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For a century, L.L. Bean had an extremely liberal product-return policy, with no time limit and no receipt requirement. You could get a full refund for boots purchased decades ago. But many people abused the policy, returning products fished from dumpsters or bought used on eBay. Over the past five years, worthless returns cost L.L. Bean $50 million per year. That amounts to roughly 30% of the company's annual profits. [1]

So in February 2018, the company established a new policy that limits all product returns to one year from the date of purchase. The change led to bad publicity, a class-action lawsuit, and vows from once-loyal customers to stop shopping at L.L. Bean because they felt unfairly penalized for the actions of others. Some of those customers say L.L. Bean is no longer special and has become just another store. [2]

L.L. Bean is not alone. Best Buy, REI, Lands' End, and Costco have instituted return restrictions such as restocking fees, shorter time limits, and requirements for the original receipt. [3] Some retailers still have more liberal policies, but they are becoming rare. [4]

Regardless of how generous or restrictive companies are when it comes to returns, they tend to apply a one-size-fits-all approach to their entire customer base. They ignore wide variations in individuals' behaviors, lumping loyal, compliant customers in with those who game the system.

Yet new tools and technologies make it possible to segment customers and impose strict return policies only on those whose past behavior warrants it. We recently analyzed customer data for a large, high-end U.S. retailer and identified transactional patterns that indicate which people are most likely to abuse return policies. Though highly accurate for the company we studied, our predictive model is unique to that retailer; in another setting, other factors might be identified — or the same ones might be weighted differently. Still, the overall approach to identifying and managing the people most likely to abuse return policies is broadly instructive, so we are sharing it here to help retailers manage returns profitably while delivering a positive customer experience.

Finding the Most- and Least-Profitable Customers

Returns are big business. In 2017, consumers returned $351 billion worth of purchased products. (Our analysis shows that if the hypothetical Consumer Returns Inc. were an independent company, it would rank second on the Fortune 500, trailing only Walmart.) On average, 10% of everything going out of a U.S. store comes back. Unfortunately, many returns cannot be put back on the shelf, and it takes a lot of staff time to determine which items can be restocked and then handle them appropriately. After receiving returned goods, employees must sort through them and then repair, repackage, and restock items that still have value.

Return fraud and abuse exacerbate the problem, costing U.S. retailers $23 billion per year. That's enough to wipe out the profits of the three largest U.S. retailers — Walmart, Costco, and Home Depot — combined. [5] Return abuse takes many forms, some of which are quite creative. For instance, customers sometimes buy large-screen TVs to watch the Super Bowl or purchase expensive clothes for special events, only to return them afterward. Such behavior takes many names, including retailer borrowing, renting, wardrobing, and de-shopping.

Other people purchase things for which they have no use at all but nonetheless gain value from them via returns. For example, they might buy items on credit cards with travel rewards and return them for cash, accumulating airline miles or hotel points while the merchant gets stuck paying transaction fees. In another money-making gambit, some people buy items on sale but then return them and claim to have lost the receipt, making it possible to collect the full retail price for the return. The simplest form of return abuse is to shoplift and return an item for cash.

The key to combating fraudulent returns is identifying the likeliest offenders and tightening restrictions only on them — ideally before their next transaction. For those customers, companies can charge restocking fees, for instance, or reject certain returns altogether. That way, they can afford to keep a generous policy in place for loyal customers who return things for legitimate reasons.

This approach focuses on the lifetime value of the customer, and we've found that it can be far more profitable than either restrictive or liberal blanket return policies. It's also much easier from a PR standpoint. If a company can justify clamping down on a customer with a history of questionable return behavior, it can avoid coming under public fire for instituting broad return restrictions — the way L.L. Bean did.

About the Research

The analytics methods we've used to conduct our research vary from relatively straightforward multiple regression to nuanced classification models, including random forests, support vector machines, and shrinkage methods. Even simple methods provide surprisingly accurate, robust classification of customer behaviors over time.

Of great interest to most retail executives is the risk of misidentifying a nonabusive customer as abusive, because implementing return restrictions or denials as a result of this mistake may alienate loyal customers. But the rate of inaccurate identifications is quite low: Out of more than 1 million customers examined, our model misidentifies only 400 customers based on five transactions, and it misidentifies fewer than 200 customers based on 10 or more transactions. Our analysis breaks the exemplar company's data down into greater detail, showing correlations between customer profitability and the various explanatory variables ranging from 2% to 76%. For more information about the methods, data, and core analytics used to isolate and understand segment behavior, please contact the authors.

The retailer we studied operates more than 100 brick-and-mortar properties, along with discount outlets and catalog and online sales channels. In all, we looked at more than 1 million customers and more than 75 million transactions recorded over seven years, totaling $2.9 billion in sales and $466 million in returns.

Examining this data, we identified seven key variables that collectively explained an incredible 94% of the variance in overall customer profitability. (See "About the Research" and "Signs of a Profitable Customer.") Interestingly, demographic variables such as age and income were insignificant and not incorporated in the predictive model. Transactional data such as total number of purchases to date, number of purchase categories, and average time to return mattered much more.

Signs of a Profitable Customer

For the retailer we analyzed, here's what mattered — and what didn't.

Significant Variables	Insignificant Variables
Customer's purchases to date	Income
Customer's refunds to date	Age
Amount of current refund	Number of items purchased
Number of purchase categories	Number of items returned
Average time to return	Length of relationship
Value of average item returned	Purchase frequency
Return frequency	Percentage of purchase value returned

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By identifying customers with negative lifetime profitability, we were able to predict which ones were most likely to make fraudulent returns in the future. We found that the model was accurate 99.96% of the time after just five observed transactions. With 10 or more transactions, the accuracy rate increased to more than 99.98%.

We divided customers into three segments: legitimate returners, nonreturners, and “abusive” returners — those whose frequency and timing of returns caused the company to lose money on them. (See “Segmenting Customers by Profitability.”)

Segmenting Customers by Profitability

Customers who made legitimate returns were significantly more profitable, on average, than those who never made any returns. And the few who abused return policies cost the company a great deal.

	Legitimate Returners	Nonreturners	Abusive Returners
Proportion of customers:	51.9%	47.7%	0.4%
Gross sales:	$5,034 per year	$592 per year	$14,022 per year
Profit contribution:	$1,445 per year	$222 per year	-$1,254 per year (for an aggregate loss of more than $60 million)
Length of customer relationship:	4.4 years	1.7 years	5.3 years
Time to return:	23 days	Not applicable	59 days
Return rate:	23% of items purchased per year	0% of items purchased	60% of items purchased per year

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On average, legitimate returners contributed about $1,445 each to the retailer’s profits each year — they were by far the most profitable group we studied. And they appeared to place considerable value on the option to return products, with an average return rate of 23%. Furthermore, the relatively small set of abusive returners had an extraordinarily negative impact: A mere 0.4% of customers, who returned an average of 60% of their purchases, accounted for a combined loss of $60 million in profits annually. Because these customers took an average of two months to complete their returns, the value of the products at the time of return was significantly lower than it had been at the time of purchase, particularly for seasonal goods.

Customizing Return Policies

By analyzing transactional behaviors and segmenting customers according to profitability, retailers can figure out when to impose — and, just as important, when *not* to impose — return restrictions. Of course, companies should give the greatest leeway to customers who value flexible return policies *and* contribute significantly to the bottom line to avoid disregarding those individuals’ needs in an effort to rein in the costly unethical behavior of others. With that approach, they’re more likely to increase customer satisfaction, enhance loyalty, and encourage future purchases that will stick.

Companies could adapt their return policies in several ways. A simple method is to make clear during the return process that returns are welcome but are also monitored for unreasonable volume. In a case where a customer has a clear history of excessive returns, the retailer could restrict or refuse transactions on the spot.

However, retailers need not wait until the return attempt occurs. They could make differentiated return policies explicit at the point of sale. And based on the results of predictive analytics models such as the one described above, they could flag excessive returners as they make purchases and tell them that they will be given a limited amount of time to bring items back, and that they will be assessed restocking fees or charged shipping fees if they do make returns. Additionally, retailers could apply fees and shorter time windows to particular product categories that lose value quickly, such as seasonal products or electronics. Though many mechanisms are available, the retailer we analyzed began denying returns for any customer deemed to be unfairly exploiting the return policy. It decided to make this change as we were conducting our analysis, partly in response to industry trends toward stricter policies.

We uncovered a hidden opportunity regarding nonreturners, as well. Our data shows that, compared with customers who make legitimate returns from time to time, nonreturners have a lower purchase volume overall and represent significantly lower lifetime profitability. But companies might be able to change how those customers behave by enticing them to sample products risk-free, perhaps even encouraging them to buy several competing products at the same time and then choose a favorite and (quickly) return the rest. Or they could try to convert nonreturners into legitimate returners at the point of purchase by offering targeted coupons or future discounts should a return be needed. If such a conversion is not feasible, a retailer can offer nonreturners rewards that may induce them to buy more — say, lower prices on certain products in exchange for forgoing future return options.

This is an approach already taken by some online retailers, including Jet.com and Walmart.com. Though not yet common, such incentives may become more widely implemented over time. Just as return policies can become more restrictive for customers who engage in abusive behaviors, they can become more generous over time for less costly customers.

Since most major retailers now have massive amounts of data related to customer transactions and behaviors, it's within their reach to institute flexible return policies that can be adapted to individual customers. Note that the model discussed here is behavioral, not demographic. Behavior can shift over time. Should that happen in response to customized return policies, companies can keep recalibrating on the basis of the most recent transactions — and continue to encourage the customer behavior they'd like to see.

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