Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

How Does Adoption of the Outlet Channel Impact Customers' Spending in the Retail Stores: Conflict or Synergy?

Gonca Soysal, Lakshman Krishnamurthi

MANAGEMENT SCIENCE
Vol. 62, No. 9, September 2016, pp. 2692–2704
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2015.2262

How Does Adoption of the Outlet Channel Impact Customers' Spending in the Retail Stores: Conflict or Synergy?

Gonca Soysal
Naveen Jindal School of Management, University of Texas at Dallas, Richardson, Texas 75080,
gonca.soysal@utdallas.edu

Lakshman Krishnamurthi
Kellogg School of Management, Northwestern University, Evanston, Illinois 60208,
laksh@kellogg.northwestern.edu

We investigate how adoption of a retailer's factory outlet channel impacts customers' spending in the retailer's traditional retail store channel. In recent years, many retailers have added exclusively sourced factory outlet stores into their channel mix to achieve market expansion and customer segmentation. However, the impact of adoption of this lower-quality, lower-price alternative channel on spending at the retailer's higher-quality, higher-price retail store channel is not clear. Customers adopting the outlet channel might increase their spending in the retail store channel because of the opportunity to become familiar with the brand at a lower price point or transfer of positive associations formed through patronage of the outlet channel to the store channel. Customers adopting the lower-quality channel might also decrease their spending in the retail store channel because of brand dilution or cannibalization. To investigate this issue, we use a unique individual-level panel data set from a specialty apparel retailer from a period during which the retailer opened many factory outlet stores. This allows us to study how purchase behavior changes after customers adopt the outlet channel while carefully controlling for alternative explanations including customer heterogeneity and selection effects. We find that although customers who adopt the outlet channel spend less with the retailer compared to store-only customers, the difference cannot be attributed to the impact of adoption of the outlet channel. After controlling for heterogeneity and selection effects, we uncover a positive spillover to the retail store channel from adoption of the outlet channel. Customers who adopt the outlet channel not only make incremental purchases at the outlet channel, but also increase their spending in the retail store channel after adoption. The increase in spending is due to more frequent retail store purchases and not to larger per-purchase expenditure.

Keywords: multichannel marketing; channel strategy; segmentation; factory outlets
History: Received October 8, 2013; accepted March 30, 2015, by J. Miguel Villas-Boas, marketing. Published online in *Articles in Advance* November 24, 2015.

1. Introduction

In this paper we empirically investigate how the adoption of the lower-quality, lower-price factory outlet channel impacts customers' spending in a retailer's higher-quality, higher-price traditional retail store channel using a unique individual-level panel data set from a large specialty apparel retailer.

Once considered a dumping ground for excess or imperfect merchandise, factory outlets have gained prestige and gone through significant growth and change in the last decade, as retailers have realized the potential of this channel as a means to reach new customers and employ price discrimination strategies. Ranking as the fastest growing segment of the retail industry, factory outlets generated $22.4 billion in retail sales in 2010, with over 13,000 stores in 179 centers across the United States (International Council of Shopping Centers 2011). Many retailers are expanding rapidly in this channel and offering more and more merchandise exclusively for their outlet stores. Whereas Coach, Nordstrom, and Saks all report that approximately 80% of the goods sold at their outlet stores were designed and produced solely for this channel in 2010 (Geller and Wahba 2010), many other retailers like Gap, Old Navy, Polo Ralph Lauren, Talbots, and Gymboree exclusively source all products sold in their outlet stores. These outlet stores offer designs very similar to the retailer's offerings in the retail store channel at a lower but acceptable quality and at an average discount of 40% (*Value Retail News* 2012). In addition to lower product quality, outlet stores are also differentiated from retail stores through lower levels of in-store services such as the availability of sales assistance, less luxurious store environments, and narrower assortments (Coughlan and Soberman 2005, *Consumer Reports* 2011). Most retailers also operate their outlet stores under the same brand name (as a brand extension), aiming to exploit their brand equity by capitalizing on recognition and positive associations.

Although both the retailers and Wall Street have been very enthusiastic about this dual distribution strategy, it comes with some potential risks (Geller and Wahba 2010), which include cannibalization of the retail store channel and brand dilution. Cannibalization is a concern since higher valuation customers may substitute away from the higher-quality retail store channel targeted to them if the outlet channel is sufficiently attractive. Brand dilution is a concern because exposure to lower service levels and lower-quality products under the retailer's brand name at the outlet channel could negatively impact customers' associations with the brand, which might transfer to the retail store channel and reduce customers' spending with the retailer (Loken and John 1993, Kirmani et al. 1999). Although not all customers may be aware that the outlet stores sell lower-quality products, the differences in service levels, assortment, and store atmosphere between the two channels are quite visible.

Despite the rush to outlet retailing witnessed in practice, the academic literature has not yet provided either a general theory or empirical evidence concerning how adoption of this lower-quality, lower-price alternative channel impacts the customers' spending levels in the retail store channel. In a related stream of literature, a number of studies examine multichannel consumer behavior in the context of alternative channels that sell similar goods at similar prices, such as the retail store, catalogs, and the Internet (Kumar and Venkatesan 2005, Ansari et al. 2008, Thomas and Sullivan 2005). Neslin et al. (2006) summarize the findings by stating that multichannel research "generates the provocative empirical generalization that multichannel customers have higher expenditure levels than do single-channel customers." This empirical generalization was also supported by industry reports. Nordstrom (Clifford 2010) reports that customers who buy both through their online and retail stores spend four times more than single-channel customers, and J.C. Penney reports that customers who shop through all three of their channels (store, online, and catalog) spend well over three times more than single-channel customers (Stringer 2004). Previous literature also suggests that when alternative channels offer similar products at similar prices, multichannel contact can grow customer spending due to complementary channel capabilities and transfer of knowledge and associations gained through the use of one channel into other channels (Avery et al. 2012).

The empirical generalization that multichannel customers have higher spending levels compared to single-channel customers, however, does not extend to our setting, where the alternative channel is further differentiated from the traditional retail store channel in price and quality. In our data, the average annual retail store spending for a multichannel customer is approximately 30% less than that for a (retail) store-only customer ($455.39 versus $657.92), and average annual combined (outlet and retail store) spending for a multichannel customer is approximately 10% less than that for a store-only customer ($597.46 versus $657.92). Both differences are statistically significant ($p < 0.01$).

One might think that the observation that multichannel consumers have lower spending levels compared to store-only customers, in the context of an alternative outlet channel, points to a negative impact from adopting the outlet channel on customers' spending levels. Although the outlet channel might complement the retail store channel in certain aspects (e.g., increase reach and convenience for certain customers), the differences in prices, quality, and service levels between the channels introduce the risk of cannibalization and brand dilution as discussed earlier, which might lead to a decrease in customers' retail store spending after adopting the outlet channel. However, observed differences in purchase behavior across customers could also be due to selection. For example, if customers who don't spend much in the retail store channel (because of low willingness to pay or any other unobserved reason) are more likely to adopt the outlet channel, everything else equal, a model that does not control for this correlation will produce a downward biased estimate for the effect of adoption of the outlet channel on retail store spending. In this study, we investigate whether observed differences in spending between multichannel and store-only customers are due to selection and whether there is a positive or negative causal effect from adopting the outlet channel on customers' retail store spending. Answering these questions calls for the use of customer-level panel data on outlet and retail store purchases as well as an exogenous shock affecting customers' outlet channel adoption decisions.

To satisfy these requirements, we use a unique individual-level panel data set from a leading specialty apparel retailer that operates a large network of retail stores and exclusively sourced outlet stores. The data set is very rich and enables us to track very detailed information on individual customers' purchases across the retailer's different channels starting with their first transaction with the retailer. One important strength of the data is that the observations are not limited to loyalty card purchases, because the retailer utilizes a technology that enables matching of all credit/debit card and check purchases to an individual customer. The panel structure of the data helps us control for heterogeneity in unobservable individual characteristics that are unlikely to change during our observation period, which might explain the observed differences in purchase behavior. Another important feature of the data is that they corresponds to a period when the retailer opened many factory outlet stores. The data report opening dates and exact locations of the retailer's outlet stores, which enables us to track the change in each customer's distance to the closest outlet store over time. We use distance to the nearest outlet store as an instrument for outlet adoption, since individuals living in areas that have seen the entry of outlet stores experience transportation cost changes that impact the utility of purchasing from the outlet channel (Zentner et al. 2013, Forman et al. 2009, Brynjolfsson et al. 2009).

Our key finding is that although customers who adopt the outlet channel spend less compared to store-only customers, adoption of the outlet channel leads to an increase in these customers' retail store spending. Furthermore, the increase is a result of more frequent retail store purchases and not due to increased expenditure per purchase. The estimated effects are statistically and economically significant. The adoption of the outlet channel leads to a large (43%) increase in a multichannel customer's probability of making a purchase in the retail store channel in a given month (from 0.28 to 0.40), coupled with a small (4%) decrease in the average per-purchase expenditure (from \$125 to \$120). The resulting increase in the customer's average annual spending in the retail store channel amounts to \$155, which corresponds to a 34% increase in retail store spending. If we also consider the additional \$142 spent by multichannel customers on average annually in the outlet stores, the impact of adoption of the outlet channel on a customer's overall spending with the retailer (across the two channels) is also rather large (65%). Whereas 52% (=\$155/(\$155 + \$142)) of this incremental spending comes from increased spending in the retail stores, the remaining 48% comes from purchases in the outlet stores.

We believe that our results are important for the multichannel customer management literature for two reasons. First, they showcase the importance of controlling for the bias introduced by customer heterogeneity and selection effects that may be especially pronounced in a channel structure where channels are differentiated in price and quality to induce customer segmentation through self-selection. Second, they demonstrate that some of the benefits from multichannel contact documented previously in the context of channel structures consisting of channels providing similar goods at similar prices *extend* to a setting where the retailer's channels are differentiated in price and quality.

Understanding how the adoption of the lower-quality outlet channel impacts customers' spending with the retailer is not only important for the academic literature, but also important for managerial practice. If the observed differences in purchase behavior between multichannel and single-channel customers are only due to selection, then the channel structure induces self-selection as intended, and the retailer does not need to worry about the interaction between the channels. If adopting the lower-quality outlet channel, on the other hand, impacts customers' purchase behavior in the higher-quality retail store channel, the retailer may want to reconsider its channel strategy or encourage multichannel shopping for certain segments of customers depending on the direction of the impact. Our results show that, when managed properly, a dual distribution strategy utilizing higher-quality, higher-price retail stores and lower-quality, lower-price outlet stores not only enables the retailer to successfully segment its customers, but also generates a large positive spillover from the outlet channel to the retail store channel.

2. Literature

Our study adds to the literature on the use of distribution channel characteristics for customer segmentation, the brand extension literature, and the multichannel customer management literature.

Iyer (1998) and Coughlan and Soberman (2005) use analytical models to investigate the use of sales and distribution channel characteristics for customer segmentation. Iyer (1998) shows that a manufacturer can find it profitable to induce differentiation among competing retailers, who can make strategic service investments, whereas Coughlan and Soberman (2005) show that a retailer will be motivated to sell through outlet stores in addition to retail stores when the range of service (quality) sensitivity across customers is low relative to the range of price sensitivity. We add to this literature by providing empirical evidence on the successful use of sales and distribution channels for customer segmentation.

Brand extension research shows that although extensions carry the promise of adding value (Smith and Park 1992, Balachander and Ghose 2003), they also carry the risk of harming the parent brand when they either communicate inconsistent information or fail. Kirmani et al. (1999) show that the risk of brand dilution is particularly high when the original brand is a prestige brand associated with status and exclusivity while the brand extension is a price-based downward extension. We do not find evidence of brand dilution due to the adoption of a price-based downward extension in our data.

Both proliferation in alternative channel offerings and a dramatic increase in the percentage of multichannel customers have created significant interest in multichannel customer management among practitioners and academicians. A common theme in this literature is concerned with investigating whether and how purchasing through multiple channels influences customer behavior. This stream of literature provides empirical evidence for the claim popular in the press (e.g., Stringer 2004) that multichannel customers shopping across alternative channels offering similar products at similar prices spend more than single-channel customers (Kumar and Venkatesan 2005, Thomas and Sullivan 2005, Neslin et al. 2006). Most of the studies in this literature use cross-customer analysis. One exception to this is the study by Ansari et al. (2008), who use panel data from a retailer who sells through an online channel as well as catalogs. Using a longitudinal comparison, they show that even though customers who migrate to the online channel have higher sales volumes ex post, they were not heavy users to start with, and there is little difference in baseline sales between those who migrate and those who do not. Our study also uses panel data and documents that although the empirical generalization that multichannel customers spend more does not extend to a setting where channels are differentiated in price and quality, multichannel contact still has a positive impact on total customer spending. When the alternative channel is the lower-quality outlet channel, adopters are inherently low spenders, but they increase their spending in the retail stores after they adopt the lower-quality channel.

Another related stream in the multichannel customer management literature investigates how a new channel offering impacts a retailer's business in existing channels. This literature primarily investigates the impact of either adding a direct channel to an existing physical channel or adding a physical channel to existing direct channels where all channels offer goods at similar price and quality levels. We first examine studies investigating the impact of the introduction of the Internet channel on the retailer's existing physical channel. Deleersnyder et al. (2002), Gentzkow (2007), Biyalogorsky and Naik (2003), and Pozzi (2013) all show that the online channel does not significantly cannibalize or threaten the survival of the off-line channel. We next examine studies investigating the impact of adding a physical store to a retailer's existing mix of direct channels (Internet and catalog). Pauwels and Neslin (2015) use data from a durables and apparel catalog retailer and show that Internet sales are not cannibalized by the entry of a retail store, although catalog sales are. Avery et al. (2012) use data from an apparel retailer and show that despite the cannibalization of the catalog channel in the short run, the introduction of a retail store increases sales in both the catalog and Internet channels in the long run. They also state that a physical store complements sales in direct channels since it offers a number of benefits that direct channels cannot offer. Some of these important benefits are (1) reducing purchase risk by offering the ability to physically examine the products and talk to sales personnel, (2) reducing transaction costs by eliminating shipping and handling charges as well as the cost of returning products by mail, (3) offering instant gratification by eliminating wait time, (4) and acting as "living advertisement billboards to generate brand awareness" (Avery et al. 2012, p. 99). Our paper extends this literature on the interaction between direct and physical channels that are not differentiated in price and quality by investigating the interaction between two physical channels differentiated in price and quality. As discussed earlier, price and quality differentiation between channels introduces new benefits and risks that are worth investigating.

Our study is also related to a recent paper by Qian et al. (2013) that empirically investigates how customers' spending in existing direct channels (catalog and online) are impacted when a direct retailer opens a physical store in a low-price factory store format. Our paper is different from that by Qian et al. (2013), since we focus on studying the interaction between two *physical* channels that have similar capabilities, but are differentiated in price and quality. Our data enable us to isolate the benefits/costs to a retailer from price and quality differentiation in channel offerings by allowing us to abstract away from the benefits/costs associated with differences in channel capabilities between physical and direct channels.

3. Data

The data used in our analysis come from a leading specialty apparel retailer that sells its own private label fashions. The name of the retailer cannot be disclosed due to confidentiality concerns. The retailer operates over 300 retail stores located in shopping malls and close to 100 factory outlet stores located in outlet malls across the United States. The factory outlet channel is exclusively sourced with products that are similar in style and fit, but are of lower quality compared to the products sold in the retail stores. No products move from the retail stores to the outlet stores; any remaining inventory in the retail stores is either deeply discounted to facilitate sales or discarded at the end of the season. The retailer also does not allow products purchased in the retail stores to be returned to the outlet stores and vice versa. The data consist of individual-level transactions from a sample of over 100,000 customers over a 25 month period. This sample was randomly selected by the retailer

Table 1 Summary Statistics for the Marketing Mix Variables Used in the Model

	Mean	Standard deviation	Maximum	Minimum
Store price (in $)	40.7	5.3	48.9	31.0
Outlet price (in $)	20.2	1.7	23.0	17.3
Store cost (normalized)	100.0	11.8	121.7	81.3
Outlet cost (normalized)	56.7	6.1	67.1	47.9
Store assortment	967.1	19.2	1,009.2	928.8
Outlet assortment	273.3	8.1	286.6	257.0

from the list of customers acquired on or after the data start date of May 1, 2003. For this study, we restrict our attention to active customers who bought more than four times until the cutoff date of June 1, 2005, and reach a final sample size of 19,356 customers. This restriction allows us to utilize the panel structure of the data and investigate changes in purchase behavior over time. The retailer introduced the factory outlet channel more than 10 years before the start of the data, but expanded the outlet channel significantly during our observation period, increasing the number of its outlet stores by 51%.

Table 1 presents summary statistics for the marketing mix variables used in our model. Price and cost variables are averaged across all items sold in a month and then averaged across months, whereas assortment is averaged across months. Price and quality differences across the two channels are large. Whereas the monthly average transaction price for an item sold through the retail stores during our observation period is $40.7, that for an item sold through the outlet stores is $20.2 or 50% less. On the other hand, the retailer's average acquisition cost for an item sold through the outlet stores is 43% lower than that for an item sold through the retail stores. Store and outlet cost values are normalized (such that the average store cost is equal to 100) for confidentiality. Acquisition cost is the amount the retailer pays to have the product manufactured. This is directly related to material and labor costs and serves as a good proxy for quality. The product assortment is also much larger in the retail stores. Whereas a retail store carries 967 unique products on its shelves during an average month, an outlet store carries 273.

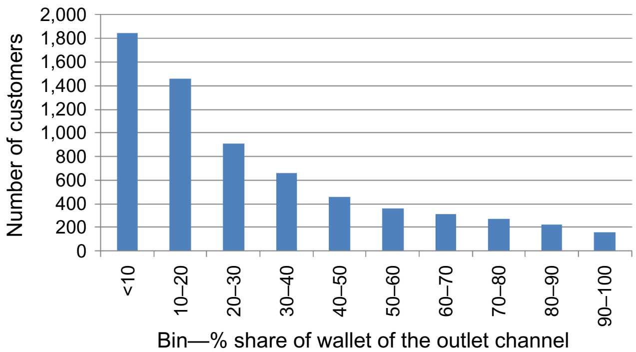
We observe the full transaction history for each customer in our sample starting from their first purchase with the retailer until the cutoff date (i.e., the data are not left censored at the individual level). The data were collected at the point of purchase and include all transactions made via either check or any type of debit or credit card at one of the retailer's three channels (retail store, factory outlet, or online store). Although the retailer has a loyalty card, observed card purchases are not limited to loyalty card purchases. The company uses an external data vendor that provides a service that enables matching all credit and debit card numbers at the individual level. Cash purchases are not captured, but are of negligible magnitude (less than 5%). For each purchase transaction we observe the channel, store number, date, and time as well as the payment method. For each item purchased in a transaction, we observe the product code, number of units purchased, dollar amount paid, dollar amount of discounts received (if any), and per-unit product acquisition cost. We also have information on exact addresses of the retail stores and outlet stores, as well as opening days for stores that began operations during the observation period.

Sales through the online channel in our sample correspond to a very small portion of the retailer's sales (4.13% of the total unit sales and 6.15% of the total dollar sales), and only 13% of all customers ever make an online purchase during the observation period. The online channel sells the same items available in the retail store channel at the same prices. Since the focus of this study is investigating the impact of adopting the lower-quality, lower-price outlet channel on customer purchase behavior in the retail store channel, we restrict our attention to those customers who interact with the company through the retail store channel and/or the factory outlet channel. Customers who make a purchase from the retailer's online channel at least once are excluded from the sample used for our analysis in the main text. We check the robustness of our results by replicating our analysis in Online Appendix A (online appendices available as supplemental material at http://dx.doi.org/10.1287/mnsc.2015.2262) using a larger sample that includes online purchasers (and their online purchase transactions) in addition to store and outlet purchasers.

Although the majority of customers in our sample (63%) only purchase through the retail store channel, 35% of customers also purchase through the factory outlet stores. We classify customers who make at least one purchase from each one of the two channels during the observation period as multichannel customers. Only 2% of customers in our sample purchase through the factory outlet stores but not through the retail stores.

The multichannel segment is rather large, but one might still wonder how big the shares of outlet purchases are for customers in this segment. Figure 1 presents the distribution of the share of wallet of the factory outlet channel (as a percentage of the total spending with the retailer) for the multichannel customers. For around 20% of the multichannel customers, the factory outlet channel corresponds to at least half of their total spending with the retailer, and for more than 50% of the multichannel customers, outlet spending exceeds 20% of their total spending

Figure 1 **(Color online) Percent Share of Wallet of the Factory Outlet Channel for Multichannel Customers**



% share of wallet of the outlet channel	*Frequency*	*% of customers*	*Cumulative %*
<10	1,844	27.7	27.7
10–20	1,461	21.9	49.6
20–30	912	13.7	63.3
30–40	659	9.9	73.2
40–50	455	6.8	80.1
50–60	359	5.4	85.5
60–70	312	4.7	90.2
70–80	273	4.1	94.3
80–90	223	3.3	97.6
90–100	159	2.4	100.0

with the retailer. These numbers show that a large number of customers distribute their spending across the two channels.

Table 2 presents the summary statistics related to the purchase behavior of store-only, multichannel, and outlet-only customers across the two channels.[1] In the retail store channel, compared to store-only customers, multichannel customers buy less often (4.62 versus 5.75 orders per year), spend less per order ($95.60 versus $115.03), and are less profitable[2] (93.1 versus 100). The average annual store spending for a multichannel customer is approximately 30% less than that for a store-only customer ($455.39 versus $657.92). After adding their annual outlet spending ($142.07), multichannel customers' total annual spending is still approximately 10% less than the annual spending of store-only customers ($597.46 versus $657.92). All differences are statistically significant with $p < 0.01$. These summary statistics show that the generalization that multichannel customers have higher spending levels than single-channel customers does not hold in our data. In the outlet channel on the other hand, when compared to outlet-only customers, multichannel customers buy much less often (1.64 versus 5.94 orders per year) but spend more per order ($87.33 versus $74.07) and are more profitable (87.6 versus 81.82). The average annual total spending for a multichannel customer is approximately 30% more than that for an outlet-only customer ($597.46 versus $454.10). All differences are statistically significant with $p < 0.01$. The summary statistics suggest that part of the difference in spending levels observed between multichannel customers and single-channel customers might be attributable to customer heterogeneity. Therefore, it is important to control for differences in purchase behavior across customers when investigating the impact of outlet channel adoption on multichannel customers' spending.

[1] The averages are calculated by averaging within each customer first and then across customers.

[2] We calculate profitability for each transaction by dividing the net price paid by the acquisition cost. Profitability is then averaged across transactions and customers. The averages for customer groups are rescaled (so that store-only customers' profitability indexes are equal to 100) to protect confidentiality.

4. Econometric Model and Results

To understand the impact of adopting the lower-quality outlet channel on total spending at the retail store channel, one might consider using a dummy variable for outlet adoption with a pooled sample of adopters and nonadopters. However, this approach would be inappropriate since the differences in spending patterns across customers and time periods picked up by the dummy variable would include not only the impact of the outlet channel adoption on store spending, but also selection effects. Selection effects arise because customers self-select into adopting the outlet channel or not, and adoption may not be random. Adoption status could be endogenous if the decision to adopt or not adopt the outlet is correlated with unobservables that also affect spending in the retail store channel. For example, if customers with low total spending levels in the retail stores (due to low income or any other unobserved reason) are more likely to adopt the lower-priced outlet channel, everything else equal, failure to control for this correlation will yield an estimated effect for the outlet channel's adoption on retail store spending that is biased downward.

We address this endogeneity problem using a longitudinal model with panel data that helps us difference out the time-invariant unobserved customer characteristics. Customer-fixed effects capture characteristics such as income or household size that are likely to remain unchanged during our observation period and allow us to control for sorting of heterogeneous customers into channels.

To investigate the impact of adoption of the outlet channel on customers' spending in the retail store channel, we model customer store purchase incidence and conditional expenditure decisions separately. Model 1, the incidence model, investigates

Table 2 Purchase Behavior Across Customers and Channels

Customer type	Store only	Multichannel			Outlet only
Channel		Store	Outlet	Overall	
# Units/Order	2.84	2.56	4.24	3.08	3.83
	(1.38)	(1.30)	(2.93)	(1.45)	(2.14)
$ Spent/Order	115.03	95.60	87.33	94.36	74.07
	(68.13)	(62.86)	(64.01)	(52.17)	(42.92)
# Orders/Year	5.75	4.62	1.64	6.26	5.94
	(3.99)	(4.26)	(1.94)	(4.72)	(4.51)
$ Net spending/Year	657.92	455.39	142.07	597.46	454.10
	(605.98)	(522.90)	(188.25)	(568.93)	(546.69)
Rescaled profitability index	100	93.1	87.6	90.14	81.82
	(33.98)	(36.3)	(21.9)	(25.82)	(19.58)
Number of customers	12,258		6,657		441

Note. Standard deviations are reported in parentheses below the means.

the impact of outlet channel adoption on customers' monthly[3] retail store purchase decisions, and Model 2, the conditional expenditure model, investigates the impact of outlet channel adoption on total monthly retail store expenditure decisions conditional on a store purchase.

4.1. Incidence Model

In the incidence model for each customer i and each month t, we define our dependent variable, $StorePurch_{it}$, as a dummy variable that is set to 1 if customer i's *retail store* spending in month t is positive and to 0 otherwise. The incidence model is specified as a linear probability model and the conditional expectation of the dependent variable can be interpreted as the probability that customer i makes a purchase from the retail store channel in month t, given the values for the independent variables:

$$StorePurch_{it} = \alpha + \beta Adopt_{it} + \delta Assortment_t + \gamma Price_t + \tau Trend_t + \varphi_i + \omega_t + \varepsilon_{it}. \quad (1)$$

The dummy variable $Adopt_{it}$ in Model 1 is set to 1 after customer i's first outlet channel purchase, and is set to 0 otherwise.[4] The coefficient β measures how a customer's monthly retail store purchase frequency changes after the customer adopts the outlet channel. The assortment variable $Assortment_t$ represents the number of unique products sold through the retail store channel in month t (divided by 100). The price variable $Price_t$ represents quality adjusted price for retail store channel in period t. We calculate $Price_t$ by dividing the average per item price in week t by the average per-unit acquisition cost for the retail store channel. Although we do not have a direct measure of quality, the per-unit acquisition cost for each product serves as a good proxy for quality as discussed earlier. Sensitivity to price is captured by γ and sensitivity to assortment is captured by δ. The model includes fixed effects for each customer, φ_i, and fixed effects for 12 calendar months (January through December), ω_t. Unobserved (to the econometrician) error terms are represented by ε_{it}.

Individual fixed effects help us control for unobserved individual heterogeneity that may be correlated with regressors, particularly the adoption dummy as discussed earlier. Time effects (calendar month fixed effects and a monthly time trend) help us control for presence of aggregate shocks to purchase frequency. The calendar month fixed effects capture seasonal changes in the monthly store purchase likelihood that can be caused by special events like the holiday shopping period, the back-to-school period, or changes in weather. The time trend variable captures an overall expansion or reduction in the retailer's store sales over time. With the inclusion of the individual fixed effects, the model parameters are identified from the within-individual variation in the variables over time (after taking time effects out). Since the adoption dummy is set to 0 at the start of the data and set to 1 after a customer's first outlet purchase, the impact of adoption on retail store purchase frequency is identified from the differences in purchase patterns of multichannel customers (who adopt the outlet channel after first purchasing at the retail stores) before and after the adoption of the outlet channel.

Table 3 presents the ordinary least squares (OLS) estimation results for Model 1. Column I presents

[3] Setting the time period of analysis at the monthly level is the natural choice in apparel data since the purchase frequency is much lower compared to other categories such as groceries. The average interpurchase time is 63 days for the retail store channel and 209 days for the outlet channel.

[4] Although the majority of customers adopt the retail store channel first, we also have some customers who adopt the outlet channel first. The adoption variable is set to 1 for such customers following their first purchase.

Table 3 **Monthly Retail Store Incidence—OLS Estimates**

	I OLS	II OLS with time FEs	III OLS with time and customer FEs
Adoption dummy	−0.076***	−0.071***	0.118***
	(0.001)	(0.001)	(0.003)
Store assortment	0.032***	0.031***	0.031***
	(0.000)	(0.000)	(0.000)
Average store price	−0.066***	−0.143***	−0.142***
	(0.001)	(0.001)	(0.002)
Intercept	−0.115***	0.012***	−0.007
	(0.003)	(0.004)	(0.005)
Time trend	NA	−0.001***	−0.003***
	NA	(0.000)	(0.000)
Observations	392,347	392,347	392,347
R-squared	0.827	0.834	0.862
Month fixed effects	No	Yes	Yes
Customer fixed effects	No	No	Yes

Notes. Standard errors in parentheses are clustered by customer in column III. The mean of the dependent variable is 0.291.
***Significant at 1%.

results from a specification that does not include customer fixed effects or time effects. The parameter estimate for the adoption dummy is negative and significant. Although one might think that this finding points to a negative impact from adoption of the outlet channel on the retail store purchase incidence (frequency), the adoption dummy in this specification, as discussed earlier, captures not only the impact of outlet adoption on a customer's retail store purchase frequency, but also unobserved differences across customers that might be correlated with the decision to adopt the outlet channel. Store assortment impacts incidence positively, and store price impacts incidence negatively. Column II presents results from a specification that includes time effects. Estimates for the adoption dummy and the store assortment variable are fairly similar in columns I and II, but the estimate for the price variable is larger in magnitude in column II. In the apparel industry, sales are seasonal, and both prices and demand are higher at the start of a season and lower at the end of a season. Controlling for overall demand trends using time effects is therefore critical to obtain a good estimate of the impact of price on demand.

Column III presents the estimation results for our main specification of Model 1 that includes both customer fixed effects and time effects. Including the 19,356 customer fixed effects helps control for the selection problem, and the sign of the adoption dummy reverses to positive and the effect is statistically significant. These results demonstrate that although customers who adopt the outlet channel have a lower purchase frequency in the retail store channel compared to those who do not, their store purchase frequency increases after adoption. The average probability of purchasing from the retail store channel in a given month for multichannel customers is 0.278 in our sample. The size of the coefficient estimate on the adoption dummy indicates that, on average, the probability of purchasing from the retail store channel in a given month increases by approximately 43% (=0.118/0.278) after a customer adopts the outlet channel. This corresponds to 1.42 (=0.118 ∗ 12) additional months out of 12 that a customer will purchase from the retail store channel. Assortment impacts incidence positively, and price impacts incidence negatively. The time trend coefficient estimate is negative and significant. Estimated calendar month fixed effects are not reported here, but are included in Table A3 of Online Appendix C.

4.2. Conditional Expenditure Model

In the conditional expenditure model for each customer i and each month t, we define our dependent variable $LCondExpend_{it}$ as the log[5] of the total dollar expenditure of customer i in the retail store channel in month t conditional on a purchase. All other variables are defined as before:

$$\begin{aligned} LCondExpend_{it} = \alpha + \beta Adopt_{it} + \delta Assortment_t \\ + \gamma Price_t + \tau Trend_t + \varphi_i \\ + \omega_t + \varepsilon_{it}. \quad (2) \end{aligned}$$

The identification of the conditional expenditure model is similar to that of the purchase incidence model. Since we include individual fixed effects, the model parameters are identified from the within-individual variation in the variables over time (after taking time effects out). The differences between the conditional expenditure levels of multichannel customers (who adopt the outlet channel after first purchasing at the retail stores) before and after the adoption of the outlet channel help to identify the impact of adoption on retail store conditional expenditure levels.

Table 4 presents the OLS estimation results for Model 2. Out of the 19,356 customers in our sample, 441 outlet-only customers drop out from this analysis since they do not make any retail store purchases. Column I presents results from a specification that does not include customer fixed effects or time effects. The parameter estimate for the adoption dummy is negative and significant. Although one might think that this finding points to a large negative impact

[5] We use a log transformation because the monthly conditional dollar expenditure variable has a significant right skew due to some very large values, although the mass of cases are bunched at lower values.

Table 4 Conditional Retail Store Expenditure—OLS Estimates

	I OLS	II OLS with time FEs	III OLS with time and customer FEs
Adoption dummy	−0.198***	−0.196***	−0.044***
	(0.007)	(0.007)	(0.014)
Store assortment	0.000	−0.003***	−0.006***
	(0.001)	(0.001)	(0.001)
Average store price	0.329***	−0.200***	−0.314***
	(0.015)	(0.038)	(0.038)
Intercept	3.936***	4.904***	5.361***
	(0.037)	(0.085)	(0.086)
Time trend	NA	0.005***	−0.002***
	NA	(0.001)	(0.001)
Observations	119,112	119,112	118,668
R-squared	0.009	0.019	0.361
Month fixed effects	No	Yes	Yes
Customer fixed effects	No	No	Yes

Notes. Standard errors in parentheses are clustered by customer in column III. The mean of the dependent variable is 4.57.
***Significant at 1%.

($1 - \exp(-0.198) = 18\%$) from adoption of the outlet channel on the conditional monthly retail store expenditure of adopters, the adoption dummy in this specification captures not only the impact of outlet adoption on a customer's conditional retail store expenditure, but also unobserved differences across customers that might be correlated with the decision to adopt the outlet channel. The store assortment parameter is not statistically significant, and the store price impacts conditional expenditure positively. Column II presents results from a specification that includes time effects. The calendar month fixed effects capture changes in conditional monthly store expenditure that can be caused by seasonality. The time trend variable captures an overall increase or decrease in conditional expenditure over time. Estimates for the adoption dummy coefficient are fairly similar in columns I and II; however, the estimate for the assortment variable coefficient is now negative and significant. Similar to the purchase incidence model, controlling for time effects mostly impacts the price coefficient estimate. The estimated price coefficient changes sign from positive to negative and is still significant in column II.

Column III presents the estimation results for our main specification of Model 2 that includes customer fixed effects and time effects. In addition to the 441 outlet-only customers, 444 customers who only have a single store purchase also drop out from this analysis because of the inclusion of the customer fixed effects. Inclusion of the customer fixed effects helps control for the selection problem. The parameter estimate for the adoption dummy is still negative and significant, but the size of the coefficient decreases dramatically after we control for selection. These results demonstrate that for customers who adopt the outlet channel, the conditional retail store expenditure decreases slightly after adoption. The size of the coefficient estimate on the adoption dummy indicates that, on average, the conditional monthly expenditure at the retail store channel decreases by approximately 4% ($\exp(-0.044) = 0.96$) after a customer adopts the outlet channel. Assortment and price both impact conditional expenditure negatively. The time trend coefficient estimate is negative and significant. The estimated month fixed effects are not reported here but are included in Table A3 of Online Appendix C.

These results, combined with the OLS results from Model 1, point to an increase in retail store spending after adoption of the outlet channel for adopters. Model 1 points to a 43% increase in monthly purchase probability, and Model 2 points to a 4% decrease in expenditure conditional on incidence. The average conditional monthly expenditure for multichannel customers is \$124.88 in our data. Model 2 points to a decrease of \$5.00 ($=0.04 * \$124.88$) in conditional monthly expenditure to \$119.88, which, coupled with the estimated 0.118 increase in monthly purchase probability from 0.278 (from Model 1), results in an increase of \$12.76 in average monthly spending ($=119.88 * (0.278 + 0.118) - 124.88 * 0.278$) or \$153.07 in average annual retail store spending. This corresponds to a 34% (=153.07/455.39[6]) increase in average annual total spending in the retail store channel. Combined with the additional \$142.07 multichannel customers spend on average annually in the outlet channel (from Table 2), the impact of outlet channel adoption on a customer's overall combined spending with the retailer is rather large (65%). Increased spending in the retail stores after adoption of the outlet channel accounts for 52% ($=153.07/(153.07 + 142.07)$) of the incremental purchases, whereas the remaining 48% come from purchases in the outlet stores. Another important point to note here is that the impact of adoption on total spending in the retail store channel is mainly through increased frequency; the impact on conditional expenditure is relatively very small.

Comparing the estimation results with and without the customer fixed effects, we observe that the inclusion of customer fixed effects results in a reversal of the sign of the adoption dummy from negative to positive in Model 1 (see columns II and III

[6] Since all averages are calculated by averaging first within each customer and then across customers, the average total annual retail store spending (\$455.39, from Table 2) is not exactly equal to *the average monthly conditional expenditure * average monthly purchase probability * 12* (=\$124.88 * 0.278 * 12 = \$416.60).

in Table 3) and a large decrease in the size of the negative adoption dummy variable in Model 2 (see columns II and III in Table 4). These findings point to the possibility that customers who adopt the outlet channel *buy less frequently* and *spend less per monthly purchase* in the retail store channel compared to store-only customers. We further investigate whether customers who adopt the outlet channel have lower retail store purchase frequencies and conditional expenditure levels by conducting a cross-customer analysis in Online Appendix B. Models A3 and A4 of Online Appendix B show that after controlling for marketing mix and time effects, the customers who adopt the outlet channel have lower retail store purchase frequencies and conditional expenditure levels *before* outlet adoption, compared to those who do not.

4.3. Incidence and Conditional Expenditure Models—Instrumental Variables Results

Although the panel data approach allows us to control for sorting of heterogeneous customers into channels, there might also be changes over time that may be of concern for endogeneity. One such concern would be that customers facing an increase (or decrease) in their purchase frequency or conditional expenditure might be more (or less) likely to adopt an additional channel. Adopting the outlet channel is a choice, and there will be an endogeneity problem if changes in customers' purchase frequency or conditional expenditure over time influence their channel adoption. Previous research has shown that not accounting for endogeneity of customers' decisions (Zentner et al. 2013) or firms' decisions (Villas-Boas and Winer 1999) when it is a concern may result in substantial bias when estimating demand models. To address this concern, we need to observe changes in the customer's likelihood to adopt the outlet channel that are not caused by monthly changes in the customer's purchase frequency or conditional expenditure levels. In this section, we present results from an instrumental variables (IV) analysis and show that our main findings from the OLS analysis are still valid after we remove the part of the variation in customers' outlet channel adoption that might be endogenous.

For this purpose, we use the customer's distance to the closest outlet store as an instrument. Our identification assumption is that the retailer's decision to open an outlet store in an area is unlikely to be driven by changes in individuals' current or expected retail store purchase frequency or conditional expenditure levels. When the retailer opens a new outlet store close to a customer's home, reducing her distance to the closest outlet store, cost of purchasing from the outlet channel decreases, and the customer will be more likely to start purchasing from the outlet channel. We believe distance to the closest outlet store is a good instrument since there is a high likelihood that the exogenous change in this distance will impact the customer's likelihood of adopting the outlet channel (i.e., the instrument is correlated with the endogenous regressor) and impact incidence or conditional expenditure in the retail store channel exclusively working through the adoption likelihood (i.e., the instrument is not correlated with the error term). Distance to the closest outlet store should not impact how often a customer buys from a retail store or how much a customer spends in the retail store (conditional on a purchase) unless she adopts the outlet channel. This instrument has been used extensively in the literature for channel choice/adoption decisions (Zentner et al. 2013, Forman et al. 2009, Brynjolfsson et al. 2009).

In our fixed effects IV regression model, inclusion of distance as an instrument for outlet adoption introduces exogenous within-individual variation in the adoption likelihood and enables the identification of the effect of adoption on incidence and conditional expenditure free of the endogeneity concern. In the first-stage model, impact of distance on outlet adoption is identified from the within-customer variation in the distance variable over time. All other model parameters are identified from the within-individual variation in the related variables over time (after taking time effects out).

In our model, once a customer adopts the outlet channel, she does not make the decision to adopt the outlet channel or not anymore, and the adoption dummy is set to 1 for all periods following the adoption by definition. To handle this characteristic of our model setup in the IV estimation, we conduct the first stage using data from periods up to and including the month of each customer's outlet adoption (preadoption period) only. After the first stage is run and the fitted values are calculated for the "adoption dummy," we run the second stage using data from both pre- and postadoption periods. In the second stage, the adoption dummy is set to 1 for all observations in the postadoption period, and the standard errors are corrected.

Tables 5 and 6 present our first-stage and second-stage results, respectively, for the IV analysis for the incidence and conditional expenditure models. In the IV analysis we include, in addition to each customer's distance to the closest outlet store, the log and square of this distance as instruments to allow for a flexible functional form for the relationship between distance and adoption likelihood. Although we do not have data on individual customers' geographic locations, we have very detailed data on the geographic locations of the stores they shop at. Since the retailer's retail stores are widespread around the country, with over 300 locations, we use the location of the retail store a customer most frequently

Table 5 Monthly Retail Store Incidence and Conditional Expenditure—First-Stage IV Estimates

	Adoption
Distance to the closest store in miles	0.00005***
	(0.00002)
Log of distance to the closest store in miles	−0.00794***
	(0.00211)
Square of distance to the closest store in miles	−0.00000**
	(0.00000)
Average store price	0.02305***
	(0.00131)
Store assortment	−0.00002
	(0.00004)
Time trend	0.00189***
	(0.00004)
Intercept	−0.01911**
	(0.00749)
Observations	299,343
R-squared	0.29090

Notes. The estimated model includes fixed effects for both months and individuals. Standard errors are clustered by customer.
**Significant at 5%; ***significant at 1%.

Table 6 Monthly Retail Store Incidence and Conditional Expenditure—Second-Stage IV Estimates

	I Model 1	II Model 2
Adoption dummy	0.078***	−0.022
	(0.012)	(0.041)
Store assortment	0.031***	−0.006***
	(0.000)	(0.002)
Store price	−0.140***	−0.314***
	(0.007)	(0.086)
Intercept	−0.008	5.359***
	(0.020)	(0.198)
Time trend	−0.003***	−0.002
	(0.000)	(0.002)
Observations	392,347	118,668
R-squared	0.839	0.361
Month fixed effects	Yes	Yes
Customer fixed effects	Yes	Yes

Note. Standard errors in parentheses are clustered by customer.
***Significant at 1%.

shops at as an approximation to that customer's geographic location. We calculate the shortest distance (in miles) between a customer's location and the outlet stores open on a particular month using the Haversine formula widely used in geocoding to calculate the distance between two points on earth from their longitudes and latitudes. Combining these data with the store opening dates for outlet stores enables us to calculate each customer's distance to the closest outlet store for each month in our observation period. As we have discussed earlier, one unique feature of our data is that they correspond to a period where the retailer was rapidly expanding its outlet store network. The number of outlet stores increased by 51% during the two-year observation period for our data. This rapid expansion results in a pronounced decrease in an average customer's distance to the closest outlet store. Whereas the sample average of the distance to the closest outlet store is 97 miles at the start of the observation period, this average drops to 55 miles at the end; the average across all customers and time periods is 77 miles.

The first-stage results presented in Table 5 show that when the retailer opens an outlet store, the probability of adopting the outlet channel increases for customers who live close to the new outlet store (and thus face a reduction in their distance to the closest outlet store). To evaluate the magnitude of the estimated effect, we can perform a back of the envelope calculation. The mean of the adoption dummy in our data conditional on the fact that the customer has not already adopted the outlet channel is 0.018. The parameter estimates for the three distance variables (log of distance in miles, distance in miles, and square of distance in miles) show that the customer's probability of adopting the outlet channel increases by 0.013 (which is a 72% increase compared to the mean of 0.018) when her distance from the closest outlet store decreases from 77 miles (sample mean) to 10 miles due to the opening of an outlet store. The opening of an outlet store close to a customer's residence decreases the transportation cost to the closest outlet store and as a result increases the customer's adoption probability.

In our first-stage regression model, all distance variables are significant as well as the overall first-stage model (F statistic for the joint significance of all model parameters is $F(17, 19{,}062) = 212.11$; $p < 0.01$). The F statistic for the joint significance of the three distance variables (partial F), on the other hand, is $F(3, 19{,}062) = 6.42$ ($p < 0.01$). The incremental R-squared for the three distance variables is 0.00012.

Table 6 presents results from the second-stage analysis of Models 1 and 2. The purchase incidence model IV results presented in column I show that retail store assortment has a positive effect on retail store purchase incidence, whereas retail store price has a negative effect. The parameter estimate for the time trend is negative and significant. The parameter estimate for the adoption dummy is positive and significant, and the size of the coefficient from our IV analysis is close to the estimate from our OLS analysis (0.118 versus 0.078). The conditional expenditure model IV results presented in column II show that both retail store assortment and retail store price have negative impacts on retail store expenditure conditional on purchase. The size of the parameter estimate for the adoption dummy from our IV analysis is once again close to the estimate from our OLS analysis (−0.044

versus −0.022), but it is not significant. The standard error of the adoption dummy in the IV analysis is considerably larger than that of the OLS analysis.

Our IV results are useful in demonstrating that the main findings from the OLS results are still valid after we remove the part of the variation in the adoption dummy that might be endogenous.[7] However, since the incremental R-squared and the partial F statistics from the first stage are small, we cannot rule out the possibility of weak instrumental variables. We also cannot rule out the possibility that the retailer has located its outlet stores in areas where the retail stores face an increase in customers' current or expected purchase frequencies or conditional expenditure levels. For these reasons, the IV results might not be the best estimate of the effect of adoption of the outlet channel on retail store purchase frequency and conditional expenditure. We view the IV results as a sensitivity check of our OLS results.

5. Summary and Discussion

In this paper, we study whether adopting the lower-quality, lower-price outlet channel helps or hurts a customer's spending in a retailer's traditional higher-quality, higher-price retail store channel. The unique individual-level panel data set we use provides purchase transaction details for a specialty apparel retailer's customers across several retail stores and factory outlet stores. Our model of customer purchase incidence and conditional expenditure decisions enables us to control for time-varying marketing mix factors such as prices, product quality, and product assortment as well as concerns for endogeneity due to unobserved customer heterogeneity and selection.

We find that although customers who adopt the outlet channel buy less often and spend less per purchase occasion compared to customers who purchase only through the retail stores, the difference cannot be attributed to the causal effect of adopting the lower-quality channel on customers' total retail store spending. Utilizing the panel structure of our data and instrumenting for outlet adoption to control for selection, we recover a positive impact from adoption of the outlet channel on customers' total retail store spending. This result is important for two reasons. First, it showcases the importance of controlling for the bias introduced by selection effects and customer heterogeneity that may be particularly pronounced in a channel structure where channels are differentiated in price and quality to induce customer segmentation through self-selection. Second, it demonstrates that some of the benefits from multichannel contact previously documented in the context of channel structures consisting of channels providing similar goods at similar prices extend into a setting where the retailer's channels are differentiated in price and quality.

Contrary to the predictions from the brand extension literature (Kirmani et al. 1999) and concerns of practitioners (Geller and Wahba 2010), we do not find evidence of brand dilution and cannibalization in our data. On the other hand, one should acknowledge that the absence of brand dilution and cannibalization in our data might be partly due to the retailer's success in creating enough differentiation and separation between the two channels. In addition to much lower product quality and smaller assortment in the outlet stores compared to the retail stores, the retailer in our application has also managed to separate the two channels by limiting the flow of merchandise from retail stores to the outlet stores, excluding returns across the two channels, and locating outlet stores far from the retail stores.

Although our focus in this study is not on explaining the reason behind the documented increase in retail store spending after adoption of the outlet channel, the fact that multichannel customers have lower spending levels before adoption and that they are less profitable in the retail stores compared to store-only customers points to the possibility that the outlet channel may provide budget-conscious or risk-conscious customers unfamiliar with the brand the opportunity to learn about the retailer's styles and product fit at a low cost, since designs are similar across the two channels despite quality differences. This learning could, over time, translate into higher purchase probability in the retail store channel. This explanation is also in line with the widely held belief in the industry that the outlet channel could serve as an entry point for the retailer (Geller and Wahba 2010) in the price-conscious segment, which may trade up to the retail store over time. The outlet channel may also extend the reach of the brand to more purchase occasions. For example, a customer who only buys work clothes through the retail stores might find the newly opened outlet store with its lower price point to be a good fit for her daily clothes. This would lead to incremental purchases at the outlet channel. Over time, the positive associations formed through learning and repeated patronage of this channel may transfer to the store channel and increase purchases at this channel as well (Avery et al. 2012).

Our results highlight the effectiveness of the outlet channel in capturing incremental business from customers who would otherwise not buy much from the traditional retail store channel and also in increasing these customers' spending in the retail store channel. In light of these results, it might be a good idea for

[7] The IV results point to a 0.078 increase in monthly purchase probability coupled with no change in conditional expenditure, which amounts to an increase of \$9.74 in average monthly spending (=124.88 $*$ 0.078) or \$116.89 in average annual retail store spending.

retailers to focus on (1) customer acquisition through the outlet channel, possibly through joint marketing programs with outlet centers; (2) transitioning outlet customers over time to the retail store channel using targeted marketing communications and incentives; and (3) encouraging low spenders among store-only customers to adopt the outlet channel.

Our data set comes from a large apparel retailer that is also among the largest chains operating outlet stores in the United States. The retailer is a typical player in the outlet segment, with its large network of retail stores and exclusively sourced outlet stores located in outlet malls. The cross-channel assortment, pricing, and in-store service policies followed by our retailer are also very similar to those followed by many others. *Value Retail News* (2012) reports that apparel is the largest segment of outlet retailing, and the industry's average discount is close to 40%, which is close to the price difference we documented in our data. Although our results are only from one retailer, we therefore believe they may apply more generally to other similar retailers.

One should still be careful, however, in generalizing these results to less typical settings such as direct retailers' outlet stores or other product categories, since the interactions in a channel structure may be affected by the industry characteristics and relative positioning of the channels. In the absence of data from multiple retailers with varying retail settings and channel structures consisting of channels differentiated in price and quality, we follow other empirical studies that have also studied multichannel customer behavior in a single retailer setting (Avery et al. 2012, Ansari et al. 2008, Biyalogorsky and Naik 2003, Pauwels and Neslin 2015, Venkatesan et al. 2007) with the objective of moving the field in the direction of empirical generalizations.

The retailer in our application did limit its marketing activities to (very limited) brand-level national TV and magazine advertising and did not engage in either local advertising or any targeted marketing activities during our observation period. Although this provides us a clean setting for investigating the impact of adoption of the outlet channel on customer purchase behavior, it also limits our ability to investigate the impact of targeted marketing programs on customer channel choice and expenditure decisions. Future research might benefit from investigating the potential use of marketing activities in managing channel interactions within a channel structure where channels are differentiated in both price and quality.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2015.2262.

References

Ansari A, Mela CF, Neslin SA (2008) Customer channel migration. *J. Marketing Res.* 45(1):60–76.

Avery J, Steenburgh TJ, Deighton J, Caravella M (2012) Adding bricks to clicks: Predicting the patterns of cross-channel elasticities over time. *J. Marketing* 76(3):96–111.

Balachander S, Ghose S (2003) Reciprocal spillover effects: A strategic benefit of brand extensions. *J. Marketing* 67(1):4–13.

Biyalogorsky E, Naik P (2003) Clicks and mortar: The effect of on-line activities on off-line sales. *Marketing Lett.* 14(1):21–32.

Brynjolfsson E, Hu Y, Rahman M (2009) Battle of the retail channels: How product selection and geography drive cross-channel competition. *Management Sci.* 55(11):1755–1765.

Clifford S (2010) Nordstrom links online inventory to real world. *New York Times* (August 23), http://www.nytimes.com/2010/08/24/business/24shop.html?_r=0.

Consumer Reports (2011) Outlet stores: Worth the trip. (November 2011), http://www.consumerreports.org/cro/magazine-archive/2011/november/shopping/outlet-stores/overview/index.htm.

Coughlan AT, Soberman DA (2005) Strategic segmentation using outlet malls. *Internat. J. Res. Marketing* 22(1):61–86.

Deleersnyder B, Geyskens I, Gielens K, Dekimpe MG (2002) How cannibalistic is the Internet channel? A study of the newspaper industry in the United Kingdom and the Netherlands. *Internat. J. Res. Marketing* 19(4):337–348.

Forman C, Ghose A, Goldfarb A (2009) Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management Sci.* 55(1):47–57.

Geller M, Wahba P (2010) In rush to outlets, retailers tread fine line. *Reuters* (May 23), http://mobile.reuters.com/article/idUSTRE64M0YK20100523?irpc=932.

Gentzkow M (2007) Valuing new goods in a model with complementarity: Online newspapers. *Amer. Econom. Rev.* 97(3):713–744.

International Council of Shopping Centers (2011) State of the global outlet industry. *Internat. Outlet J.* 7(2):8–14.

Iyer G (1998) Coordinating channels under price and nonprice competition. *Marketing Sci.* 17(4):338–355.

Kirmani A, Sood S, Bridges S (1999) The ownership effect in consumer responses to brand line stretches. *J. Marketing* 63(1):88–101.

Kumar V, Venkatesan R (2005) Who are the multichannel shoppers and how do they perform?: Correlates of multichannel shopping behavior. *J. Interactive Marketing* 19(2):44–62.

Loken B, John DR (1993) Diluting brand beliefs: When do brand extensions have a negative impact? *J. Marketing* 57(3):71–84.

Neslin SA, Grewal D, Leghorn R, Shankar V, Teerling ML, Thomas JC, Verhoef PC (2006) Challenges and opportunities in multichannel customer management. *J. Service Res.* 9(2):95–112.

Pauwels K, Neslin SA (2015) Building with bricks and mortar: The revenue impact of opening physical stores in a multichannel environment. *J. Retailing* 91(2):182–197.

Pozzi A (2013) The effect of Internet distribution on brick-and-mortar sales. *RAND J. Econom.* 44(3):569–583.

Qian Q, Anderson E, Simester D (2013) Multichannel spillovers from a factory store. NBER Working Paper 19176, National Bureau of Economic Research, Cambridge, MA.

Smith DC, Park CW (1992) The effects of brand extensions on market share and advertising efficiency. *J. Marketing Res.* 29(3):296–313.

Thomas JS, Sullivan U (2005) Managing marketing communication with multichannel customers. *J. Marketing* 69(4):239–251.

Value Retail News (2012) 2012 State of the outlet industry. 30(7):12–22.

Venkatesan R, Kumar V, Ravishanker N (2007) Multichannel shopping: Causes and consequences. *J. Marketing* 71(2):114–32.

Villas-Boas JM, Winer RS (1999) Endogeneity in brand choice models. *Management Sci.* 45(10):1324–1338.

Stringer K (2004) Shoppers who blend store, catalog, Web spend more. *Wall Street Journal* (September 3):A7.

Zentner A, Smith M, Kaya C (2013) How video rental patterns change as consumers move online. *Management Sci.* 59(11):2622–2634.