012)	(0.024)	(0.034)
Linear Trend		-0.050***		-0.048***		0.002***		0.003***		-0.061***		-0.068***
		(0.001)		(0.001)		(0.000)		(0.001)		(0.002)		(0.004)
R^2	0.014	0.023	0.015	0.024	0.001	0.001	0.001	0.001	0.006	0.018	0.007	0.023

Notes: Reports the estimates from a fixed effects panel regression of sale (a binary variable) on dist and a vector of quarter dummies. T-Statistics are in brackets. Standard errors are clustered by store, and regressions are weighted by Revenue Share of Cell. * denotes significance at 10%; ** at 5% level and *** at 1% level.

Table 5: Summary of Dominick's Sample

Category	Avg. Quantity Sold	Units Sold Rank	Avg. Revenue	Revenue Rank	Coeff. On Dist
Soft Drinks	33.1	2	14,045	1	-0.038***
Cereals	9.5	6	7,786	2	-0.074***
Cookies	16.7	4	3,161	3	0.015***
Laundry Detergent	23	3	2,984	4	0.049***
Toilet Tissue	13.9	5	2,738	5	-0.226***
Bottled Juices	72.7	1	2,569	6	-0.084***
Snack Crackers	7.6	8	1,894	7	0.167***
Paper Towels	5.6	10	1,698	8	-0.015
Fabric Softeners	9	7	1,116	9	0.009**
Dish Detergent	6.1	9	1,057	10	-0.005
Analgesic	1.4	12	949	11	0.071***
Toothpaste	2.8	11	720	12	0.044***
All Products	16.8				

Notes: The selection of the sample is described in Appendix C. We visited modern stores to determine whether a product category was sold in Wal-Mart.

Table 6: UPC Panel Regression of Sale Indicator (times 100) on Distance to Wal-Mart and Share of Revenue times Distance to Wal-Mart

Analgesics

	Store-Week (N=4,522,140)		Zone-Week (N=1,095,181)	
Distance to Wal-Mart	0.104*** (0.003)	0.119*** (0.003)	0.074*** (0.004)	0.090*** (0.005)
Dist x Share	-4.418*** (0.313)	-4.336*** (0.312)	-3.262*** (0.680)	-3.006*** (0.677)
Linear Trend		0.003*** (0.000)		0.003*** (0.000)
R^2	0.002	0.002	0.002	0.002

Bottled Juice

	Store-Week (N=4,095,872)		Zone-Week (N=777,736)	
Distance to Wal-Mart	-0.044*** (0.005)	-0.288*** (0.007)	-0.054*** (0.012)	-0.343*** (0.016)
Dist x Share	-4.639*** (0.443)	-6.123*** (0.489)	-6.014*** (1.094)	-7.662*** (1.233)
Linear Trend		-0.044*** (0.001)		-0.045*** (0.002)
R^2	0.002	0.009	0.002	0.010

Cereal

	Store-Week (N=4,704,742)		Zone-Week (N=885,996)	
Distance to Wal-Mart	0.015*** (0.003)	-0.004 (0.003)	0.014** (0.007)	-0.015** (0.007)
Dist x Share	-14.073*** (0.328)	-14.372*** (0.337)	-16.389*** (0.780)	-16.739*** (0.808)
Linear Trend		-0.004*** (0.000)		-0.005*** (0.001)
R^2	0.003	0.003	0.004	0.004

Cookies

	Store-Week (N=7,968,211)		Zone-Week (N=1,522,596)	
Distance to Wal-Mart	0.015*** (0.002)	-0.052*** (0.003)	0.008 (0.005)	-0.057*** (0.007)
Dist x Share	0.380 (0.306)	-0.052 (0.319)	0.009 (0.687)	-0.463 (0.722)
Linear Trend		-0.012*** (0.000)		-0.010*** (0.001)
R^2	0.001	0.001	0.000	0.001

Dish Detergent

	Store-Week (N=2,367,874)		Zone-Week (N=462,489)	
Distance to Wal-Mart	0.055*** (0.007)	-0.048*** (0.008)	0.075*** (0.016)	-0.042** (0.018)
Dist x Share	-4.223*** (0.448)	-5.102*** (0.465)	-5.902*** (1.049)	-6.791*** (1.087)
Linear Trend		-0.020*** (0.001)		-0.020*** (0.001)
R^2	0.001	0.004	0.002	0.004

Fabric Softener

	Store-Week (N=2,674,779)		Zone-Week (N=512,926)	
Distance to Wal-Mart	0.091*** (0.007)	-0.076*** (0.008)	0.110*** (0.017)	-0.103*** (0.020)
Dist x Share	-7.044*** (0.602)	-7.600*** (0.631)	-8.574*** (1.578)	-9.103*** (1.656)
Linear Trend		-0.032*** (0.001)		-0.034*** (0.001)
R^2	0.002	0.007	0.002	0.009

Laundry Detergent

	Store-Week (N=3,354,941)		Zone-Week (N=645,351)	
Distance to Wal-Mart	0.116*** (0.006)	-0.154*** (0.007)	0.140*** (0.014)	-0.178*** (0.017)
Dist x Share	-7.958*** (0.593)	-7.710*** (0.659)	-8.314*** (1.472)	-7.985*** (1.648)
Linear Trend		-0.055*** (0.001)		-0.055*** (0.001)
R^2	0.001	0.017	0.002	0.018

Paper Towels

	Store-Week (N=1,110,969)		Zone-Week (N=243,761)	
Distance to Wal-Mart	0.101*** (0.019)	-0.222*** (0.019)	0.119*** (0.043)	-0.235*** (0.045)
Dist x Share	-3.705*** (0.377)	-4.589*** (0.420)	-4.493*** (0.842)	-5.129*** (0.927)
Linear Trend		-0.061*** (0.002)		-0.055*** (0.004)
R^2	0.002	0.017	0.002	0.017

Soft Drinks

	Store-Week (N=10,900,000)		Zone-Week (N=2,085,206)	
Distance to Wal-Mart	0.056*** (0.004)	0.003 (0.005)	0.058*** (0.010)	0.022* (0.012)
Dist x Share	-33.521*** (0.826)	-33.721*** (0.839)	-39.093*** (2.115)	-39.249*** (2.132)
Linear Trend		-0.009*** (0.001)		-0.005*** (0.001)
R^2	0.003	0.003	0.004	0.004

Snack Crackers

	Store-Week (N=3,523,478)		Zone-Week (N=661,460)	
Distance to Wal-Mart	0.111*** (0.005)	-0.147*** (0.006)	0.106*** (0.012)	-0.174*** (0.015)
Dist x Share	6.601*** (0.386)	4.214*** (0.404)	7.996*** (0.842)	5.303*** (0.904)
Linear Trend		-0.049*** (0.001)		-0.047*** (0.001)
R^2	0.014	0.023	0.016	0.024

Toothpaste

	Store-Week (N=3,831,736)		Zone-Week (N=819,487)	
Distance to Wal-Mart	0.125*** (0.004)	0.131*** (0.004)	0.127*** (0.008)	0.138*** (0.009)
Dist x Share	-9.793*** (0.365)	-9.708*** (0.366)	-11.130*** (0.831)	-10.960*** (0.836)
Linear Trend		0.001*** (0.000)		0.002** (0.001)
R^2	0.002	0.002	0.002	0.002

Toilet Tissue

	Store-Week (N=1,032,093)		Zone-Week (N=199,385)	
Distance to Wal-Mart	-0.196*** (0.019)	-0.524*** (0.019)	-0.196*** (0.044)	-0.627*** (0.048)
Dist x Share	-0.988** (0.421)	-2.038*** (0.474)	-2.243** (0.994)	-3.463*** (1.182)
Linear Trend		-0.061*** (0.002)		-0.068*** (0.004)
R^2	0.006	0.019	0.007	0.023

Notes: Share is the upc's average share of category revenue. See notes to Table 4 for other details. * denotes significance at 10%; ** at 5% level and *** at 1% level.

Table C1 Sample Selection Summary

Category	Stores		UPCs		Store - UPCs		Revenue $Millions		
	Selected	Raw	Selected	Raw	Selected	Raw	Selected	Raw	% of Total
Analgesics	85	93	320	641	15,163	40,775	29	39	75%
Bottled Juice	85	93	217	511	14,598	36,656	80	100	80%
Cereals	85	93	227	490	16,221	36,620	227	268	85%
Cookies	85	93	428	1,126	27,669	78,731	98	128	76%
Dish Detergent	85	93	125	287	8,428	22,005	33	46	73%
Fabric Softeners	85	93	156	318	10,244	25,184	35	47	76%
Laundry Detergent	85	93	236	581	14,143	45,047	95	153	62%
Paper Towels	80	93	76	164	4,183	11,741	50	67	75%
Soft Drinks	85	93	564	1,720	36,614	112,017	438	526	83%
Snack Crackers	85	93	180	425	12,425	30,603	58	71	82%
Toothpaste	85	93	288	608	14,281	39,263	23	31	73%
Toilette Tissue	81	93	57	128	3,627	9,867	81	100	81%
Total			**2,874**	**6,999**	**177,596**	**488,509**	**1,247**	**1,576**	
Percent			**41%**		**36%**				**80%**

Notes: Comparison of selected sample to raw sample. See description above for selection criteria.