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MARKETING SCIENCE DATA

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Amazon challenged by product returns

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TECH

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'

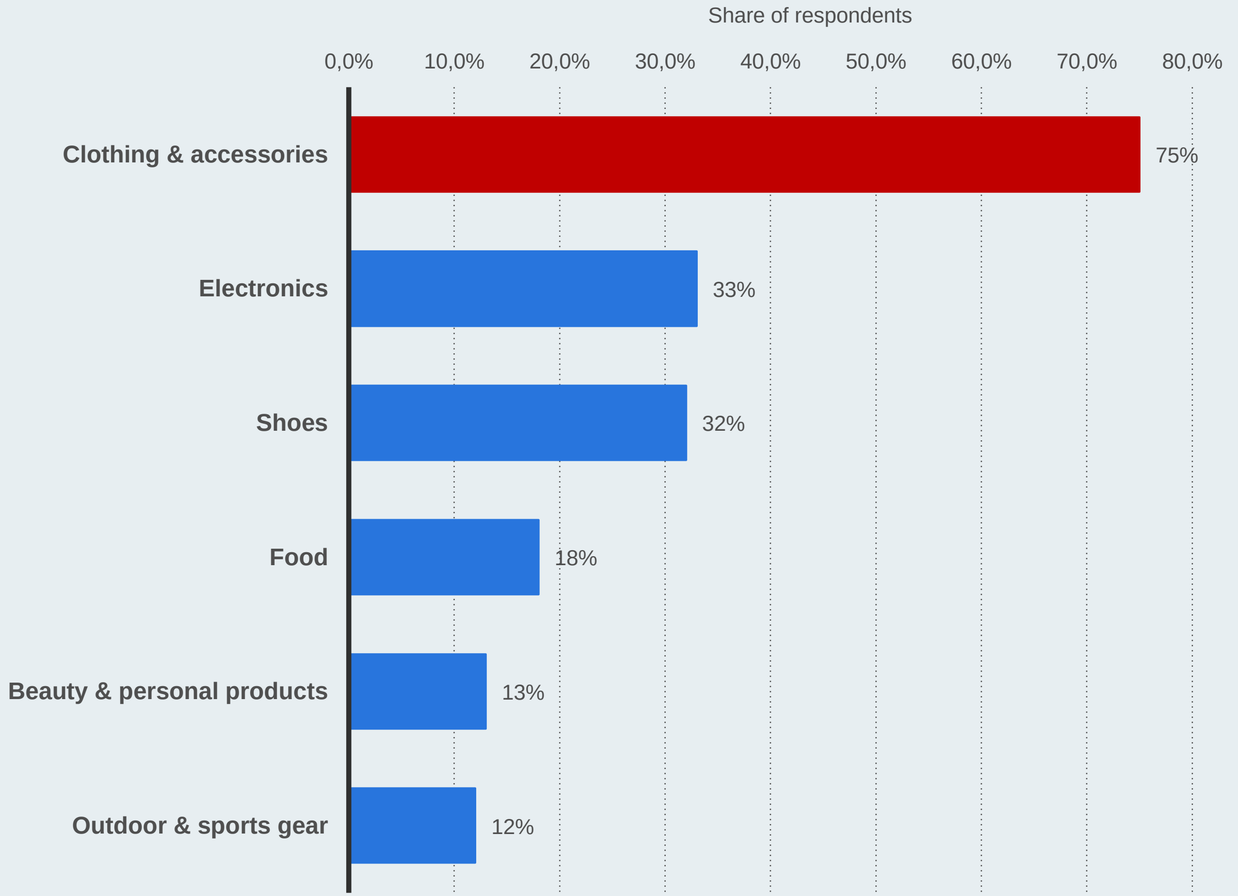
By *Khadeeja Safdar* and *Laura Stevens*

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



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*:

Price	Cost	Return cost	Return rate	Online profit (returns)	Offline profit (no returns)
€ 30.00	€ 10.00	€ 9.31	**53%**	**€ 4.47**	**€ 20.00**

*El Kihal, Schulze, Skiera 2018

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€ 30.00	€ 10.00	€ 9.31	**53%**	**€ 4.47**	**€ 20.00**
€ 30.00	€ 10.00	€ 9.31	**68%**	**€ 0.07**	**€ 20.00**
€ 30.00	€ 10.00	€ 9.31	**40%**	**€ 8.28**	**€ 20.00**

*El Kihal, Schulze, Skiera 2018

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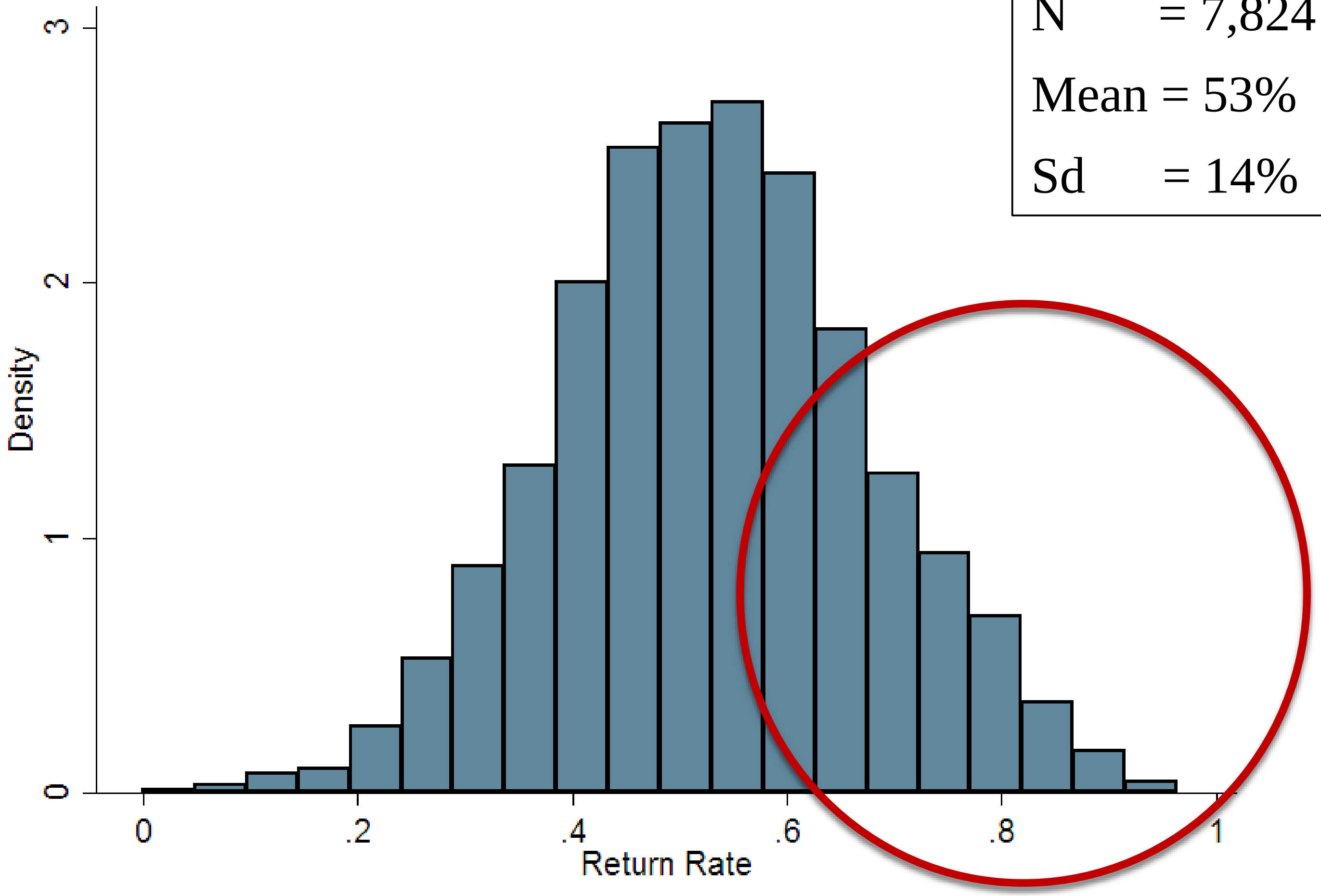
Heterogeneity in product return rates



N = 7,824 products

Mean = 53%

Sd = 14%

Is there something systematic about products with high return rates?

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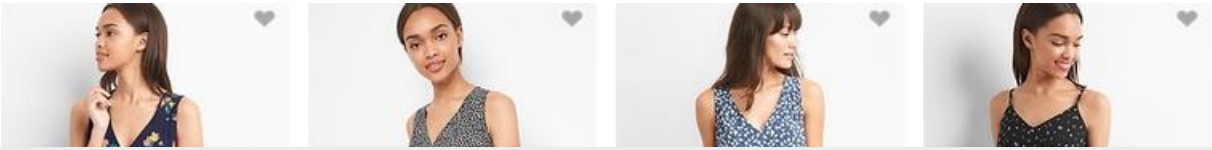
Product return rate as important input for several complex decisions

- 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:

$$(Price\ - Cost) \cdot \Pr(Buy) \cdot (1 - \Pr(return|buy)) - Cost_{return} \cdot \Pr(Buy) \cdot \Pr(return|buy)$$

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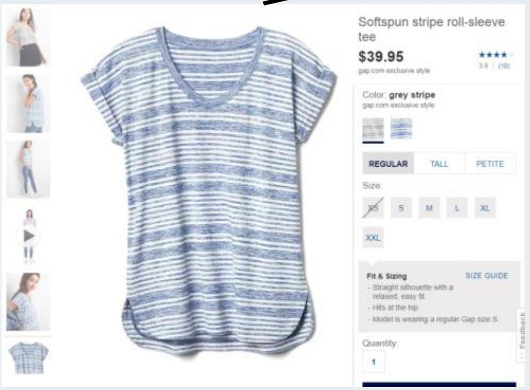
Main reason behind high return rates in the fashion industry

Gap



Online Channel

Offline Channel

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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

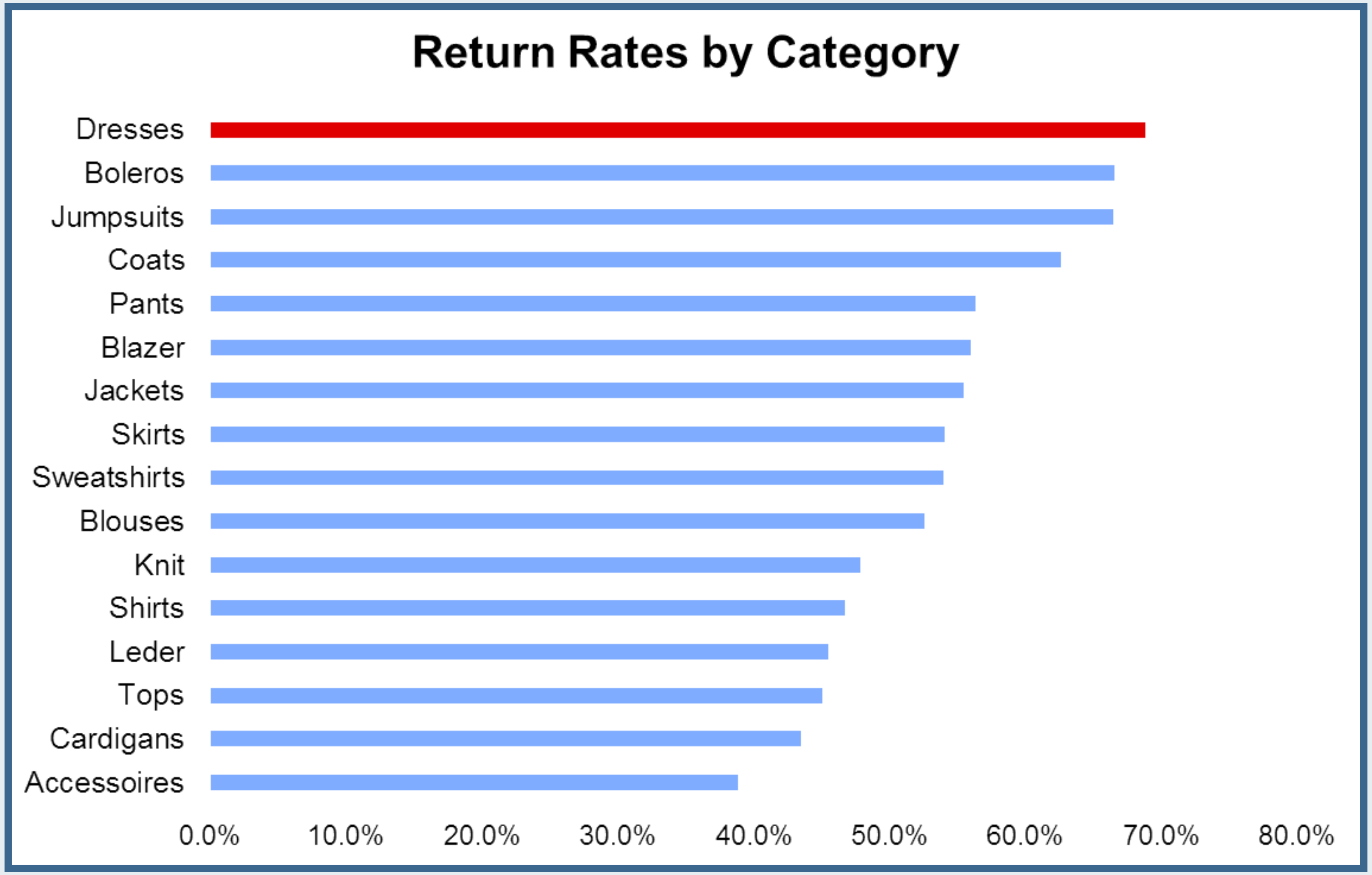
Online vs. offline demand and product returns

Online Channel		VS.	Offline Channel	
U_{on}	Purchase Decision*		U_{off}	Purchase Decision
U_{off}	Return/keep?			

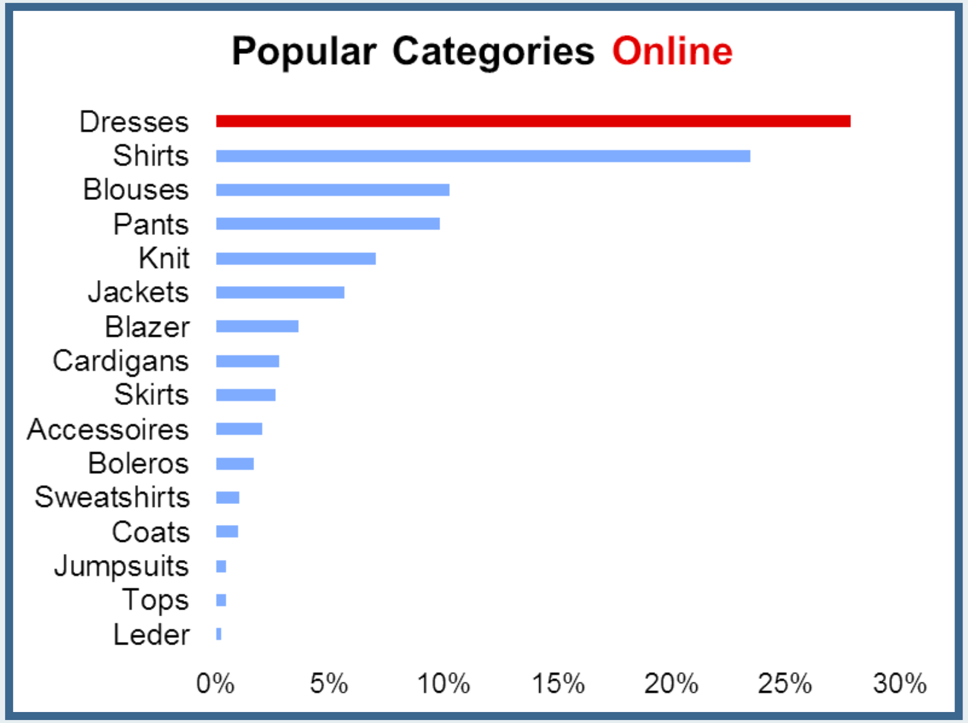
- Difference in preferences* → discrepancy in online/offline demand
- High discrepancy in demand → high return rate
- Implications for product, place, price & promotion decisions
- Accurate forecasting of return rate using all available product info (attributes, image)

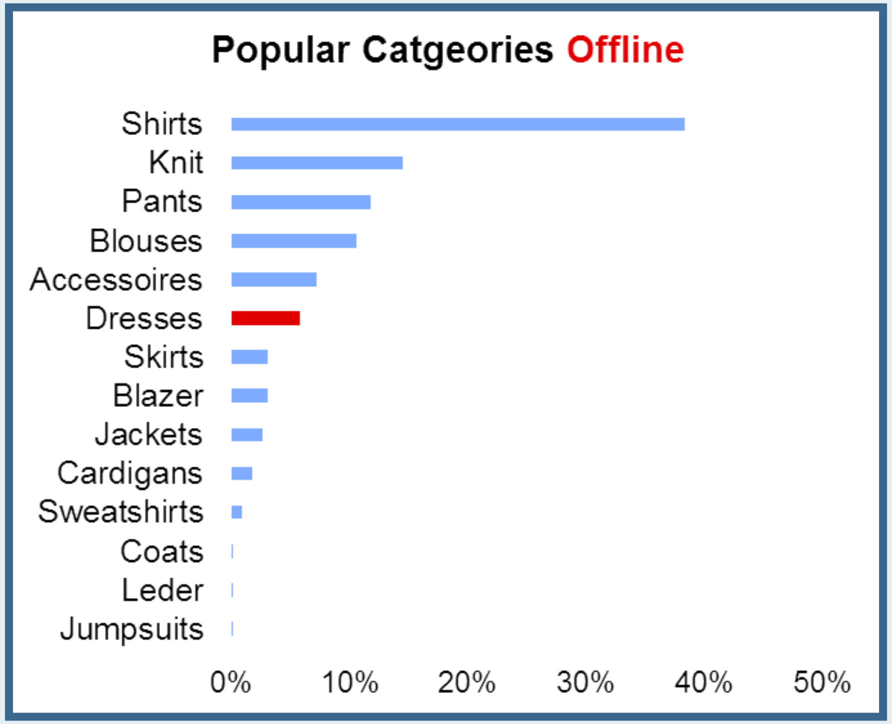
*Dzyabura, Jagabathula, Muller 2017

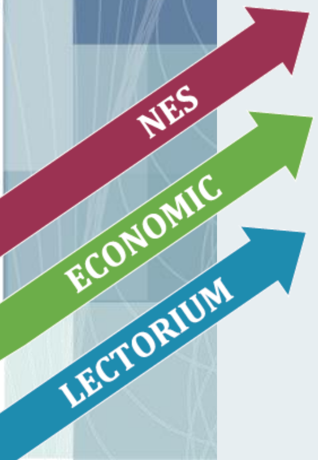
Return rates by category



Popular categories online vs. offline







Product level online & offline demand and returns

Indeed,…

$$salesOff = \beta_0 + \beta_1 * salesOn + \beta_2 * returns$$

	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

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Hypothesis: High $u_j^{online} - u_j^{offline} \leftrightarrow$ high return rate

$$returnRate = \beta_0 + \beta_1 * propOn + \beta_2 * propOff$$

IV's are sales relative to channel and category:

$$propOn = \frac{salesOn}{\sum_{\text{category}} salesOn}$$

$$propOn = \frac{salesOff}{\sum_{\text{category}} salesOff}$$

$$returnRate = \frac{returns}{salesOn}$$

	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!

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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
- …

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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

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Color analysis:
Blue and Black sell better offline

$$salesOff = \beta_0 + \beta_1 * salesOn + \beta_2 * pink + \beta_3 * purple + \cdots$$

	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	24.963	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

$$returns = \beta_0 + \beta_1 * salesOn + \beta_2 * Pinks + \beta_3 * Purples + \cdots + \beta_{14} * price$$

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

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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

- $R^2_{model} = 1 - \frac{\sum_{i \in K_{test}} (RR_i - \widehat{RR}_i^{model})}{\sum_{i \in K_{test}} (RR_i - \widehat{RR}_i^{random})}$

Features	Holdout R^2	St. Dev.
Category, price	33.88	2.93
Category, price, color descriptions	35.51	2.79
Category, price, **image – RGB**	44.12	2.44
Category, price, **image – Gabor**	42.16	2.57
Category, price, **image – Deep learned**	44.64	2.45

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Predicting return rates for new products

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Category, price, **image – Gabor**	42.16	2.57
Category, price, **image – Deep learned**	44.64	2.45
Category, price, **image**, **offline sales**	45.86	2.40

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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

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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

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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

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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

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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

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

Attribute	Level	Partworth
Color	Reflective	-0.31**
	Colorful	-1.06**
	Blue	-0.22**
	Black	
Size	Large	0.27**
	Small	
Price	$120 – $180	-0.22**
Strap pad	Yes	0.51**
	No	
Water bottle	Yes	0.45**
	No	
Interior	Divider for files	0.41**
	Laptop sleeve	0.62**
	No dividers	
Intercept		3.72**

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We checked

Regression results

Attribute	Level	Online Partworth	Offline Partworth	Difference
Color	Reflective	-0.31**	-0.60**	-0.28*
	Colorful	-1.06**	-0.71**	0.36**
	Blue	-0.22**	-0.11	-0.12
	Black			
Size	Large	0.27**	-0.31**	-0.58**
	Small			
Price	$120 – $180	-0.22**	-0.15**	0.06**
Strap pad	Yes	0.51**	0.25**	-0.26**
	No			
Water bottle	Yes	0.45**	0.17**	-0.28**
	No			
Interior	Divider for files	0.41**	0.52**	0.11
	Laptop sleeve	0.62**	0.88**	0.26**
	No dividers			
Intercept		3.72**	3.39**	-0.33

Discrepancy between preferences

- Why?

Lack of information

Abstract vs. concrete thinking

Attribute salience

- So what?

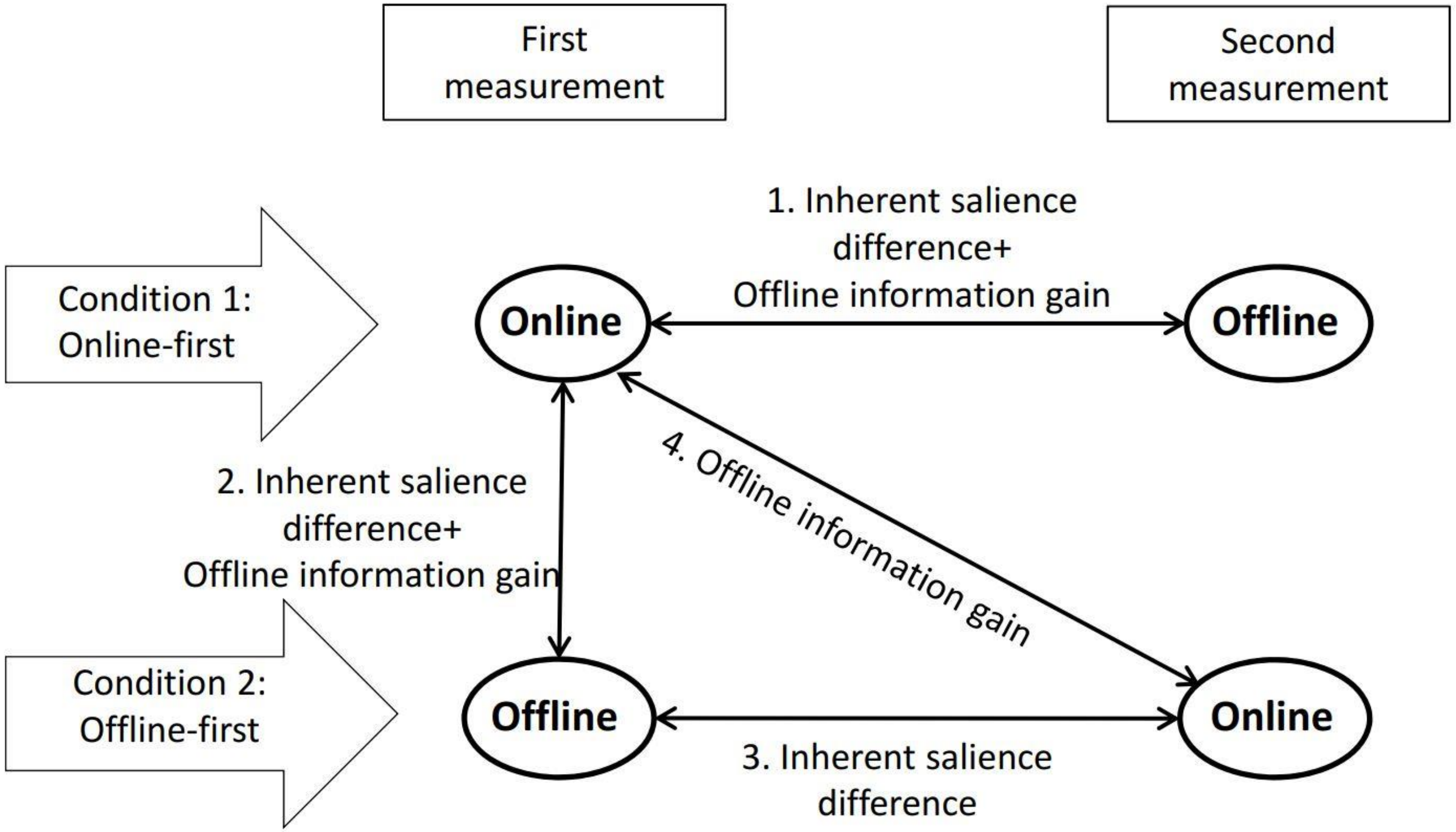
Product returns

Product assortments

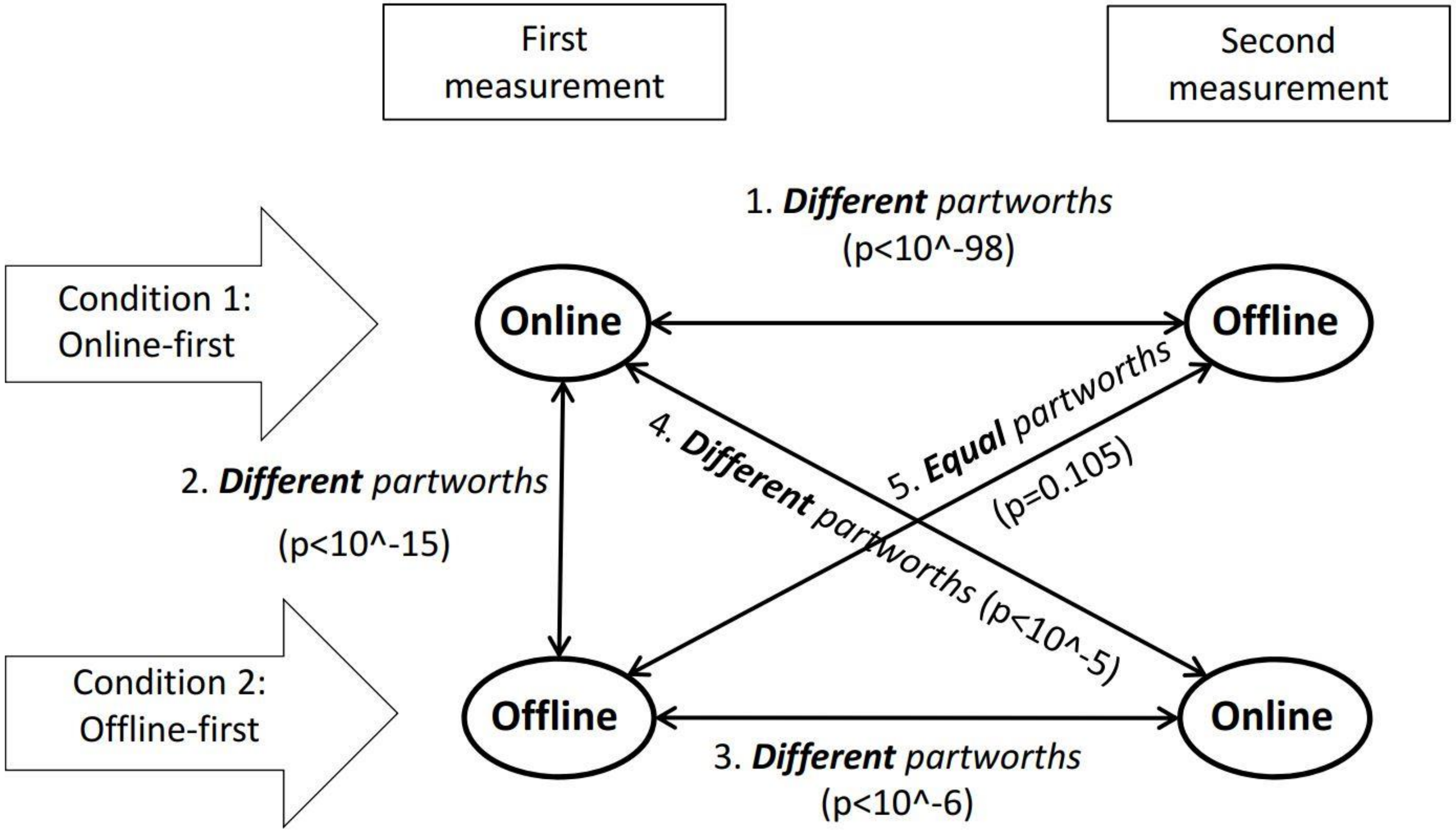
The causal question: why change?

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

Why change?


First
measurement
Second
measurement
Condition 1:
Online-first
Condition 2:
Offline-first
Online
Offline
Offline
Online
1. Inherent salience
difference+
Offline information gain
2. Inherent salience
difference+
Offline information gain
3. Inherent salience
difference
4. Offline information gain

Why change?


First measurement
Second measurement
Condition 1: Online-first
Condition 2: Offline-first
Online
Offline
Offline
Online
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!

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