Trade-offs in Leveraging External Data Capabilities: Evidence from a Field Experiment in a Search Market

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External Data as a Lever for Product Growth?

- Practitioners highlight the need to use external data:
 - Firms may gain an edge by incorporating external data to build their data ecosystems (Deloitte Insights 2019; McKinsey 2021)
 - Data sharing through large players' application programing interfaces (APIs) is increasingly common (Fatemi 2019): e.g., Google search API for publishers and developers
- Despite its economic relevance, it is challenging to pin down its causal impact
 - Firms may self-select into API adoption (Benzell, Hersh, and Van Alstyne 2022).



New Regulations

What the European DSA and DMA proposals mean for online platforms

January 14, 2021 | Aline Blankertz and Julian Jaursch



Internal Market Commissioner Thierry Breton attend the presentation of the European Commission's data/digital strategy in Brussels, Belgium February 19, 2020. REUTERS/Yves

The Digital Markets Act imposes obligations on "gatekeepers":

• Provide to any third-party providers of online search engines with access to ranking, query, click, and view (deidentified) data generated by end users (Article 6.11).

The latest guidelines published by the State Council in China proposes a 20-point agenda around the data economy:

• data sharing to enable growth of small and medium sized companies. Sharing should not compromise personal information or "public interest".



Recent Court Verdict: US DOJ vs. Google

Google avoids break-up but must share data with rivals

2 September 2025

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Lily Jamali North America Technology Correspondent, San Francisco and **Rachel Clun** Business reporter, BBC News



Questions and Overview of Results

- 1. What is the causal impact of access to the **market leader's data** on the **focal company's** product performance?
 - Removing access to market leader's data leads to a 4.6% decrease in CTR.
 - Downstream Elasticity of 0.12-0.18 (Search Engine Results Page)
- 2. Does the effect vary across types of content?
 - Only popular content affected.
- 3. Impact in the **short term vs. longer term**?
 - Average effect is much smaller than short-run decline in performance.
 - Using the API can impede improved prediction due to internal data.



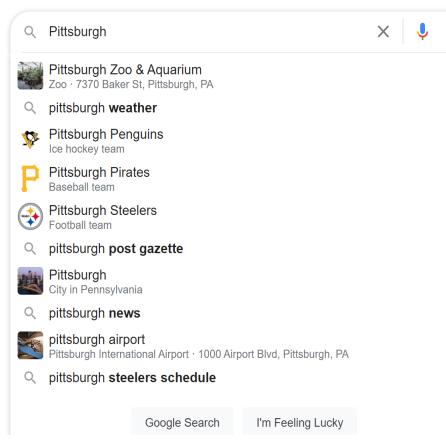
Empirical Context

- Partnership with a leading Chinese technology company
 - Millions of monthly active users
- An app with hybrid functions:
 - News feed, streaming, eBooks, search engine, file management
- Our focus: search suggestion, a product developed by the company in 2020.
 - A start-up like team within a larger company.
 - A new product embedded within a "super-app".



Economic Relevance





- An early application of generative AI models. (Serban et al. 2016)
- Bridge the gap between users' intent and content consumption (Agrawal, Gans, and Goldfarb 2018)
- Clicks imply revenue (sponsored words)
- Hence, our outcomes of interest:
 - (a) Click-through rate (CTR = Clicks / Exposures) (also probability of click, total number of clicks)
 - (b) Downstream: Top Slot Clicks on Search Results Page (SERP)



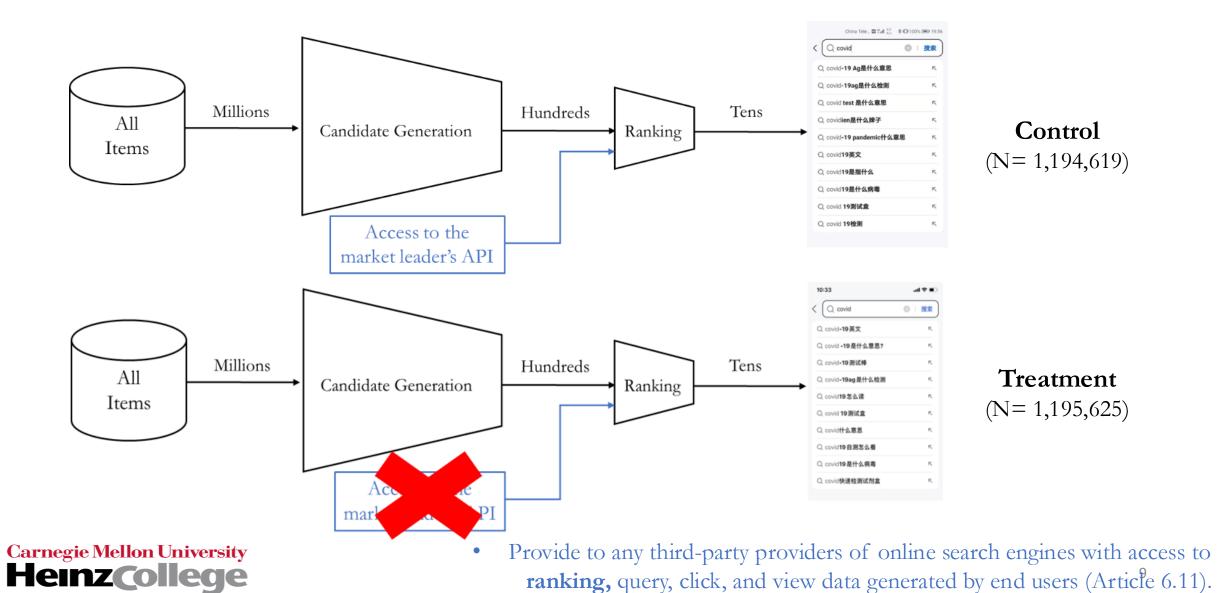
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Between-Subject (3.5 Month Long) Field Experiment



Baseline Results

	(1)	(2)
VARIABLES	Lift CTR	Lift CTR
API Removal	-0.0462*** (0.001)	-0.0539*** (0.0013)
Controls	N	Y
Observations	2,390,244	1,932,886

• Back of the envelope (including SERP) suggests this is economically meaningful.



Impact on Types of Content: Popular vs. Niche

	(1)	(2)
Variables	Lift in CTR	Lift in CTR
	(Popular)	(Niche)
API Removal	-0.0134***	0.0021
	(0.0017)	(0.0050)
Observations	764,119	764,119

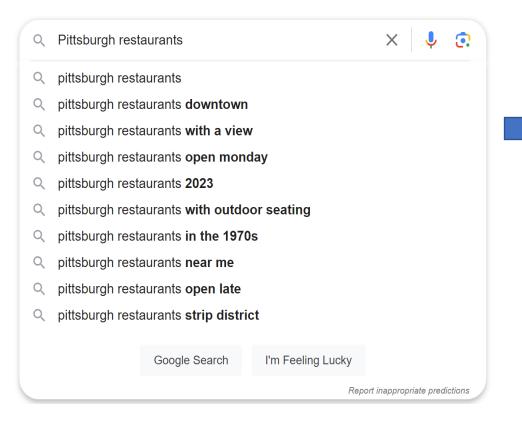
^{*} p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

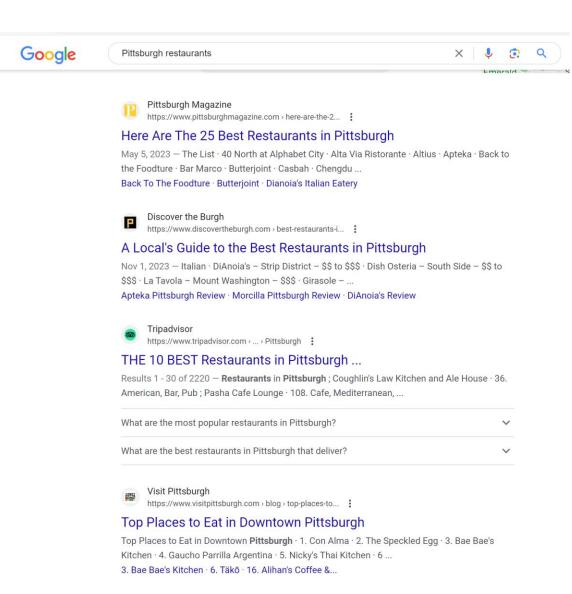
• Popular vs. niche: due to depersonalization, the long tail suffers.



Downstream Effects

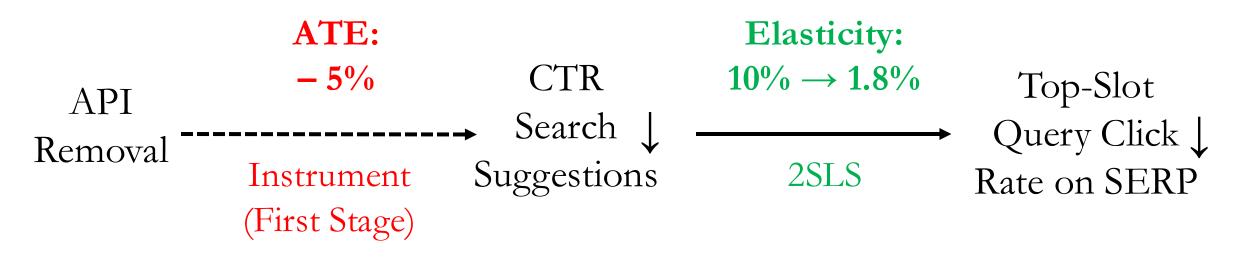








Implications for Search Engine Results Page (SERP)



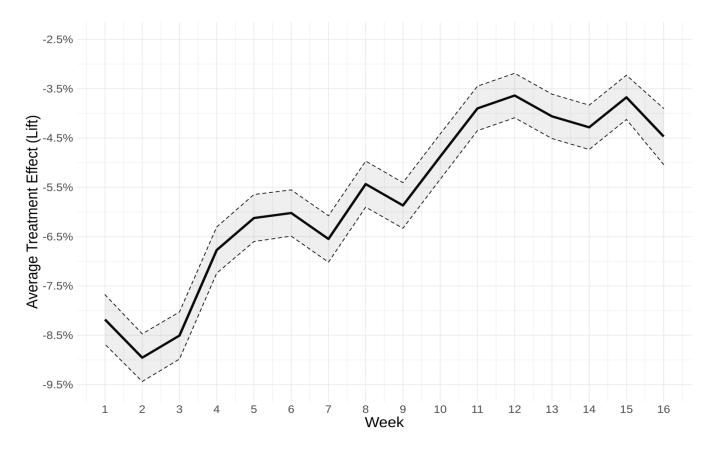
$$log(SERP_i) = \mu_1 + \mu_2 log(\widehat{SUGG_i}) + \vartheta_i$$

$$log(SUGG_i) = \gamma_0 + \beta \times APIRemoval_i + \epsilon_i$$

- Fang, Chen, Farronato, Yuan (2023): 3.2% in orders due to text-based search aid.
- Burtch, Kwon, and Tong (2023): 1.2% increase in sales due to keyword recommender system.



Longer-Term Effects: CTR



- Magnitude of the effect is half as large in longer run relative to first few weeks.
- We rule out differential attrition, diminishing returns, other behavioral adjustments.
- We posit the role of improved prediction due to internal data.



(Some) Suggestive Evidence for Learning Effects



Contextual Information: Learning from API Candidates?

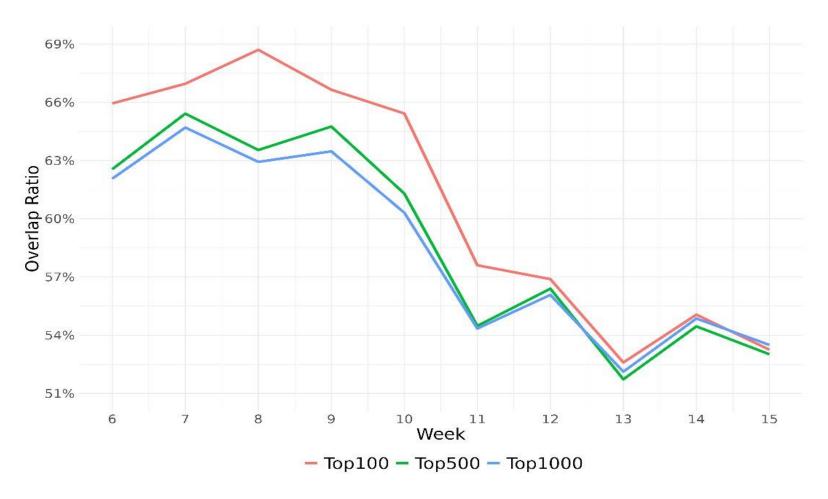
- All else equal, if the company's algorithmic system is learning from API candidates over time, the longer-term effect should become more negative.
- Lack of features of API candidates makes model training challenging (Duan and Lalor, 2023).
- Further, even if training is feasible, it can be legally prohibited. e.g., OpenAI API.



(c) **Restrictions**. You may not (i) use the Services in a way that infringes, misappropriates or violates any person's rights; (ii) reverse assemble, reverse compile, decompile, translate or otherwise attempt to discover the source code or underlying components of models, algorithms, and systems of the Services (except to the extent such restrictions are contrary to applicable law); (iii) use output from the Services to develop models that compete with OpenAl; (iv) except as permitted through the API, use any automated or programmatic method to extract data or output from the Services, including scraping, web harvesting, or web data extraction; (v) represent that output from the Services was human-generated when it is not or otherwise violate our Usage Policies; (vii) buy, sell, or transfer API



Improved Prediction based on Internal Data?



- Suggestions in T become more different relative to C over time.
- Combined with increased CTR might suggest improved prediction based on internal data



Improved Prediction based on Internal Data? Within and Across-User Learning User-query-day data

	(1)	(2)	(3)
Variables	CTR	CTR	CTR
API Removal	-0.0030*** (0.0005)	-0.0171*** (0.0040)	-0.0044*** (0.0009)
API Removal \times Repeated Query		0.0145*** (0.0041)	
API Removal \times Query Histories			0.0004** (0.0002)
Unit of analysis	User-Query-Day	User-Query-Day	User-Query-Day
Query fixed effects	\checkmark	\checkmark	\checkmark
Day fixed effects	\checkmark	\checkmark	\checkmark
R^2	0.2289	0.2289	0.2289
Observations	1,636,900	1,636,900	1,636,900

- Treatment effect is significantly smaller for repeat queries within and across individuals.
- Suggests learning in the treated group.

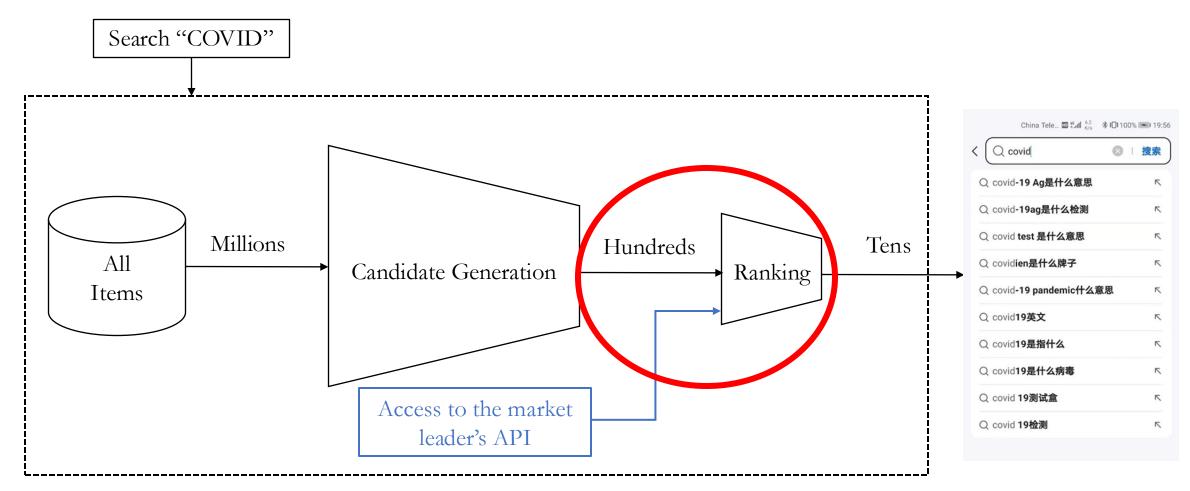


Some Additional Field Experiments: Training Data



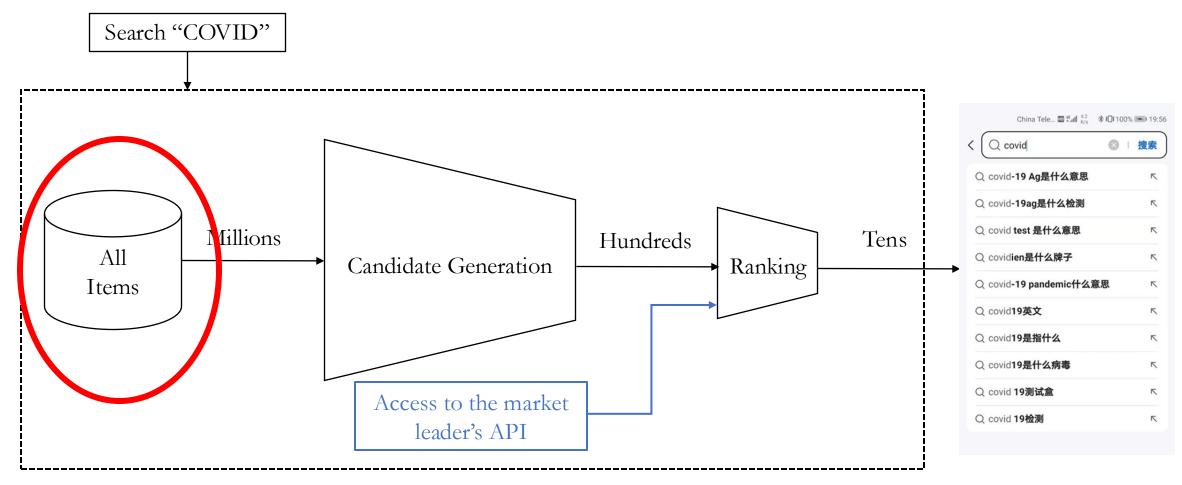
Till Now

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- 1. Candidate generation uses simpler algorithms to evaluate a larger set of items, while ranking uses more sophisticated and computationally intensive algorithms (Nandy et al. 2021).
- 2. A sizable proportion of final search suggestions come from the market leader's API. **Carnegie Mellon University**

Training Data Experiments



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Training Data: Public Data versus Internal Data

Q&A

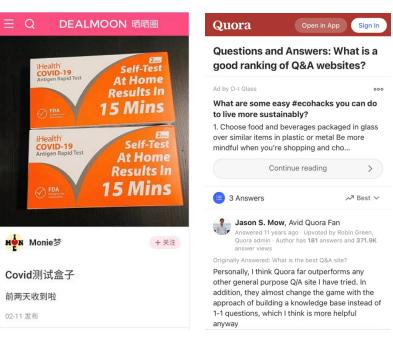
Public Items

Focal Firm's Internal Items

Trending News



UGC



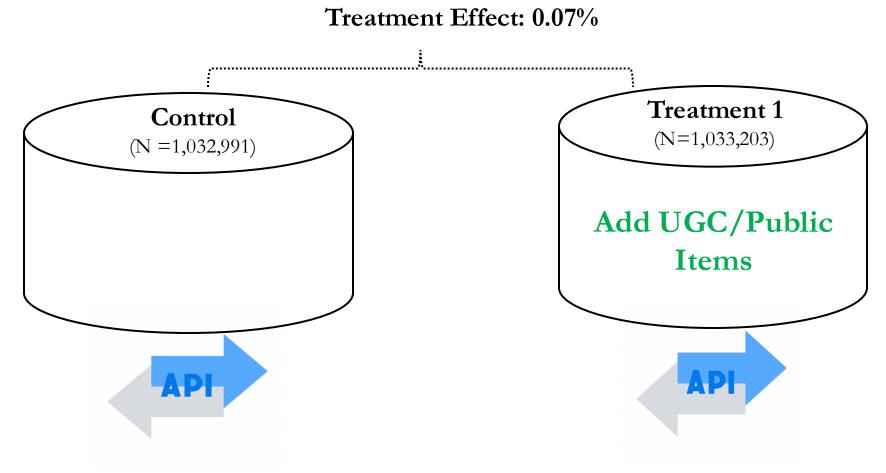
Content resources by the focal firm (update real-time): e.g.,

- Articles and video clips by content creators
- Videos (e.g., TV shows)
- Real-time new resources from other focal firm's products (e.g., news feed, eBooks streaming)
- Users' search histories



Experiment 2: Add Public Data & Remove Competitor Data

• Addition of User Generated Content doesn't seem to impact performance.

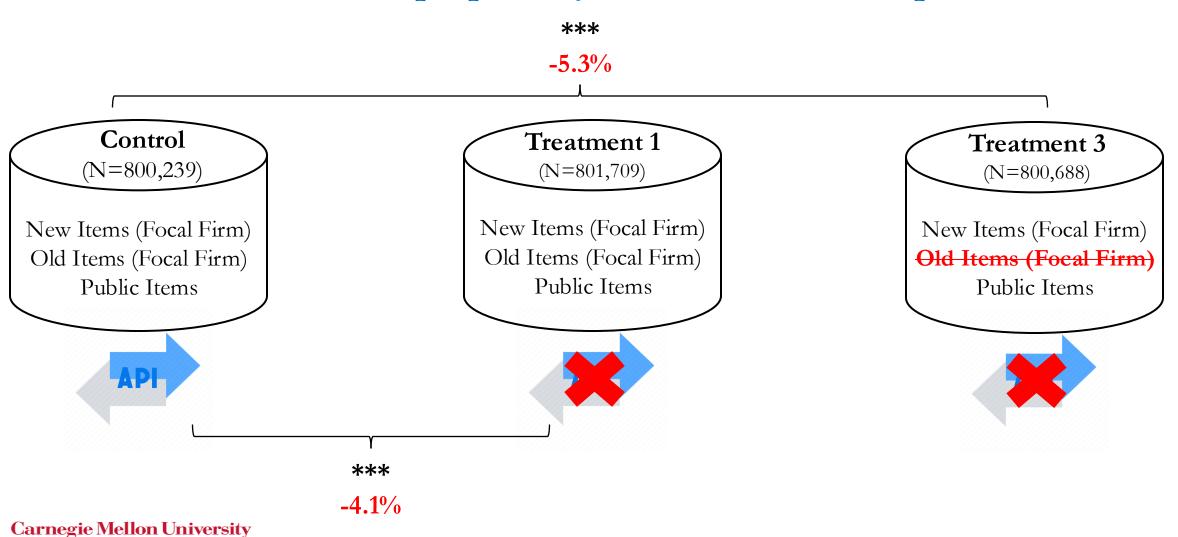




Experiment 3: Remove Competitor Data & Own Data

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• Removal of older proprietary data had modest impact.



EVIDENCE-DRIVEN POLICY FRAMEWORKS TO UNLOCK THE POWER OF DATA



EVIDENCE-DRIVEN POLICY FRAMEWORKS TO UNLOCK THE POWER OF DATA

September 15, 2025

Ananya Sen, Michael D. Smith and Rahul Telang

ANTITRUST AND COMPETITION

During the past two decades, recommender systems and targeted advertising have used personal data collected at scale in their quest to transform how we consume news, shop, and interact online. The more relevant and high-quality the data, the better the results—or at least that's been the guiding assumption. That principle now appears to hold true for the new wave of GenAl products as well. But if data matters, then so do the questions of when,

