EDUCATIONAL LECTURES FROM THE BEST ECONOMISTS

With the support of SAFMAR foundation
Amazon challenged by product returns

Banned From Amazon: The Shoppers Who Make Too Many Returns

Customers say their accounts were closed without warning; it happens when ‘you’re creating a lot of headaches for Amazon’

By Khadeeja Safdar and Laura Stevens
May 22, 2018 5:30 a.m. ET
Even Amazon.com Inc. has its limits.
Fashion categories suffer from highest return rates

U.S. online shoppers who returned items back to retailers 2016, by product type

<table>
<thead>
<tr>
<th>Product Type</th>
<th>Share of respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clothing &amp; accessories</td>
<td>75%</td>
</tr>
<tr>
<td>Electronics</td>
<td>33%</td>
</tr>
<tr>
<td>Shoes</td>
<td>32%</td>
</tr>
<tr>
<td>Food</td>
<td>18%</td>
</tr>
<tr>
<td>Beauty &amp; personal products</td>
<td>13%</td>
</tr>
<tr>
<td>Outdoor &amp; sports gear</td>
<td>12%</td>
</tr>
</tbody>
</table>

Note:
United States; 2016;
18 years and older;
1,005 Respondents,
Statista 2018
Product returns with substantial costs

Processing returns in the online channel is very expensive*:

<table>
<thead>
<tr>
<th>Price</th>
<th>Cost</th>
<th>Return cost</th>
<th>Return rate</th>
<th>Online profit (returns)</th>
<th>Offline profit (no returns)</th>
</tr>
</thead>
<tbody>
<tr>
<td>€ 30.00</td>
<td>€ 10.00</td>
<td>€ 9.31</td>
<td>53%</td>
<td>€ 4.47</td>
<td>€ 20.00</td>
</tr>
</tbody>
</table>

*El Kihal, Schulze, Skiera 2018
Product returns with substantial costs

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<th>Online profit (returns) (€)</th>
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</tr>
</thead>
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<tr>
<td>30.00</td>
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<td>53</td>
<td>4.47</td>
<td>20.00</td>
</tr>
<tr>
<td>30.00</td>
<td>10.00</td>
<td>9.31</td>
<td>68</td>
<td>0.07</td>
<td>20.00</td>
</tr>
<tr>
<td>30.00</td>
<td>10.00</td>
<td>9.31</td>
<td>40</td>
<td>8.28</td>
<td>20.00</td>
</tr>
</tbody>
</table>

*El Kihal, Schulze, Skiera 2018
Heterogeneity in product return rates

Is there something systematic about products with high return rates?

- $N = 7,824$ products
- Mean = 53%
- Sd = 14%
Product return rate as important input for several complex decisions

- Online and offline product assortment optimization
- Reverse logistics decisions
- Rank order decisions
- …
Profit input necessary to rank order products

Rank by expected profit:

\[(Price - Cost) \cdot Pr(Buy)\]

With Returns:

\[(Price - Cost) \cdot Pr(Buy) \cdot (1 - Pr(return|buy)) - Cost_{return} \cdot Pr(Buy) \cdot Pr(return|buy)\]
Main reason behind high return rates in the fashion industry

Gap

Online Channel

Offline Channel
Main reason behind high return rates in the fashion industry

Online Channel
Purchase Decision
Return/keep?
53% Return Rate

Offline Channel
Purchase Decision
3% Return Rate

…with huge costs associated for each return in online channel
Online vs. offline demand and product returns

### Online Channel
- $U_{on}$: Purchase Decision*
- $U_{off}$: Return/keep?

### Offline Channel
- $U_{off}$: Purchase Decision

---

- Difference in preferences* $\rightarrow$ discrepancy in online/offline demand
- High discrepancy in demand $\rightarrow$ high return rate
- Implications for product, place, price & promotion decisions
- Accurate forecasting of return rate using all available product info (attributes, image)

---

*Dzyabura, Jagabathula, Muller 2017*
Return rates by category

Return Rates by Category

<table>
<thead>
<tr>
<th>Category</th>
<th>Return Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dresses</td>
<td>75.0%</td>
</tr>
<tr>
<td>Boleros</td>
<td>65.0%</td>
</tr>
<tr>
<td>Jumpsuits</td>
<td>55.0%</td>
</tr>
<tr>
<td>Coats</td>
<td>45.0%</td>
</tr>
<tr>
<td>Pants</td>
<td>35.0%</td>
</tr>
<tr>
<td>Blazer</td>
<td>25.0%</td>
</tr>
<tr>
<td>Jackets</td>
<td>15.0%</td>
</tr>
<tr>
<td>Skirts</td>
<td>10.0%</td>
</tr>
<tr>
<td>Sweatshirts</td>
<td>5.0%</td>
</tr>
<tr>
<td>Blouses</td>
<td>5.0%</td>
</tr>
<tr>
<td>Knit</td>
<td>2.5%</td>
</tr>
<tr>
<td>Shirts</td>
<td>2.5%</td>
</tr>
<tr>
<td>Leder</td>
<td>2.5%</td>
</tr>
<tr>
<td>Tops</td>
<td>2.5%</td>
</tr>
<tr>
<td>Cardigans</td>
<td>2.5%</td>
</tr>
<tr>
<td>Accessoires</td>
<td>2.5%</td>
</tr>
</tbody>
</table>
Popular categories online vs. offline

**Popular Categories Online**

- Dresses
- Shirts
- Blouses
- Pants
- Knit
- Jackets
- Blazer
- Cardigans
- Skirts
- Accessories
- Boleros
- Sweatshirts
- Coats
- Jumpsuits
- Tops
- Leder

**Popular Categories Offline**

- Shirts
- Knit
- Pants
- Blouses
- Accessories
- Dresses
- Skirts
- Blazer
- Jackets
- Cardigans
- Sweatshirts
- Coats
- Leder
- Jumpsuits
Product level online & offline demand and returns

Indeed,…

\[ salesOff = \beta_0 + \beta_1 \times salesOn + \beta_2 \times returns \]

|       | coef   | std err  | z        | P>|z|     |
|-------|--------|----------|----------|---------|
| Intercept | 138.4729 | 7.370e+00 | 1.879e+01 | 9.561e-79 |
| salesOn  | 1.0936  | 1.831e-01 | 5.974e+00 | 2.311e-09 |
| ret      | -0.5717 | 2.162e-01 | -2.645e+00 | 8.174e-03 |
Hypothesis: High $u^\text{online}_j - u^\text{offline}_j \leftrightarrow$ high return rate

\[ \text{returnRate} = \beta_0 + \beta_1 \times \text{propOn} + \beta_2 \times \text{propOff} \]

IV’s are sales relative to channel and category:

\[ \text{propOn} = \frac{\text{salesOn}}{\sum\text{category salesOn}} \]
\[ \text{propOn} = \frac{\text{salesOff}}{\sum\text{category salesOff}} \]
\[ \text{returnRate} = \frac{\text{returns}}{\text{salesOn}} \]

|        | coef  | std err     | z       | P > |z|     |
|--------|-------|-------------|---------|-----|--------|
| Intercept | 0.4600 | 6.149e-03   | 7.481e+01 | 0.000e+00 |
| propOn   | 0.0395 | 4.999e-03   | 7.898e+00 | 2.823e-15   |
| propOff  | -0.0266 | 2.411e-03 | -1.101e+01 | 3.320e-28  |
What we know so far

- High & expensive product returns
- Great variance in product return rates
- Profits very sensitive to product return rates
- Knowledge about product’s offline performance would be valuable!
Offline performance often not accessible pre-launch

- Retailer might not have an offline channel
- Retailer might want to launch products simultaneously in both channels
- Retailer might not be able to wait until he has enough data on offline performance
- Retailer needs often pre-launch predictions of return rate to optimize product lines
- Online & offline category management do not share information on product performance
- …
How do marketers predict demand pre-launch?

- Define consumer preferences over product characteristics

- But in fashion characteristics are not quantifiable, so we use images (contain relevant product information)

- To convince you that visual features contain important information which is predictive
# Color analysis: Blue and Black sell better offline

\[ \text{salesOff} = \beta_0 + \beta_1 \ast \text{salesOn} + \beta_2 \ast \text{pink} + \beta_3 \ast \text{purple} + \ldots \]

|       | coef  | std err | z      | P>|z|  | [0.025] | [0.975] |
|-------|-------|---------|--------|-------|--------|--------|
| Intercept | 227.2432 | 20.642  | 11.009 | 0.000 | 186.786 | 267.700 |
| salesOn  | 0.6016  | 0.207   | 2.901  | 0.004 | 0.195   | 1.008   |
| Pinks    | -23.5886| 32.552  | -0.725 | 0.469 | -87.390 | 40.213  |
| Purples  | 8.7271  | 26.023  | 0.335  | 0.737 | -42.276 | 59.730  |
| Reds     | 49.9117 | 27.795  | 1.796  | 0.073 | -4.565  | 104.389 |
| Oranges  | 0.6168  | 101.987 | 0.006  | 0.995 | -199.274 | 200.508 |
| Yellows  | -43.3496| 63.669  | -0.681 | 0.496 | -168.138 | 81.439  |
| Greens   | -38.2311| 40.546  | -0.943 | 0.346 | -117.700 | 41.238  |
| Cyans    | 160.1235| 107.095 | 1.495  | 0.135 | -49.778 | 370.025 |
| Blue     | 94.7550 | 26.560  | 3.568  | 0.000 | 42.698  | 146.812 |
| Browns   | -84.8600| 24.471  | -3.468 | 0.001 | -132.823 | -36.897 |
| Whites   | 28.1769 | 24.962  | 1.129  | 0.259 | -20.751 | 77.104  |
| Greys    | -17.3652| 16.370  | -1.061 | 0.289 | -49.450 | 14.720  |
| Black    | 92.3267 | 22.894  | 4.033  | 0.000 | 47.456  | 137.198 |
| priceOn  | -1.6030 | 0.218   | -7.341 | 0.000 | -2.031  | -1.175  |
Color analysis: Pink more likely to be returned

\[ \text{returns} = \beta_0 + \beta_1 \times \text{salesOn} + \beta_2 \times \text{Pinks} + \beta_3 \times \text{Purples} + \cdots + \beta_{14} \times \text{price} \]

\[ \begin{array}{lcccccc}
\text{coef} & \text{std err} & z & P>|z| & [0.025] & [0.975] \\
\hline
\text{Intercept} & -9.4306 & 0.912 & -10.340 & 0.000 & -11.218 & -7.643 \\
\text{salesOn} & 0.5423 & 0.011 & 49.733 & 0.000 & 0.521 & 0.564 \\
\text{Pinks} & 3.5295 & 0.929 & 3.800 & 0.000 & 1.709 & 5.350 \\
\text{Purples} & 1.0744 & 0.976 & 1.101 & 0.271 & -0.838 & 2.987 \\
\text{Reds} & -0.3147 & 1.041 & -0.302 & 0.762 & -2.356 & 1.726 \\
\text{Oranges} & 1.0611 & 2.109 & 0.503 & 0.615 & -3.072 & 5.194 \\
\text{Yellows} & -2.8983 & 2.373 & -1.221 & 0.222 & -7.549 & 1.753 \\
\text{Greens} & 0.0020 & 1.402 & 0.001 & 0.999 & -2.747 & 2.751 \\
\text{Cyan} & -18.5559 & 4.258 & -4.358 & 0.000 & -26.902 & -10.210 \\
\text{Blue} & -0.4504 & 1.067 & -0.422 & 0.673 & -2.542 & 1.641 \\
\text{Browns} & 5.4571 & 1.094 & 4.988 & 0.000 & 3.313 & 7.601 \\
\text{Whites} & 1.7661 & 0.787 & 2.244 & 0.025 & 0.224 & 3.309 \\
\text{Greys} & 2.2107 & 0.563 & 3.927 & 0.000 & 1.107 & 3.314 \\
\text{Black} & -2.3121 & 0.808 & -2.861 & 0.004 & -3.896 & -0.728 \\
\text{priceOn} & 0.1228 & 0.014 & 9.000 & 0.000 & 0.096 & 0.150 \\
\end{array} \]
Examples of product images
Image classification

Feature Extraction

- Color features: RGB histograms
- Texture/pattern features: capture periodicity in the image, e.g. striped or checkered pattern
- Deep learned features: second to last layer of pre-trained CNN (VGG-19, Simonyan and Zisserman 2014)

Model: Gradient boosted regression trees (GBRT)

Train on 75% of data, predict on 25%, average over 100 splits
Predicting return rates for new products

\[ R_{model}^2 = 1 - \frac{\sum_{i \in K_{test}} (RR_i - \hat{RR}_i^{model})}{\sum_{i \in K_{test}} (RR_i - \hat{RR}_i^{random})} \]

<table>
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<tr>
<th>Features</th>
<th>Holdout R²</th>
<th>St. Dev.</th>
</tr>
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<tbody>
<tr>
<td>Category, price</td>
<td>33.88</td>
<td>2.93</td>
</tr>
<tr>
<td>Category, price, color descriptions</td>
<td>35.51</td>
<td>2.79</td>
</tr>
<tr>
<td>Category, price, image – RGB</td>
<td>44.12</td>
<td>2.44</td>
</tr>
<tr>
<td>Category, price, image – Gabor</td>
<td>42.16</td>
<td>2.57</td>
</tr>
<tr>
<td>Category, price, image – Deep learned</td>
<td>44.64</td>
<td>2.45</td>
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Predicting return rates for new products

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<td>42.16</td>
<td>2.57</td>
</tr>
<tr>
<td>Category, price, image – Deep learned</td>
<td>44.64</td>
<td>2.45</td>
</tr>
<tr>
<td>Category, price, image, offline sales</td>
<td>45.86</td>
<td>2.40</td>
</tr>
</tbody>
</table>
Summary & Future Directions

- Returns are an important issue with implications for firm marketing decisions
- Discrepancy in performance of products in online and offline channels
- Products that sell well online but poorly offline likely to be returned
- Use product visual features to accurately predict product return rates
- Methodologically, incorporating images can also be used for pre-launch demand forecasting
Primary data: measuring discrepancy between online and offline preferences

• Keeping the customer constant, measure preferences

• Specifically interested in preferences for particular product ATTRIBUTES
Product attributes and willingness to pay

Electronics

iSonic Protab 7 HD Google Android 4.2 Dual-Core 1.9GHz 8GB 2-in-1 Pico Projector & 7" Dual-Camera Tablet PC

Tablets are unbeatable when it comes to slimline handheld computing convenience, but this iSonic Protab 7 Pico Projector Tablet PC combines all the functionality of a very capable tablet with the versatility of a built-in DLP projector. It’s a real performer for anyone who gives presentations or more simply wants to be able to watch digital content “big screen” style on any wall or other clear right-angled surface. Google Android 4.2 and a dual-core 1.9GHz CPU plus 8GB of memory give the Protab 7 HD plenty of processing pep and 1024p HD playback is standard for watching on the 7" HD display. You’re able to project images from 5 to 80" away at 35 lumens.

$389.00 Our Price
$799.00 Retail

BUY NOW

51% SAVINGS
TIME LEFT
12:43:39

SHARE & EARN UP TO $1,000
Preference elicitation

- Respondents select the utility maximizing product from those available
- Products vary on several attributes
- Which of the following Tablet PCs would you prefer?

A. Apple with 12 hour battery life, no built-in projector, 10 inch screen, for $500
B. Toshiba with 10 hour battery life, built-in projector, 7 inch screen, for $400
Suppose you are designing a Maserati SUV

What features should you include and emphasize in marketing?

• automatic parking
• auto-adjust acceleration – fuel saver, normal, sport, OMG
• Bose active suspension
• fire suppression
• four vs. five seats
• true off-road capability
• Jeep vs. Ferrari engine
• towing capability
• active cruise control
• standard transmission
• Etc.
Willingness to Pay

Maserati SUV
- Auto-adjust acceleration = $1,250
- Off-road capability = – $500
- Auto parking = $2,000
- Etc.

Market share predictions, design of optimal products/services, pricing

Consider segments, combinations of features, competition, and core strengths.

18,000 + Applications yearly
- EZPass highway payment system
- Courtyard by Marriott
- RIM’s Blackberry smartphones
- SiriusXM service
- AMEX card service
- Intel chips
- Hallmark Cards
- Procter & Gamble (pricing)
- GM (OnStar, Northstar engine, bumper-to-bumper warranty)
- Audi product-line design
- Boeing employees credit union
- Canadian Dept of Fisheries and Oceans
- Woman’s health in rural Tanzania
- Apple iPhone
- Microsoft
- Lifetime Products, Inc. (integrated manufacturing)
- Consumer goods: bar soaps, shampoos, carpet cleaners, synthetic-fiber garments, gasoline pricing, panty hose, lawn chemicals, cameras, batteries
- B2B products: copiers, printing equipment, data transmission, enterprise software, portable computers
- Financial services: branch bank services, auto insurance policies, health insurance, credit cards, auto-retailing facilities
- Transportation: domestic airlines, transcontinental airlines, train service, electric cars, car rentals
- Other: automotive styling, automotive tires, ethical drugs, telephone services, employment agencies, medical laboratories
- Non-marketing: forest health, HR benefits, energy savings programs, food safety, recreation
Ratings-Based Elicitation Task

Size: Small (10 x 19 x 14 in)
Price: $140
Strap pad: Yes
Water bottle pocket: No
Inside Compartment: Empty bucket with no dividers

- Definitely Would Not Buy
- Probably Would Not Buy
- Might or Might Not Buy
- Probably Would Buy
- Definitely Would Buy

New Economic School
Do you think any of these are likely to change offline?

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Level</th>
<th>Partworth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Color</td>
<td>Reflective</td>
<td>-0.31**</td>
</tr>
<tr>
<td></td>
<td>Colorful</td>
<td>-1.06**</td>
</tr>
<tr>
<td></td>
<td>Blue</td>
<td>-0.22**</td>
</tr>
<tr>
<td></td>
<td>Black</td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>Large</td>
<td>0.27**</td>
</tr>
<tr>
<td></td>
<td>Small</td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>$120 – $180</td>
<td>-0.22**</td>
</tr>
<tr>
<td>Strap pad</td>
<td>Yes</td>
<td>0.51**</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Water bottle</td>
<td>Yes</td>
<td>0.45**</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Interior</td>
<td>Divider for files</td>
<td>0.41**</td>
</tr>
<tr>
<td></td>
<td>Laptop sleeve</td>
<td>0.62**</td>
</tr>
<tr>
<td></td>
<td>No dividers</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>3.72**</td>
</tr>
</tbody>
</table>
We checked
## Regression results

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Level</th>
<th>Online Partworth</th>
<th>Offline Partworth</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Color</td>
<td>Reflective</td>
<td>-0.31**</td>
<td>-0.60**</td>
<td>-0.28*</td>
</tr>
<tr>
<td></td>
<td>Colorful</td>
<td>-1.06**</td>
<td>-0.71**</td>
<td>0.36**</td>
</tr>
<tr>
<td></td>
<td>Blue</td>
<td>-0.22**</td>
<td>-0.11</td>
<td>-0.12</td>
</tr>
<tr>
<td>Size</td>
<td>Large</td>
<td>0.27**</td>
<td>-0.31**</td>
<td>-0.58**</td>
</tr>
<tr>
<td></td>
<td>Small</td>
<td></td>
<td></td>
<td></td>
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<td>-0.22**</td>
<td>-0.15**</td>
<td>0.06**</td>
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<tr>
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<td>0.51**</td>
<td>0.25**</td>
<td>-0.26**</td>
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<td>Yes</td>
<td>0.45**</td>
<td>0.17**</td>
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Discrepancy between preferences

- Why?
  Lack of information
  Abstract vs. concrete thinking
  Attribute salience

- So what?
  Product returns
  Product assortments
The causal question: why change?

- Two hypotheses:
  - Information gain through offline evaluation
  - Inherent property of the format
- Test using the order conditions
Why change?

1. Inherent salience difference
   Offline information gain

2. Inherent salience difference
   Offline information gain

Condition 1: Online-first

Condition 2: Offline-first

First measurement

Second measurement
Why change?

1. Different partworths (p<10^-98)
2. Different partworths (p<10^-15)
3. Different partworths (p<10^-6)
4. Different partworths (p<10^-5)
5. Equal partworths (p=0.105)
Thank you!
New Economic School

www.nes.ru
lectorium@nes.ru