How are Demand and Returns Related?

Theory and Empirical Evidence

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Abstract

 The relationship between demand and customer returns represents an important input to inventory planning models. While poor estimates of this relationship can dramatically increase inventory management costs (de Brito and van der Laan, 2002), there is surprisingly little research on the topic. In this paper we investigate the relationship between demand and returns by comparing how customers' returns behavior for apparel items varies both across items and within an item. To guide our empirical analysis, we develop an economic model of customer purchase and returns behavior that yields testable predictions. We reject the model that customer return rates are independent of price paid. Instead, we find support for the perceived value hypothesis, which predicts that customer return rates increase with the price paid. This finding has important implications for the coordination of marketing and operations decisions. Our analysis also yields a number of additional empirical insights into customer returns behavior that are expected to generalize to other contexts.

Key Words: inventory planning, returns, pricing, field-study

1. Introduction

Sophisticated inventory models must account for not just new merchandise but also the flow of returned merchandise. While optimization of inventory is often sophisticated, the prediction of returns behavior is generally not as advanced. Most inventory models assume either that returns occur as a fixed proportion of sales or that returns are independent of sales. Surprisingly, a search of the literature reveals little empirical research describing the relationship between returns and sales. This absence of empirical work occurs despite recognition in the theoretical literature that poor estimates of returns behavior can significantly increase total inventory management costs (de Brito and van der Laan, 2002).

In this paper we examine the relationship between demand and returns. We distinguish between two types of relationships: across items and within an item. The across item relationship compares how returns vary across items when the items have different demand. The within-item relationship focuses on a single item and considers how returns change as demand for that item changes. This distinction is important as the two relationships are relevant in different settings. A firm designing a single inventory system to manage all of its products requires insights that generalize across products. For example, a firm may want to understand whether it can safely assume a common return rate for all items or whether it should adjust the return rate according to the characteristics of the items. In these settings the across-item results will be of primary relevance.

In contrast, the within-item results are of greater relevance when a firm focuses on optimizing inventory policies for a specific item. Results of the within-item analysis highlight the importance of integrating inventory policies with marketing decisions that affect product demand. In particular, we show that varying the price of a product affects both the demand for that product and the rate at which customers return the product.

A truly optimal inventory policy obviously needs to consider both effects. The across-item effects illustrate how the demand/returns relationship for a specific item differs from the average item. The within-item effects illustrate how marketing actions that affect demand for a specific item, such as lowering the price, also affect returns.

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Measuring the across-item relationship between demand and returns is relatively straight-forward as there is natural variation in demand across items. As a result we can compare how demand and returns co-vary without having to induce demand variations. In contrast, the within-item analysis requires that there is demand variation for a single item. If prices have varied over time, it may be possible to use historical variation in demand. However, this introduces a potential confound because the temporal price changes may be correlated with other factors.

We create exogenous within-item variation in demand using a large-scale field experiment conducted with a women's clothing catalog. A large sample of customers are randomly assigned to one of three experimental conditions. Within each condition, a single catalog is mailed to each customer on the same date. The catalogs are identical with the same products and layouts. The only exception is that the prices of some products vary across the three experimental conditions, so that the same product is offered to equivalent customer groups at different price levels. As expected, lower prices increase demand. The focus of this paper is on how prices affect the number of items returned and the rate of returns. Importantly, we measure the actual purchase and return behavior of real customers.

To help understand these relationships we develop a theoretical model of customer returns. The model illustrates two opposing effects: an *incremental demand* effect and a *perceived value* effect. Raising the price of an item generally decreases demand, which yields a smaller number of customers who can return an item (items can only be returned if they have first been purchased). We label the reduction in returns that result from these lost sales as the *incremental demand* effect. It is this effect that motivates the "straw man" prediction that returns and sales are positively related. The *perceived value* effect is perhaps more subtle. We will present evidence that customers are more likely to return an item when the price paid is higher. This is consistent with customers showing increased willingness to return items that offer less perceived value. The loss of perceived value leads to two predictions when prices are increased: a decrease in demand and an increase in the rate (and number) of returns.

The *perceived value* effect influences the relationship between demand and returns across items and within a single item. But, a priori the direction of this effect

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across items is ambiguous. For example, a comparison of the perceived value of a $20 shirt and a $200 evening gown is unclear. The extent to which either product offers more perceived value rests on a comparison of each product to similar shirts or evening gowns. But, within a specific item, the perceived value effect offers a clear prediction. The same shirt offers more perceived value at $20 than $25.

The *incremental demand* effect predicts that more demand leads to more returns. The effect clearly predicts that the number of returns will increase, but the impact on the rate of returns is ambiguous. The rate of return will depend on both the number of additional buyers and their characteristics. For example, customers who purchase at a high price may have different return rates than customers who purchase at a low price. Predicting the impact of a price change on the rate of return requires that we account for both the number of additional customers and potential heterogeneity in customer return rates.

Together, these two effects reveal an important and generalizable insight: the theoretical relationship between demand and returns for a product is ambiguous. Our theory shows that the two effects can have opposing implications for both the number and rate of returns. As demand changes, the net outcome could be an increase, no change or even a decrease in the number of returns (or rate of returns).

This theoretical ambiguity highlights the need for empirical research on this topic. In our empirical application the *perceived value* effect dominates, and so we see a positive relationship between prices and returns. Because the magnitude of the two effects (*perceived value* and *incremental demand*) may vary across markets, this relationship between prices and returns may not hold in all contexts. However, managers that recognize the role played by these two effects will have a better understanding of the relationship between demand and returns.

It is important to clarify that this paper focuses on returns of unwanted merchandise by customers. Another common reason for returns is recycling of consumed merchandise for remanufacturing. For example, printer cartridges, disposable cameras, and automobile parts are often returned for remanufacturing (Rogers and Tibben-Lembke 2001). This is an important source of returns in some industries, but is not considered in this paper. It is also helpful to clarify our terminology. We use the term "rate of returns"

(or "return rate") to describe the proportion of items that a customer orders and then subsequently returns. We distinguish this proportion from the "number of returns", which represents a count of how many items are returned.

Previous Literature

The field of inventory management includes a wide range of models designed to support production planning and procurement processes. All of these models require a prediction of the relationship between sales and returns. Returns are typically assumed to be a constant proportion of sales, so that if a retailer sells more items the number of items returned will increase (Kiesmüller and van der Laan 2001, Savaskan et al. 2004). In remanufacturing contexts, researchers have assumed that returns are independent of sales (see for example Fleischmann et al. 2002). To our knowledge, no models have assumed a negative relationship between demand and returns, though our theory will demonstrate that such a relationship is possible.

While the literature on inventory management is extensive it offers few empirical studies investigating the role of returns. One exception is Hess and Mayhew (1997), who analyze customer returns to an apparel catalog. The authors' main focus is on predicting the time between purchase and return. Using both actual and simulated data they show that a split adjusted hazard model is better at predicting return times than a regression model. The authors find that price paid is unrelated to return times.

As part of their analysis, Hess and Mayhew (1997) also estimate a logit model of return rates, which is closely related to our across-item analysis. Similar to our results, they find that more expensive items are more likely to be returned. We extend their results by demonstrating that the number of sizes and number of colors offered also affect return rates across items. Hess and Mayhew (1997) do not consider the within-item variation in returns. Indeed, their data does not allow them to do so as it does not contain any exogenous sources of variation of demand for the same item.

The paper also contributes to an emerging research stream that recognizes the need to coordinate marketing and operations decisions (Ho and Tang 2004). While research activity is growing, published research on the issue still remains somewhat limited. For example, Karmarkar (1996) points to "a lack of applied research that

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extends across marketing and manufacturing parameters and has consequences for practice" (p. 127). Our search of the literature revealed limited empirical research on either intra-firm coordination or inter-firm coordination between marketing and operations decisions. One exception is Kulp, Lee and Ofek (2004), who conduct a large-scale survey to investigate the value of inter-firm coordination between manufacturers and retailers. They find that there are limited gains from information sharing. They do report that collaborative initiatives in inventory management and new products and services increase performance, but caution that inter-firm coordination on reverse logistics programs can lead to the unexpected consequence of greater manufacturer stockouts.

A number of theoretical models have investigated inter-firm and intra-firm coordination. Eliashberg and Steinberg (1987) examine coordination of price and inventory policy in an industrial supply chain. Researchers have also examined the integration of marketing programs with operations decisions. This includes customer reward programs and capacity decisions (Kim, Shi and Srinivasan 2004) and customer advance booking programs with production policies (Tang, Rajaram and Alptekinoglu 2004). In related work, Hess and Lucas (2004) examine how a firm should allocate scarce resources between marketing and manufacturing.

Structure of the Paper

The remainder of this paper is organized as follows. In §2, we present a formal model of customer returns behavior. We then introduce our empirical work in §3, where we describe the implementation of the field study. The findings from the study are presented in §4 and the paper concludes in §5 with a review of the findings, limitations and opportunities for future work.

2. A Model of Customer Return Behavior

The intuition for the "straw man" that more sales lead to more returns is so strong that it requires little modeling effort. However, the within-item variation in demand and returns is more subtle and to help understand this relationship we develop a model of

customer purchase and return behavior. The model yields opposing predictions that will provide hypotheses to guide and interpret our empirical work.

The Model

Consider a consumer with utility $U = v - p$, where v is the valuation of the item and p is the price. Prior to purchasing an item, consumer h is uncertain about the item's valuation and has a prior cumulative distribution $F_h(V)$. For example, a consumer purchasing from a catalog may read an item description and see a photograph of an item prior to purchasing. After the item is received and inspected the true value, v, is revealed. At that point, the customer decides whether to keep or return the item. Due to variation in fit, styling, color and other item characteristics the true valuation may differ from the customer's expectations.

In contemplating the return decision, the customer considers the value of the outside option, $\tilde{U}$, and the return costs, c. The outside option represents the expected surplus when purchasing from a competing store. For ease of exposition we scale $\tilde{U} - c$ to zero ($\tilde{U} - c = 0$). Given these assumptions, a customer will keep an item valued at v and purchase at price p iff:

$$v - p \geq \tilde{U} - c \equiv 0 \tag{1}$$

Customers are forward looking and incorporate the return option into their purchasing decision. Let $\bar{V}_h = E_h(V \mid V \geq p)$ represents the expected value of an item that is not returned by customer h. Customer h will purchase an item iff:

$$\left[1 - F_h(p)\right]\left(\bar{V}_h - p\right) + F_h(p)\left(\tilde{U} - c\right) = \left[1 - F_h(p)\right]\left(\bar{V}_h - p\right) \geq \tilde{U}. \tag{2}$$

As we would expect, inequality (2) implies that customer demand for an item is negatively correlated with price paid. Inequality (1) predicts that the probability that a customer returns an item is positively correlated with price.

To illustrate the relationship between sales and returns we will focus on a market with two segments of customers: a mass of n_H high type customers and a mass of n_L low type customers. We consider two exogenous price levels, p_H and p_L, such that only the

high type customers purchase at p_H and both types of customers purchase at p_L. Each customer segment has the same prior distribution of valuations, $F_h(V)$ where $h \in (H, L)$, and receives an independent draw from this distribution. If upon arrival of the item, inspection reveals that $v < p$ then the customer returns the item. Otherwise the customer keeps the item.

At the high price the return rate is $r(p_H) = F_H(p_H)$ and the total number of items returned is: $R(p_H) = n_H F_H(p_H)$. At the low price, the number of items returned is $R(p_L) = n_H F_H(p_L) + n_L F_L(p_L)$ and the return rate is $r(p_L) = R(p_L)/(n_H + n_L)$. If the price increases from p_L to p_H, then demand decreases. The change in total returns is:

$$\Delta R = R(p_H) - R(p_L) = n_H \left[F_H(p_H) - F_H(p_L) \right] - n_L F_L(p_L), \tag{3}$$

and the change in the return rate is:

$$\Delta r = r(p_H) - r(p_L) = \frac{n_H \left[F_H(p_H) - F_H(p_L) \right] + n_L F_H(p_H)}{n_H + n_L} - \frac{n_L F_L(p_L)}{n_H + n_L}. \tag{4}$$

In equations (3) and (4), the first term is positive and captures the *perceived value effect*. The second term is negative and captures the *incremental customer* effect. The resulting change in the return rate and number of returns is ambiguous and depends on the net magnitude of these two effects.

We can further illustrate this ambiguity by evaluating some alternative scenarios. First, consider a market in which the low type customers are relatively certain of their valuations. It is helpful to start with the extreme assumption in which they have no uncertainty, so that they effectively know v before purchasing. Under this assumption the low type customers always purchase an item priced at p_L and never return the item: $F_L(p_L) = 0$. As a result, there is no *incremental demand* effect (the incremental customers do not contribute returns) and the last terms in Equations 4 and 5 are both zero. This isolates the effect of a price change to just a decrease in *perceived value* for the high type customers, which increases both the number of returns and the return rate.[1]

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[1] Recall that $F_H(p_L) < F_H(p_H)$.

Alternatively, it is possible that low type customers tend to return items much more frequently than the high type customers: $n_H F_H(p_H) << n_L F_L(p_L)$. The loss of these low type customers amplifies the *incremental customer* effect. If this effect outweighs the increase in the return rate amongst the high type customers (due to increased *perceived value*), the result will be reversed: raising the price will lead to a decrease in both the number of returns and the return rate ($\Delta R < 0$ and $\Delta r < 0$).

We conclude that the predicted change in the number of returns that results from a price increase is ambiguous. The *perceived value* effect predicts an increase in returns but the *incremental demand* effect predicts a decrease. Because of these opposing effects, the overall number of returns is ambiguous. There is also no *a priori* prediction of return rates because the incremental demand effect is ambiguous with respect to the return rate. Whether the return rate increases, remains unchanged, or decreases depends on both the number of additional customers (n_L) and the return rate of these incremental customers ($F_L(p_L)$). Given the ambiguity of the theoretical predictions, the actual outcome is an empirical question.

We summarize these within-item predictions in Table 1, and in the next section present findings from a field test in which we measure actual return behavior for a large sample of real customers. Although the findings should be interpreted as a case study for a single firm, they do represent the first opportunity to measure the net impact on returns when prices are varied.

Table 1. Within-Item Price Variations
Predicted Impact of a Price Increase

	Perceived Value	Incremental Demand
Number of Returns	Increase	Decrease
Return Rate	Increase	Ambiguous

3.   Design of the Studies

The field test was conducted in a mail-order catalog that sells women's fashion clothing, in the plus-size category, which is one of the fastest growing segments in the apparel industry. For confidentiality reasons we are unable to identify the name of the catalog. The items are all sold under the firm's own private label brand and are only available through the company's catalog. Although clothing with the same brand is not available in retail stores, other companies offer competing brands in both direct and traditional store channels.

The company offers a very liberal return policy: customers can return any item for any reason provided they pay for return shipping and handling.[2] A pre-paid mailing label allows customers to return the item via the US Postal service with no immediate out-of-pocket expense. After receipt of the item, the company refunds the item price less $4.00 for return shipping.

The catalog used in the study contained 308 items. Three catalog versions were produced, and each version was distributed to a random selection of 90,000 customers. The study was designed to investigate how varying the price, the price ending and the use of "Sale" cues impacted demand. The findings, which are reported in a previous paper (Anderson and Simester 2003), confirm that all three cues were effective at increasing demand. Our current analysis will focus on the price manipulations and investigate how they affect returns.[3]

The prices of the items in the Control version were the standard prices for the items and averaged approximately $58. In Version A, the prices of 55 items were raised by $1 to $6 and the prices of 53 items were lowered by $0.50 to $4. In Version B the prices of 58 items were raised by $1 to $4.50 and the prices of 52 items were lowered by $0.50 to $10. The resulting average prices across the three experimental versions are summarized in Table 2.[4]

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[2] Theoretical models have identified conditions under which such polices are optimal (see for example Hess et al. 1996; and Davis et al. 1998).
[3] In additional analysis we also investigated how the price endings and sale signs affected the return rate. The findings revealed that the impact (if any) was small and was not statistically significant.
[4] A more detailed description of the manipulations can be found in Anderson and Simester (2003).

Table 2: Average Prices in the Test Catalog

	Control	Version A	Version B	Number of Items
Test Items	$58.39	$58.32	$58.44	148
Non-Test Items	$49.64	$49.64	$49.64	160
All Items	$53.84	$53.81	$53.87	308

The catalog company determined which items were involved in the test. However, the same items appeared in all three catalog versions, providing an explicit control for item selection. The use of a control also excludes alternative explanations arising from intervening events, such as competitive actions. By exogenously varying prices and price cues between the three catalog versions, we also overcome endogeneity concerns that potentially arise in non-experimental data. As a result, our model parameters are readily interpretable and not subject to confounds.

When customers place an order they provide a code printed on the back of the catalog that they are ordering from. This code allows the firm to identify the specific version of the catalog that the customer received (Control, Version A or Version B). The data we received describes the catalog code, an order identification number, customer identification number, quantity purchased, price paid for each item, and whether the item was returned. The date of the return is not provided, which prevents us from investigating the timing of returns. The retailer also tracked whether a customer purchased with a credit card or check and whether the customer ordered over the phone or via mail. Finally, for a sample of approximately 10% of the customers we also received past transaction histories. This historical data describes the customers' previous orders and their previous returns decisions. We describe this sample of customers in more detail in later discussion.

4. Empirical Analyses

We begin by comparing how the return rate varies across items and evaluating whether it is influenced by the characteristics of the items. We then use the experimental

manipulations to investigate how varying the price of a specific item affects both the number and rate of returns for that item.

Across-Item Results

On average, in each condition 16.9 units of each of the 308 items were sold and 3.9 units were returned. The average return rate was 22.9%, which is typical for the direct marketing industry (Rogers and Tibben-Lembke 1998, Hess and Mayhew 1997). Item return rates varied from 0% to 100% and there is considerable variation both across and within items. To illustrate the variation in return rates across items, we plot the total units sold and returned for all 308 items in the Control version of the catalog in Figure 1.

As we would expect, Figure 1 indicates a strong positive correlation between the number of items ordered and the number of returns. This relationship provides the basis of the *incremental demand* effect: because items can only be returned if they have first been ordered, an increase in orders will tend to lead to an increase in the number of returns. We can analyze this relationship more formally using a multivariate approach. In particular, in Table 3 we report the coefficients that result from regressing the *Number of Returns* against the *Quantity Sold* together with separate variables describing the characteristics of each item. We consider three item characteristics:

Price	The item price.
Number of Colors	The number of color options available for that item.
Number of Sizes	The number of size options available for that item.

Figure 1: Total Units Purchased and Returned
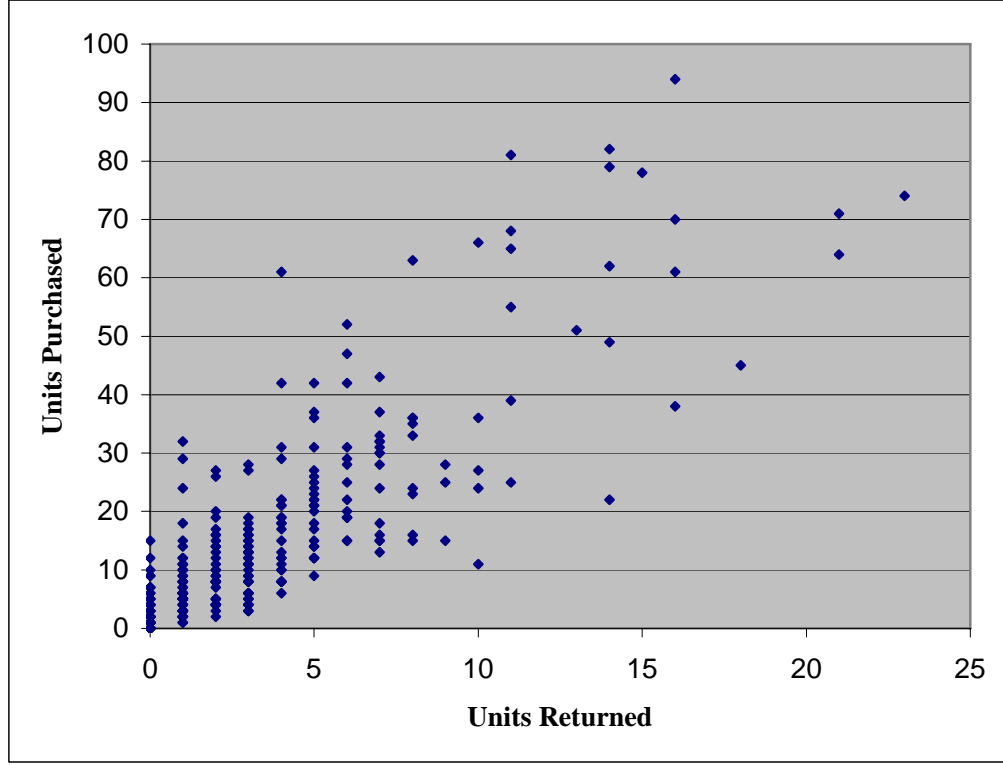
We aggregate across the three experimental conditions and use the total number of returns and total demand as dependent and independent variables (respectively). For the *Price* variable we use the average price charged in the three conditions. This yielded the following model (where the subscript *i* identifies the different items):

$$Number\ of\ Returns_i = \alpha + \beta_1 Quantity\ Sold_i + \beta_2 Price_i + \beta_3 Number\ of\ Colors_i + \beta_4 Number\ of\ Sizes_i$$

For completeness we report the findings when including just the *Quantity Sold* together with separate models in which we add the other independent variables both separately and jointly. The findings reveal that the *Quantity Sold* explains approximately 76% of the variance in the *Number of Returns*. Adding the other explanatory variables only explains an additional 1% of the variance. Although they explain only a relatively small portion of the overall variance, there is evidence that the *Price*, *Number of Colors*

and *Number of Sizes* significantly affect the number of returns. Customers return more items when the price of the item is higher. If an item is available in more sizes customers also return more items. This is consistent with customers facing a more difficult task of matching their own size with the item size when they have a larger range of sizes available to choose from.

Table 3: Units Returned Across All Catalog Versions

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	1.380** (0.231)	3.080** (0.673)	-0.048 (0.756)	-0.763 (0.870)	0.078** (1.267)
Qty Sold	0.196** (0.006)	0.204** (0.007)	0.197** (0.006)	0.203** (0.007)	0.209** (0.007)
Number of Colors		-0.689** (0.205)			-0.533* (0.211)
Number of Sizes			0.279* (0.119)		0.200 (0.119)
Price				0.033** (0.012)	0.025* (0.012)
Adj. R-squared	0.76	0.76	0.77	0.77	0.77
Sample size	308	308	308	308	308

Standard errors are in parentheses.
** Significantly different from zero ($p < 0.01$).
* Significantly different from zero ($p < 0.05$).

Given the size result it is perhaps surprising that if an item is available in more colors then returns are less frequent. These differing results may partly be explained by the source of customers' preferences for variety. Customers only have demand for a single size but may have demand for multiple colors. When a size fails to meet expectations then it is always a negative outcome and a customer is likely to return an item. But, when a color fails to meet expectations the outcome is not necessarily bad. Some customers may like the actual color more than the color they expected.

An alternative explanation for this effect is that the firm may have expanded the color options for items that have both high demand and low return rates. If firms increase the level of variety for such items, this would also explain why an increase in color

varieties leads to fewer returns. If correct, this explanation cautions managers that merely increasing color options may not lead to fewer returns.

We can more directly estimate the impact of these item characteristics on the return rate by calculating the *Return Rate* for each item and using this as the dependent variable in our analysis. The findings of this analysis are reported in Table 4. We omit three items for which there was zero demand across all three conditions. For these items the return rate is undefined. We estimate a weighted OLS regression where we weight each observation by the *Quantity Sold*. This approach places greater weight on observations for which we have a more precise estimate of the item return rate.

Table 4: Return Rate Across All Catalog Versions

	Model 1	Model 2	Model 3	Model 4
Intercept	0.279** (0.012)	0.183** (0.013)	0.153** (0.011)	0.170** (0.022)
Number of Colors	-0.015** (0.003)			-0.007* (0.003)
Number of Sizes		0.009** (0.002)		0.005* (0.002)
Price			0.002** (0.000)	0.001** (0.000)
Adj. R-squared	0.075	0.038	0.135	0.164
Sample size	305	305	305	305

Standard errors are in parentheses. Missing observations reflect no demand across all three conditions for those items.
** Significantly different from zero ($p < 0.01$).
* Significantly different from zero ($p < 0.05$).

The findings for all three of the item characteristics measures replicate our analyses of the number of returns. Jointly the variables explain just over 16% of the variation in the return rate.[5] We conclude that price, number of colors and number of sizes can explain a meaningful proportion of the variation in return rates.

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[5] As a benchmark, a naïve model that predicts a constant return rate for all products explains 0% of the variation in return rates.

The analysis reported in Tables 3 and 4 does not make use of the exogenous variation in prices across the three experimental conditions. In the next sub-section we explicitly control for item effects. This allows us to focus on how the variation of prices for a specific item affected demand for that item.

Within-Item Analysis

To evaluate how the experimental manipulation of prices across the three conditions affected the return rate we begin by presenting univariate findings. The experimental manipulations resulted in 65 items for which we observe a return rate at three different price levels (omitting items with zero demand in one or more conditions). For ease of exposition we label the three price levels: "Low" Medium" and "High". Aggregating across the 65 items yields measures of the return rate at each price level. The findings reveal a significant increase ($p < 0.05$) in the return rate in the High (28.2%) and Medium (28.5%) price conditions compared to the Low price condition (24.3%), but no significant difference between the Medium and High conditions.

In our multivariate analysis we focus on the same 65 items and adopt a similar approach to the multivariate model used to analyze the across-item results. For the within-item analysis we introduce a binary variable *Item j* identifying each item. The dependent variable, $Y_{i,v}$, is either the *Number of Returns*$_{i,v}$ or the *Return Rate*$_{i,v}$ for item *j* in catalog version *v*. This leads to the following model specification:

$$Y_{j,v} = \sum_{j=1}^{65} \alpha_j Item\ j\ + \beta_1 Price_{j,v}$$

These item "fixed effects" allow the intercept to vary across each item and control for all item effects that are invariant across the experimental conditions. This includes the number of available sizes and colors, and so the *Number of Sizes* and *Number of Colors* variables are omitted from the model. The only effects not captured by these fixed item effects are the features that were experimentally manipulated across the conditions. In particular, we retain the price variable, and its coefficient allows us to directly estimate the impact that the exogenous variation in prices had on customers' returns behavior. The findings are reported in Table 5.

Table 5: Within-Item Variation in Return Rates

	Number of Returns	Return Rate
Price	0.6137[**]	0.0130[*]
	(0.2092)	(0.0061)
Adj. R-squared	0.704	0.289
Sample size	195	195

Standard errors are in parentheses. We omit coefficients for the binary
variables identifying each item.
[**] Significantly different from zero ($p < 0.01$).
[*] Significantly different from zero ($p < 0.05$).

In previous analysis of this data, Anderson and Simester (2003) showed that price
and demand exhibit the typical negative relationship. Despite the fact that fewer items
are sold at a higher price, we find the number of returns increases with price paid. While
surprising, our theory suggests why this is happening. When the price is increased the
perceived value effect increases the probability that a customer will return an item. For
these products, this effect is large enough to dominate the *incremental demand* effect.

We also find that the return rate is positively associated with price paid. The
effect is relatively large, leading to an average increase of over 4% in the return rate in
the high price conditions. Recall from our theoretical model that there are at least two
competing explanations for why return rates increase with the price:

1. **Incremental Demand**: Customers who purchase in the Low price condition have a
   different tendency to return items than customers who purchase in the Medium and
   High price conditions.

2. **Perceived Value**: A given customers is more likely to return an item in the Medium
   and High price conditions than in the Low price condition.

We use two approaches to evaluate these alternative explanations. In the first
approach we use the sample of historical data to identify customers' individual return
tendencies. This allows us to compare how these customer characteristics vary across
customers who purchase at the High, Medium and Low price levels. We also investigate
whether the positive relationship between prices and returns holds even when controlling
for these customer characteristics. A limitation of this first approach is that we are forced
to restrict attention to a relatively small subset of the data. In our second approach we
use a series of other metrics to control for customer characteristics. We also explicitly

control for the conditional relationship between demand and returns. Because items can only be returned if they have been first purchased, any stochasticity in demand also affects our measure of returns.

Historical Data

We have historical data describing the past returns behavior of 623 customers who ordered from one of the three versions of the Test Catalog. This represents just over 10% of the customers who ordered from the Test Catalog. The historical sample of data was obtained as part of another unrelated study that focused on customers who had purchased relatively recently and frequently from the firm. As a result, the customers for whom we have historical data do not represent a random sample of customers in the current study. Instead they tend to be more valuable customers, ordering more items from the Test Catalog and spending more money than other customers in our sample.

Although the customers for whom we have historical data were not randomly selected, they were randomly assigned to our three experimental conditions. As a result, when restricting attention to this sample, we can still exploit the exogenous variation in the prices across the three conditions to evaluate our two explanations.

We begin with the first prediction that customers who purchase in the Low price condition have a different tendency to return items than customers who purchase in the Medium and High price conditions. To evaluate this prediction we calculated the average *Historical Return Rate* for each customer, which represents the average number of returns made prior to the Test Catalog by each of the 623 customers in the sample.[6] Recall that we only measure returns when we observe demand. Because we use just 10% of the total sample, there are many items for which we only observe demand at a single price level. Restricting attention to items for which there is demand in at least two price conditions yields a total of 467 purchases across 77 items.

We averaged the *Historical Return Rate* across customers, calculating a separate average at each price level for each of the 77 items. A pairwise comparison of these

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[6] The average number of historical items purchased by these 623 customers was 18.9, with an average of 4.4 returns (at a rate of 21.3%). Subsequently these customers purchased 1,790 units from the Test Catalog, of which 326 were returned (18.2%).

averages across the price levels provides a test of whether the *Historical Return Rate* varied systematically across the price levels. For example, consider a pair of shoes priced at $55, $57 and $59 in three different catalogs. We compute the average *Historical Return Rate* and the the average *Historical Number of Returns* among customers who paid $55 (low), $57 (medium) and $59 (high). A comparison of these averages reveals whether customer return characteristics vary with the price level. Results of these pairwise comparisons are reported in Table 6.

Table 6: Historical Return Rates By Price Paid in the Test Catalog

Comparison	High	Medium	Low	Difference	Number of Items
Number of Returns					
High vs. Low	3.74	n.a.	7.20	-3.46* (1.46)	34
Medium vs. Low	n.a.	4.32	4.32	0.00 (0.96)	48
High vs. Medium	5.09	3.90	n.a.	1.19 (1.51)	33
Return Rate					
High vs. Low	21.4%	n.a.	28.1%	-6.7% (4.5)	34
Medium vs. Low	n.a.	20.7%	24.7%	-4.0% (3.3)	48
High vs. Medium	23.2%	22.5%	n.a.	0.7% (4.4)	33

Standard errors are in parentheses.
** Significantly different from zero ($p < 0.01$).
* Significantly different from zero ($p < 0.05$).

Our earlier analysis revealed that customers were more likely to return items for which they paid higher prices. Explaining this finding using the *incremental demand* explanation requires that customers who purchase at higher prices tend to be <u>more likely</u> to return items than customers purchasing at lower prices (Prediction 1). The findings in Table 6 do not support this claim. We find that the *Historical Number of Returns* is significantly lower among customers who purchase items at the High price compared to the Low price ($p < 0.05$). Although the other pairwise comparisons are not significantly

different, if anything the averages suggest that customers purchasing at higher prices tend to have <u>lower</u> historical return rates. We conclude that the increase in the number and rate of returns at higher prices cannot be explained by differences in characteristics of customers purchasing at each price level.

The second explanation for the positive impact of prices on returns is that increasing the price lowers customers' perceived value, and increases the probability of a return. To evaluate this explanation we use the historical return rate to explicitly control for customers' return characteristics. By doing so we can evaluate whether customers with the same return characteristics are more likely to return in the high price condition than in the low price condition.

The observations in this analysis are the 1,790 units purchases by the customers for whom we have historical data. The dependent measure, *Returned,* is a 0 or 1 variable indicating whether customer h returned product j. Given the binary nature of the dependent measure we estimated a logit model, which allows us to estimate the return rate. The independent measures are the *Price* of the item, the *Historical Return Rate*, and binary variables controlling for item fixed effects. The findings are reported in Table 7.

Table 7: Controlling for Customers' Historical Return Tendencies

	Return Rate
Historical Return Rate	6.414^{**} (0.446)
Price	0.320^{*} (0.149)
Log Likelihood	-473.6
Sample size	1,790

Standard errors are in parentheses. We omit coefficients for the fixed item effects.
** Significantly different from zero ($p < 0.01$).
* Significantly different from zero ($p < 0.05$).

The results reveal several interesting findings. First, the *Historical Return Rate* is an excellent predictor of which customers returned items during the test. Customers who had returned a higher percentage of their past orders were also more likely to return items

from the Test Catalog. This finding supports our interpretation that the *Historical Return Rate* provides a metric of customers' individual tendencies to return items.

Second, the positive relationship between the price customers' paid for an item and the probability that customers return the item survives even after controlling for customers' historical return characteristics. This suggests that this relationship between price paid and returns is robust. Note that the analysis controls not just for customer characteristics, but also for the item characteristics. These item characteristics account for the variation in prices across items, so that the relationship between price and returns can be attributed solely to the exogenous manipulation of prices within an item. As a result, we can conclude that we have measured a causal relationship: increasing the prices of items in this study led to a higher return rate on those items.

Finally, we also conclude that the findings are consistent with the *perceived value* explanation and cannot be explained by the *incremental demand* explanation. If the positive relationship between prices and returns was due to differences in customers' individual return characteristics, the finding would not survive controlling for these characteristics. Recall that the *perceived value* explanation argues that the increase in the return rate reflects the loss of value for customers when prices are increased. This is consistent with the logit specification, which explicitly estimates how the price variations affect customers' perceived value. We caution that there may be other as yet unidentified explanations for why higher prices lead to an increase in the return rate. However, in the absence of an alternative explanation it seems likely that the relationship between prices and returns is at least partly explained by the *perceived value* interpretation.

Full Sample

The advantage of using the historical sub-sample of customers is that we can directly observe historical return behavior for these customers. The primary disadvantage is that the analysis is restricted to just 10% of the customers. In this section, we use a variety of alternative metrics to control for individual customer return characteristics. Although these alternative metrics provide a less direct measure of customer behavior, the metrics are available for all of the customers who purchased from the Test Catalog.

We also address another potential limitation of the previous analysis. Because we can only observe returns when there is demand, any stochasticity in demand also affects our measure of returns. This introduces a correlation between the stochastic variance in demand and the variance in returns. By jointly estimating demand and returns we can explicitly address this correlation. In particular, we will jointly estimate the number of items each customer purchased from the Test Catalog (the customer "basket") together with the number of those items that were returned. In doing so, we will allow for correlation in the error terms of both models. The basket size (number of items purchased) will be estimated using customers' characteristics. To estimate the number of returns we will use the characteristics of the customers, the basket, and the items in that basket.

The number of items in each customer's basket and the number of items returned are both "count" measures, which might be expected to follow Poisson distributions. Therefore we begin by assuming that customer demand for an item follows a Poisson process with parameter λ_h. A customer who purchases q_h items may return $r_h \le q_h$ items and so the number of returns follows a truncated Poisson process with parameter $\tilde{\lambda}_h$. We introduce the notation $X_{h,k}$ to identify item characteristics, $Y_{h,k}$ to identify basket characteristics, and $Z_{h,k}$ to identify customer characteristics. The actual variables are described in detail in the next section.

To allow for possible correlation between demand and return rates we include a parameter to estimate this correlation (if any). The final specifications for the demand and return models rates are as follows:

$$\ln(\lambda_h) = \pi_0 + \sum_{k=1}^{K} \gamma_k Z_{h,k} + \varepsilon_h, \tag{5}$$

$$\ln(\tilde{\lambda}_h) = \tilde{\pi}_0 + \sum_{j=1}^{J} \tilde{\alpha}_j X_{h,j} + \sum_{k=1}^{K} \tilde{\beta}_k Y_{h,k} + \sum_{l=1}^{L} \tilde{\gamma}_l Z_{h,l} + \rho \varepsilon_h, \tag{6}$$

where $\varepsilon \sim N(0,\sigma^2)$ and ρ captures the correlation in the error terms. The covariance between λ_h and $\tilde{\lambda}_h$ equals $\rho\sigma^2$ and if $\sigma=0$ then we obtain a model without correlation. Conditional on the error term, both demand and returns retain a Poisson distribution.

Additional details are provided in the Appendix. We turn next to an overview of the item, basket and customer characteristics used to estimate the model.

Item Characteristics

The company categorizes its items into eight mutually exclusive product categories: accessories, bottoms, dresses, ensembles, intimates, shoes, and tops. The variable *Accessories* is a dummy variable indicating whether an item is in that category. Analogous variables are constructed for the other seven categories. Summary statistics are provided in Table 8.

Because the unit of analysis in this model is a customer, item-level variables must be aggregated to the customer-level. We considered two types of aggregation: averages and summations and obtained similar results with both approaches. For the remainder of this paper, we aggregate via summation. For example, if a customer purchased two bottoms and one top the variable *Bottoms* equals 2, *Tops* equals 1, and all other category variables equal zero. Using this approach, the *Price* variable equals the sum of all items purchased. To capture the experimental variation in price, we code prices as +1 if an item is purchased at a high price, 0 for medium price, and -1 for low price. The variable *Price Level* is the summation of this variable for each customer's basket of items.

Table 8: Product Category Summary Statistics

Variable	Average Price Paid	Units Sold	Return Rate
Accessories	$68.10	130	0.22
Bottoms	$35.6	2,585	0.26
Dresses	$48.2	2,508	0.23
Ensembles	$73.7	779	0.27
Intimates	$32.3	743	0.18
Shoes	$44.7	285	0.27
Tops	$36.7	5,302	0.20

Basket Characteristics

We include five variables to describe the composition of each customer's shopping basket. The variable *Same Item Multiple Sizes* is a sum of the number of items

purchased for the same item in two or more sizes. For example, a customer who is uncertain about fit may purchase both a large and extra-large shirt. While only 1.5% of customers use this strategy, we expect a higher return rate amongst these customers. A more popular strategy is to purchase multiple colors of the same item, such as both blue and red versions of the same shirt. Over 26% of customers adopt this strategy. The variable *Same Item Multiple Colors* is the sum of the number of items purchased for the same item in two or more colors.

Customers also purchase sets of complementary items rather than single items. Following Anderson and Simester (2002), we define two items as complements if they are displayed in a photograph being worn by the same model. The variable *Complements* is the total number of complementary items that a customer purchases (13% of customers purchase two or more complements).

Our previous results show that the likelihood of returning an item depends on the variety of sizes offered. Preliminary analysis also revealed that size variety varies by category and is highly correlated with the category dummy variables. Therefore to capture within category variation in the number of sizes offered we calculated the number of sizes offered for each item, s_i, compute a mean and standard deviation for every category ($\bar{s}_c, \sigma_c^s$), and then compute a z-score equal to: $(s_i - \bar{s}_c)/\sigma_c^s$. The variable *Size Score* is the sum of this z-score for the basket of items purchased. We adopt an analogous approach to control for color variation. We use the number of colors offered for item i, c_i, compute a mean and standard deviation for every category ($\bar{c}_c, \sigma_c^c$), and then compute a z-score equal to $(c_i - \bar{c}_c)/\sigma_c^c$. The variable *Color Score* is the sum of this z-score for the basket of items purchased.

Customer Characteristics

The only past purchasing information that is available for all customers is a coarse measure of the recency of their prior purchases. Customers fall into three groups: those who purchased within the prior 12 months (63.2% of the sample), those whose most recent purchase was over 12 months ago (18.8%); and new customers who had not previously purchased from the company (18.0%). We use three dummy variables to identify these segments: *Recent Customers*; *Non-Recent Customers*; and *New Customers*

For a $25 fee, any customer may purchase a catalog club membership and receive 10% off all current and future orders for 12 months. The dummy variable *Member* indicates catalog club membership. Just over 11% of customers were members of this club. As we might expect, nearly all customers who place large orders also purchase memberships. However, members also include customers who place small, frequent orders.

We do not observe individual demographic data but we do know each customer's zip code. This allowed us to merge U.S. census data at the zip code level. While there are hundreds of demographic variables, our final model specification includes a wealth index (*Wealth*), median years of schooling (*Schooling*), and two age measures: percentage of population aged between 35 and 44 (*Age 35-44*), and percentage aged 45-54 (*Age 45-54*). The variable *Wealth* is coded on a 0-9 scale, *Schooling* is measured in years, and the age variables are measured on a percentage scale. Compared to the U.S. population averages for these variables, customers who purchase from the catalog tend to be wealthier (5.59 vs. 3.62) and more educated (13.49 vs. 12.69). The catalog targets middle-aged women and so these age-groups are over-represented in the sample (*Age 35-44:* 23.07 vs. 21.58; *Age 45-54:* 16.25 vs. 15.92).

Finally, we include variables that characterize each customer's preferred methods of ordering and payment. At the time of the study, the company did not have online ordering and so all orders were either placed over the phone (81.8%) or via mail (18.2%). Customers could pay for an order with either a credit card (86.7%) or a personal check (13.3%). Most customers who purchased over the phone also ordered with a credit card. To place an order via mail, a customer had to fill out an order form located in the center of the catalog and either enter a credit card number or include a personal check. In the demand model, we include dummy variables for whether a customer ordered via mail (*Mail*) or paid with a check (*Check*). Summary statistics for the customer measures are provided in Table 9.

Table 9: Customer Characteristics
Summary Statistics

Variable	Mean	Min	Max
Recent Customers	0.632	0	1
Non-Recent Customers	0.188	0	1
New Customers	0.180	0	1
Member	0.112	0	1
Wealth	5.59	0	9
Schooling	13.49	10.1	18.3
Age 35-44	23.07	0	47
Age 45-54	16.25	2	35
Check	0.133	0	1
Mail	0.182	0	1

Results

We estimate the model using the 4,847 customers who made at least one purchase from the Test Catalog. The parameter estimates are reported in Table 10. Our main focus is again the relationship between returns and the two price variables (*Price* and *Price Level*). The coefficients on these variables reveal how return rates vary across (*Price*) and within items (*Price Level*). Coefficients for both variables are positive and significant indicating that return rates are higher on higher priced items, and are also higher when the price of a specific item is increased. Reassuringly, these results corroborate our earlier findings: the result for the *Price* coefficient replicates the across-item findings (Tables 2 and 3), while the *Price Level* analysis replicates the within-item findings (Tables 4, 5 and 7). Moreover, they do so using a different unit of analysis, a different set of control variables, and a more complete sample of customers.

The results also illustrate how returns co-vary with basket and other customer characteristics. Recall that the *Size* and *Color Score* variables measure the range of available sizes and colors, while the *Same Item Multiple Sizes* and *Multiple Colors* variables measure how many multiple sizes and colors of an item that a customer placed in their basket. We see an interesting pattern in the coefficients of these variables, which also replicates the findings in our across-item analysis. When customers purchase the same item in multiple sizes they return 38.1% (p<0.01) more items than other customers.

However, when they purchase multiple colors they return 14.0% (p<0.05) fewer items. The results suggest that customers who purchase multiple colors are not purchasing variants because of uncertainty. Rather, these customers appear to purchase multiple colors because they appreciate the availability of different colors. This is consistent with a broad set of findings in the marketing literature that have demonstrated customers' preferences for variety (McAlister and Pesemier 1982). The *Size Score* and *Color Score* reveal a similar contrasting pattern. If the item is available in more colors then returns are 2.3% lower (p < 0.01). If an item is available in more sizes then customers return 2.3% more items, but this result is not statistically significant. We reported analogous results in Tables 2 and 3 in our across-item analysis.

A related issue is the purchase of complementary items. We find that customers who purchase complementary items return 18.0% (p<0.01) more items than other customers. For example, if a customer purchases both a top and bottom that are photographed on the same model, the customer is more likely to return the items. In a similar finding we find that items sold as *Ensembles* tend to have higher return rates.

Table 10: Results of Poisson System

	Demand Model		Return Model	
	Coefficient	Std. Error	Coefficient	Std. Error
Customer Characteristics				
Recent Customers	0.071**	(0.014)	-0.091**	(0.022)
Non Recent Customers	0.067**	(0.021)	0.025	(0.029)
Schooling	0.017**	(0.001)	-0.005	(0.043)
Age 35-44	0.004**	(0.001)	-0.006**	(0.002)
Age 45-54	0.002**	(0.001)	-0.028**	(0.001)
Member	0.982**	(0.021)	0.906**	(0.001)
Wealth	-0.004*	(0.002)	0.066	(0.038)
Check	-0.353**	(0.035)	-0.878**	(0.004)
Mail	0.116**	(0.028)	-0.519**	(0.083)
Basket Characteristics				
Same Item Multiple Colors			-0.140*	(0.064)
Color Score			-0.023**	(0.004)
Same Item Multiple Sizes			0.381**	(0.008)
Size Score			0.023	(0.061)
Complements			0.180**	(0.002)
Item Characteristics				
Price Level			0.050**	(0.006)
Price			0.021*	(0.011)
Accessories			-0.319**	(0.001)
Bottoms			-0.064	(0.111)
Dresses			-0.063**	(0.009)
Ensembles			-0.051**	(0.010)
Intimates			-0.152**	(0.033)
Shoes			-0.002	(0.040)
Tops			-0.154**	(0.055)
Intercept	0.094**	(0.011)	-0.748**	(0.005)
σ			0.526**	(0.004)
ρ			2.314**	(0.030)
Log Likelihood			-12,083	
Sample Size			4,847	

** Significantly different from zero (p < 0.01)

* Significantly different from zero (p < 0.05)

We also find that customer demographics, payment method, and purchase history significantly affect returns. The results confirm that customer's in the catalog's target age range of 35-54 purchase more items and return fewer items than other customers. Despite the fact that most customers place their orders over the phone and pay with a credit card, there are still a number of customers who purchase by mail and pay by check. These customers return significantly fewer items than others. Customers who have purchased in the last 12 months also return significantly fewer items. Recent purchases may provide these customers with additional information that allows them to more accurately select items. Finally, customers who are members of the buying club purchase more units and return more units. Despite the large number of returns, net demand from these customers (after accounting for returns) is on average 9.7% greater than from other customers.

5. Conclusion

We investigate the relationship between demand and returns by comparing variation both across items and within an item. We motivate the empirical findings by first presenting a theoretical model of customer return behavior. The theoretical findings yield an important generalizable result: the relationship between demand and returns is governed by two opposing effects, which we label the *incremental demand* and *perceived value* effects. As a result of these opposing effects, the predicted impact of price changes on both the number of returns and the return rate is ambiguous. Progress on this issue must be made empirically.

In our empirical application the *perceived value* effect dominates the *incremental demand* effect, and this leads to a positive relationship between price paid and both the number and rate of returns. We find support for this relationship in both the across-item and within-item analyses. While we recognize that the relative magnitude of the effects may vary across markets, the role played by these effects in determining the relationship between demand returns is expected to generalize to other markets.

Our findings on the number of colors and sizes also speak to an issue that affects many firms. If an increase in product variants is a response to customers' needs for a

more precise product match, then returns may increase. But, if the increase in product variants is in response to customer demand for variety, then product returns may decrease.

A final contribution of our study is that we highlight the need to coordinate marketing decisions with operations decisions. In particular, our findings on the relationship between price paid and returns demonstrates a clear need to coordinate pricing and inventory policies. If a marketing manager offers a lower price on an item, then customers will be more likely to purchase and less likely to return. The relative magnitude of the *perceived value* and *incremental demand* effects dictate how this price change will affect both the overall number of returns and the rate of return.

It is important to distinguish results that are causal versus those that are descriptive. The experimental variation in prices allows us to claim causality for these results: increasing the price leads to more returns and a higher return rate. However, our findings on number of sizes and colors rely on natural variation. It is possible that the factors that lead to this variation may also explain the change in returns behavior. Given this limitation, we caution that changing the number of size and color options may not have the same impact on returns as reported in this study.

An additional limitation is that we study the behavior of customers from a single firm. While the firm offers a variety of products, we have not examined the return behavior of customers at other apparel firms or in other industries. Given the importance of empirical research on this topic, such research is warranted. We also do not have detailed historical data for all customers, which limits our ability to estimate a structural model of customer purchase and return behavior. We anticipate that future research will address this limitation.

References

Alexander, Deborah (2004), "Stores tighten return policies," Omaha World-Herald.

Anderson, Eric and Duncan Simester (2001), "Are sales sign less effective when more products have them?" *Marketing Science*, 20 (2), 121-42.

---- (2003), "Effects of $9 price endings on retail sales: evidence from field experiments," *Quantitative Marketing and Economics*, 1 (1), 93-110.

---- (1998), "The role of sale signs," *Marketing Science*, 17 (2), 139.

Davis, S., M. Hagerty, and E. Gerstner (1998), "Return policies and the optimal level of 'hassle'," *Journal of Economics and Business*, 50, 445-60.

de Brito, M.P. and E.A. van der Laan (2002), "Inventory management with product returns: The impact of (mis)information," Economic Institute Report EI 2002-29.

Eliashberg, J. and R. Steinberg (1987), "Marketing-production decisions in an industrial channel of distribution", *Management Science*, 33(8), 981-1000

Fleischmann, M., P. Beullens, J.M. Bloemhof-Ruwaard, R. Dekker, E.A. van der Laan, J.A.E.E. Nunen, and L.N. Van Wassenhove (1997), "Quantitative models for reverse logistics," *European Journal of Operational Research*, 103, 1-17.

Fleischmann, M., R. Kuik, and R. Dekker (2002), "Controlling inventories with stochastic item returns: A basic model," *European Journal of Operational Research*, 138, 63-75.

Gentry, C.R. (1999), "Reducing the Cost of Returns," Chain Store Age, 75 (10), 124-26.

Greene, W. (2003), Econometric analysis, Prentice Hall, 5th Edition.

Guide, Jr., V.D.R. (2000), "Production planning and control for remanufacturing: Industry practice and research needs," *Journal of Operations Research*, 18 (4), 467-83.

Hess, James D. and Glenn E. Mayhew (1997), "Modeling merchandise returns in direct marketing," *Journal of Direct Marketing*, 11 (2), 20-35.

Hess, James, Wujin Chu, and Eitan Gerstner (1996), "Controlling product returns in direct marketing," *Marketing Letters*, 7 (Oct), 307-17.

Hess, James D. Marilyn T. Lucas (2004), "Doing the right thing or doing the thing right: allocating resources between marketing research and manufacturing", *Management Science,* 50 (4), 521-526

Ho, Teck H. and Christopher S. Tang (2004), "Introduction to the special issue on marketing and operations management interfaces and coordination", *Management Science,* 50 (4), 429-430

Karmarkar, Uday S. (1996), "Integrative research in marketing and operations management", *Journal of Marketing Research,* 33(2), 125-133

Kiesmueller, G.P. and E.A. van der Laan (2001), "An inventory model with dependent product demands and returns," *International Journal of Production Economics*, 72 (1), 73-87.

Kim, Byung-Do, Mengze Shi, and Kannan Srinivasan (2004), "Managing capacity through reward programs", *Management Science,* 50 (4), 503-520

Kulp, Susan Cohen, Hau L. Lee, and Elie Ofek (2004), "Manufacturer renefits from information integration with retail customers", *Management Science,* 50 (4), 431-444

McAlister, L. (1982), "Variety Seeking Behavior: An interdisciplinary review," *Journal of Customer Research*, 9 (3), 311-322.

Rogers, D.S. and R.S. Tibben-Lembke (2001), "An examination of reverse logistics practices," *Journal of Business Logistics*, 22 (2), 129-248.

---- (1998), "Going backwards: reverse logistics trends and practices," Reverse logistics executive council, Pittsburgh, PA.

Savaskan, R., S. Bhattacharya, and L.N. Van Wassenhove (2005) "Channel choice and coordination issues in a remanufacturing environment," Management Science, forthcoming.

Savaskan, R., S. Bhattacharya, and Van Wassenhove (2004), "Closed-loop supply chain models with product remanufacturing," *Management Science*, 50 (2), 239-52.

Tang, Christopher S., Kumar Rajaram and Aydin Alptekinoglu (2004), "The benefit of advance booking discount programs: model and analysis", *Management Science,* 50(4), 465-478

Toktay, L.Beril, E.A. van der Laan, and M.P. de Brito (2003), "Managing product returns: the role of forecasting," in Reverse logistics: quantitative models for closed-loop supply chains, R. Dekker, M. Fleischmann, K. Inderfurth, L. N. Van Wassenhove, Editors.

Technical Appendix: Poisson Demand System

The truncated Poisson model of demand and return is

$$\Pr(Q = q_h \mid Q > 0, \lambda_h) = \frac{\Pr(Q = q_h)}{1 - \Pr(Q = 0)} = \frac{\lambda_h^{q_h}}{\exp(\lambda_h - 1)q_h!}, \qquad q_h = 1,2,\ldots$$

and

$$\Pr(R = r_h \mid R \le q_h, \tilde{\lambda}_h) = \frac{\tilde{\lambda}_h^{r_h}}{r_h! \displaystyle\sum_{m=1}^{q_h} \tilde{\lambda}_h^{m} / m!}, \qquad r_h = 0,1,\ldots,q_h$$

We specify the log Poisson parameters as

$$\ln(\lambda_h) = \pi_0 + \sum_{k=1}^{K} \gamma_k Z_{h,k} + \varepsilon_h,$$

$$\ln(\tilde{\lambda}_h) = \tilde{\pi}_0 + \sum_{j=1}^{J} \tilde{\alpha}_j X_{h,j} + \sum_{k=1}^{K} \tilde{\beta}_k Y_{h,k} + \sum_{l=1}^{L} \tilde{\gamma}_l Z_{h,l} + \rho \varepsilon_h,$$

where $\varepsilon_h \sim N(0,\sigma^2)$. Conditional on ε_h the joint probability of observing (q_h, r_h) is

$$\Pr(Q = q_h, R = r_h \mid \lambda_h(\varepsilon_h), \tilde{\lambda}_h(\varepsilon_h)) = \Pr(Q = q_h \mid Q > 0, \lambda_h(\varepsilon_h)) \Pr(R = r_h \mid R \le q_h, \tilde{\lambda}_h(\varepsilon_h)).$$

The likelihood contribution for this observation is then

$$L_h = \int \Pr(Q = q_h, R = r_h \mid \lambda_h(\varepsilon_h), \tilde{\lambda}_h(\varepsilon_h)) \phi(\varepsilon_h \mid 0, \sigma^2) d\varepsilon_h$$

The final likelihood is

$$L = \prod_{h=1}^{H} L_h$$

We use a Simulated Maximum Likelihood procedure to maximize the log-likelihood function with respect to the parameter vector $\pi_0, \gamma, \tilde{\pi}_0, \tilde{\alpha}, \tilde{\beta}, \tilde{\gamma}, \rho, \sigma$.