Measuring Price Discrimination and Steering on E-commerce Web Sites

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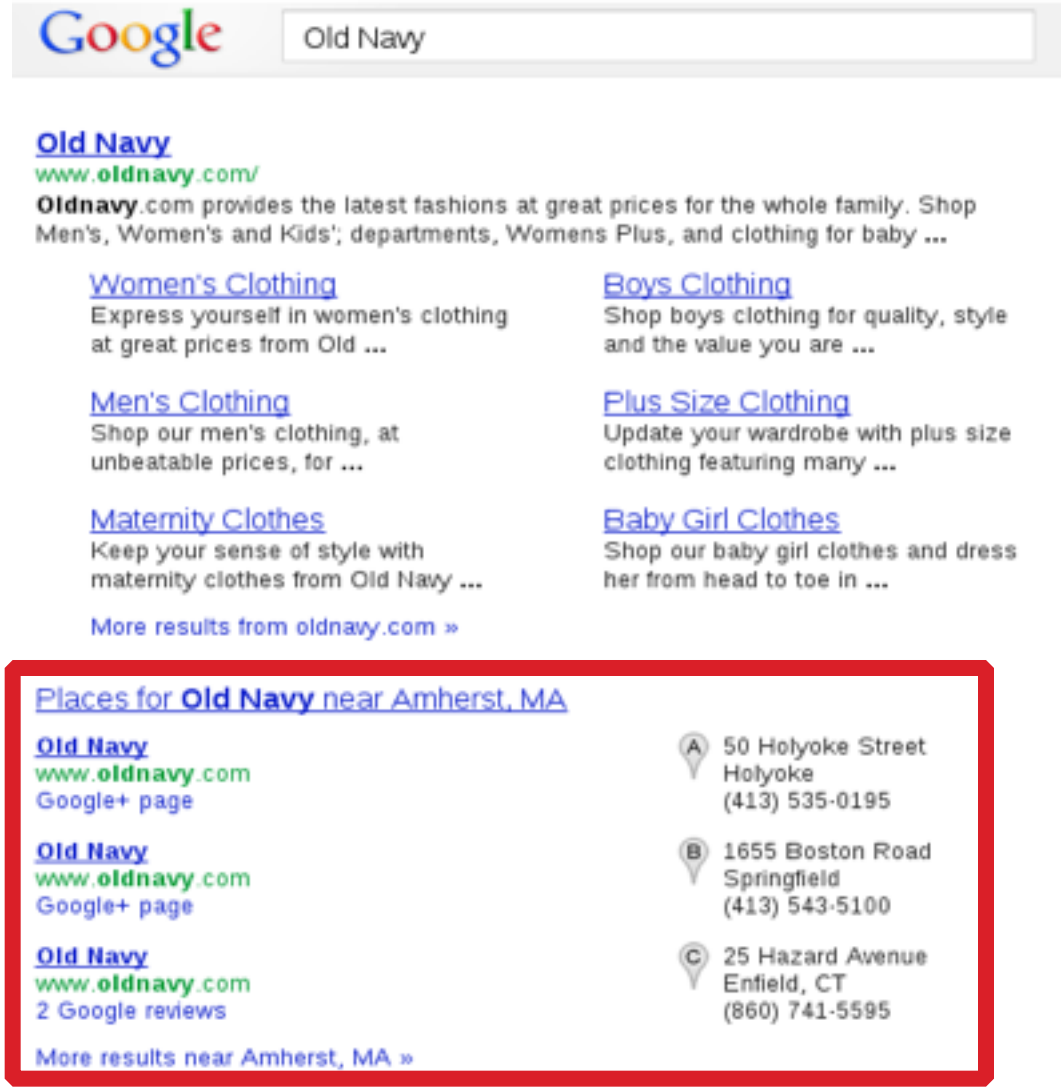
Northeastern University

Personalization on the Web



Personalization on the Web

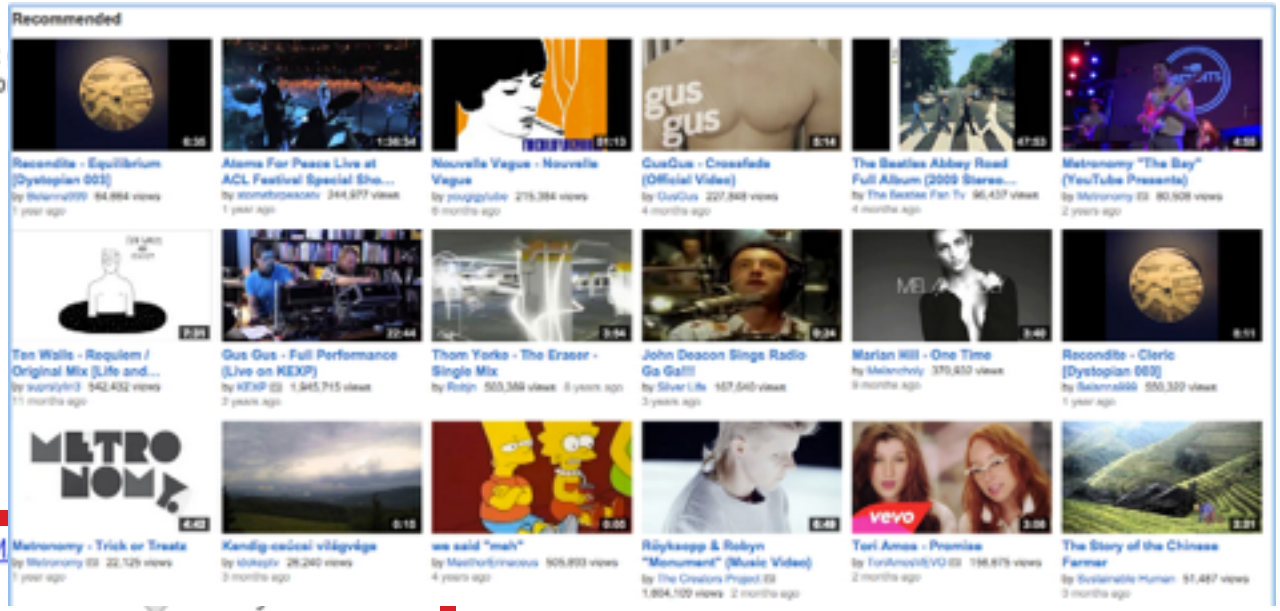
Old Navy
www.oldnavy.com/
Oldnavy.com provides the latest fashions at Men's, Women's and Kids'; departments, Wo

Women's Clothing
Express yourself in women's clothing at great prices from Old ...

Men's Clothing
Shop our men's clothing, at unbeatable prices, for ...

Maternity Clothes
Keep your sense of style with maternity clothes from Old Navy ...

More results from oldnavy.com »



Places for **Old Navy** near Amherst, M

Old Navy
www.oldnavy.com
Google+ page

Old Navy
www.oldnavy.com
Google+ page

Old Navy
www.oldnavy.com
2 Google reviews

More results near Amherst, MA »

Holyoke
(413) 535-0195

B 1655 Boston Road
Springfield
(413) 543-5100

C 25 Hazard Avenue
Enfield, CT
(860) 741-5595

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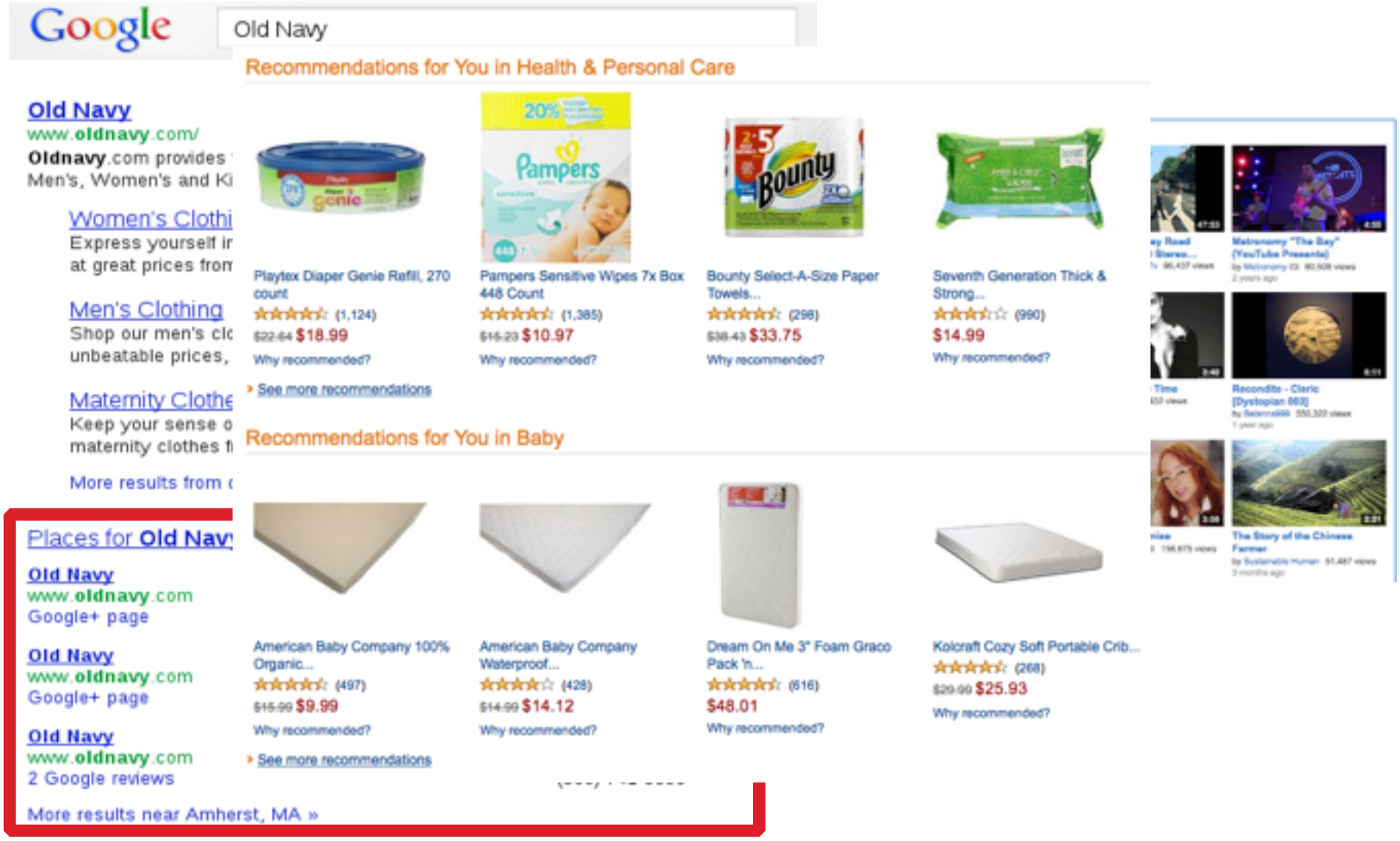


Focus of this work: E-commerce sites

Online purchasing now extremely common

Significant, comprehensive user tracking

- Clear economic incentive to use data to increase sales

These processes are hidden from users

- What personal data is collected?
- How is it used? Possibly to users' disadvantage

Examine two trends: Price discrimination and steering

Price Discrimination

Showing users different prices

- In econ: differential pricing

Example: Amazon in 2001

- DVDs were sold for $3-4 more to some users

Surprisingly, not illegal

- Anti-Discrimination Act does not protect consumers

Price Steering

Altering the rank order of products

- Steering
- E.g. high priced items rank higher for some people

Example: Orbitz in 2012

- Users received hotels in a different order when searching
- Normal users: cheap hotels first; Mac users: expensive hotels first

Goals of Our Work

Methodology to measure personalization of e-commerce

Measure personalization on e-commerce sites

- Price Discrimination
  - Are the same products offered at different prices to people?
- Price Steering
  - Are products presented in a different order?
  - Do some people see more expensive products?

Explore how online retailers personalize

- What features do their algorithms personalize on?

Outline

- Methodology
- Measuring Price Discrimination
  - Real User Accounts (extent)
  - Synthetic User Accounts (features)
- Conclusion

Scope of measurements

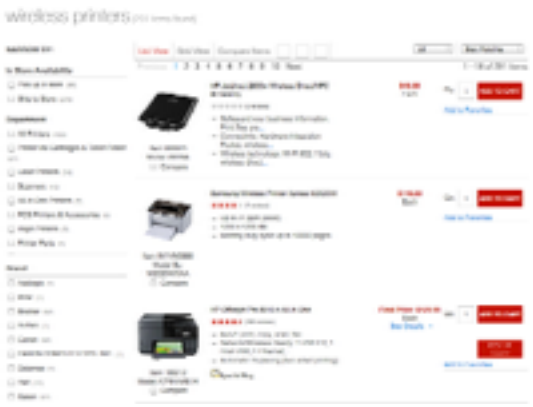
10 General retailers

BestBuy CDW HomeDepot JCPenney Macy's NewEgg OfficeDepot Sears Staples Walmart

6 travel sites (hotels & car rental)

CheapTickets, Expedia, Hotels, Priceline, Orbitz, Travelocity

Focus on products retuned by searches, 20 search terms / site



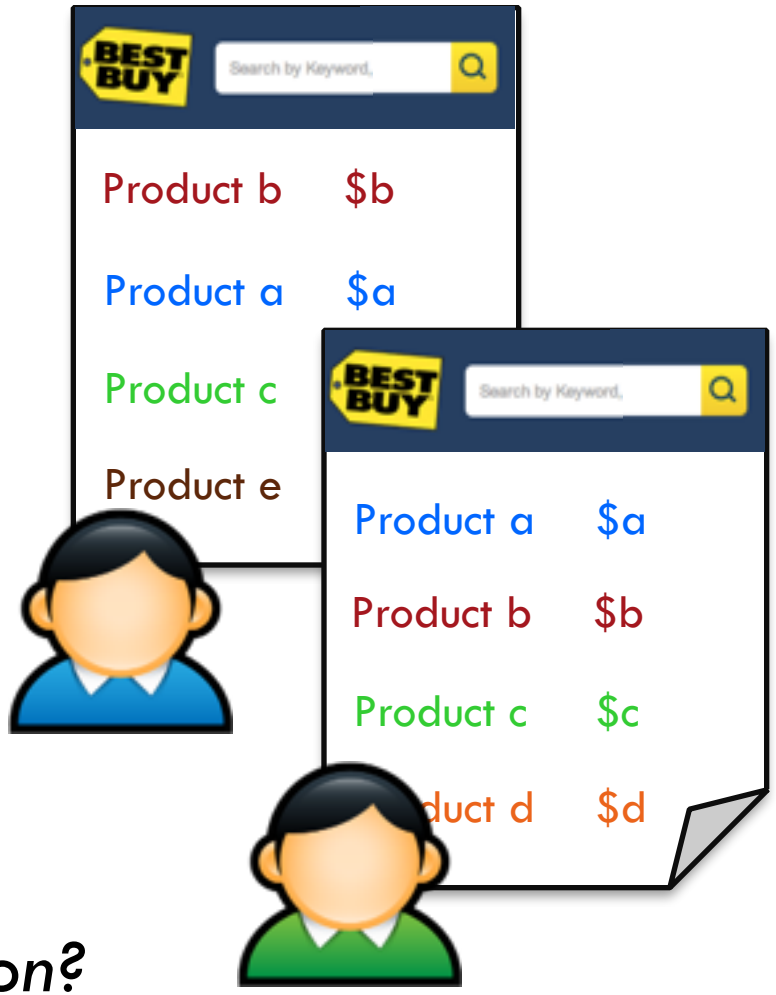
Are all differences *personalization*?

No! Could be due to

- Updates to inventory/prices
- Tax/Shipping differences
- Distributed infrastructure
- Load-balancing

Only interested in *personalization due to client-side state associated with request*

How do we measure *personalization*?



Measuring personalization

129.10.115.14

129.10.115.15

74.125.225.67

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IP addresses in the same /24

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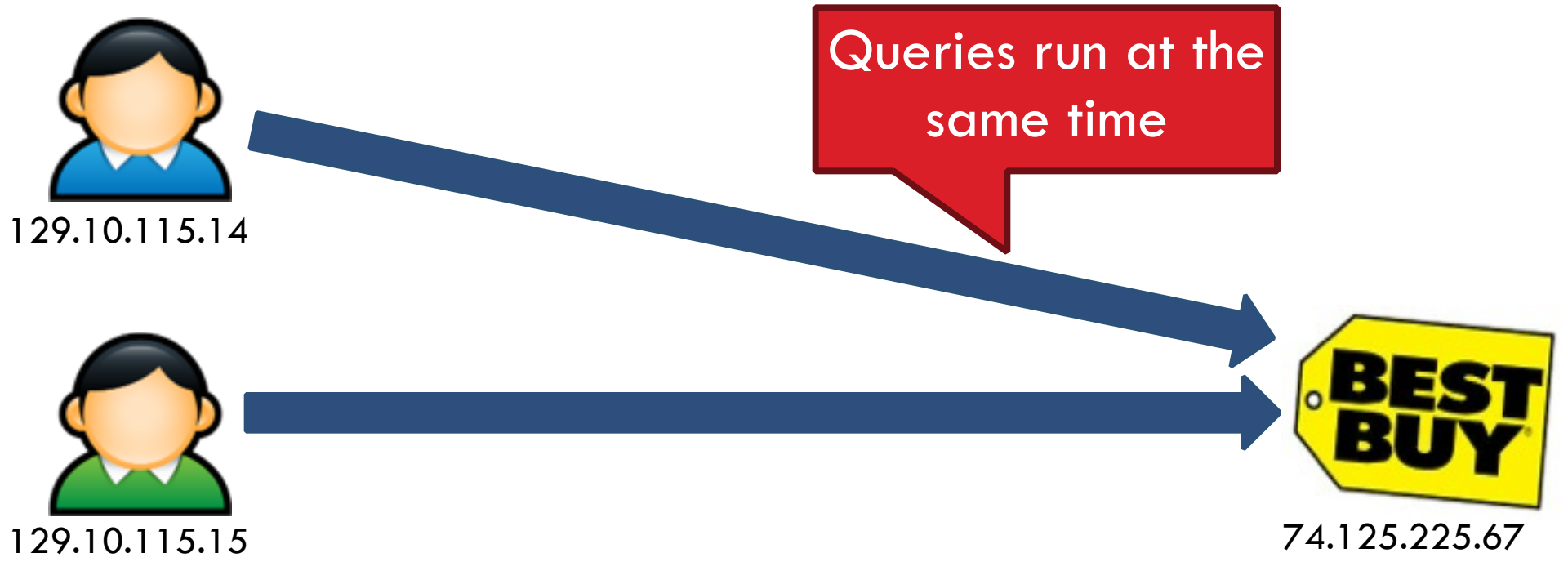

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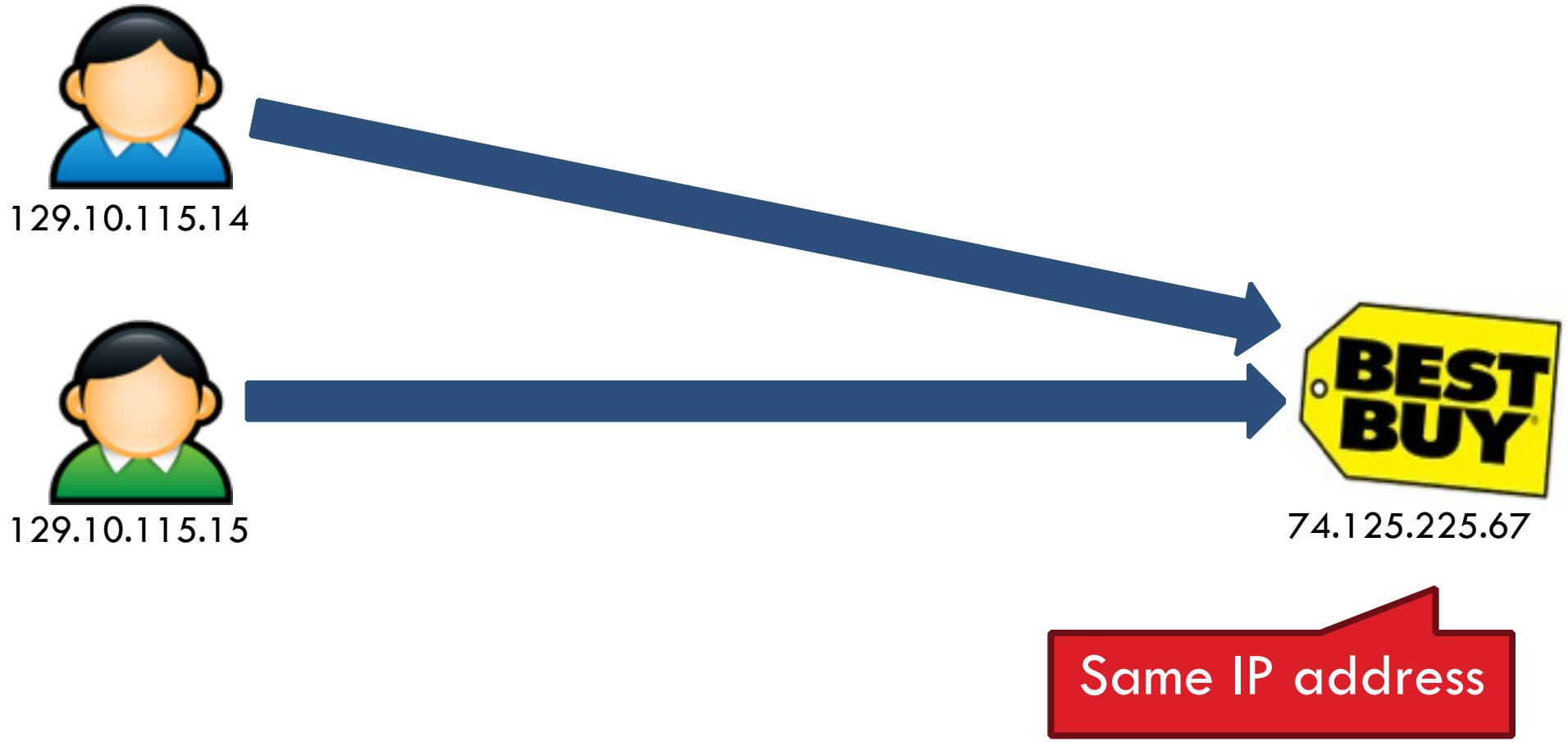

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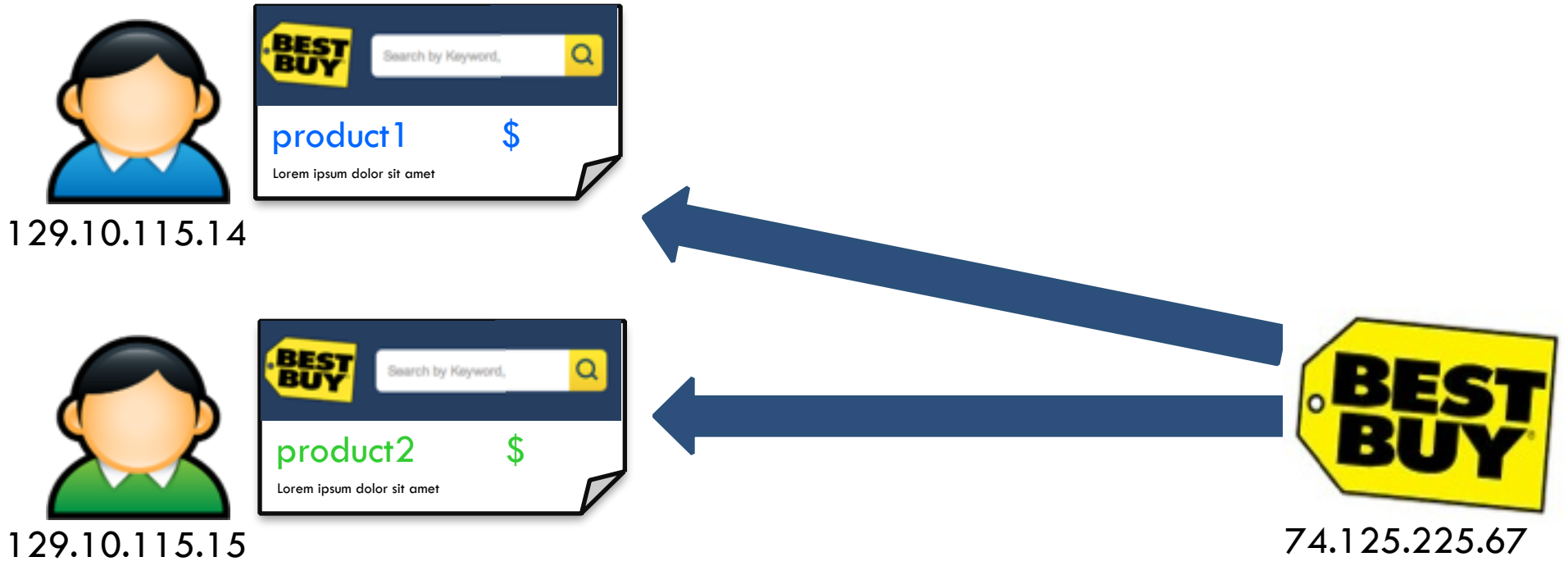

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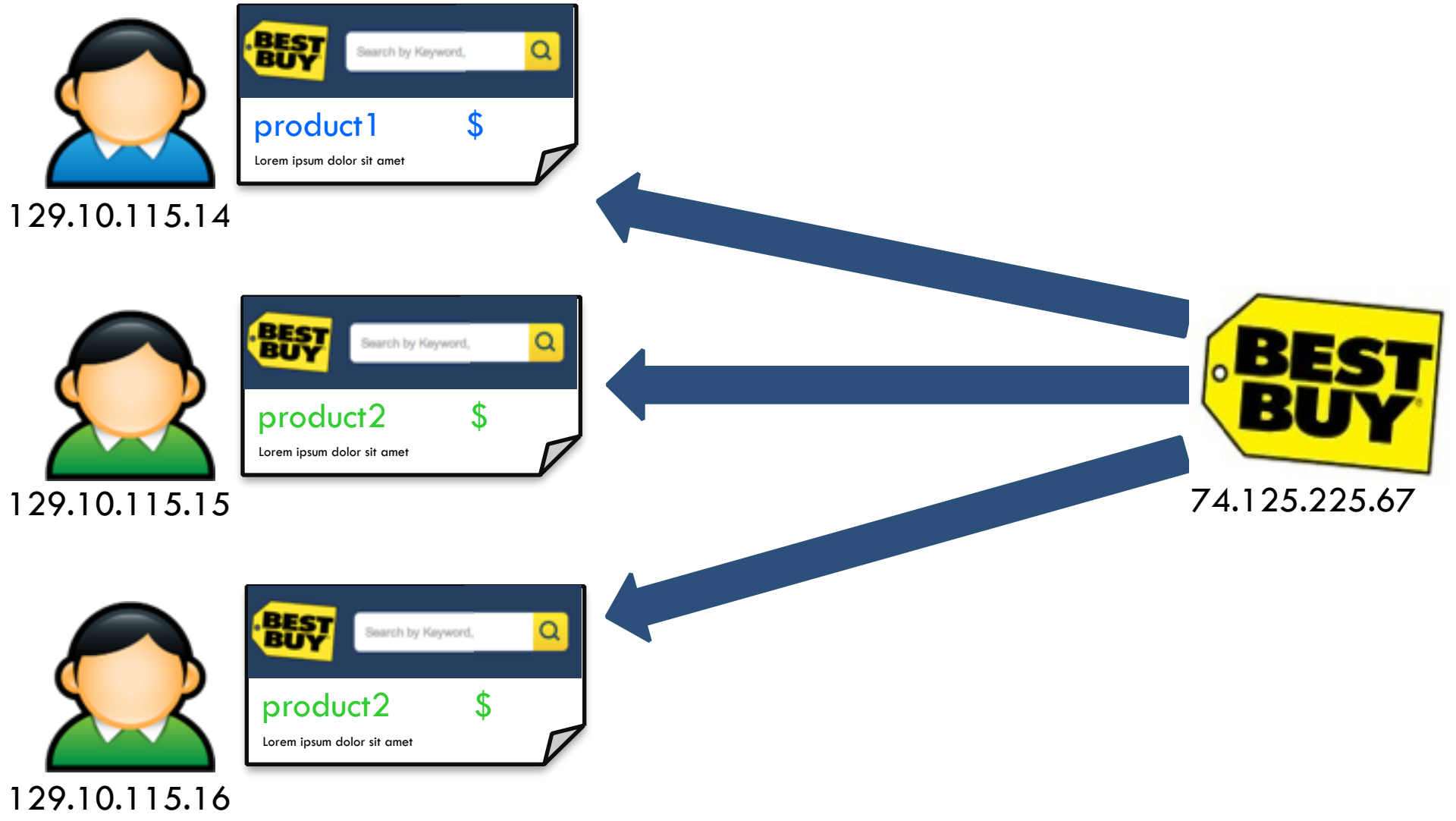

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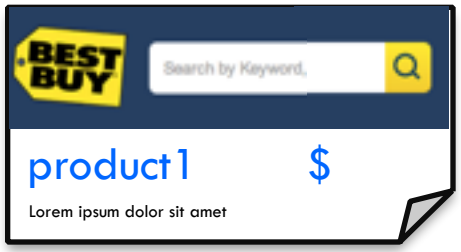

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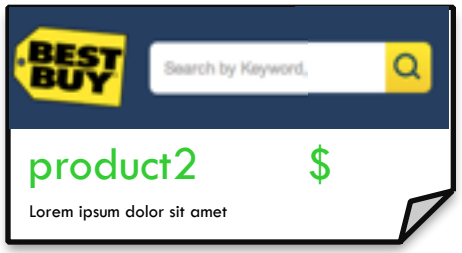

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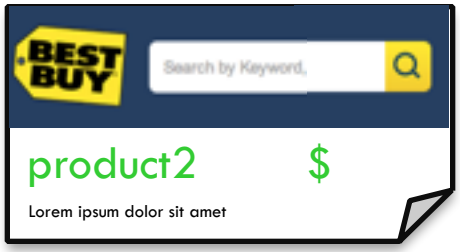

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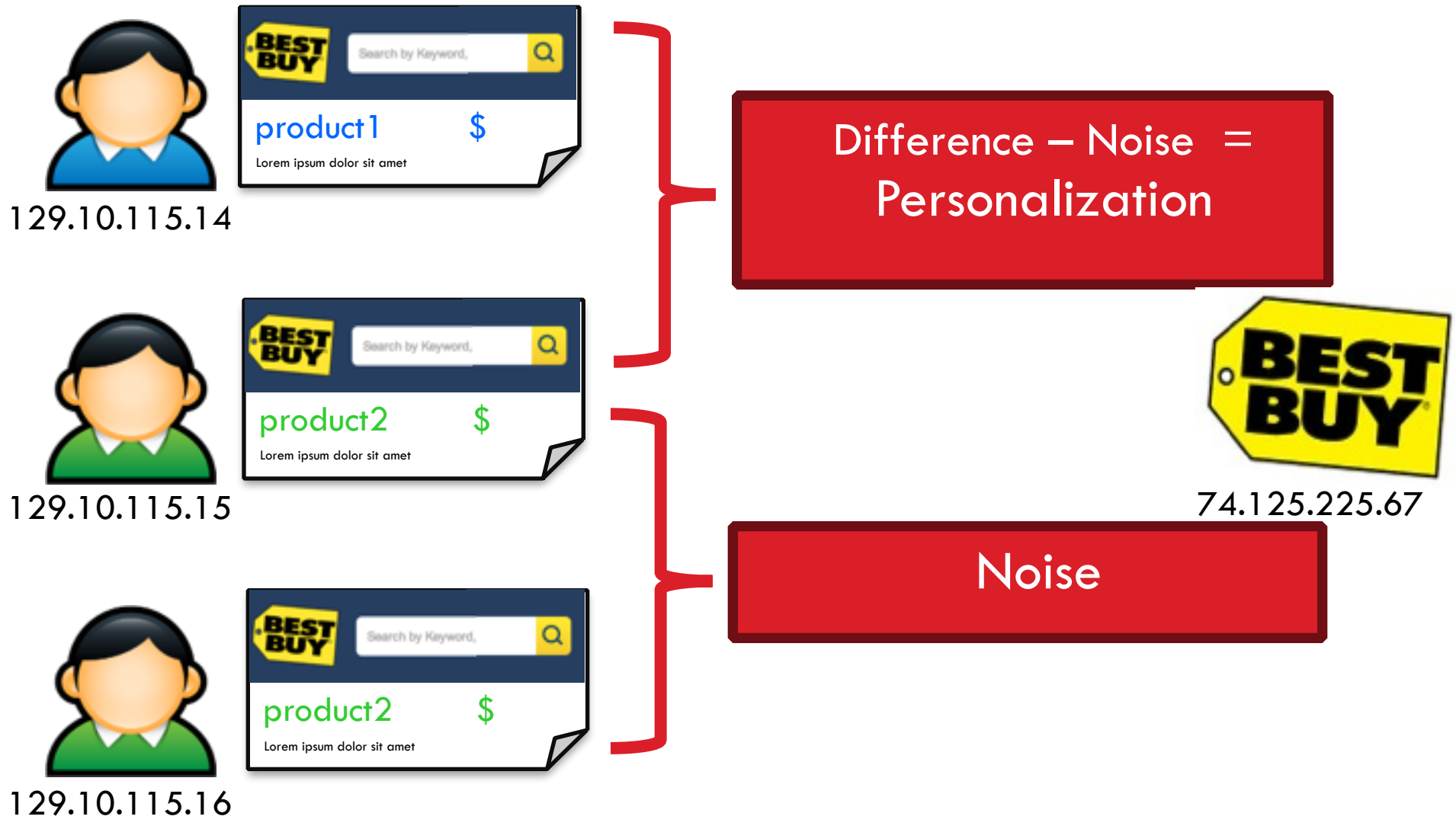

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Experimental Treatments

Questions we want to answer:

- To what extent are products personalized?
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Leverage real users who have history

Measure personalization in real life

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Measure personalization in real life

Synthetic User Accounts

Create accounts that each vary by one feature

Measure the impact of specific features

Collecting personalization for real users

HTTP Proxy

Walmart

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- 300 participants
  - 100 users each for for e-commerce, hotel, rental car sites
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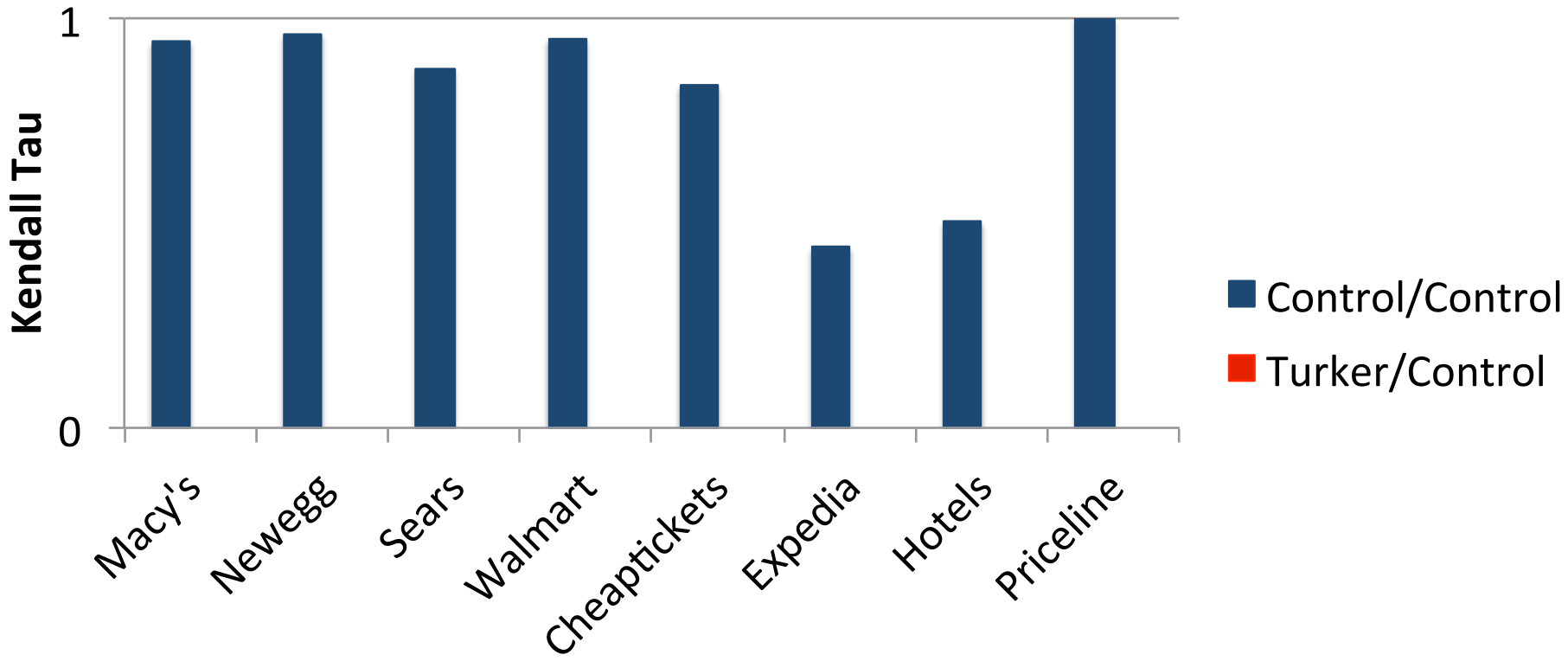

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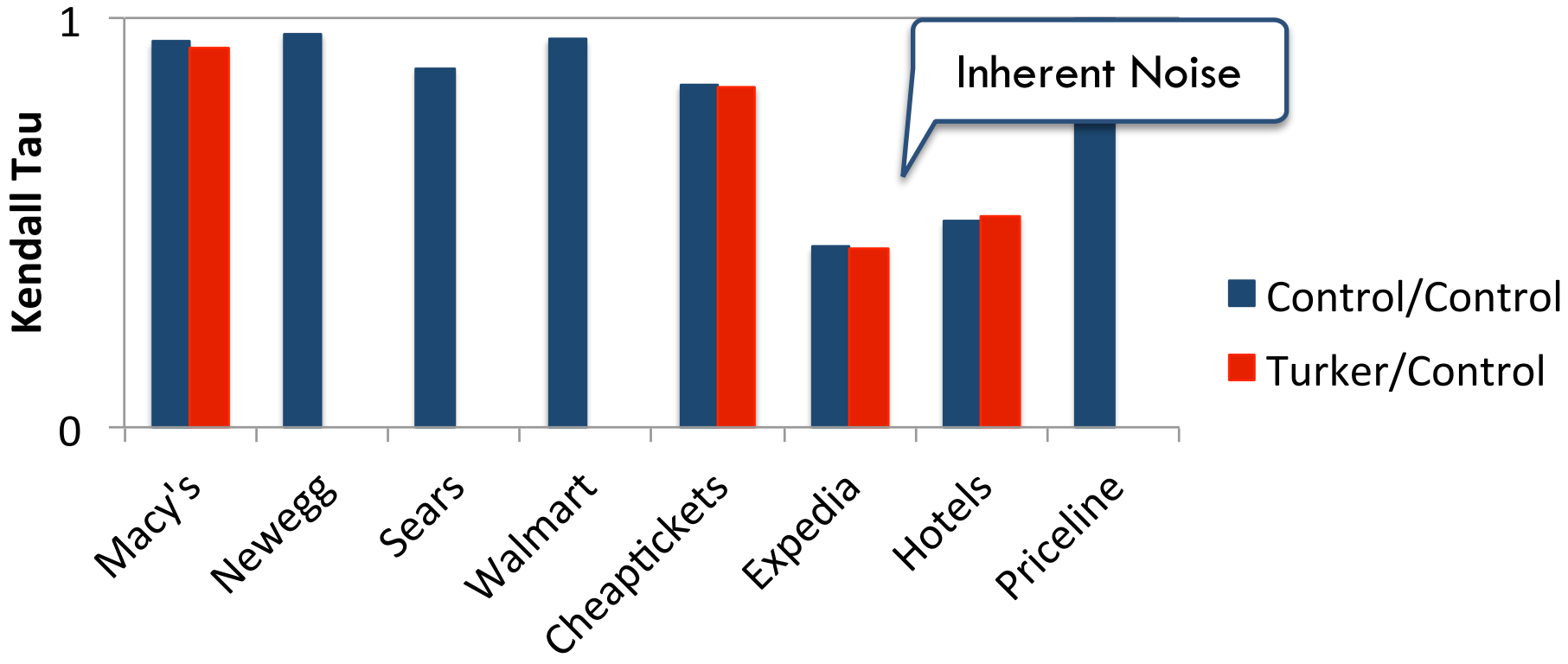

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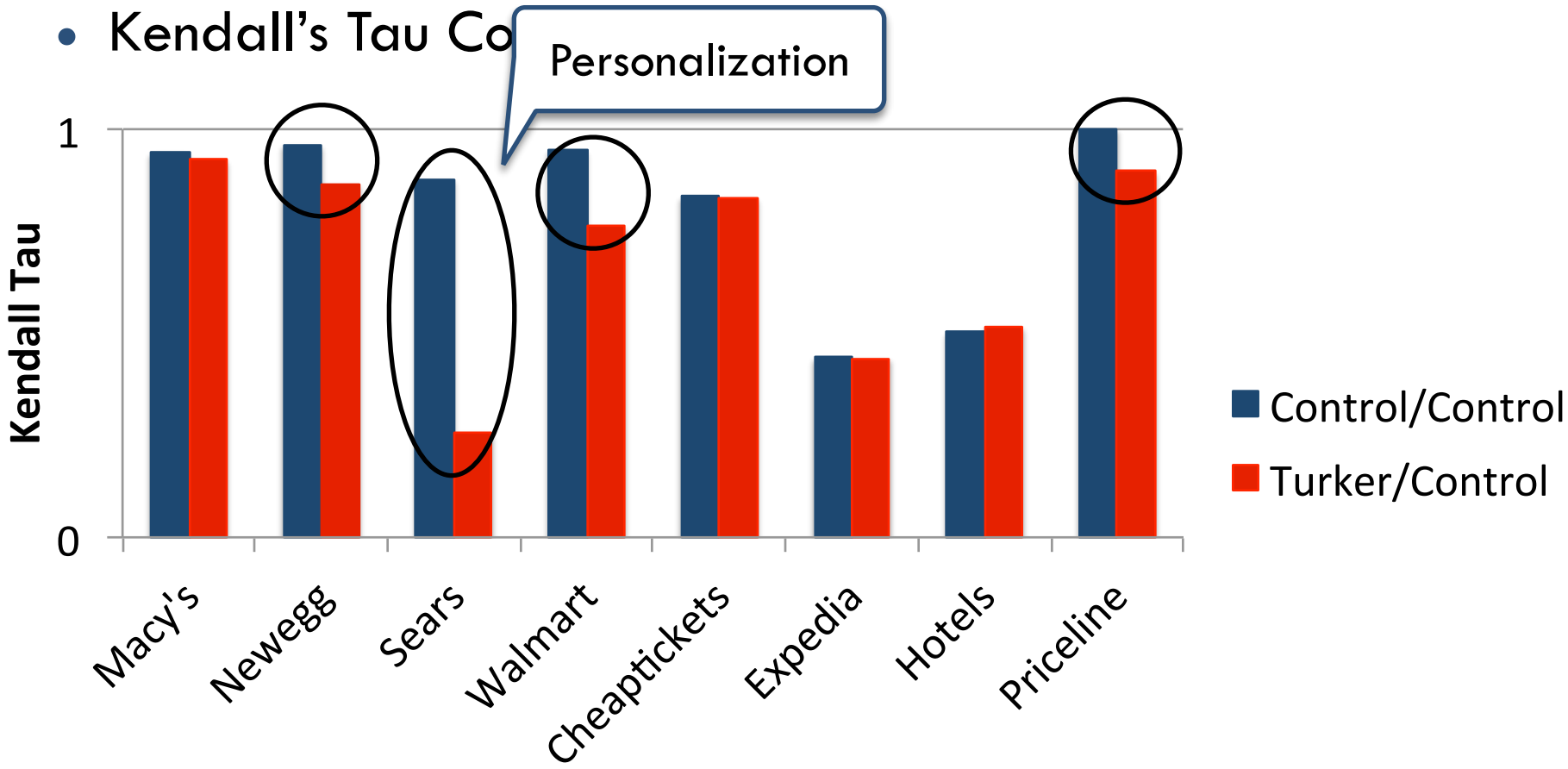

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Percentage of products with inconsistent pricing

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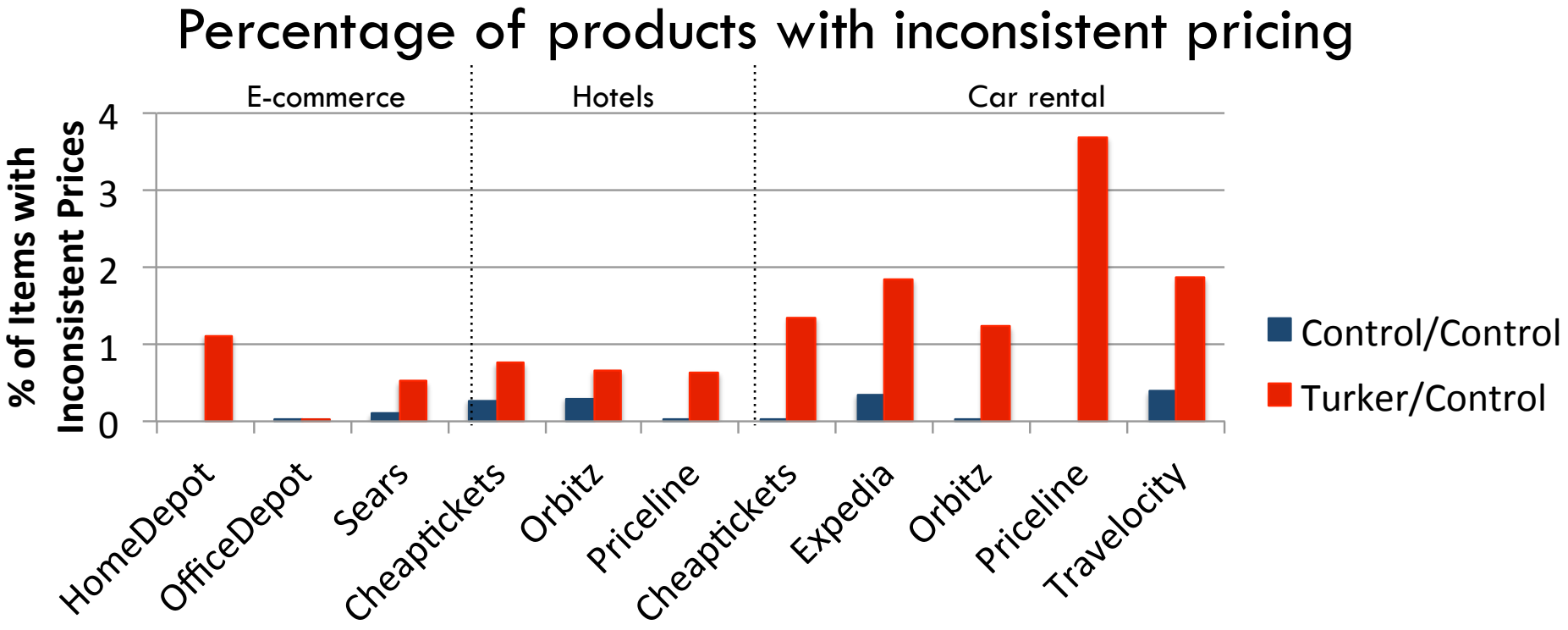

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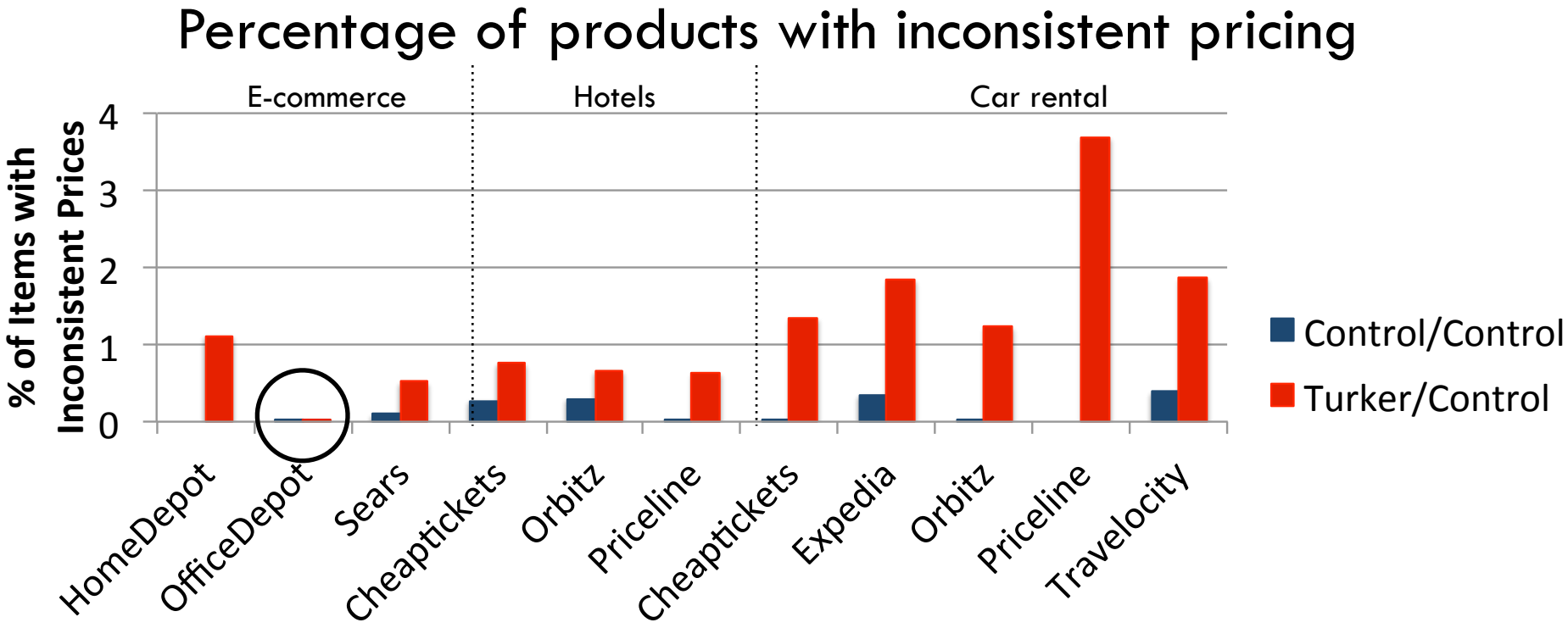

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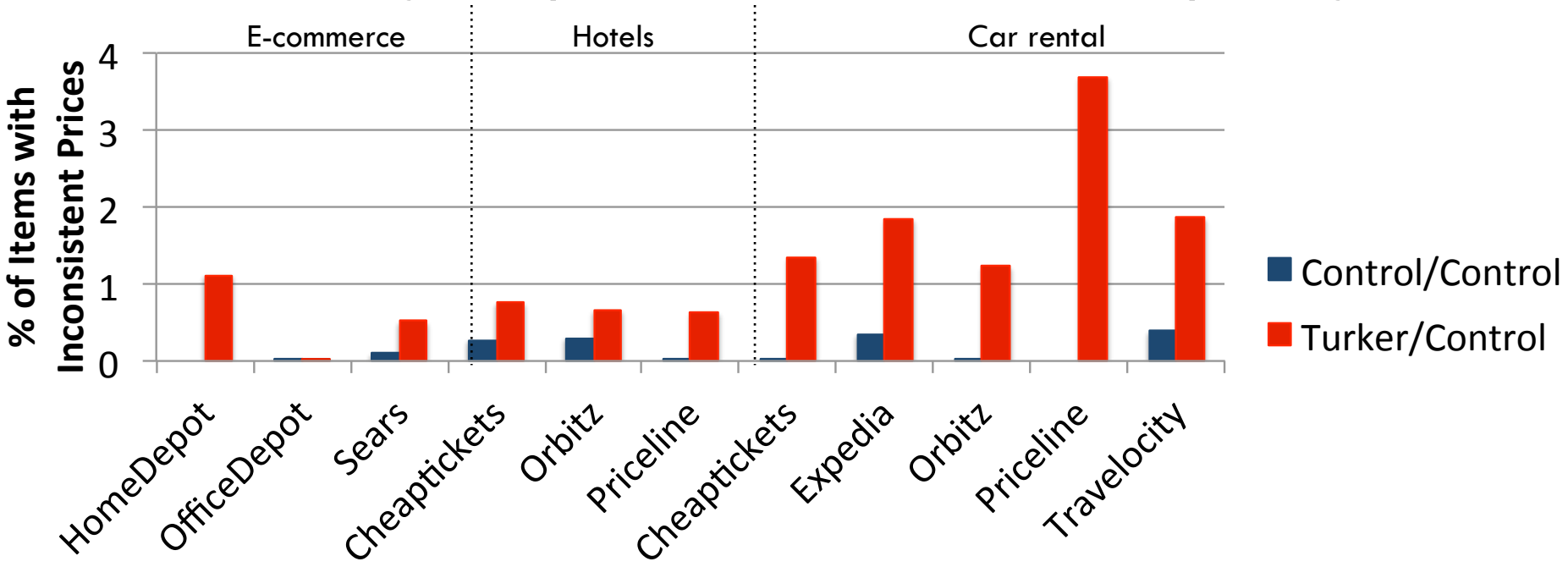
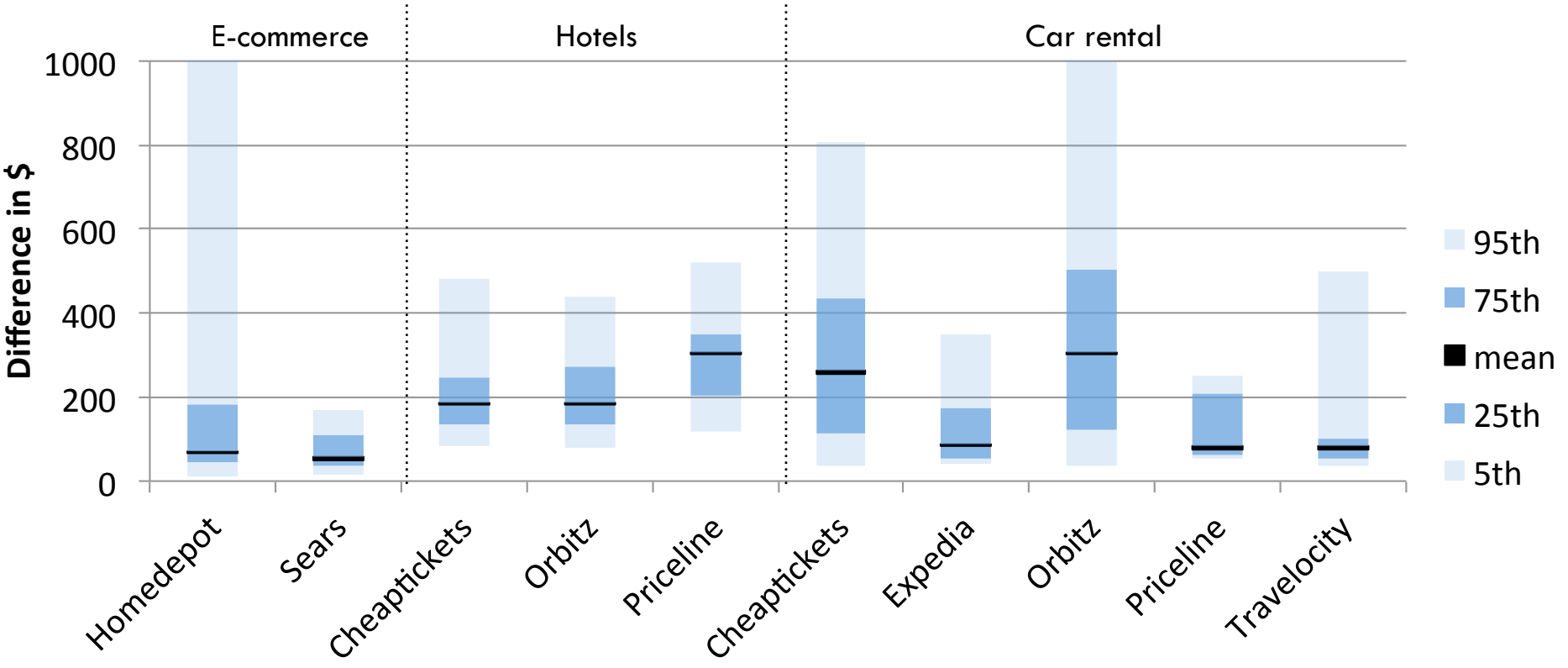


Many sites show more inconsistencies for real users

Up to 3.6% of all products!

Price *discrimination* for real users

How much money are we talking about..?



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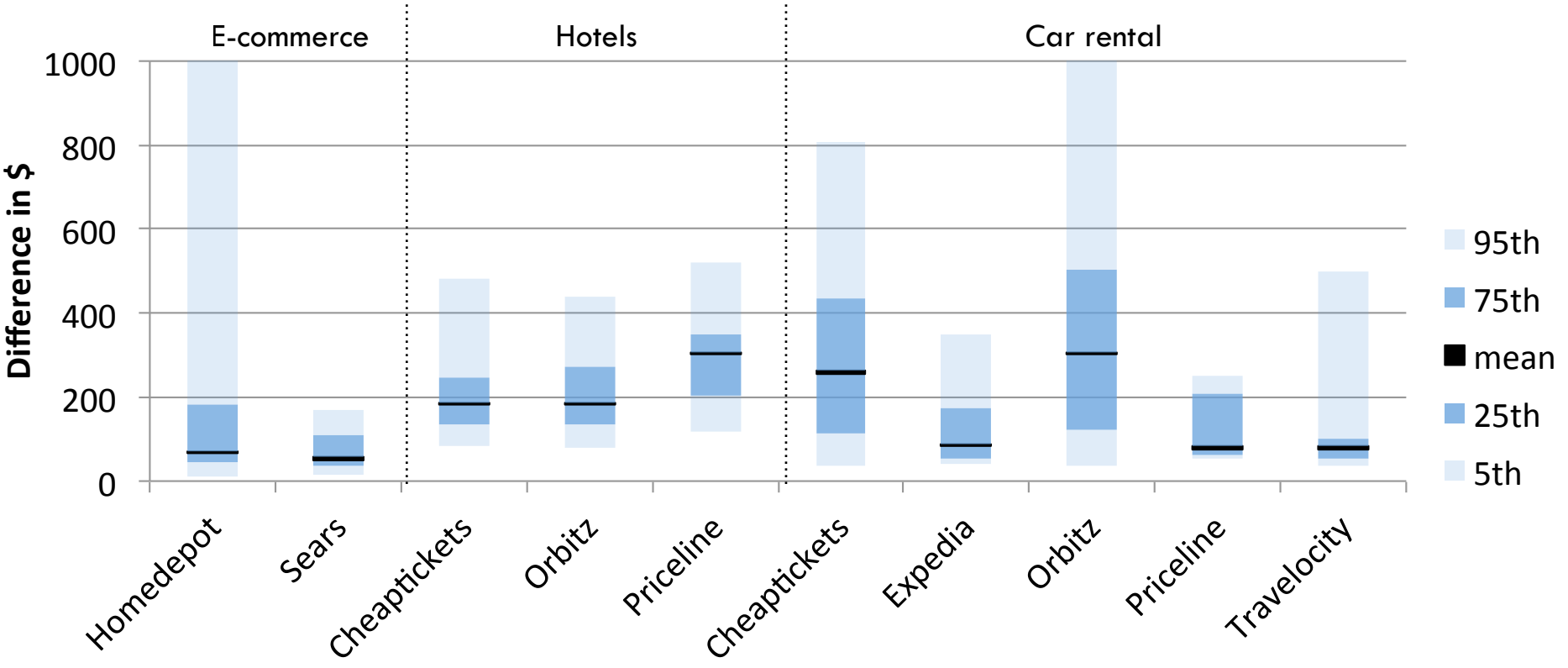

Inconsistencies can be $100s! (per day/night for hotels/cars)

Take-aways

Methodology is able to identify personalization

- Manually verified incidents in HTML source

Significant levels of price steering and discrimination

- Not random — a small group of users are often personalized

But, cannot say how or why these users get different prices

- Could be due to browsers, purchase history, etc

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What user features enable personalization?

Methodology: use synthetic (fake) accounts

- Give them different features, look for personalization
- Each day for 1 month, run standard set of searches
- Add controls

Category	Feature	Tested Features
Account	Cookie	No Account, Logged In, No Cookies
User-Agent	OS	Win XP, Win 7, OS X, Linux
	Browser	Chrome 33, Android Chrome 34, IE 8, Firefox 25, Safari 7, iOS Safari 6
History	Click	Big Spender, Low Spender
	Purchase	Big Spender, Low Spender

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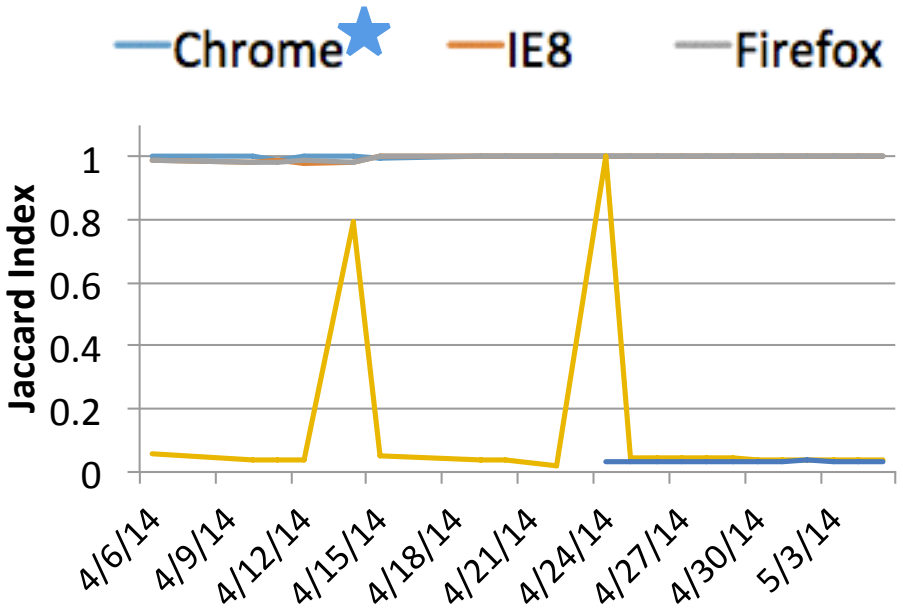

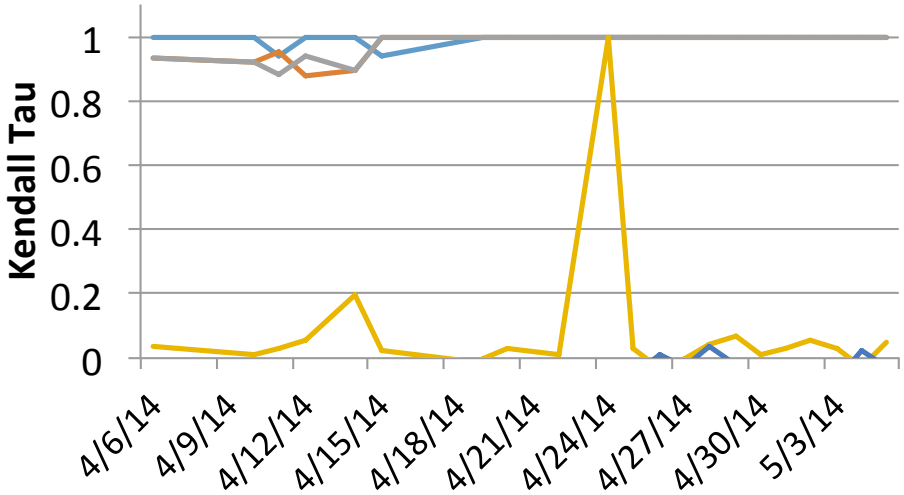

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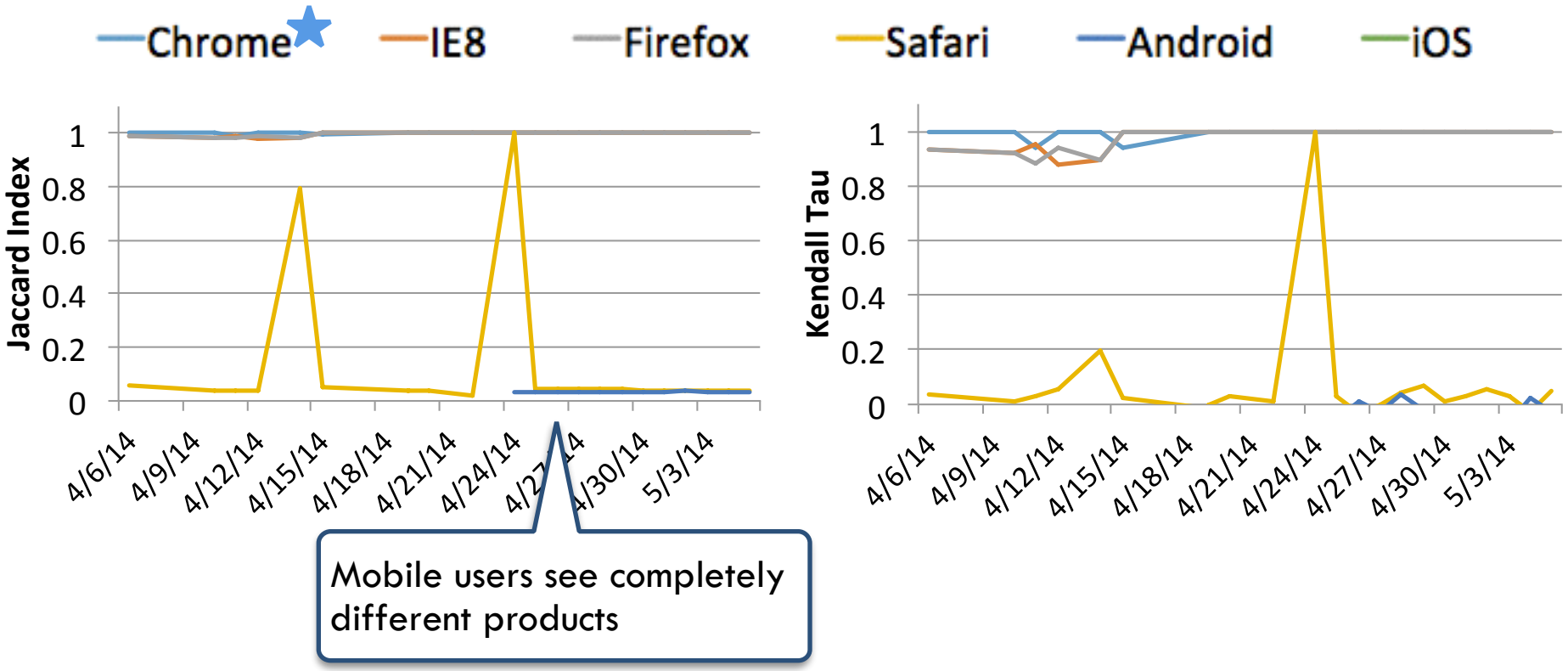

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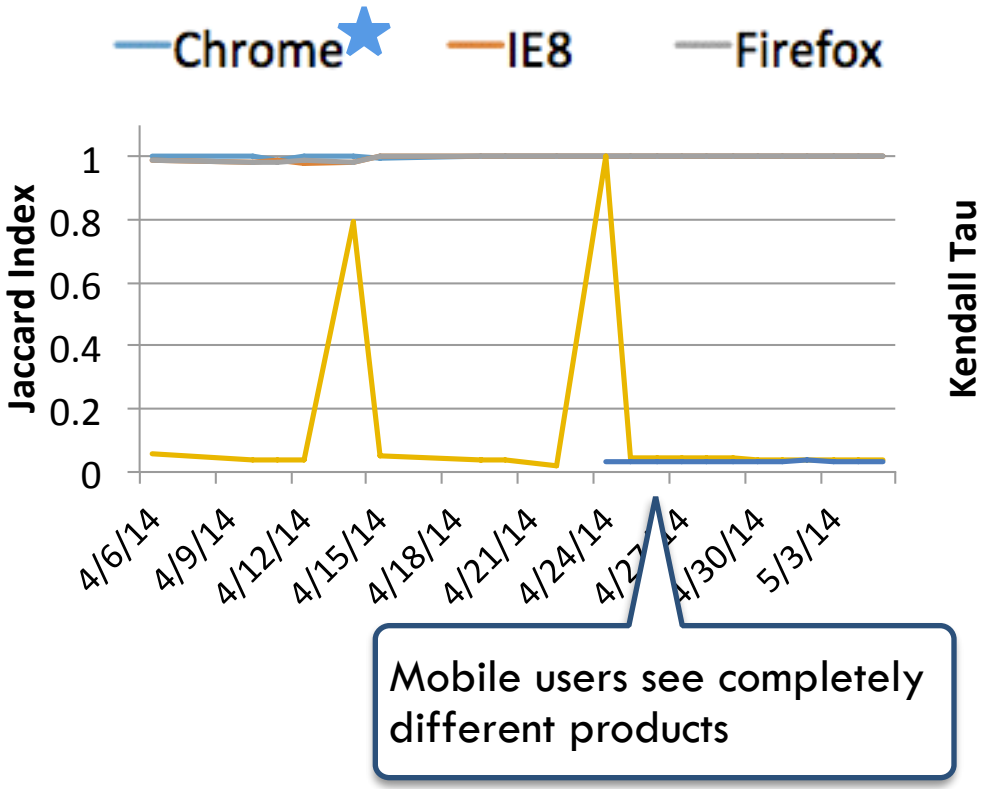

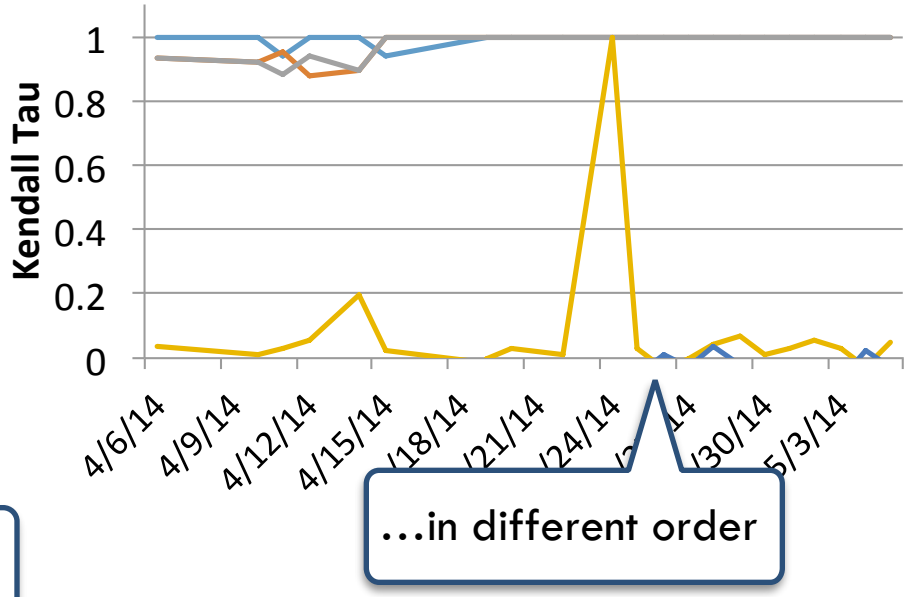

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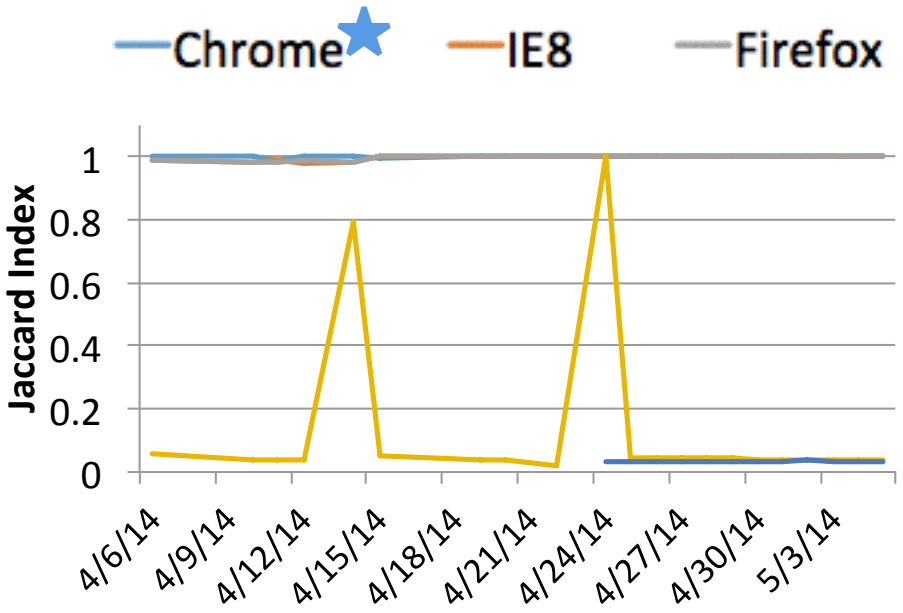

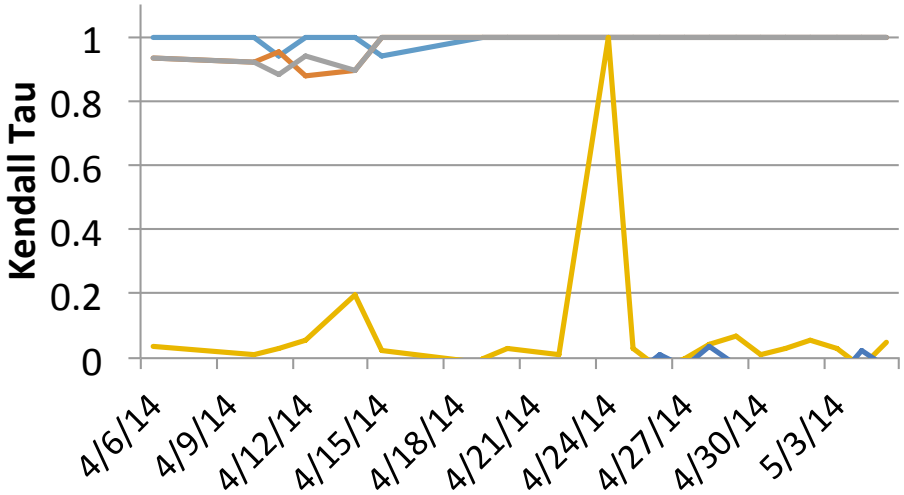

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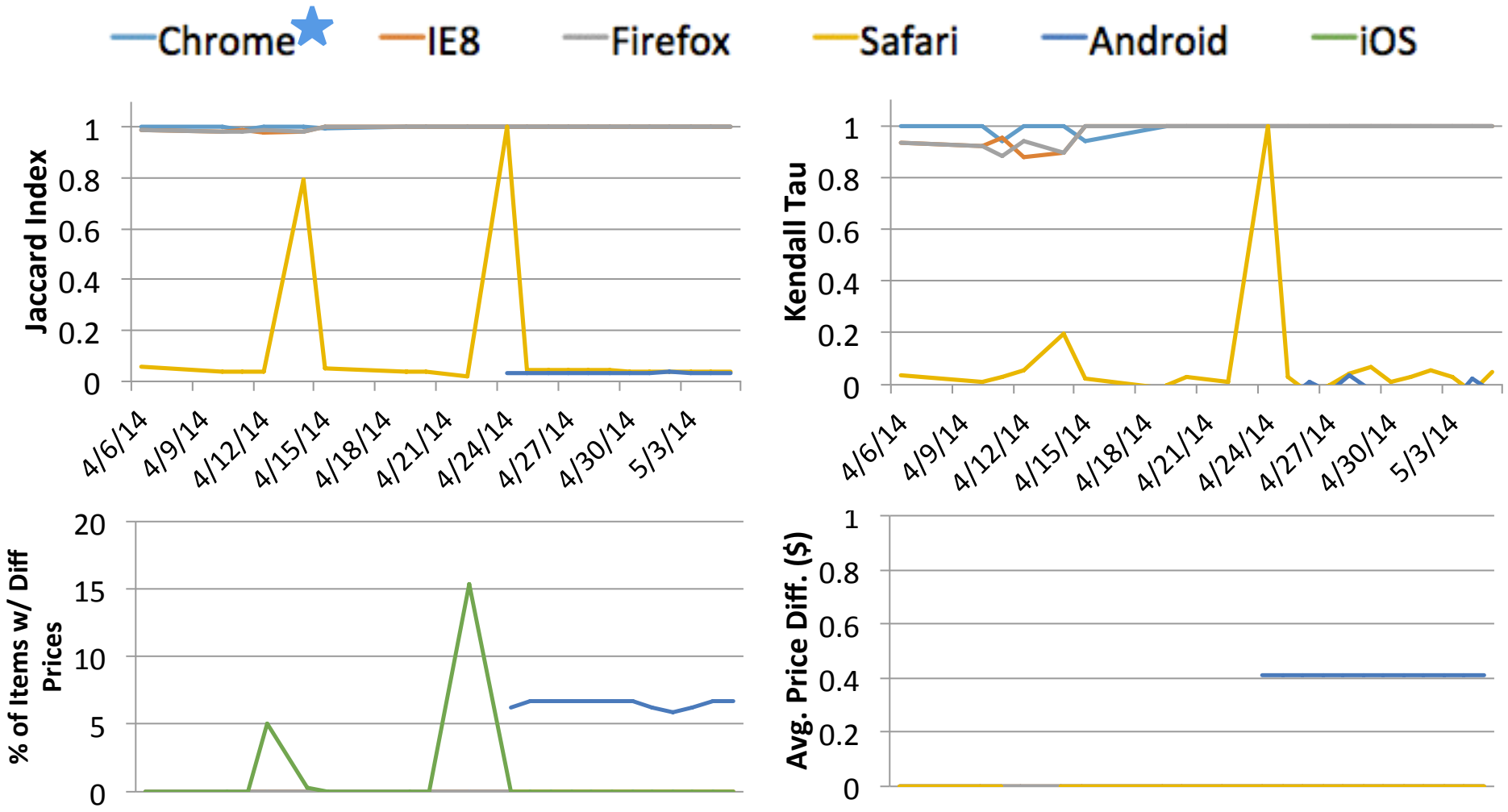

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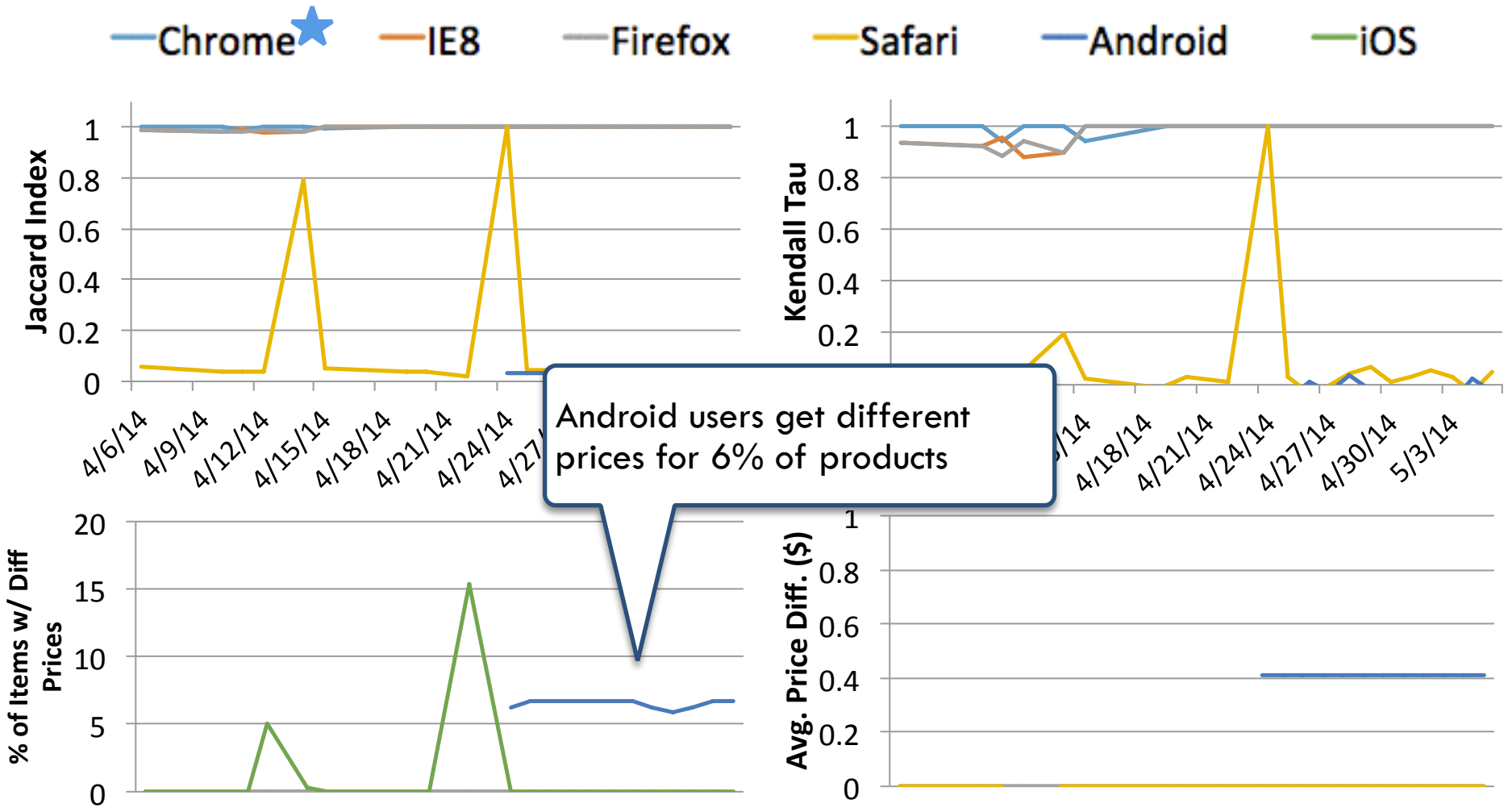

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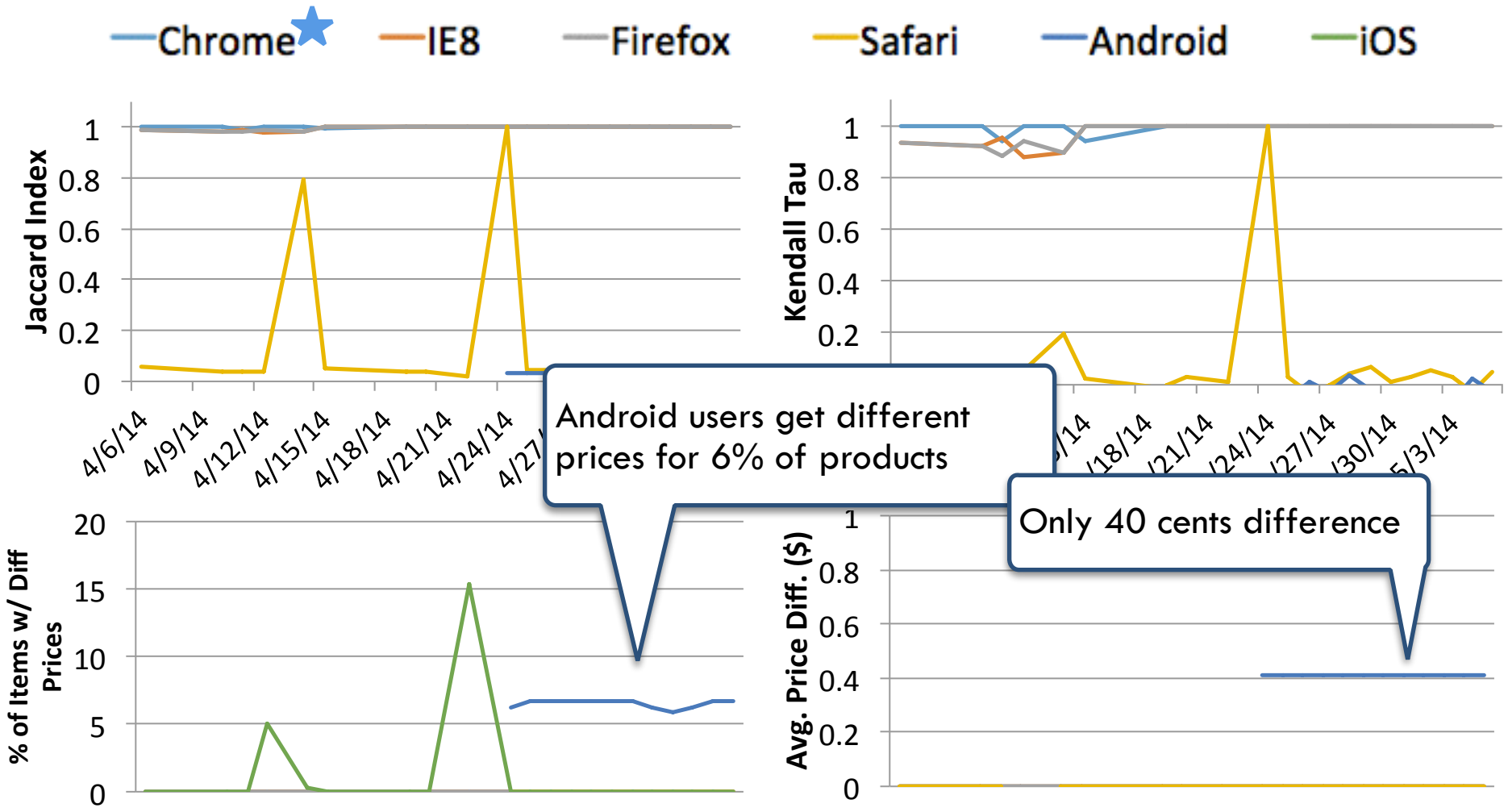

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Priceline: recognizes cheapskates

- They get different products in different order

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Recap

Developed methodology, measurement infrastructure to study price discrimination and steering

Collected real-world data from 300 users

- Evidence of personalization on 9 of the measured sites

Conducted controlled experiments to identify features

- Observed sites altering results based on based on: Account, Browser/OS, Purchase History

Discussion

Part of a larger project

- Understanding how web services collect data
- How it effects the information users see

Transparency

- People don't know when and how they are discriminated
- Raising awareness is important

Continuous Monitoring

- Observe if, when, and how algorithms are changing
- Develop active defense mechanisms

Questions?

http://personalization.ccs.neu.edu