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ABSTRACT

We study how the opening of a factory store impacts a retailer's demand in its other channels. It is possible that a factory store may damage a retailer's brand image and lead to substitution away from its higher quality core channels. Alternatively, the opening of a factory store may have positive effects as it may attract new buyers and serve as a form of brand advertising. In this paper, we use a natural experiment that arises from a retailer introducing a factory store in 2002. We analyze data that spans all customers and all channels from 1995 to 2007. This allows for careful pre and post analysis of the factory store opening. We find that the introduction of the factory store led to substantial positive spillovers to the core channels that lasted for multiple years. Customers purchase more items from the higher priced, higher quality channels after the factory store is opened. These positive spillovers represent approximately 17% of all of the incremental sales that result from the factory store opening (the other 83% are contributed by sales in the factory store itself).

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1. Introduction

Firms often extend their brands by offering products of varying qualities and prices. Manufacturers like Proctor and Gamble and Levi's offer products that are higher priced/higher quality (Charmin, Levis 501) and lower priced/lower quality (Charmin Basic, Levi's Signature). Vertical extensions are also common among retailers. Brooks Brothers offers its products through traditional stores, factory stores and “Brooks Brothers 346” stores, which offer products that are lower quality and typically priced 25% below the traditional store. These vertical line extensions may come with both costs and benefits. There is a risk that the vertical line extension either cannibalizes sales of the core brand or erodes brand equity. Alternatively, a vertical line extension may increase overall brand awareness and create positive spillovers for the entire portfolio.

We study the phenomenon of vertical line extensions in the context of a multi-channel retailer. The retailer's primary distribution channels (the core channels) include regular retail stores and a direct-mail channel from which customers order over the telephone, Internet and mail. The core channels typically offer in-season merchandise that is sold at full price. In addition to these core channels, the retailer also sells products through a number of factory stores, which primarily sell imperfect items or excess inventory from previous seasons. In this sense, the factory stores offer lower quality items at substantial discounts.

The firm’s expansion into factory stores provides a unique natural experiment. In November 2002 the company opened a new factory store approximately 1-hour from a major metropolitan area. We observe transactions over a period of 12 years, which includes several years both before and after the factory store opens. To measure spillovers, we examine the change in consumer spending through the company's core distribution channels (excluding the factory store itself). This provides a clean test of whether there are positive or negative spillovers in the core channels. Negative spillovers could stem from cannibalization (switching from core channels to the factory store) or damage to brand equity. Positive spillovers could stem from advertising and awareness effects.

Our analysis provides strong evidence of positive spillovers: customers who purchase from the factory store increase the number of orders that they place in the core channels. This increased spending is a large effect that endures for several years. We also observe a change in the composition of customers’ orders: after the factory opens these customers are more likely to purchase discounted items in the core channels. To further explore these results we perform additional analysis at a more granular product level. These findings confirm that much of the effect is due to spillovers in a truly different retail channel: the incremental purchases are almost all in the firm’s direct channel (mail, telephone and the Internet) rather than other physical stores. We also see that the effect is not limited to additional purchases of existing categories. Approximately 52% of the spillovers represent purchases from new categories that customers had not purchased prior to the factory store opening.

The remainder of the paper is organized as follows. In Section 2 we review related literatures. In Section 3 we describe the data and in Section 4 we estimate the impact that the factory store entry had on customers' orders in the core channels. We provide additional results in Section 5, including how the factory store impacted the composition of customers' orders, which of the core channels had the largest spillovers, and a comparison of incremental purchases from new categories versus categories customers had purchased from before. Section 6 concludes the paper.

2. Literature Review

Our findings contribute to the literatures on vertical line extensions, multi-channel retailing, product line pricing and design, and the impact of counterfeit products. We discuss each of these literatures in turn.

The literature on vertical line extensions is relatively small (Heath et al. 2011). Randall, Ulrich, and Reibstein (1998) study vertical brand extensions in the context of mountain bikes. They use field data on prices and attributes to develop a hedonic regression that relates the price premium offered by a brand to the length of the vertical product offering. Kirmani, Sood, and Bridges (1999) use a combination of field and lab studies to examine how product ownership moderates the impact of vertical line extensions. More recently, Lei et al. (2008) investigate vertical service line extensions in the hotel industry using a series of lab experiments. Collectively, the results of these papers are mixed with no clear pattern of positive or negative spillovers to the core brand from a vertical line extension.

Heath et al. (2011) contribute to this literature by demonstrating a novel finding through a series of laboratory studies. They show that line extensions have an asymmetric effect: higher quality extensions have a larger absolute impact than lower quality extensions. A high quality extension results in positive spillovers to brand reputation but the cost of negative spillovers is typically smaller in absolute value. Moreover, offering additional variety via a lower quality extension offsets some of the negative impact. Our results are consistent with this finding as we find that the negative spillovers are small in magnitude but we extend this research by documenting a positive spillover effect from a low quality extension.

A common, stylized fact from both academic research and industry reports is that customers who shop through multiple channels typically spend more than those who shop through a single channel (Neslin and Shankar 2009, Target Marketing 2005, Shop.org 2001, and Myers et al. 2004). Evidence supporting this finding has been reported in both consumer and business-to-business markets (Kumar and Venkatesan 2005) and has been shown to extend beyond spending to profits (Venkatesan et. al 2007). Our findings are also consistent with these results as we show that customers who buy from the factory store increase their spending in the core channels.

In a recent paper on multi-channel retailing, Avery et al. (2012) conduct an empirical study of retail channel expansion by a multichannel retailer. Their study is similar to ours in that they consider how existing channels are affected by opening a new retail store. Our papers are distinct in several regards. Most importantly, Avery et al. consider the opening of a full price store rather than a factory store. In the short-run they show there is substitution away from direct channels towards the new retail store. In contrast, we show that there are positive spillovers to the direct channels that endure for multiple years. Our dataset also enables us to measure treatment effects at the customer level using a model that controls for both observed and unobserved heterogeneity.

Our work also contributes to the literature on product line design (Villas-Boas 1998), much of which has focused on how to optimally price a product line (Mussa and Rosen 1978, Reibstein and Gatignon 1984, Dobson and Kalish 1988, Moorthy 1988, and Zenor 1994, Anderson and Dana 2009) or how to develop an optimal quantity discount schedule (Oren, Smith and Wilson, 1984). Our work is perhaps more closely related to theoretical research by Deneckere and McAfee (1996), who examine optimal pricing of a fully functional product and a lower quality, damaged good. In our empirical context, the retailer sells out-of-season and imperfect products, which are analogous to the damaged goods studied by Deneckere and McAfee. While we do not directly test predictions from Deneckere and McAfee's model, our empirical approach complements their theoretical model.

Finally, the introduction of counterfeit products is also related to our research as counterfeit products may be interpreted as vertical line extensions. Counterfeit products often mimic key features of an established brand, but typically provide lower overall quality at a very low price. One market where counterfeits have been extensively studied is the music industry (see Liebowitz 2006; and Oberholzer-Gee and Strumpf 2009) and much of the research documents negative spillovers to the authentic products (Givon et al. 1995, Hui and Png 2003, Liebowitz 2006 and 2008; and Hong 2008). In contrast, work by Oberholzer-Gee and Strumpf (2007) and Mortimer et al. (2010) show the opposite: positive spillovers. In Mortimer et al. (2010), the authors show that illegitimate redistribution of digital goods can increase revenue from non-digital complementary products, notably live performances. Research by Qian (2011) in the Chinese footwear industry documents the heterogeneous impact of counterfeits on sales of authentic branded products of different quality tiers. In particular, counterfeits can have both advertising effects and substitution effects that linger for several years. Since the counterfeit and authentic products share the same brand, the advertising effect benefits both brands. Qian finds that for high quality shoes, the advertising effect dominates the substitution effect and there are positive spillovers. However, for lower quality shoes the opposite occurs and there are negative spillovers. Finally, Richardson (2009) surveys a sample of consumers, and finds that they purchased more branded purses when a counterfeit brand is offered. Our research complements these findings in that we also find positive spillovers to the higher quality, full priced products when a lower quality brand extension is introduced.

3. Data

Data Description

We study data provided by a U.S. apparel retailer that sells mostly apparel through multiple distribution channels, including regular retail stores and direct-mail. Essentially all of the products are private label products carrying the retailer's own brand. Although competitors sell close substitutes, products carrying this retailer's private label brand are only available through this retailer. The dataset includes all of the transactions that customers made between November 1994 and December 2007. In November 2002, the company opened a new factory store in an existing outlet mall within one hour's drive of a major metropolitan area. The practice of locating factory stores approximately one hour from a major city is common (Coughlan and Soberman 2005) as firms try to maintain some geographic separation between factory stores and their traditional retail stores. This factory store primarily sells apparel (99% of sales). The majority of the items are liquidated or outdated (86% of sales), with the median discount approximately 25% off the full price.

We will label the period before October 2002 as the "pre-entry" period and the period after November 2002 as the "post-entry" period. We restrict attention to the 815,486 customers who had purchased from the firm prior to the factory store opening and who live within 150 kilometers driving distance of the new store. The firm defines this 150 kilometer radius as the store's "Retail Trade Area" (RTA).

Our data contains several demographics variables, including the customer's age, whether they are married, their estimated annual income, and the number of children in the household. Age and income are normalized (a request from the company that provided the data). We also know the household zip code and so we use both Google and Yahoo Maps to estimate the driving distance (measured in kilometers) from each household to the factory store.

We construct several variables from the pre-entry transaction data. These customer-level variables include:

Tenure	The number of years between the customer's first purchase from the firm and the date that the factory store opens.
Recency	The number of years between the opening date and the most recent purchase prior to that date.
Pre-Entry Annual Order Rate	The average annual order rate (excluding the first order) in the period between the date of the first order and the date the factory store opened.
Pre-Entry Order Size	The average size in dollars of the orders placed during the pre-entry period.
Pre-Entry Items Per Order	The average number of items in orders placed during the pre-entry period.
Pre-Entry Selling Price	The average price paid for each item purchased during the pre-entry period.
Pre-Entry % Full Price Paid	The Selling Price divided by the Full Price and then averaged across items purchased during the pre-entry period.
Pre-Entry Discount Frequency	The fraction of items purchased at a discount during the pre-entry period.

Summary statistics for all of these variables are presented in Table 1. Note that these statistics are for customers who had purchased from the brand through the core channels <u>before</u> the factory store opened. In this study, we focus on how the factory store opening affected purchasing by these existing customers. Each customer's purchase history will serve as a natural control for the customer's purchasing after the factory store opens.

Insert Table 1 about here.

Recall that prior to the factory store opening the customers in our sample had all made at least one purchase from the firm. These purchases were made in what we will describe as the "core channels," including other retail stores and the firm's direct mail channel (primarily telephone orders). In the 24-months before the introduction of the new factory store, the 815,486 customers made 9.4% of their purchases in other retail stores, and the remaining 90.6% of their purchases in the direct channel.

4. Estimating the Factory Store Spillover Effects

Our analysis is conducted at a customer level. In particular, we calculate before and after purchases by individual customers. We then compare the change in purchases according to whether the customer made a purchase from the factory store ("adopters") or never purchased from the factory store in our data period ("non-adopters"). Much of this customer-level analysis is focused on addressing the inherent differences in the characteristics of these two customer groups.

Adopters and Non-Adopters

We define the customers who purchased at least once from the factory store as "adopters", and those who never purchased from the factory store as "non-adopters". In Table 2 we compare the demographic characteristics and the pre-entry purchases by these two groups of customers.

Insert Table 2 about here.

The findings reveal several important differences. The adopters live much closer to the factory store and are more likely to be married, richer and older. They have significantly longer tenure with the retailer, and historically (pre-entry) have higher annual order rates and larger order sizes. These differences confirm that we need to control for self-selection to accurately estimate the causal impact of opening the factory store. We will do so by combining propensity-score matching and difference-in-difference estimates to control for individual customer differences.

Overview of Methods

Difference-in-difference estimation has become a widely adopted method for analyzing natural experiments (Bertrand, Duflo and Mullainathan 2004). However, when the control group is very different from the treatment group, the before-after change in the control group can give a poor prediction of the before-after change in the treatment group. It is therefore important to find similar customers to serve as the counterfactual for what these factory-store shoppers would do if they did not adopt the factory store.

We will use propensity score sub-classification to establish strata (groups) of customers who are comparable in all of our observable variables except their factory store status. We then execute difference-in-difference estimations within each stratum. The advantage of this semi-parametric approach is that it controls for both observable differences and time-invariant unobservable differences. We can calculate the average treatment effects for the entire sample of active customers as well as heterogeneous effects for each stratum of customers.

We also introduce an additional control through the design of the customer sample. When using a fixed panel of customers who have all made a prior purchase, we would expect that over time some of these customers will become "inactive". This attrition reflects changing customer preferences and a range of other factors that could lead customers to stop purchasing (including the reality that some customers literally die). For this reason using a purchase from the factory store after it opens as our identifying variable may introduce a potential confound; customers who make a purchase from the factory store are by definition still active. Therefore, it is possible that the customers who did not adopt have a higher proportion of customers who have become inactive by the end of the data period. We can address this concern by restricting attention to customers who made at least one purchase (from any channel) after the factory store opened. This ensures that the decision to purchase after the factory store opened is common to both adopters and non-adopters of the factory store.

We next describe the propensity score approach used to match customers in the adopter and non-adopter samples.

Propensity Score Approach

The propensity score method for matching samples (Rosenbaum and Rubin, 1983) has been increasingly used in economics and other disciplines (see for example Busse et al. 2006; and Qian 2007). The propensity score, which in this setting is the predicted propensity to adopt a factory store, is interpreted as a sufficient statistic for all the relevant covariates that may influence both the treatment (consumer's adoption of factory store) and the outcome (changes in purchasing behaviors).

We begin by modeling the probability that a customer adopts (purchases) from the factory store. Let $Adopt_i$ equal one if a customer purchases from the factory store, and zero otherwise. We estimate a logistic regression with $Adopt_i$ as the dependent variable:

$$logit\ P(Adopt_i = 1) = \boldsymbol{\alpha X_i} \qquad (1)$$

The propensity score for each customer ($Score_i$) is simply the fitted values from this logistic regression. The vector $\boldsymbol{X_i}$ includes the demographic variables and pre-entry purchasing characteristics of each customer *i*, together with their quadratic terms and interaction terms. A complete list of the variables is reported in Table A1, together with goodness of fit measures. The coefficients are available from the authors.

The *Pre-Entry Annual Order Rate*, *Pre-Entry Discount Frequency*, *Recency*, and *Distance* are strong predictors of whether a customer will purchase from the factory store. Not surprisingly, the further the customer lives from the factory store, the less likely the customer will make a purchase at the store. The results also show that factory store adopters are more likely to be married. The probability of adopting the factory store increases with age and income, although the effects are diminishing as indicated by the negative coefficients on the quadratic terms in the model. The factory store adopters are also more likely to be customers who purchased more recently and more frequently, and they tend to have had longer relationships with the company (their first purchases were earlier). They also tend to be more price sensitive.

Effectiveness of Propensity Score Sub-Classification

Rubin (2001) shows that propensity score sub-classification to five strata is expected to eliminate 95% of the biases in the final estimate resulting from differences in confounding covariates. For this reason we focus on five strata, but later also conduct robustness checks with up to 24 strata. We assign the customers to the five strata using the quintiles of the propensity scores for the adopting customers. We label the strata in order, so that Stratum 1 includes the customers with the lowest propensity to adopt the factory store, while the Stratum 5 customers have the highest propensity to adopt.

In the Appendix (Table A2) we report the means and standard deviations for each covariate for both the adopters and non-adopters. Comparing across strata these means vary substantially. Notably, consumers in Stratum 1 live significantly farther away from the factory store (about 80 km more in driving distance) than consumers in Stratum 5. Customers in Strata 1 and 2 also have lower average incomes than customers in Strata 3 through 5, and purchase less frequently and place smaller orders prior to the factory store entry. The *Pre-Entry % Full Price Paid* and *Pre-Entry Discount Frequency* indicate that the average price sensitivity also increases by strata, with the lowest price sensitivity in Stratum 1 and the highest in Stratum 5. This is intuitive as more price sensitive customers have a higher propensity to adopt the factory store (and we would expect them to be classified in the strata with the highest propensity score values).

Within each stratum the propensity score method helps to preserve homogeneity among customers between the adopter and non-adopter customers. Notably, within each stratum there are no significant differences in the adopter and non-adopter averages for any of the covariates. We can be confident that any difference between adopters and non-adopters in the amount of change in their purchasing behavior after the factory store opens cannot be attributed to differences in these covariates. In other words, all customers within each stratum were (approximately) equally likely to adopt the factory store based on the set of observed traits, and the realized adoption status can be considered independent of these observable customer characteristics.

To estimate the impact of the factory store opening on purchases in the core channels we will use a difference-in-difference approach. In particular, we will compare the difference in purchasing before and after the factory store opened for the adopters and non-adopters in each stratum (excluding any purchases from the factory store itself). This provides an additional control for customer differences. In particular, our identifying assumption is that without the factory store opening there would be no difference in the change in purchasing from the core channels for adopters versus non-adopters (we will later test this assumption). We describe our difference-in-difference analysis next.

Difference-In-Difference Estimation within Strata

We estimate the effect of factory store adoption on the customers' shopping behaviors in the core channels within each propensity score stratum. Customers' purchasing behaviors through all the core channels excluding the factory store are used as the outcome measures so that we can cleanly isolate the potential spillover effects of the factory store on the other channels. The unit of analysis is a customer x period. For each customer we include both a 2-year pre-entry period (November 2000 – October 2002) and a 2-year post-entry period (November 2002 – October 2004). The sample includes all of the customers who made at least one purchase in both the pre-entry and post-entry periods.

The dependent variable is the *Number of Orders* that customer *i* placed in period *t*. Notice this is a "count" measure and so we estimate a quasi maximum likelihood (QML) Poisson model with (conditional) customer fixed effects (Wooldridge 1999). This estimator is consistent under very general conditions. In contrast to the regular Poisson model the estimator is consistent even if there is over-dispersion or under-dispersion in the latent variable model. Moreover, the robust variance-covariance matrix allows for deviations from the Poisson distribution together with arbitrary customer-level fixed effects. We include the following system of independent variables:

$$\ln(\lambda_{it}) = \beta_0 + \beta_1\, Adopt_i * Open_t + \beta_2\, Open_t \qquad (2)$$

λ_{it} is the purchase rate for customer *i* in period *t*. $Open_t$ is a binary flag that is set equal to one in the post-entry period and zero in the pre-entry period. $Adopt_i$ is a binary variable identifying customers who make a purchase in the factory store at any time in the post-entry period. The coefficient of interest is the interaction coefficient β_1, which estimates the difference-in-difference effect. Notice that the *Adopt* variable is co-linear with the customer-fixed effects and so the main effect is subsumed by these fixed effects (for the same reason we did not include customers' estimated propensity scores as control variables).

We estimate this model separately for each of the five strata. The coefficients are reported in Table 3 together with standard errors clustered by customer. The key finding is that in all five strata the β_1 interaction coefficients are positive and highly significant. This indicates that adoption of the factory stores had a positive spillover on the number of orders placed in the core channels. Aggregating across the five strata we calculate that customers increase their orders in the core channels by 0.35 orders per year.[1] This average has a standard error of 0.02, and is significantly different from zero at the 1% level.

Insert Table 3 about here.

To help evaluate these findings, the average number of orders that the adopters placed in the factory store itself was 1.73 orders per year. Therefore, the positive spillovers contributed approximately 17% of the incremental orders received.

The factory store was associated with the smallest increase in purchasing among adopters in Stratum 5. Recall that these customers live closest to the factory store and had the highest pre-adoption purchase rates. Because these customers are close to the factory store it seems likely that the transaction costs of visiting the factory store are low and this may have reduced their spillover purchasing to the core channels.

Verifying the Identifying Assumption

The identifying assumption in our model is that in the absence of the factory store opening there would have been no difference in the change in purchasing behavior of the adopters and non-adopters. A standard approach to evaluating this assumption is to investigate whether the changes in purchasing behavior around the factory store opening are unique to these periods, or whether they also occurred in other periods (see for example Busse, Silva-Risso and Zettelmeyer 2006; and Busse, Simester and Zettelmeyer 2010). We repeated the analysis using the same sample of customers and five alternative time periods. Each of these alternative periods included a two-year pre-period, and a two-year post-period. The actual data periods and the findings for these replications are reported in the Appendix (Table A3). The β_1 coefficients (for the *Open * Adopt* interaction) average just 0.78%, as compared to effect sizes of 15.4%, 17.8%, 14.8%, 12.9% and 5.8% in Table 3. We conclude that the coefficients estimated around the factory store opening are uncommonly large compared to what we would expect from estimating the same model in different time periods.

Additional Robustness Checks

While the propensity score classification into five strata already ensures considerable overlap in the covariate distributions for the adopters and non-adopters, we replicated the analysis when classifying the observations into finer groups, up to 24 strata. The distributions of the propensity score within each stratum are indistinguishable for the adopters and non-adopters by the Kolmogorov-Smirnov test. The detailed results for these replications are available from

[1] This is calculated by multiplying the estimated average treatment effect across the five strata (15.5%) by the baseline order rate (2.23).

the authors. They replicate our earlier findings: adopters of the new factory store increased their annual orders in the core channels after the store entry compared to the non-adopters. The effects are statistically significant at the 5% or 1% levels. The trend that the positive spillover effects are weakest for the customers living closest to the store also survives.

We also re-estimated the models adding year fixed effects.[2] Reassuringly, the pattern of results remains unchanged. We have also considered other specifications. For example, we investigated using a random effects specification instead of fixed effects. These changes had little impact on the coefficients of interest.

It is at least theoretically possible that customers who purchased from the factory store were treated differently by the firm. In particular, the firm regularly sends catalogs to its customers. Although the firm did not have an explicit policy of making different mailing decisions for customers who purchased from factory stores, it is possible that the algorithms it uses to make mailing decisions led to customers who adopted the factory store receiving additional catalogs. To control for this possibility we obtaining detailed data from the company describing which customers received each of the firm's catalogs. In Table 4 we re-estimate the Poisson QML models when explicitly controlling for the number of catalogs mailed to each customer each year. The findings survive when we include this additional control.

Insert Table 4 about here.

Recall that in the findings in Table 3 we used two-year pre-entry and post-entry periods. In Table 5 we report the results when using pre-entry and post-entry periods of 1, 2, 3, 4, 5 and 6 years duration. The findings are robust to these different period lengths. They also reveal a consistent pattern. The effect sizes are larger when we use periods of 4 to 6 years compared to 1 to 3 years. This suggests that the effect may have endured beyond the 2-year window that we used in Table 3. In the next sub-section we explicitly investigate this issue by evaluating the persistence of the effect.

Insert Table 5 about here.

Temporal Effects

To study how long the effect endured we modified Equation 2 as follows:

$$\ln(\lambda_{it}) = \Upsilon_0 + \Upsilon_{1t}\, Adopt_i * Year_t + \sum_t \Upsilon_{2t}\, Year_t \qquad (3)$$

The dependent variable Y_{it} is again the *Number of Orders* from customer *i* in the core channels in year *t*. $Year_t$ is a set of binary flags identifying the 12 years under observation. Because the

[2] Because the store-entry dummy ($Open_t$) is collinear with the year-fixed effects the main effect for this variable was omitted in the year fixed effects regressions

factory store opened in November we will start each annual period in November of the previous year. For example, the year 2000 extends from November 1, 1999 through October 31, 2000. We use the Poisson QML model to estimate Equation (3) within each stratum. Recall that this model includes (conditional) customer fixed effects.

The interpretation of this model is straightforward. The parameter vector γ_{1t} describes the difference in the *Number of Orders* placed by adopters versus the non-adopters in each stratum in each of the 12 years. Because we omitted the dummy indicating the entry year 2002 from the regression model, these effect sizes are all differences compared to the first year the factory store was open. Notice that our definition of an adopter is fixed across the 12-year period ($Adopt_i$ is not sub-scripted by t). This ensures that any difference in the γ_{1t} and γ_{2t} across the years cannot be attributed to changes in the composition of these sub-samples.

The findings are illustrated in Figure 1, where we report the γ_{1t} coefficients. The coefficients for the interactions between the adoption dummy and the year dummies (γ_{1t}) are positive and significant for several years after the factory store opens in 2002. This demonstrates a positive structural break in the *Number of Orders* after the entry of the factory store.

Insert Figure 1 about here.

The trends in Figure 1 also clearly illustrate that the positive spillovers peaked more than two years after the entry of the new factory store for most strata and lasted for at least four years. We conclude that the positive spillovers from the factory store on adopters' spending in the core channels were felt almost immediately after the store entry and persisted throughout the sample period.

Summary

Recall that in the introduction of the paper we recognized that retailers face an important trade-off when introducing a new distribution channel, particularly one that sells discounted, lower-quality products. There is a risk that the vertical line extension cannibalizes sales of the core brand or erodes the brand equity of the core brand. Our evidence that the introduction of a factory store increased purchases in the firm's core channels indicates that any cannibalization or brand erosion effects were outweighed by positive spillovers.

There are also at least three reasons to believe that the positive spillovers that we have reported may be conservative. First, our model defines the date of adoption as the date of store opening for all customers. In practice the actual date varied, with some customers making their first purchase in the factory store many months after the store opened. In these interim periods the model treats customers who have not yet adopted as if they had adopted. This will tend to reduce the size of any adoption effects. However, this approach offers some important advantages. As we discussed above, we can compare the decisions of adopters and adopters over time, without having to worry about changes in the composition of these sub-samples. Even more importantly, when estimating the impact of adoption we simply need to control for the propensity to adopt, we do not need to control for any self-selection introduced by the timing of the adoption decision.

The second reason that we may believe that our findings are conservative is that we constructed the sample to ensure that all of the customers made a purchase from the firm after the entry of the factory store (they also all purchased before the factory store opened). Recall that this restriction was designed to ensure that customers in the two samples were all active after the factory store was opened. However, we note that one way that a positive spillover from the factory store could be manifested is in an increased probability that customers remain active. By restricting attention to customers who were all active after the factory store opened, we eliminate the potential for this positive spillover. In doing so we may be under-estimating the extent of the positive spillover effects.

Finally, it is possible that some adopters of the factory store may be misclassified as non-adopters. The firm invests considerable effort to match customers in its retail stores with customers from its catalog and Internet channels. They do so by asking for identifying information at the point of sale and matching customers' credit card numbers. Some of this matching is done for them by specialized firms that use sophisticated matching algorithms. However, the matching process is not perfect. As a result, it is possible that some of the customers we treat as non-adopters may actually have purchased in the factory store (the reverse in which we treat customers as adopters when they are non-adopters is a much less likely occurrence). These misallocation errors will tend to reduce estimates of the differences in the behavior of the two groups of customers.

In the next section we explore a series of additional results, including how the entry of the factory store affected the composition of customers' orders, and how the findings varied across the core channels.

5. Additional Results

Composition of the Orders

To investigate how the entry of the factory store affected the composition of customers' orders through the core channels we constructed three new dependent variables:

Items Per Order The number of items per order.

Selling Price The average price paid.

Discount Frequency The fraction of items purchased at a discount.

These three measures were calculated separately for the 2-year pre-entry and post-entry periods for each customer. Notice that the measures are only well-defined if customers placed an order. Therefore in this analysis we restrict attention to customers who placed at least one order in the core channels in both the pre-entry and post-entry periods.[3] This yields two observations for each customer for each measure.

None of these dependent measures are count measures and so we use OLS rather than the QML Poisson model to estimate how the factory store entry contributed to changes in these three measures. In particular, for each measure we estimated the following model within each stratum:

$$Y_{it} = \tau_0 + \tau_1 Open_i * Adopt_i + \tau_2 Open_i + \sum_i \tau_i Customer_i \quad (4)$$

The $Customer_i$ terms are customer fixed effects. In Table 6 we report the coefficients of interest (τ_1) together with standard errors clustered at the customer-level.

Insert Table 6 about here.

Factory store adoption is not associated with a significant change in the average price that customers paid for orders purchased through the core channels. There is some evidence of an increase in the number of items per order, with a significant effect in Strata 1 and 3 and a marginally significant effect in Stratum 2. However, the largest impact that the factory store had on the composition of customers' orders in the core channel appears to be customers' purchases of discounted items. The fraction of items purchased at a discount in the core channels increased by approximately 2% (from a base of 10%).

This evidence that the factory store increased the proportion of discounted items purchased through the core channels is consistent with a series of papers showing that promotions may increase customers' price or deal sensitivities (Mela et al. 1997, 1998; Jedidi et al. 1999; Anderson and Simester 2004). It is possible that the discounts customers obtained through the factory store made customers more reluctant to purchase at full price in the future. A related group of theories argues that customers evaluate a transaction against a reference price (Thaler 1985, Kalyanaram and Winer 1995). If discounts in the factory store lowered customers' reference prices, these customers may be more likely to seek out lower-priced items in the

[3] Recall that our sample in Section 4 includes all of the customers who placed at least one order before and after the factory store entry in any channel.

future. These two theories are complementary; the reference price argument may provide an explanation for the shift in deal sensitivities.

Channel Differences

Our analysis has measured the impact of the factory store opening on sales in all of the firm's core channels (excluding the factory store itself). These core channels include two distinct channels: (1) other retail stores and (2) the firm's direct channel. The direct channel is essentially a catalog-driven channel, with customers placing orders over the telephone, via mail, and in the firm's Internet site. As we discussed in Section 2 the direct channel is considerably larger than the retail store channel, representing over 90.6% of orders.

In Table 7 we distinguish between orders placed in the retail store and direct channel. In particular, for each customer we count the number of orders placed in the retail stores pre and post-entry of the factory store (excluding the factory store itself). We then re-estimate Equation 2 using these measures. Similarly we also count the number of pre and post-entry orders in the direct channel and separately re-estimate Equation 2 with these measures.

Table 7 about here

Given that our identifying event is the adoption of the factory store we might anticipate that the strongest effects would be observed at other retail stores. Because customers have demonstrated a willingness to purchase through a (physical) factory store it might initially seem that any spillovers would be more likely in other physical stores. However, the retailer does not have other retail stores located close to the new factory store's RTA (where all of the customers in our study live). For these customers purchasing in other retail stores is relatively inconvenient. The findings are consistent with this: almost all of the incremental orders are placed in the direct channels, and there is no significant increase in orders in the firm's other retail stores. More specifically, approximately 96% of the spillovers to the core channel occurred in the direct channel, with just 4% occurring in other retail stores.

This finding confirms that the impact of factory stores is truly "cross-channel"; the incremental spillover from a new physical store extends to a completely different channel. For many of these customers ordering in the direct channel is the only convenient incremental purchasing mechanism outside the factory store and so if other physical retail stores were located in this RTA then the cross-channel effects may not be as strong. However, the results clearly establish that a retail line extension can generate cross-channel spillovers.

Category Differences

We also investigate the extent to which the positive spillovers varied across categories. A natural question is whether the spillovers led customers to make incremental purchases in new categories that they had not purchased from prior to the factory store opening.

To investigate the impact on purchases in new categories requires a different identification approach. In particular, we can no longer conduct a difference-in-difference analysis as all customers have zero pre-entry orders in these categories. Instead we are limited to observing post-entry demand, which also prevents us from including fixed effects for each individual. Therefore, to evaluate whether the spillovers extend to purchases in new categories versus existing categories, we estimated a random effects Poisson model using only post-entry purchases. We use the same sample of customers and compare post-entry purchases in the core channels for customers who adopted and did not adopt the factory store. The identifying assumption in these models is that these customers would have made the same post-entry purchases in the core channels if the factory store had not opened. This is a stronger assumption than in the difference-in-difference models that we use in the rest of the paper, and puts considerable reliance on the propensity score matching. For this reason we do not formally report these results (they are available from the authors). However, we do note that our focus is on comparing the impact on purchases from new categories and categories that customers had purchased from prior to the factory store opening. It seems likely that any limitations in these models are likely to be common to both sets of models.

The findings indicate that 48% of the spillovers to the core channels came from incremental purchases in categories that customers had purchased from before. The other 52% of the spillovers came from incremental purchases in new categories. These findings suggest that adoption of the factory story led to incremental breadth of purchases (trial of additional categories) rather than just increased depth of purchases from the same categories.

Summary

Our results reveal that the opening of a factory store by an apparel retailer led to an increased propensity to purchase discounted items in the core channels among customers who adopted the factory store. We also observe that the increase in orders placed in the core channel after the factory store opened was primarily attributable to incremental orders through the firm’s direct channel, rather than additional orders in other retail stores. Because there were no other retail stores located close to these customers the small impact on sales in this channel is unsurprising. However, the results do confirm that a retail line extension in one channel can lead to positive spillovers in another channel.

6. Conclusion

In this paper, we analyzed a natural experiment to measure spillovers from introducing a lower priced, lower quality channel on other channels. The results demonstrate that the factory store led to positive spillovers on purchases by existing customers through the higher priced higher quality core channels. We estimate that approximately 17% of all of the incremental sales from the factory store opening are due to spillovers to the core channel. Failing to recognize these positive spillovers would greatly under-estimate the impact of the factory store. The analysis reveals that the effect primarily results from an increase in the frequency of orders through the core channels, rather than a change in the size of those orders. The positive spillovers persist throughout our multi-year data period and almost all comprise incremental orders in the firm's direct channels (mail, telephone and Internet), rather than additional purchases in other retail stores.

Introduction of a lower price lower quality product has often been viewed as a threat to higher price higher quality co-branded products. However, we find virtually no evidence of cannibalization or substitution away from the core channel. This is a robust result that survives replication using different estimation approaches. This finding suggests the extending a brand downward in the price-quality spectrum may not necessarily damage the higher quality core brand. The absence of cannibalization may in part reflect the firm's careful separation of the factory store from the core channels. The factory store is located geographically distant from the existing customers and offers merchandise that is out of season. In the apparel industry, these differences may be sufficient to prevent cannibalization and facilitate segmented pricing.

A limitation of our study is that we cannot fully explain why customers place additional orders via the core channel. This is not unique to this study as other researchers (Avery et al. 2012) have also struggled to identify a specific mechanism. In our context, we speculate that the new channel created both awareness and trial of new products and these may have enhanced the perceived value of the brand. Future work is needed to fully understand the source of positive spillovers in multichannel retailing.

7. References

Anderson, Eric T. and James Dana (2009), "When is Price Discrimination Profitable," *Management Science*, 55(6), 980-989.

Anderson, Eric T., and Duncan I. Simester (2004), "Long-Run Effects of Promotion Depth on New Versus Established Customers: Three Field Studies," *Marketing Science*, 23(1), 4-20.

Anderson, Eric T., Karsten Hansen and Duncan I. Simester (2009), "The Option Value of Returns: Theory and Empirical Evidence," *Marketing Science*, 28(3), 405-423.

Arndt, J. (1967), “Role of Product-Related Conversations in the Diffusion of a New Product,” *Journal of Marketing Research*, 4(3), 291-295.

Avery, Jill, Thomas J. Steenburgh, John Deighton, & Mary Caravella (2012), “Adding Bricks to Clicks: Predicting the Patterns of Cross-Channel Elasticities Over Time,” *Journal of Marketing*, 76 (May), 96–111.

Berger, J., A. Sorensen, and S. Rasmussen (2010), “Positive Effects of Negative Publicity,” *Marketing Science*, 29(5), 815-827.

Betrand, Marianne Esther Duflo and Sendhil Mullainathan 92004), “How Much Should We Trust Differences-in-Differences Estimates?” *Quarterly Journal of Economics*, 119(1), pp. 249-75.

Blackshaw, P. (2008), *Satisfied Customers Tell Three Friends, Angry Customers Tell 3,000: Running a Business in Today’s Consumer-Driven World*, Broadway Business, New York.

Busse, Meghan, Jorge Silva-Risso and Florian Zettelmeyer (2006), “$1,000 Cash Back: The Pass-Through of Auto Manufacturer Promotions,” *American Economic Review*, 96(4), 1253-1270.

Busse, Meghan, Duncan I Simester and Florian Zettelmeyer (2010), “The Best Price You’ll Ever Get: The 2005 Employee Discount Promotions in the U.S. Automobile Industry,” *Marketing Science*, 29(2), 268-290.

Chevalier, Judith. A., and Dina Mayzlin (2006), “The Effect of Word of Mouth on Sales: Online Book Reviews,” *Journal of Marketing Research*, 43(3), 345-354.

Coleman, J. S., E. Katz, H. Menzel (1966), *Medical Innovation: A Diffusion Study,* Bobbs-Merrill, Indianapolis.

Coughlan, Anne and David A. Soberman (2005), “Strategic Segmentation Using Outlet Malls,” *International Journal of Research in Marketing*, 22, 61-86.Deneckere, Raymond and Preston McAfee (1996), “Damaged Goods,” Journal of Economics & Management Strategy, Volume 5, Number 2, Summer 1996, 149-174

Deneckere, R. and P. McAfee (1996) “Damaged Goods,” Journal of Economics & Management Strategy, Volume 5, Number 2, Summer 1996, 149-174.

Dobson, Gregory and Shlomo Kalish (1988), “Positioning and Pricing a Product Line,” *Marketing Science*, 7(2), 107-125.

Gabszewicz, J. and J.-F. Thisse (1979), “Price Competition, Quality and Income Disparities,” *Journal of Economic Theory*, 20, 340-359.

Givon, M. and E. Muller (1995), “Software Piracy -- Estimation of Lost Sales and the Impact on Software Diffusion,” *Journal of Marketing*, 59 (1): 29-37.

Godes, David and Dina Mayzlin (2009), “Firm-Created Word of Mouth Communication: Evidence from a Field Test,” *Marketing Science*, 28(4), 721-739.

Goldenberg, J., B. Libai, S. Moldovan, E. Muller (2007), “The NPV of Bad News,” *International Journal of Research in Marketing*, 24(3), 186-200.

Heath, Timothy, Devon DelVecchio, and Michael S. McCarthy (2011), “The Asymmetric Effects of Extending Brands to Lower and Higher Quality,” *Journal of Marketing*, 75(3), 3–20.

Hong, S.-H. (2008), “Measuring the Effect of Napster on Recorded Music Sales,” Manuscript available at https://netfiles.uiuc.edu/hyunhong/www/research.htm.

Hui, Kai-Lung and I.P.L. Png (2003), “Piracy and the Legitimate Demand for Recorded Music,” *Contributions to Economic Analysis and Policy*, 2(1), Article 11.

Iyengar, R., C. Van den Bulte, T. W. Valente (2008), “Opinion Leadership and Social Contagion in New Product Diffusion,”' *Marketing Science Institute Report 08-120*, Marketing Science Institute, Cambridge, MA.

Jedidi, Kamel, Carl F. Mela and Sunil Gupta (1999), “Managing Advertising and Promotion for Long-Run Profitability,” *Marketing Science*, 18(1), 1–22.

Kalyanaram, Gurumurthy and Russell S. Winer (1995), “Empirical Generalizations from Reference Price Research,” *Marketing Science*, 14(3), Part 2, G161–G169.

Kirmani, Amna, Sanjay Sood and Sheri Bridges (1999), “The Ownership Effect in Consumer Responses to Brand Line Stretches,” *Journal of Marketing*, 63, 88-101.

Kumar V. and Rajkumar Venkatesan (2005), “Who Are Multichannel Shoppers and How Do they Perform?: Correlates of Multichannel Shopping Behavior,” *Journal of Interactive Marketing*, 19 (Spring), 44-61.

Lei, Jing, Ko de Ruyter, and Martin Wetzels (2008), ‘‘Consumer Responses to Vertical Service Line Extensions,’’ *Journal of Retailing*, 84 (3), 268-280.

Liebowitz, S. J. (2006), ``Economists Examine File-Sharing and Music Sales,'' in *Industrial Organization and the Digital Economy*, eds. G. Illing and M. Peitz. Cambridge: MIT Press, 145-174.

Liebowitz, S. J. (2008), ``Research Note: Testing File Sharing's Impact on Music Album Sales in Cities,'' *Management Science*, 54, 852-859.

Mela, Carl F., Sunil Gupta and Donald R. Lehmann (1997), “The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice,” *Journal of Marketing Research*, 34(2), 248–261.

Mela, Carl F., Kamel Jedidi and Douglas Bowman (1998), “The Long-Term Impact of Promotions on Consumer Stockpiling Behavior,” *Journal of Marketing Research*, 35(May), 250–262.

Moorthy, Sridar (1988), “Product and Price Competition in a Duopoly,” *Marketing Science*, 7(2), 141-168.

Mortimer, J. and J. H., C. Nosko, and A. Sorensen (2010), “Supply Responses to Digital Distribution: Recorded Music and Live Performance,” *Information Economics and Policy*, forthcoming.

Mussa, M. and S. Rosen (1978), “Monopoly and Product Quality,” *Journal of Economic Theory*, 18, 301-317.

Myers, Joe, Evan Van Metre, and Andrew Pickersgill (2004), "Steering Customers to the Right Channels," *The McKinsey Quarterly: McKinsey on Marketing*, October.

Neslin, Scott and Venkatesh Shankar (2009), “Key Issues in Multichannel Customer Management: Current Knowledge and Future Directions,” *Journal of Interactive Marketing*, 23(1), 70-81.

Oberholzer-Gee, Felix and Koleman Strumpf (2007), “The Effect of File Sharing on Record Sales: An Empirical Analysis,” *Journal of Political Economy*, 115(1), 1-42.

Oberholzer-Gee, Felix and Koleman Strumpf (2009), “File-Sharing and Copyright,” in Joshua Lerner and Scott Stern (Eds.) *Innovation Policy and the Economy*, Volume 10, MIT Press, Cambridge MA.

Oren, S., S. Smith and R. Wilson (1984), “Pricing a Product Line,” *Journal of Business*, 57, S73-S99.

Qian, Yi (2007), “Do National Patent Laws Stimulate Domestic Innovation In A Global Patenting Environment? A Cross-Country Analysis of Pharmaceutical Patent Protection: 1978-2002,” *Review of Economics and Statistics*, 89(3), 436-453.

Qian, Yi (2008), “Impacts of Entry by Counterfeiters,” *Quarterly Journal of Economics*, 123(4), 1577-1609.

Qian, Yi (2011), “Counterfeiters: Foes or Friends,” NBER Working Paper 16785.

Randall, Taylor, Karl Ulrich and David Reibstein (1998), “Brand Equity and Vertical Product Line Extent,” *Marketing Science*, 17(4), 356-379.

Reibstein, David J., and Gatignon Hubert (1984), “Optimal Product Line Pricing: The Influence of Elasticities and Cross-Elasticities,” *Journal of Marketing Research*, 21(3), 259–267.

Richardson, R. (2009), “Simultaneous Distinction, Democratization and Omnivorism Effects: A Longitudinal Analysis of Dynamic Symbolic Boundaries in Counterfeit Consumption Networks,” *PhD Dissertation*, Harvard Business School, Cambridge MA.

Rosenbaum, P. and D. Rubin (1983), “The Central Role of the Propensity Score in Observational Studies for Causal Effects,” *Biometrika*, 70, 41-55.

Shop.org (2001), “Multichannel Report 2001”, www.shop.org .

Target Marketing (2005), “How to Find Profitable Multichannel Shoppers,” October 1, www.targetmarketingmag.com .

Thaler, Richard (1985), “Mental Accounting and Consumer Choice,” *Marketing Science*, 4(3), 199–214.

Van den Bulte, Christophe and Stefan Wuyts (2007), *Social Networks and Marketing*, Marketing Science Institute, Cambridge MA.

Venkatesan, Raj, V. Kumar and Nalini Ravishanker (2007), “Multichannel Shopping: Causes and Consequences,” *Journal of Marketing*, 71(2), 114-132.

Villanueva, Julian, Shijin Yoo, and Dominique M. Hanssens (2008), “The Impact of Marketing-Induced Versus Word-of-Mouth Customer Acquisition on Customer Equity Growth,” *Journal of Marketing Research*, 45, 48-59.

Villas Boas, Miguel (1998), “Product Line Design for a Distribution Channel,” *Marketing Science*, 17(2), 156-169.

Zenor, Michael (1994), “The Profit Benefits of Category Management,” *Journal of Marketing Research*, 31(2), 202-213.

Table 1
Summary Statistics

	Mean	Standard Deviation
Age	43.23	10.91
Married	0.69	0.46
Income	3.81	2.55
Number of Children	0.59	0.92
Distance to Factory Store (km)	81.80	30.73
Tenure	5.54	2.09
Recency	2.30	2.21
Pre-Entry Annual Order Rate	1.38	1.83
Pre-Entry Order Size	110.47	83.94
Pre-Entry Items per Order	2.39	1.89
Pre-Entry Selling Price	49.83	28.13
Pre-Entry % Full Price Paid	0.96	0.07
% of Discounted Items	0.10	0.20

The sample includes the 815,486 customers who live within 150 miles of the factory store and who have made at least one purchase from the brand prior to the entry of the factory store. The unit of analysis is a customer. *Income* and *Age* are presented as index values at the company's request (to protect privacy). *Pre-Entry % Full Price Paid* is calculated as the *Selling Price* divided by the *Full Price* and then averaged across items. *Discount Frequency* is calculated as the fraction of items purchased on sale (below full price).

Table 2
Demographics and Pre-Entry Purchasing by Adopters and Non-Adopters of the Factory Store

	Non-Adopters	Adopters	Difference
Age	43.27	42.03	1.24**
	(0.01)	(0.05)	(0.05)
Married	0.68	0.76	-0.08**
	(0.001)	(0.001)	(0.001)
Income	3.76	4.44	-0.69**
	(2.52)	(2.61)	(0.02)
Number of Children	0.59	0.65	-0.07**
	(0.92)	(0.94)	(0.01)
Distance to Factory Store (km)	83.14	45.29	37.85**
	(30.97)	(27.66)	(0.17)
Tenure	5.52	5.98	-0.46**
	(2. 09)	(1.96)	(0.01)
Recency	2.34	1.28	1.05**
	(2.22)	(1.72)	(0.01)
Pre-Entry Annual Order Rate	1.37	2.23	-0.86**
	(1.97)	(2.38)	(0.01)
Pre-Entry Order Size	109.10	121.11	-12.02**
	(90.69)	(72.74)	(0.46)
Pre-Entry Items per Order	2.36	2.63	-0.26**
	(2.09)	(1.54)	(0.01)
Pre-Entry Selling Price	50.02	49.13	0.88**
	(29.34)	(25.15)	(0.16)
Pre-Entry % Full Price Paid	0.96	0.94	0.02**
	(0.07)	(0.08)	(0.001)
Pre-Entry % Discounted Items	0.09	0.16	-0.06**
	(0.20)	(0.21)	(0.001)
Sample Sizes	789,236	26,250	

This table compares demographics and pre-entry purchases from the core channels and the factory store by the 815,486 customers who live within 150 miles of the factory store. Statistics are calculated separately for the adopters and non-adopters of the factory store. Standard errors are in parentheses. **Significantly different from zero, p<0.01. * Significantly different from zero, p<0.05.

Table 3
Impact of Factory Store Entry on Annual Order Rate in Core Channels by Stratum

	Stratum 1	Stratum 2	Stratum 3	Stratum 4	Stratum 5
Open * Adopt	0.154**	0.178**	0.148**	0.129**	0.058**
	(0.022)	(0.020)	(0.018)	(0.017)	(0.019)
Open	0.099**	-0.005	-0.068**	-0.100**	-0.200**
	(0.003)	(0.004)	(0.006)	(0.008)	(0.013)
Fixed Effects	customer	customer	customer	customer	customer
Log Likelihood	-207,495	-72,541	-33,989	-19,598	-10,887
Sample Size	402,258	125,618	56,200	31,336	15,890

This table reports the findings from estimating Equation 2 using QML Poisson. The dependent variable measures the annual number of core channel orders. The unit of observation is a customer x period. The sample includes all of the customers living within 150km of the factory store who had made at least one purchase before and after the factory store entry. We aggregate the data into 2 equal-length periods: pre-entry (November 2000 through October 2002) and post-entry (November 2002 through October 2004). Standard errors are in parentheses (clustered at the customer level). **Significantly different from zero, $p<0.01$. * Significantly different from zero, $p<0.05$.

Table 4
Controlling for Catalog Mailings

	Stratum 1	Stratum 2	Stratum 3	Stratum 4	Stratum 5
Open * Adopt	0.152**	0.178**	0.148**	0.130**	0.058
	(0.022)	(0.020)	(0.018)	(0.017)	(0.019)
Open	0.099**	-0.005	-0.067**	-0.099**	-0.198**
	(0.003)	(0.004)	(0.006)	(0.008)	(0.013)
Catalogs	0.034**	0.038**	0.031**	0.039**	0.038**
	(0.002)	(0.004)	(0.006)	(0.007)	(0.009)
Fixed effects	customer	customer	customer	customer	customer
Log Likelihood	-207,437	-72,532	-33,980	-19,593	-10,886
Sample Size	402,258	125,618	56,200	31,336	15,890

This table reports the findings from re-estimating Equation 2 using QML Poisson with the addition of an independent variable to control for the number of catalog mailings. The dependent variable measures the number of core channel orders. The unit of observation is a customer x period. The sample includes all of the customers living within 150km of the factory store who had made at least one purchase before and after the factory store entry. We aggregate the data into 2 equal-length periods: pre-entry (November 2000 through October 2002) and post-entry (November 2002 through October 2004). Standard errors are in parentheses (clustered at the customer level). **Significantly different from zero, $p<0.01$. * Significantly different from zero, $p<0.05$.

Table 5
Replication Using Different Length Pre and Post Periods

	Stratum 1	Stratum 2	Stratum 3	Stratum 4	Stratum 5
1 year pre and post	0.110** (0.029)	0.145** (0.026)	0.110** (0.022)	0.086** (0.022)	0.025 (0.024)
2 years pre and post	0.154** (0.022)	0.178** (0.020)	0.148** (0.018)	0.129** (0.017)	0.058** (0.019)
3 years pre and post	0.193** (0.020)	0.200** (0.018)	0.143** (0.016)	0.132** (0.016)	0.064** (0.017)
4 years pre and post	0.209** (0.018)	0.207** (0.017)	0.153** (0.015)	0.129** (0.015)	0.071** (0.017)
5 years pre and post	0.212** (0.017)	0.204** (0.016)	0.154** (0.015)	0.130** (0.015)	0.076** (0.017)
6 years pre and post	0.213** (0.017)	0.200** (0.016)	0.158** (0.015)	0.128** (0.015)	0.081** (0.017)

This table reports the *Open***Adopt* interaction coefficients (τ_1) when estimating Equation 2 using QML Poisson with different length pre and post-entry periods. The dependent variable measures the annual number of core channel orders. The unit of observation is a customer x period. The sample includes all of the customers living within 150km of the factory store who had made at least one purchase before and after the factory store entry. The data includes a pre-entry and a post-entry period of equal length where the length of the periods varies across the rows. In all cases the pre-entry period finishes in October 2002 and the post-entry period starts in November 2002). Standard errors are in parentheses (clustered at the customer level). **Significantly different from zero, p<0.01. *Significantly different from zero, p<0.05.

Table 6
The Impact of the Factory Store Entry on the Composition of Customers' Orders

	Stratum 1	Stratum 2	Stratum 3	Stratum 4	Stratum 5
Items per Order	0.204**	0.080	0.092*	0.059	0.040
	(0.051)	(0.043)	(0.046)	(0.053)	(0.048)
Selling Price	1.072	-0.224	0.957	-1.531	-0.174
	(0.909)	(0.871)	(0.825)	(0.819)	(0.812)
% Discounted Items	0.022**	0.026**	0.021**	0.016**	0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Sample Size	400,710	125,300	56,078	31,284	15,868

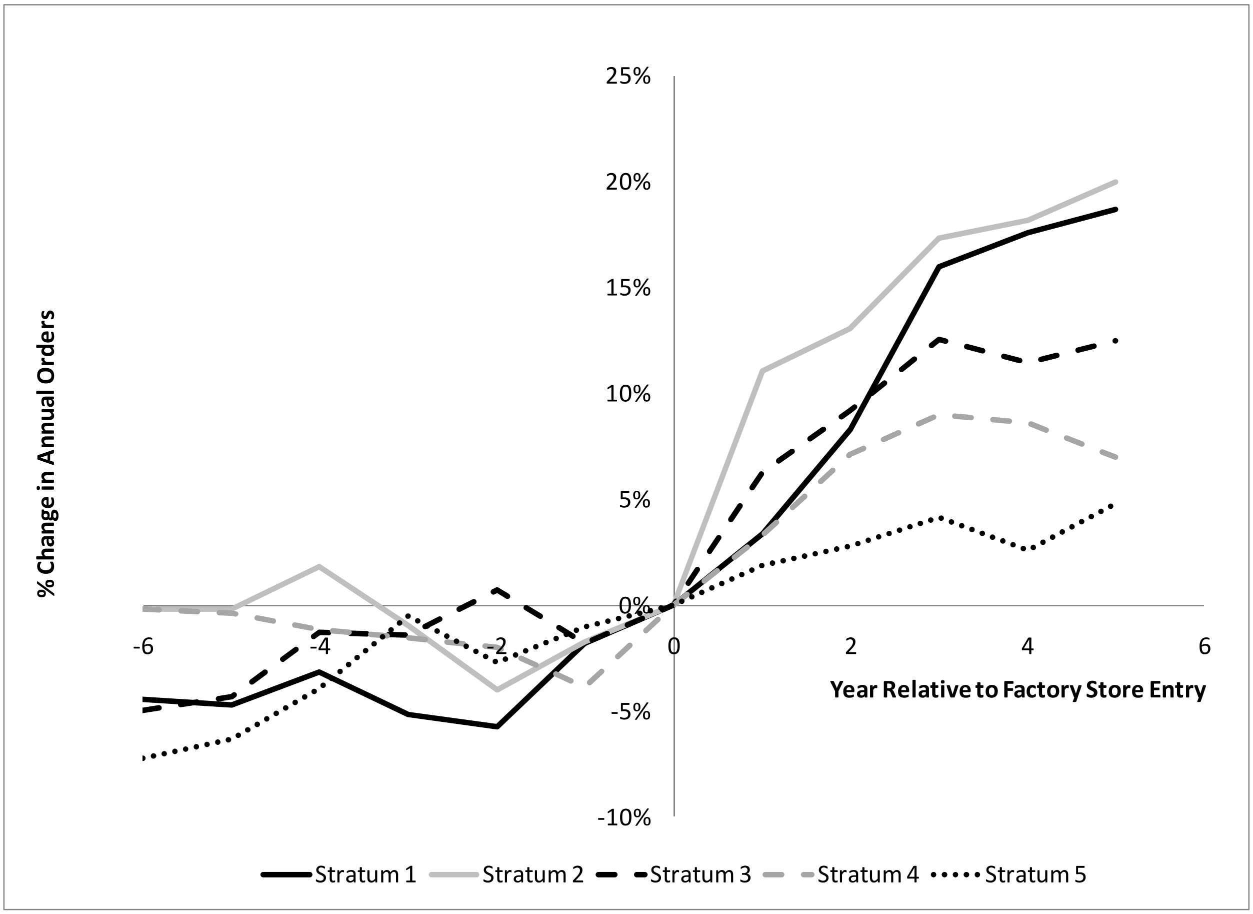
The table reports the *Open***Adopt* interaction coefficients (τ_1) estimated from Equation 4 or each of these three dependent variables. Standard errors are in parentheses (clustered by customer). The unit of observation is a customer x period. The sample includes all of the customers living within 150km of the factory store who had made at least one purchase before and after the factory store entry in the core channel (in the previous tables we include customers who made at least one pre and post-entry purchase in any channel). We aggregate the data into 2 equal length periods: pre-entry (November 2000 through October 2002) and post-entry (November 2002 through October 2004). **Significantly different from zero, p<0.01. * Significantly different from zero, p<0.05.

Table 7
The Impact of the Factory Store Entry on the Number of Orders
Direct Channels versus Retail Stores (Excluding the Factory Store)

	Stratum 1	**Stratum 2**	**Stratum 3**	**Stratum 4**	**Stratum 5**
Retail Stores	0.054	0.082	-0.056	-0.023	0.033
	(0.056)	(0.057)	(0.055)	(0.063)	(0.082)
Direct Channels	0.092**	0.143**	0.123**	0.102**	0.030
	(0.021)	(0.017)	(0.016)	(0.016)	(0.017)
Sample Size	402,258	125,618	56,200	31,336	15,890

The table reports the *Open***Adopt* interaction coefficients (β_1) from estimating Equation 2 using QML Poisson. The dependent variable measures the annual number of orders from either the retail stores (excluding the factory store) or the direct channels. The unit of observation is a customer x period. The sample includes all of the customers living within 150km of the factory store who had made at least one purchase before and after the factory store entry. We aggregate the data into 2 equal length periods: pre-entry (November 2000 through October 2002) and post-entry (November 2002 through October 2004). Standard errors are in parentheses (clustered at the customer level). **Significantly different from zero, p<0.01. *Significantly different from zero, p<0.05.

Figure 1. Average Annual Change in Order Rate for Adopters (Compared to Non-Adopters)



This figure reports the Υ_{1t} coefficients from Equation 3, which estimate the difference in the annual order rates for adopters versus non-adopters of the factory store compared to 2002 (the first year the factory store opened). We distinguish between customers in the five strata. The sample sizes are 4,884,383, 1,040,982, 452,977, 239,892and 116,004 for the five strata (respectively). All of these customers live within 150 kilometers of the factory store and made at least one purchase from the firm both before and after the factory opened.

Appendix Table A1. Variables Used to Estimate the Propensity for Adopting the Factory Store

Demographics	Historical Purchasing	Other Variables
Age	Pre-Entry Annual Order Rate	Number of catalog promotions received
Married	Pre-Entry Order Size	Distance (inversed)
Income	Pre-Entry Items per Order	Every 2-way interactions of the variables above
One Child	Pre-Entry Selling Price	3-way interaction: *Income***Recency***Tenure*
Two or more Children	Pre-Entry % Full Price Paid	Frequency of other retail promotions received
Distance to Factory Store	Pre-Entry Discount Frequency	Squared terms of each variable
Tenure		
Recency		
Goodness of Fit		
R^2 = 0.386		
Log likelihood = -134,249		
Sample size = 815,486		

This table lists all of the variables used to estimate Equation 1 (using a logistic model).

Appendix Table A2. Demographics and Pre-Entry Purchasing by Adopters and Non-Adopters by Strata

	Stratum 1		Stratum 2		Stratum 3		Stratum 4		Stratum 5	
	Non-Adopters	Adopters	Non-Adopters	Adopters	Non-Adopters	Adopters	Non-Adopters	Adopters	Non-Adopters	Adopters
Age	43.29	43.33	43.03	42.61	42.77	42.04	42.57	41.54	41.67	40.62
	(0.01)	(0.11)	(0.03)	(0.11)	(0.04)	(0.11)	(0.06)	(0.10)	(0.09)	(0.10)
Married	0.67	0.70	0.75	0.74	0.77	0.77	0.78	0.79	0.81	0.82
	(0.47)	(0.46)	(0.43)	(0.44)	(0.42)	(0.42)	(0.41)	(0.41)	(0.39)	(0.39)
Income	3.63	3.80	4.21	4.31	4.53	4.58	4.78	4.76	5.01	4.98
	(0.003)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.02)	(0.03)
Number of Children	0.58	0.56	0.59	0.57	0.62	0.63	0.66	0.65	0.78	0.84
	(0.91)	(0.87)	(0.91)	(0.89)	(0.93)	(0.94)	(0.95)	(0.94)	(1.02)	(1.03)
Distance to Factory Store	94.45	82.90	58.20	56.64	42.71	41.97	30.26	29.28	18.78	16.65
	(24.02)	(21.80)	(16.43)	(16.24)	(13.94)	(13.98)	(12.11)	(11.91)	(11.23)	(10.93)
Tenure	5.56	5.70	6.02	5.98	6.17	6.12	6.27	6.26	6.46	6.54
	(1.88)	(1.89)	(1.80)	(1.83)	(1.74)	(1.77)	(1.69)	(1.70)	(1.61)	(1.56)
Recency	2.62	2.08	1.46	1.40	1.26	1.25	1. 05	1.02	0.69	0.60
	(0.002)	(0.02)	(0.004)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Pre-Entry Annual Order Rate	1.03	1.29	1.80	1.82	2.11	2.16	2.36	2.38	3.05	3.31
	(1.20)	(1.41)	(1.81)	(1.86)	(2.05)	(2.10)	(2.21)	(2.21)	(2.59)	(2.69)
Pre-Entry Order Size	107.16	111.66	117.76	117.35	122.38	124.56	126.85	127.64	133.15	131.92
	(78.59)	(79.23)	(70.06)	(68.76)	(71.17)	(70.08)	(70.05)	(69.48)	(69.24)	(62.71)
Pre-Entry Items per Order	2.53	2.64	2.60	2.63	2.66	2.71	2.70	2.76	2.79	2.76
	(0.003)	(0.023)	(0.005)	(0.020)	(0.007)	(0.020)	(0.009)	(0.021)	(0.015)	(0.016)
Pre-Entry Selling Price	50.08	50.53	49.01	49.44	48.75	49.33	48.43	48.77	47.19	46.82
	(28.65)	(29.98)	(23.02)	(28.53)	(21.94)	(22.49)	(20.94)	(21.12)	(16.99)	(17.37)
Pre-Entry % Discount	0.03	0.04	0.05	0.06	0.06	0.06	0.06	0.06	0.08	0.09
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Pre-Entry Discount Frequency	0.09	0.11	0.14	0.14	0.16	0.16	0.17	0.17	0.21	0.23
	(0.18)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.21)
Sample Sizes	379,228	4,471	96,891	4,733	39,342	4,731	18,757	4,731	6,400	4,732

This table compares demographics and pre-entry purchases from the core channels. Statistics are calculated separately for the adopters and non-adopters of the factory store in each stratum, among the existing customers whose demographics are fully observed. Standard errors are in parentheses.

Appendix Table A3. Verifying the Identifying Assumption

	Stratum 1	Stratum 2	Stratum 3	Stratum 4	Stratum 5
Factory Store Opening Event					
2000-2002 and 2002-2004	0.154**	0.178**	0.148**	0.129**	0.058**
	(0.022)	(0.020)	(0.018)	(0.017)	(0.019)
Alternative Periods					
1994-1996 and 1996-1998	0.018	-0.025	0.040	-0.020	0.048*
	(0.022)	(0.019)	(0.021)	(0.019)	(0.020)
1995-1997 and 1997-1999	0.033	-0.008	0.015	-0.008	0.013
	(0.020)	(0.018)	(0.016)	(0.016)	(0.017)
1996-1998 and 1998-2000	0.036	0.035	0.003	-0.001	0.022
	(0.020)	(0.018)	(0.016)	(0.016)	(0.017)
1997-1999 and 1999-2001	-0.011	-0.030	0.024	-0.006	0.034
	(0.020)	(0.018)	(0.018)	(0.017)	(0.018)
1998-2000 and 2000-2002	-0.024	0.001	0.031	-0.005	0.048*
	(0.021)	(0.018)	(0.018)	(0.017)	(0.019)

This table reports the *Open***Adopt* interaction coefficients (β_1) from estimating Equation 2 using QML Poisson. The dependent variable measures the number of core channel orders. The unit of observation is a customer x period. The sample includes all of the customers living within 150km of the factory store who had made at least one purchase before and after the factory store entry. The data period includes the 2 periods: pre and post, where the dates for each period vary by row. Standard errors are in parentheses (clustered at the customer level). **Significantly different from zero, p<0.01. * Significantly different from zero, p<0.05.