Sources of Market Power in Web Search: Evidence from a Field Experiment

DMA and Beyond Conference

Hunt Allcott
(Stanford & NBER)

Juan Camilo Castillo
(UPenn & NBER)

Matthew Gentzkow
(Stanford & NBER)

Leon Musolff
(UPenn)

Tobias Salz
(MIT & NBER)

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The web search market

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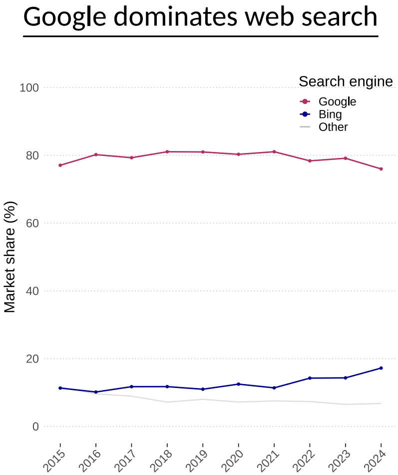
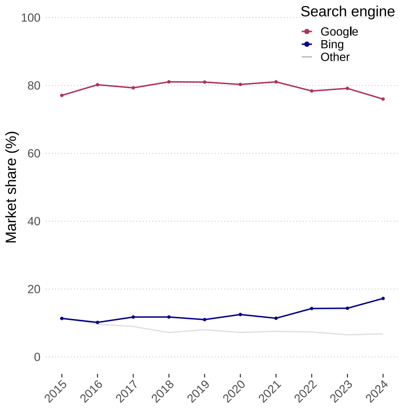


The web search market

Google dominates web search



This attracted regulatory scrutiny

The New York Times

'Google Is a Monopolist,' Judge Rules in Landmark Antitrust Case

The ruling on Google's search dominance was the first antitrust decision of the modern internet era in a case against a technology giant.

CNBC

TECH

Google paid $26 billion in 2021 to become the default search engine on browsers and phones

Research questions

1. **Why is Google's market share so high?**
   - True quality differences?
     - Driven by economies of scale in data?
   - Quality misperceptions?
   - Default effects (switching costs and/or inattention)?

Research questions

1. **Why is Google's market share so high?**
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2. **What would be the effects of competition policy?**
   - Active choice screens?
   - Changing defaults?
   - Requiring Google to share data with competitors?

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2. What would be the effects of competition policy?

- Active choice screens?
- Changing defaults?
- Requiring Google to share data with competitors?

This paper: model, field experiment, click-and-query data, counterfactuals.

Literature

Antitrust in web search

- UK CMA (2020), Scott Morton and Dinelli (2020), Heidhues et al. (2021), Ostrovsky, (2021), Decarolis, Li, and Paternello (2023), Hovenkamp (2024)

Competitive effect of choice frictions

- Schmalensee (1982), DellaVigna and Malmendier (2006), Handel (2013), Johnen (2019), Fowlie et al. (2021), Einav, Klopack, and Mahoney (2023), Miller, Sahni, and Strulov-Shlain (2023)

Returns to data

- Varian (2015), Chiou and Tucker (2017), He et al. (2017), Bajari et al. (2019), Schaefer and Sapi (2023)

Experience goods

- Schmalensee (1982), Shapiro (1983), Ackerberg (2003), Crawford and Shum (2005), Dickstein (2018)

Experimental studies of digital markets

- Brynjolfsson, Collis and Eggers (2019), Allcott, Gentzkow, and Song (2020), Aridor (2022), Bursztyn et al. (2023), Blake et al. (2023), Farronato, Fradkin, and Karr (2024)

Agenda

- Demand
  - Model
  - Experimental Design
  - Experimental Results
  - Structural Estimation
- Returns to Data
- Counterfactuals
- Conclusion

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Demand model: overview

Consumer i chooses search engine $j \in \{\textbf{Google}, \textbf{Bing}\}$ during periods t

- Search engine used at time t is x_{it}

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Quality:

- Search result relevance, # of ads, interface, etc.

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Payments:

- η is price sensitivity
- $p_{ij} = 0$ in real life, but we will pay users to switch

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Idiosyncratic preferences:

- Error is time-invariant

Demand model: quality perceptions

Search engines are **experience goods**.

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- User i's beliefs about quality at time t are such that

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Assume users unaware they misperceive quality:

- No benefits from exploration

Demand model: inertia

Default search engine at time $t = 0$ is determined by browser (Chrome $\rightarrow$ Google, Edge $\rightarrow$ Bing)

- Users perceive quality of browser-determined default correctly

Defaults influence choices via two inertia channels:

- Inattention (affects infra-marginal users)
  - If inattentive, stick with previous choice ($x_{it} = x_{i,t-1}$)
  - Fraction ϕ: permanently inattentive
  - Fraction $1 - \phi$: attentive with probability π (iid over periods)
- Switching cost σ (affects marginal users)

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Choice if attentive:

$$x_{it} = \arg\max_{j \in \{B,G\}} \left\{ E_{it}[\zeta_j] + \varepsilon_{ij} - \sigma 1\{j \neq x_{i,t-1}\} \right\}$$

- No continuation value since anticipate never switching again

Demand model: implications

Steady-state **market share of Bing** among Chrome users:

$$(1-\phi)F_{\Delta\varepsilon}\left(\Delta\tilde{\zeta}-\sigma\right),$$

where $F_{\Delta\varepsilon}(\cdot)$ is the CDF of the error and

$$\Delta\tilde{\zeta}=\tilde{\zeta}_B-\zeta_G^*=(\tilde{\zeta}_B-\zeta_B^*)+(\zeta_B^*-\zeta_G^*).$$

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Google market share can be high for four reasons:

1. True quality ($\zeta_B^*-\zeta_G^*$)
2. Quality misperceptions ($\tilde{\zeta}_B-\zeta_B^*$)
3. Switching costs (σ)
4. Inattention (ϕ)

Experiment overview

Recruit 2,354 people on Prolific in Mar/Apr ’24

- Sample: US adults on **desktop**
  - Use only one browser: Edge or Chrome
  - Usually use either Google or Bing
- Survey 1 (immediately):
  - Demographics
  - Opinions about search engines
  - Install browser extension
  - Treatments
- Survey 2 (14 days later): varies by treatment

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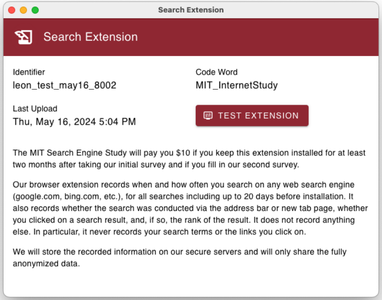
Search Extension



1. Records every time a search engine is used
   - Starting 20 days before Survey 1
2. Alters search result page

Experiment Treatments

Control (C)

- Placebo surveys

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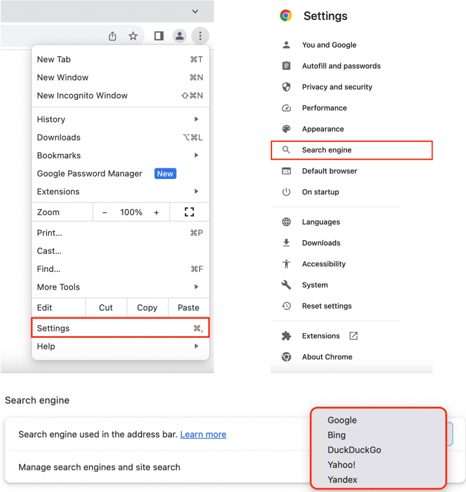
Active Choice (A)

- Ask for & implement preferred default



Experiment Treatments

Control (C)

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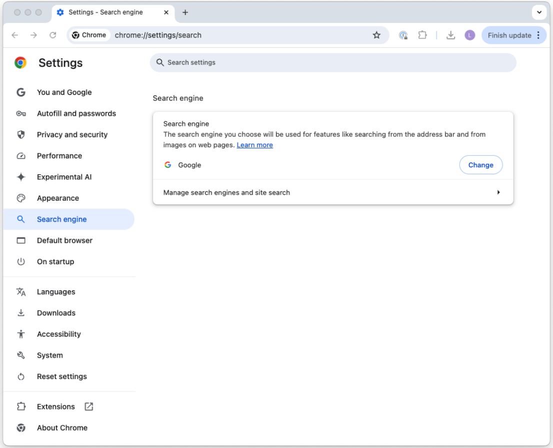

Experiment Treatments

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Switch Bonus (S)

- Offer {\$1, **\$10**, \$25} to switch for 14d
- After 14d, make active choice

Experiment Treatments

Control (C)

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Active Choice (A)

- Ask for & implement preferred default
- Verify they got to choice screen

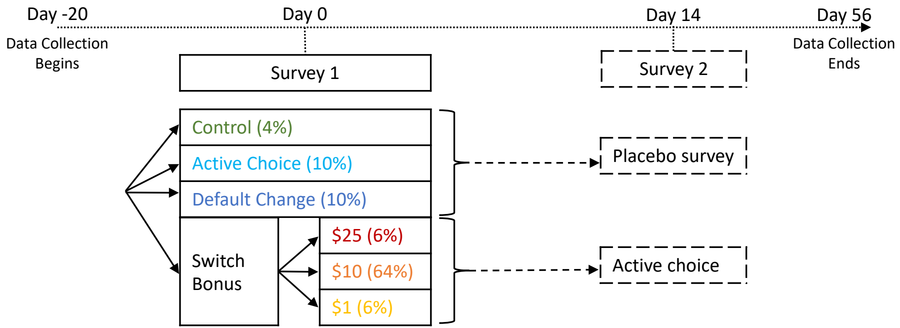
Switch Bonus (S)

- Offer {$1, **$10**, $25} to switch for 14d
- After 14d, make active choice

Default Change (D)

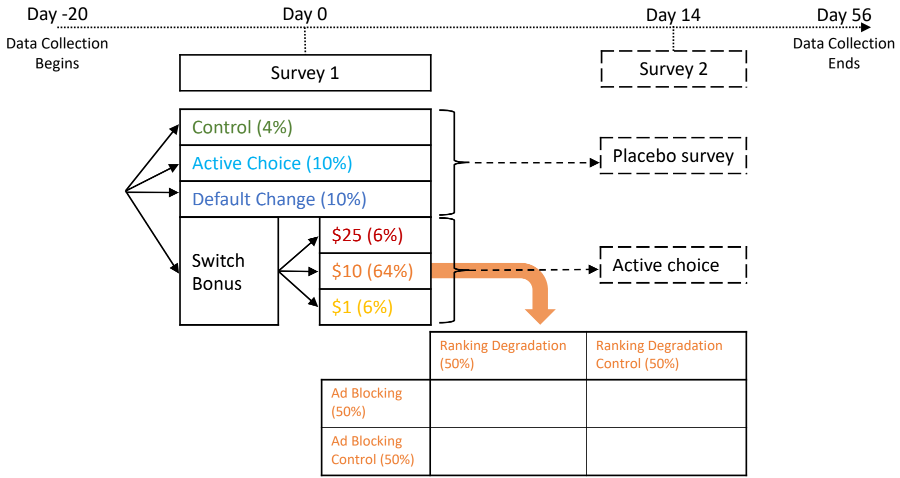
- Offer $10 to change default for 2d

Details



Day -20
Data Collection Begins
Day 0
Day 14
Day 56
Data Collection Ends
Survey 1
Survey 2
Control (4%)
Active Choice (10%)
Default Change (10%)
Switch Bonus
$25 (6%)
$10 (64%)
$1 (6%)
Placebo survey
Active choice

Details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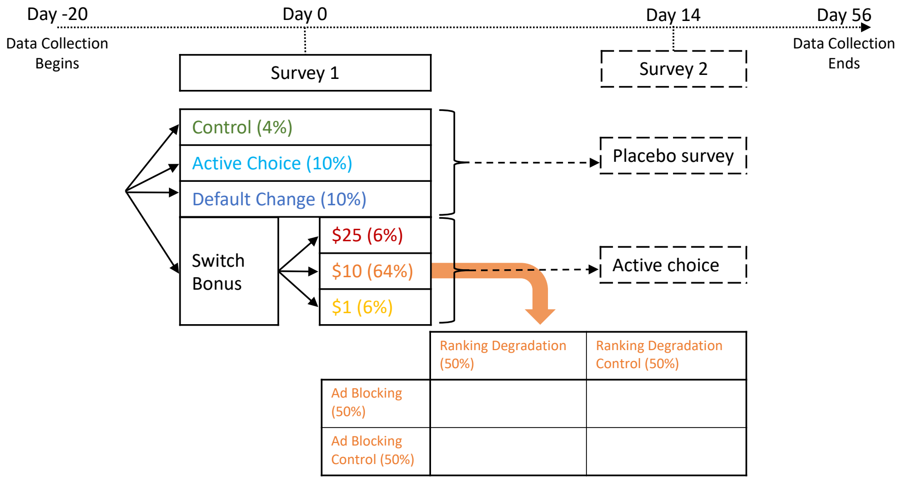
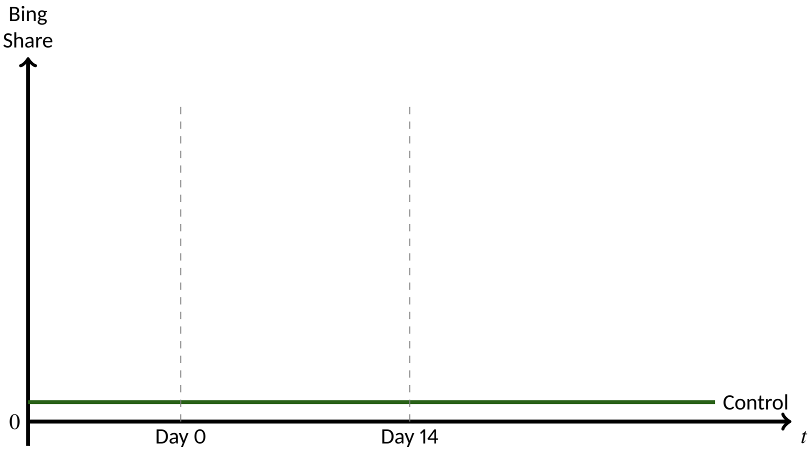
Active choice
Ranking Degradation (50%)
Ranking Degradation Control (50%)
Ad Blocking (50%)
Ad Blocking Control (50%)

Details



Heads up: model is at browser-level, experiment at search-engine level. To map, need assumption: if use SE before experiment & we pay you to use SE, you continue to use SE.

Identification for Chrome users



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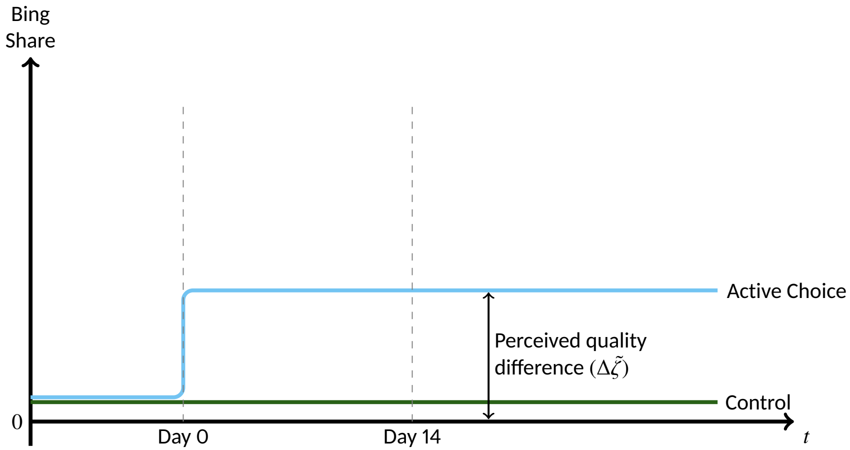

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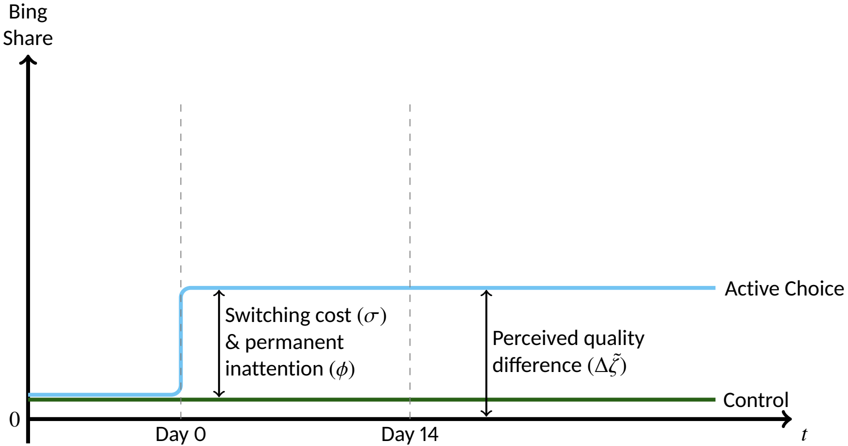

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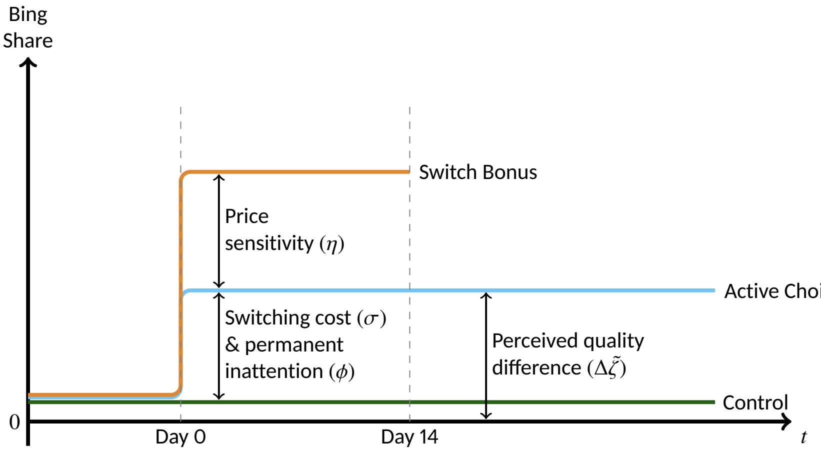

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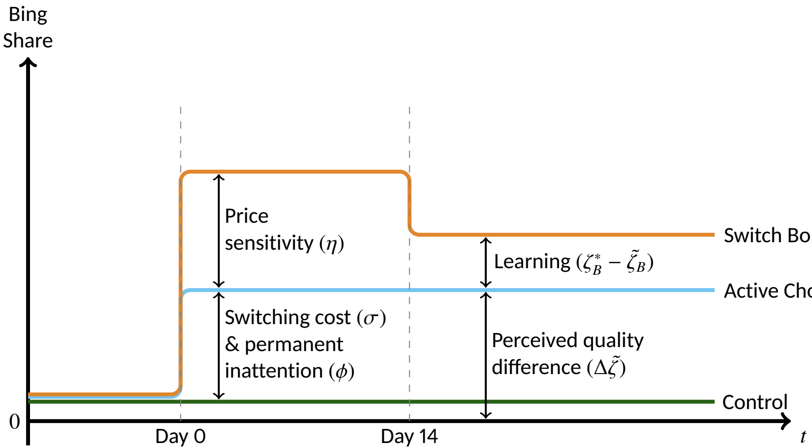

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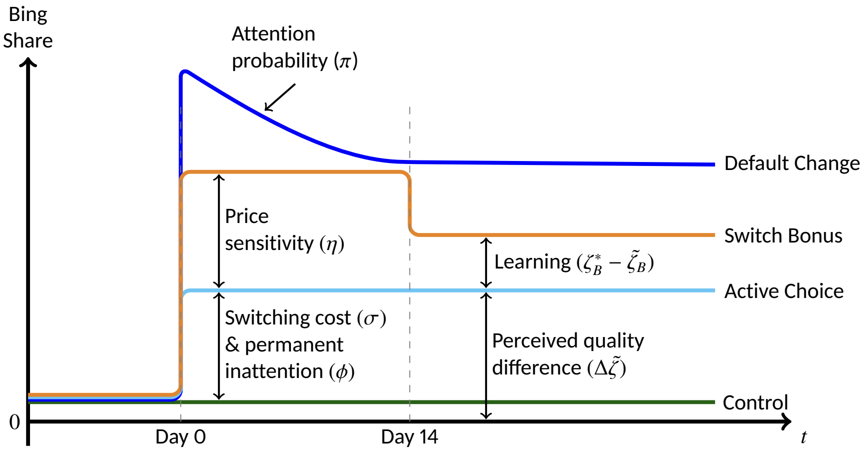

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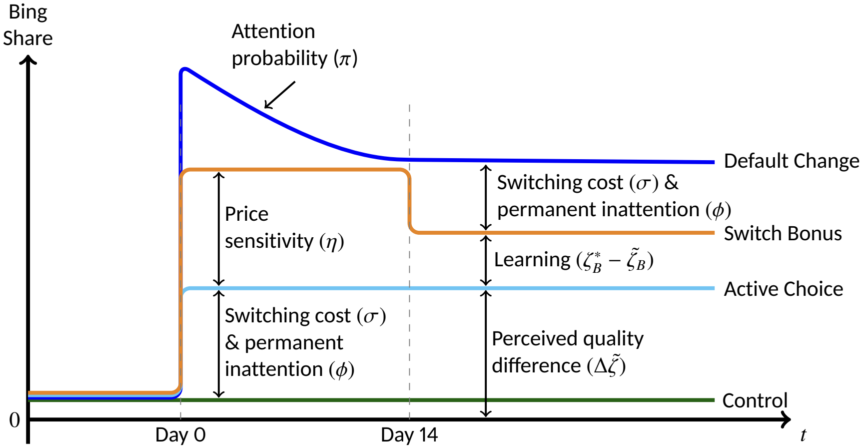

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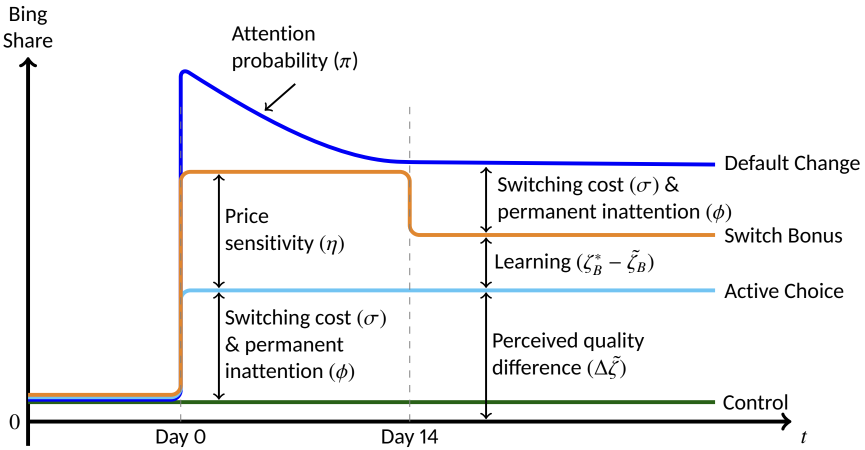

Identifying σ and ϕ: Diff. between Active Choice and Control *almost* unaffected by ϕ More

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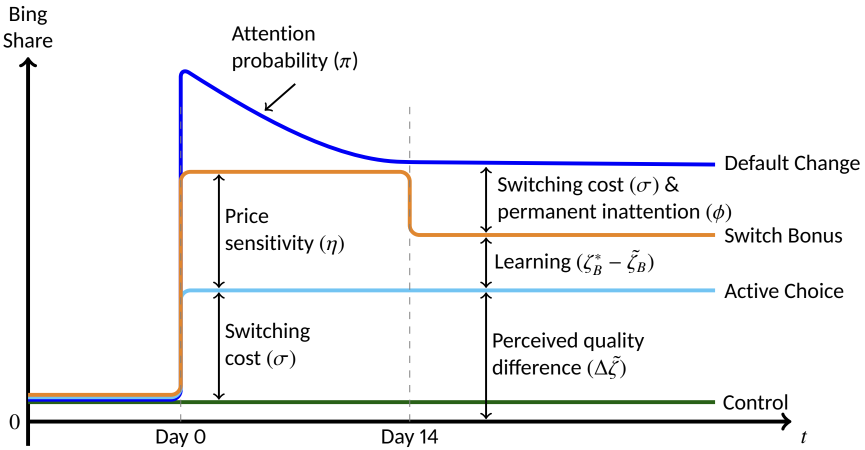

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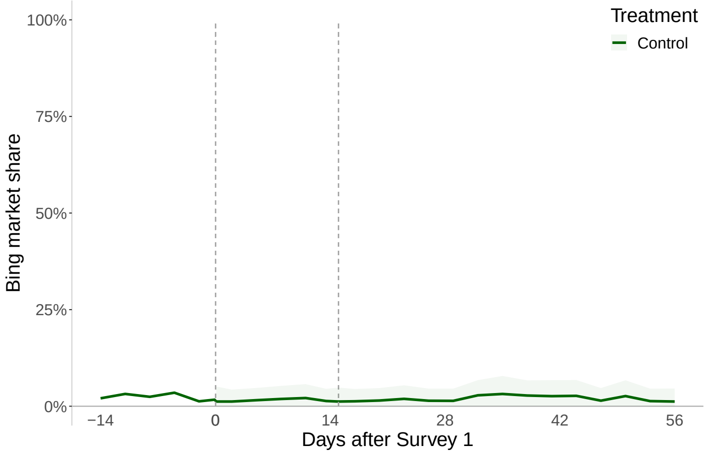
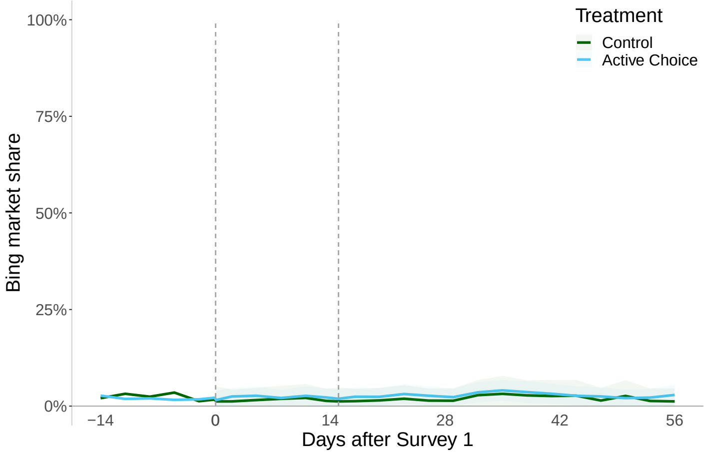
Market shares for Chrome users



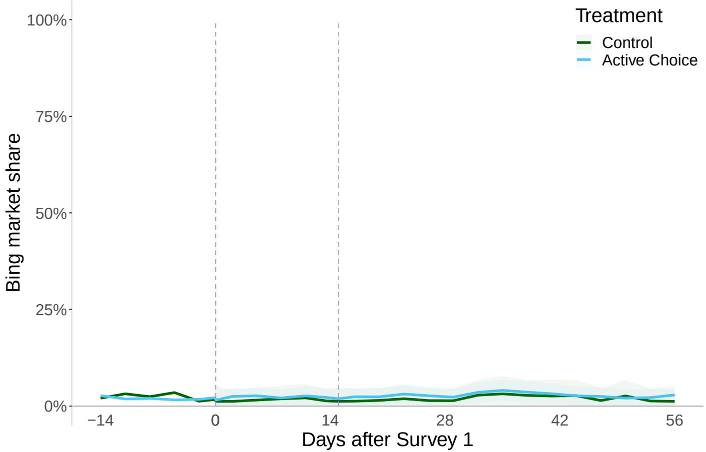
Control: no effect of placebo intervention

Market shares for Chrome users



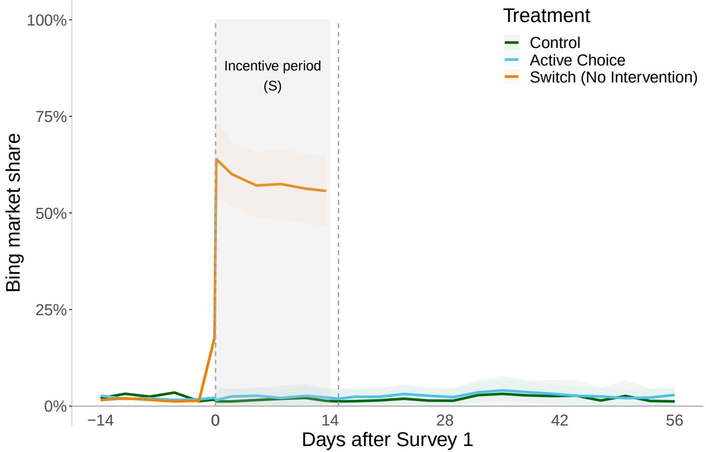
Active Choice: Small Bing share → Large perceived quality difference

Market shares for Chrome users



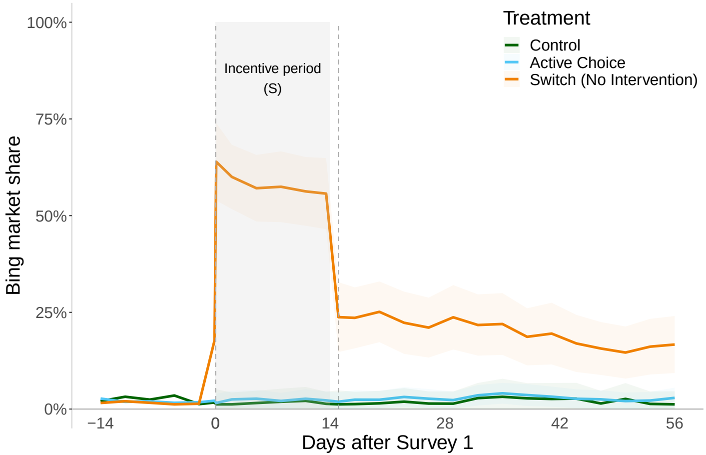
Active Choice: Same share as Control → Small switching cost

Market shares for Chrome users



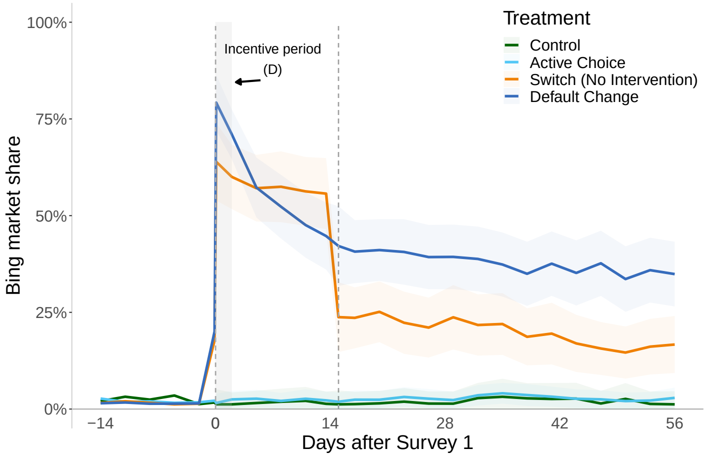
Switch Bonus: High Bing share during incentive → Users are price sensitive

Market shares for Chrome users



Switch Bonus: Bing share stays high after incentive → Users update posively about Bing

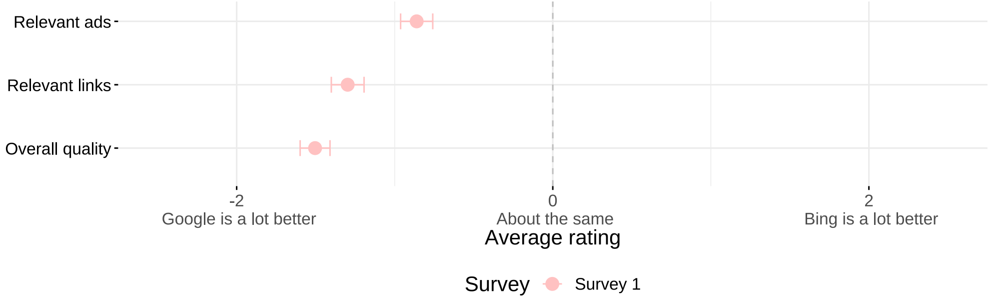
Market shares for Chrome users



Default Change: Bing share converges to above Switch → There is permanent inattention

Learning in Switch Bonus group (baseline Google)

1. Relative preference for Bing before (Survey 1) and after (Survey 2) the switch:



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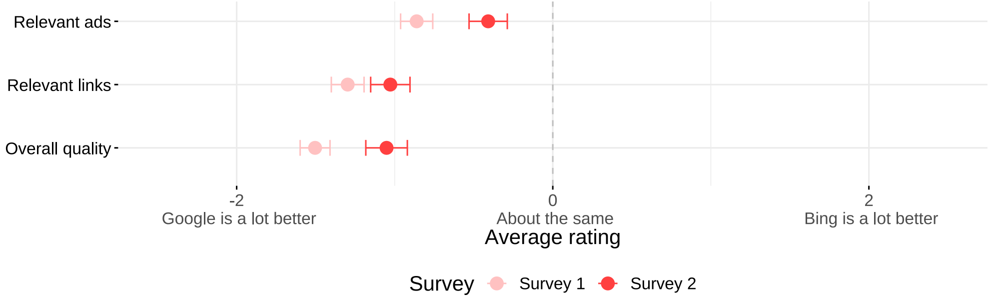

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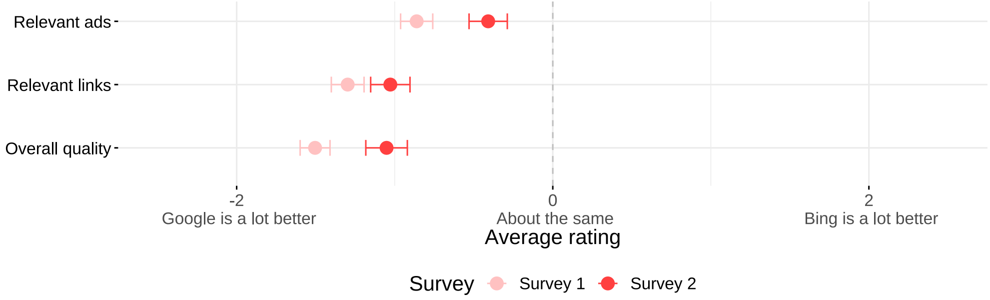

2. We surveyed stayers. Quotes:

- "I have learned I overall enjoy [Bing] more."
- "I found that I liked the results I am getting in Bing"
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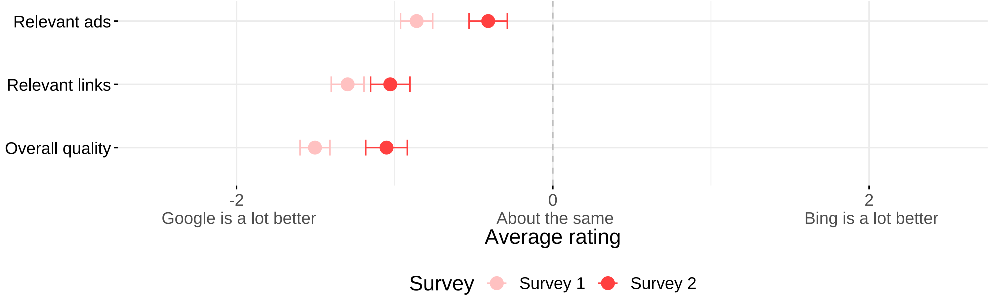

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3. Multiple Choice:

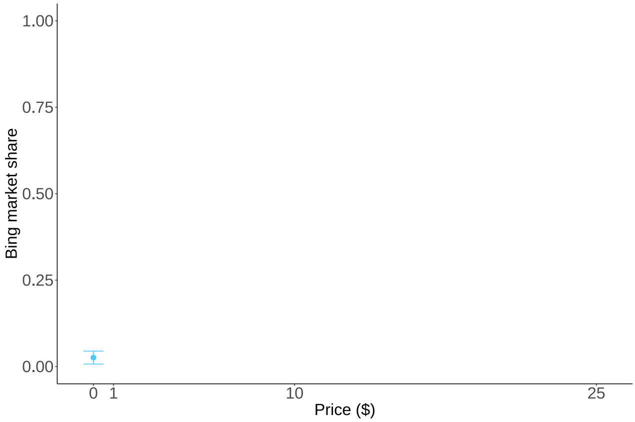
- 64.1% – Bing better than expected
- 59% – they got accustomed,

Price response

Bing market shares during incentive period:

Active

- Bing market share $\approx 1.86\%$



Price response

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Switch ($1)

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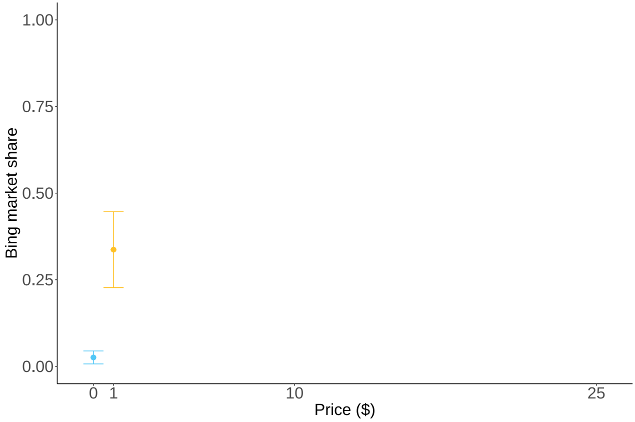

Price response

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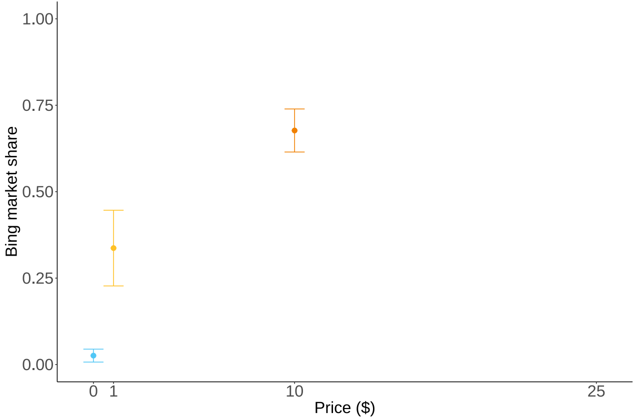

Price response

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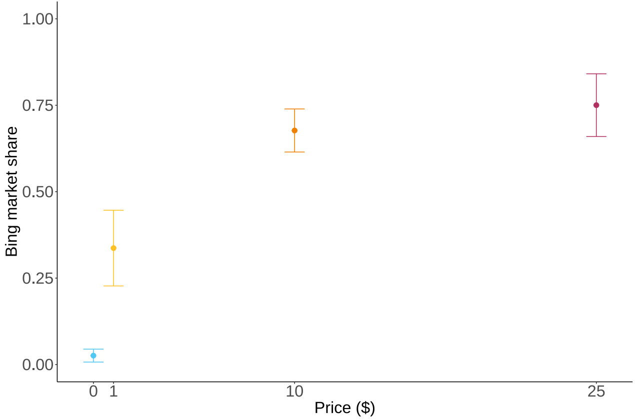
Switch ($10)

- Bing market share ≈ 64.4%

Switch ($25)

- Bing market share ≈ 74.1%



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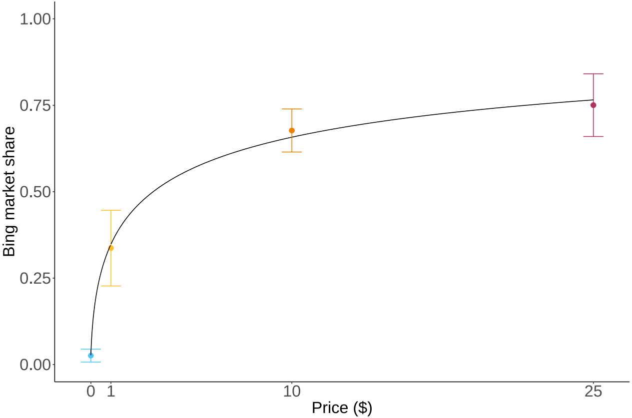

Ranking Degradation

Control

ariel pakes linkedin InPrivate

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Bing found the following results

LinkedIn
https://www.linkedin.com/in/ariel-pakes-5957b527

Ariel Pakes - Professor - Harvard University | LinkedIn

WEB Professor. Yale University. Sep 1989 - Jan 1998 8 years 5 months. Education. Hebrew University, Jerusalem, Israel, Harvard Univeristy. Bachelor of Arts (B.A.),Masters (M.A.), …

Tags: Ariel Pakes Harvard | Harvard University

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Ariel Pakes - Steven McArthur Heller Professor of Economics.

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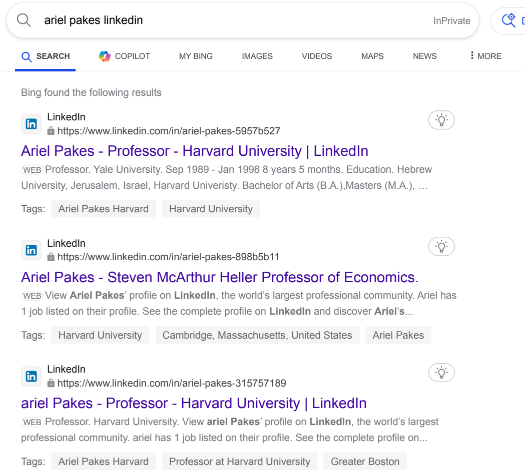
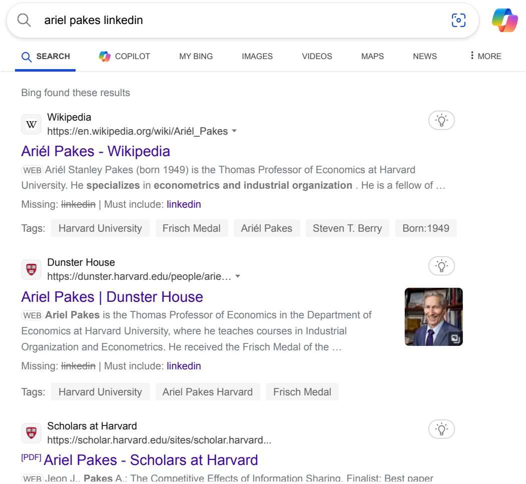
Ranking Degradation

Control



Treatment



Ranking Degradation: Effects

	(1)
Dep. var.:	**Organic click-through rate**
Ranking Degradation	-0.077***
	(0.028)
Constant	0.347***
	(0.017)

1. Reduced relevance of search result pages as measured by click-through rate.

Ranking Degradation: Effects

Dep. var.:	(1) Organic click-through rate	(2) Δ Relevance rating (-2 to +2 scale)
Ranking Degradation	-0.077^{***}	-0.311^{***}
	(0.028)	(0.072)
Constant	0.347^{***}	0.241^{***}
	(0.017)	(0.063)

1. Reduced relevance of search result pages as measured by click-through rate.
2. Worsened participants' perception of result relevance.

Ranking Degradation: Effects

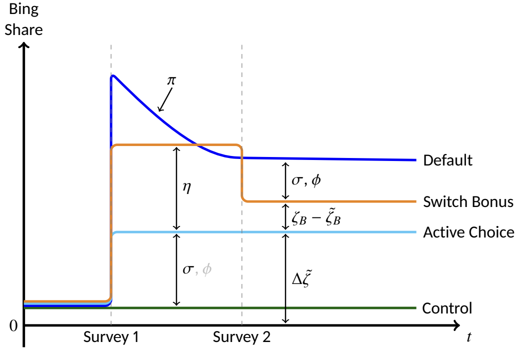
Dep. var.:	(1) **Organic click-through rate**	(2) **Δ Relevance rating (-2 to +2 scale)**	(3) **Bing share**
Ranking Degradation	-0.077***	-0.311***	-0.034
	(0.028)	(0.072)	(0.029)
Constant	0.347***	0.241***	0.244***
	(0.017)	(0.063)	(0.027)

1. Reduced relevance of search result pages as measured by click-through rate.
2. Worsened participants' perception of result relevance.
3. Had only limited impact on participant choices.

Demand estimation results

Description	Formula	Estimate	SE
Permanent inattention	ϕ	0.34	0.06
Attention probability	π	0.83	0.15
Price response	η	0.33	0.09
Switching cost	σ	\$0.004	0.007
Perceived Bing preference	$\Delta\tilde{\zeta}$	-\$3.06	0.80
Learning	$\zeta_B^* - \tilde{\zeta}_B$	\$0.26	0.18
Ad load response		-\$0.13	0.12
Relevance response		-\$0.10	0.10

For presentation, Chrome users only.



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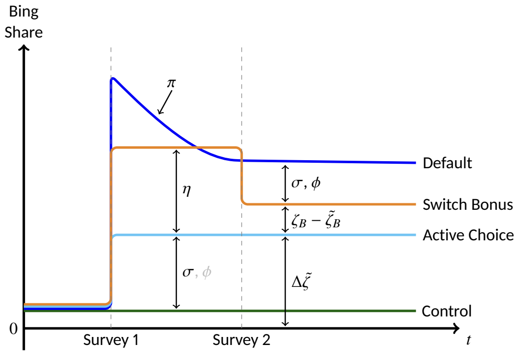

- 33% of users are permanently inattentive

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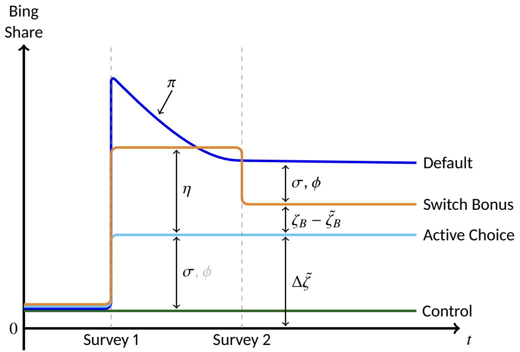

- 33% of users are permanently inattentive
- If users make active choice, Bing payment of \$3.06 per two weeks equalizes market shares

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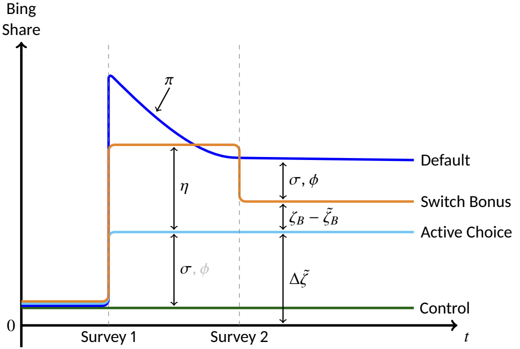

- 33% of users are permanently inattentive
- If users make active choice, Bing payment of \$3.06 per two weeks equalizes market shares
- If perceptions were corrected, required payment would shrink to \$2.80

Agenda

Returns to Data

More users (and data) $\Longrightarrow$ better ranking $\Longrightarrow$ more users

Returns to Data

$$\text{More users (and data)} \implies \text{better ranking} \overset{\checkmark}{\implies} \text{more users}$$

Returns to Data

More users (and data) $\overset{?}{\Longrightarrow}$ better ranking $\overset{\checkmark}{\Longrightarrow}$ more users

Returns to Data

$$\text{More users (and data)} \overset{?}{\Longrightarrow} \text{better ranking} \overset{\checkmark}{\Longrightarrow} \text{more users}$$

Approach

1. Estimate how any given query's click-through rate (CTR) increases with # of impressions
2. Integrate over query frequency distribution (probably effect concentrates on long tail)

Returns to Data

More users (and data) $\stackrel{?}{\Longrightarrow}$ better ranking $\stackrel{\checkmark}{\Longrightarrow}$ more users

Approach

1. Estimate how any given query's click-through rate (CTR) increases with # of impressions
2. Integrate over query frequency distribution (probably effect concentrates on long tail)

Internal Microsoft Bing data

- Random sample of 43,991 new queries (0 searches in 2021, > 100 in 2022)
- For each impression of each query: timestamp, top result id & click dummy

Returns to Data

$$\text{More users (and data)} \overset{?}{\Longrightarrow} \text{better ranking} \overset{\checkmark}{\Longrightarrow} \text{more users}$$

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1. Estimate how any given query's click-through rate (CTR) increases with # of impressions
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Internal Microsoft Bing data

- Random sample of 43,991 new queries (0 searches in 2021, > 100 in 2022)
- For each impression of each query: timestamp, top result id & click dummy

Conclusion

- If Bing had access to Google's data, CTR would increase from 23.5% to 24.8%.

  (Caveats: observational data, estimated only off 'new' search terms, no cross-query learning.)

Agenda

Counterfactuals

			Direct effects (fixed quality)	
Description	Switching cost & inattention?	Misper-ceptions?	Google share (%)	CS gain ($/year)
Status Quo	✓	✓	88.9	0.00

Counterfactuals

			Direct effects (fixed quality)	
Description	Switching cost & inattention?	Misperceptions?	Google share (%)	CS gain ($/year)
Status Quo	✓	✓	88.9	0.00
No Frictions	✗	✗	73.8	6.01

Eliminating demand-side frictions reduces Google market share (with moderate CS gain).

Counterfactuals

			Direct effects (fixed quality)	
Description	Switching cost & inattention?	Misper-ceptions?	Google share (%)	CS gain ($/year)
Status Quo	✓	✓	88.9	0.00
No Frictions	✗	✗	73.8	6.01
Choice Screen	✗	✓	87.6	0.09

An active choice screen leaves shares unchanged, but gets most CS gains.

Counterfactuals

			Direct effects (fixed quality)	
Description	Switching cost & inattention?	Misperceptions?	Google share (%)	CS gain ($/year)
Status Quo	✓	✓	88.9	0.00
No Frictions	✗	✗	73.8	6.01
Choice Screen	✗	✓	87.6	0.09
Correct Perceptions	✓	✗	78.4	0.46

Correcting perceptions lowers Google share, but with small CS change.

Counterfactuals

			Direct effects (fixed quality)	
Description	Switching cost & inattention?	Misper-ceptions?	Google share (%)	CS gain ($/year)
Status Quo	✓	✓	88.9	0.00
No Frictions	✗	✗	73.8	6.01
Choice Screen	✗	✓	87.6	0.09
Correct Perceptions	✓	✗	78.4	0.46
Bing Default	✓	✓	48.9	-70.92

Making Bing the default lowers Google share, but at a large CS loss.

Counterfactuals

			Direct effects (fixed quality)	
Description	Switching cost & inattention?	Misperceptions?	Google share (%)	CS gain ($/year)
Status Quo	✓	✓	88.9	0.00
No Frictions	✗	✗	73.8	6.01
Choice Screen	✗	✓	87.6	0.09
Correct Perceptions	✓	✗	78.4	0.46
Bing Default	✓	✓	48.9	-70.92
+ Delayed Choice Screen	✓	✓	72.1	0.06

Delayed choice screen: shows up two weeks after browser installation

$\longrightarrow$ Reduces Google share at a small CS loss

Counterfactuals

			Direct effects (fixed quality)		Equilibrium effects (endogenous quality)	
Description	Switching cost & inattention?	Misper-ceptions?	Google share (%)	CS gain ($/year)	Google share (%)	CS gain ($/year)
Status Quo	✓	✓	88.9	0.00		
No Frictions	✗	✗	73.8	6.01		
Choice Screen	✗	✓	87.6	0.09		
Correct Perceptions	✓	✗	78.4	0.46		
Bing Default	✓	✓	48.9	-70.92		
+ Delayed Choice Screen	✓	✓	72.1	0.06		

Counterfactuals

			Direct effects (fixed quality)		Equilibrium effects (endogenous quality)	
Description	Switching cost & inattention?	Misperceptions?	Google share (%)	CS gain ($/year)	Google share (%)	CS gain ($/year)
Status Quo	✓	✓	88.9	0.00	88.9	0.00
No Frictions	✗	✗	73.8	6.01	73.5	6.02
Choice Screen	✗	✓	87.6	0.09	87.6	0.09
Correct Perceptions	✓	✗	78.4	0.46	78.2	0.47
Bing Default	✓	✓	48.9	-70.92	48.5	-70.81
+ Delayed Choice Screen	✓	✓	72.1	0.06	72.0	0.08

Data feedback has only minor effects

→ Small demand response to result relevance + small effect of data on result relevance

Counterfactuals

			Direct effects (fixed quality)		Equilibrium effects (endogenous quality)	
Description	Switching cost & inattention?	Misperceptions?	Google share (%)	CS gain ($/year)	Google share (%)	CS gain ($/year)
Status Quo	✓	✓	88.9	0.00	88.9	0.00
No Frictions	✗	✗	73.8	6.01	73.5	6.02
+ Data Sharing					73.1	6.12
Choice Screen	✗	✓	87.6	0.09	87.6	0.09
Correct Perceptions	✓	✗	78.4	0.46	78.2	0.47
+ Data Sharing					77.9	0.56
Bing Default	✓	✓	48.9	-70.92	48.5	-70.81
+ Delayed Choice Screen	✓	✓	72.1	0.06	72.0	0.08

Data sharing only has minor effects

Counterfactuals

			Direct effects (fixed quality)		Equilibrium effects (endogenous quality)	
Description	Switching cost & inattention?	Misper- ceptions?	Google share (%)	CS gain ($/year)	Google share (%)	CS gain ($/year)
Status Quo	✓	✓	88.9	0.00	88.0	0.00
No Frictions	✗	✗	73.8	6.01	72.09	6.04
+ Data Sharing					71.9	6.31
Choice Screen	✗	✓	87.6	0.09	87.5	0.09
Correct Perceptions	✓	✗	78.4	0.46	77.9	0.47
+ Data Sharing					77.1	0.72
Bing Default	✓	✓	48.9	-70.92	47.7	-70.61
+ Delayed Choice Screen	✓	✓	72.1	0.06	71.4	0.11

Data sharing only has minor effects – even at 95% CI boundary of our estimate of demand response to quality

Agenda

Conclusion & Caveats

Takeaways

- Defaults are effective
  - $\sim 1/3$ of users are permanently inattentive
  - Prevent users from learning about other search engines
- How can regulators reduce Google's market share?
  - Choice screens alone do not move the needle (Decarolis, Li, and Paternello; 2023)
  - Changing the default does, but w/ large decrease in CS
  - Temporarily switching the default & delayed choice screen may work
- Economies of scale and data sharing have small effects

Caveats

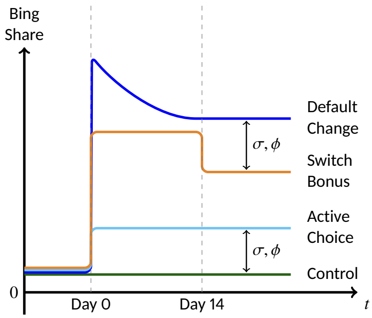
- Desktop users, sample may not be representative
- Returns-to-scale analysis is observational

Thank you!

questions, comments, concerns

lmusolff@wharton.upenn.edu

Identification: Separating switching costs σ and permanent inattention ϕ



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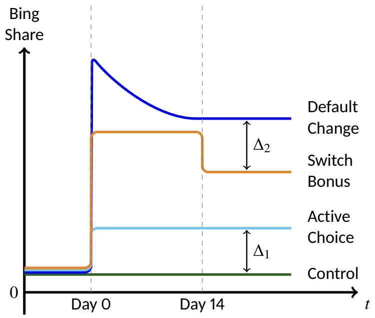
Identification: Separating switching costs σ and permanent inattention ϕ

Key idea: Switching costs and permanent inattention affect Δ_1 and Δ_2 quite differently



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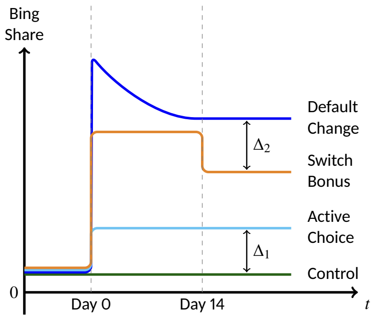
Key idea: Switching costs and permanent inattention affect Δ_1 and Δ_2 quite differently

Effect of permanent inattention ϕ: details

- In C, only affects people who would like to overrule default and use Bing ($< 5\%$)
- In D, affects all users who accepted payment but would want to switch back ($\sim 50\%$)
- Effect on Δ_2 much larger than on Δ_1.



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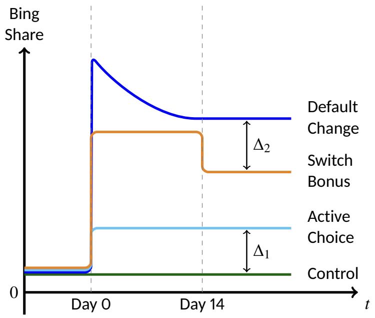
- In D, affects all users who accepted payment but would want to switch back ($\sim 50\%$)
- Effect on Δ_2 much larger than on Δ_1.

Effect of switching cost σ: details

- σ shifts utilities in C and D by the same amount
- Affect Δ_1 and Δ_2 approx. symmetrically
  - as long as similar densities of marginal users



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Identification: Separating switching costs σ and permanent inattention ϕ

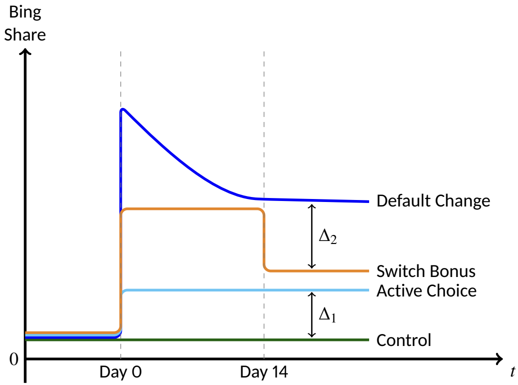
Focus on Chrome. Suppose $\sigma = 0$.

$$\begin{aligned}\Delta_1 &= F_\epsilon(\Delta\tilde{\zeta}) - (1-\phi)F_\epsilon(\Delta\tilde{\zeta}) \\ &= \phi F_\epsilon(\Delta\tilde{\zeta})\end{aligned}$$

$$\begin{aligned}\Delta_2 &= \phi + (1-\phi)F_\epsilon(\Delta\zeta^*) - F_\epsilon(\Delta\zeta^*) \\ &= \phi - \phi F_\epsilon(\Delta\zeta^*)\end{aligned}$$

If Google is good, $F_\epsilon(\Delta\tilde{\zeta}) \approx F_\epsilon(\Delta\zeta^*) \approx 0$.

Hence, $\frac{\partial \Delta_1}{\partial \phi} = 0$. But $\frac{\partial \Delta_2}{\partial \phi} = 1$.



back

Identification: Separating switching costs σ and permanent inattention ϕ

Focus on Chrome. Suppose $\phi = 0$.

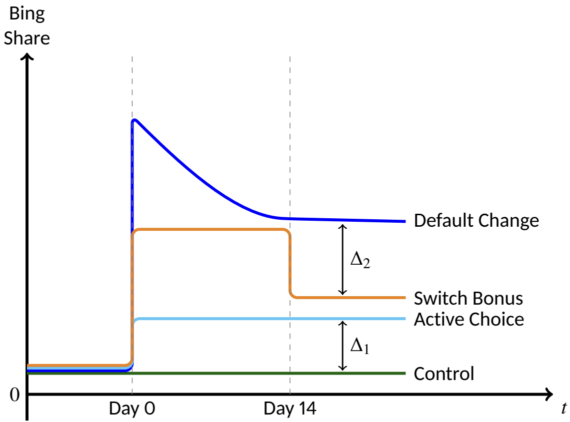
$$\Delta_1 = F_\epsilon(\Delta\tilde{\zeta}) - F_\epsilon(\Delta\tilde{\zeta} - \sigma)$$

$$\Delta_2 = F_\epsilon(\Delta\zeta^* + \sigma) - F_\epsilon(\Delta\zeta^*)$$

If learning is small relative to mean preferences, $\Delta\tilde{\zeta} \approx \Delta\zeta^*$.

$\frac{\partial\Delta_1}{\partial\sigma} = f_\epsilon(\Delta\tilde{\zeta} - \sigma)$ and $\frac{\partial\Delta_2}{\partial\sigma} = f_\epsilon(\Delta\zeta^* + \sigma)$.

Hence, $\frac{\partial\Delta_1}{\partial\sigma} \approx \frac{\partial\Delta_2}{\partial\sigma}$ for small σ.



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