The Impact of LLM Adoption on Online User Behavior

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September 2025

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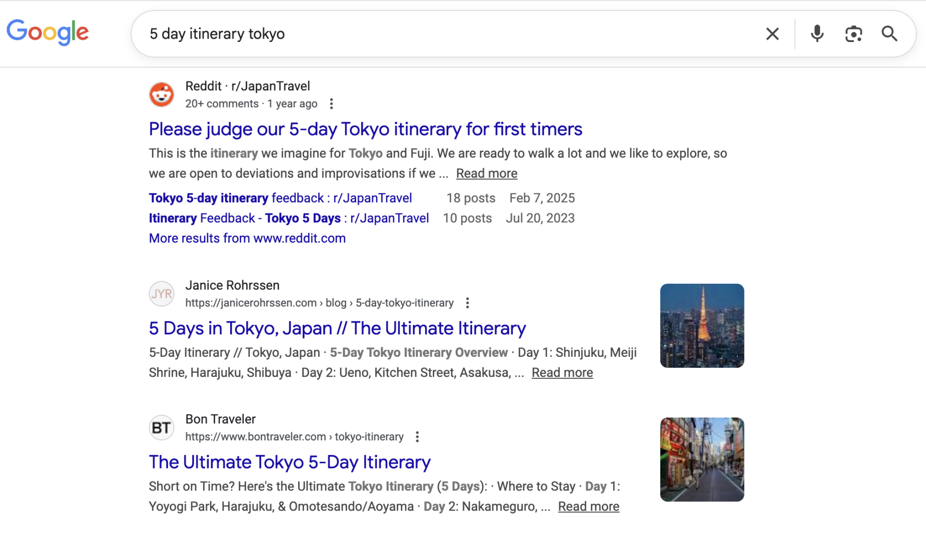
The way we search information online is changing...



The way we search information online is changing...

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Travel - Japan - Asia

5-Day Itinerary // Tokyo, Japan

Tokyo is one of my favorite cities on earth, a city where ancient traditions seamlessly blend with cutting-edge technology, and bustling urban streets coexist with serene gardens and temples. The city itself is home to more than 13 million people, and its metropolitan area houses more than 37 million. The area is 2,194 km², which is almost double the size of New York City. There's nothing else on earth like it.

Since moving here, I've explored even more of the dynamic metropolis, though it feels like I've only scratched the surface.

In this comprehensive 5-day itinerary, I'll share my insights and recommendations to help you make the most of your visit. This is geared toward first-time visitors who have never seen the city, but there are

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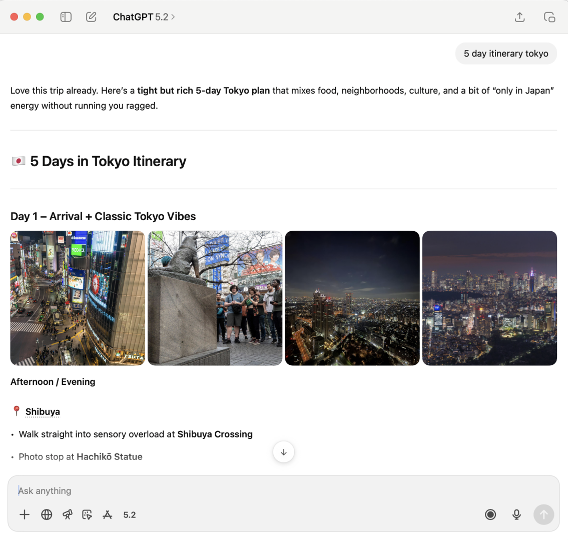

The way we search information online is changing...

Business | World wide worries

AI is killing the web. Can anything save it?

The rise of ChatGPT and its rivals is undermining the economic bargain of the internet

Share

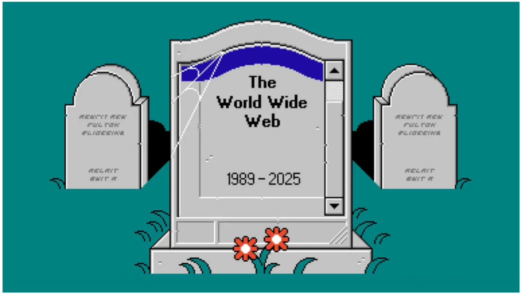

ILLUSTRATION: NICK LITTLE

...and publishers are hurting

≡ ASK FT **FINANCIAL TIMES** My Account

Chegg + Add to myFT

Chegg sues Google over claims AI search tool blocks user traffic

US edtech group explores possible sale or take-private deal as it alleges search giant's summaries have dented revenues

The AI Revolution and Content Economics

- Large Language Models (LLMs) are transforming how users engage with online content
- LLMs could be complements or substitutes to traditional online search and browsing
  - Users may redirect queries from search engines to LLMs, translating into less traffic to publishers
  - Concerns around response quality may limit benefits
  - Aggregation of information may supplement traditional search and content consumption, e.g., complex queries or prestructuring information; more efficient initial search could lead to overall larger search volume
  - Impact on UGC platforms unclear

Research Question

How does the adoption of LLMs (e.g., ChatGPT) affect users' online behavior?

- Overall Website Activities
- Specific Domain Types

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  - Browsing Activity
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- Specific Domain Types
  - Education-Related Websites
  - User-Generated Content Platforms

Preview of Empirical Approach

- User-level panel data of web browsing activities (Comscore) for 2022 - 2023
- Estimate effect of LLM adoption on a range of outcome variables
- Staggered difference-in-difference estimation controlling for general levels of online activity

Preview of Key Empirical Findings

Behavior initially unaffected but significant changes from around 20 weeks post adoption

1. **Search Behavior**: Substantial decrease in total and Google searches
2. **Browsing Activity**: No effect on frequently visited websites but drop in visits to smaller (less frequently visited) websites
3. **Advertising**: Significant drop in ad exposure, especially for high-retail-activity users
4. **Education**: Negative effects across platforms and multiple monetization models
5. **User-Generated Content Platforms**: Stack Overflow affected, Social Media, Reddit, and Wikipedia unaffected

Previous Literature

1. Technology Disruption and Digital Media Economics

   Seamans and Zhu (2014), Oberholzer-Gee and Strumpf (2007) Rob and Waldfogel (2007) Calzada and Gil (2020), Athey et al. (2021),

2. LLMs and Online Community Behavior

   Burtch et al. (2024) Fradkin (2025), Lyu et al. (2025), Li and Kim (2024), Shorakaei et al. (2025)

3. AI Adoption in Work and Productivity

   Humlum and Vestergaard (2025), Brynjolfsson et al. (2025), Cui et al. (2024), Demirci et al. (2025)

4. LLM Licensing, Fair Use and Substitution

   Gans (2024) Goldberg and Lam (2025) Yang and Zhang (2024)

5. Online Content Monetization Models

   Sun and Zhu (2013), Lambrecht and Misra (2017), Chiou and Tucker (2017), Pattabhiramaiah et al. (2019)

Agenda

- Empirical Setting & Data
- Estimation Strategy
- Results
  - Overall Website Activities
  - Specific Domain Types
- Implications & Discussion

Empirical Setting & Data

Empirical Setting: LLM Timeline

- **November 30, 2022**: ChatGPT released by OpenAI
- **March 2023**: GPT-4 update released
- **May 2023**: "Browse with Bing" feature in Microsoft search
- **Our period**: November 2022 - October 2023
  - GPT3.5 trained with pre-2021 data (before Sept. ‘23)
  - No “live" search (introduced Oct. ’24)
  - No Google AI Overviews (introduced Oct. ’24)

Data: Comscore Web-Behavior Panel 2022-2023

Comscore Web-Behavior Panel

- US panelists
- Detailed URL-level data for desktop browsing
- Comprehensive tracking of user online activities
- Complete observation period: November 2022 - October 2023

We Observe

1. All URL calls with timestamps
2. Search queries on search engines (some content masked for privacy)
3. Website categorization (ComScore classification)
4. Ad impressions (mostly Google; through URL calls to ad networks)

Sample Construction

Filtering Criteria

1. **Active users** Users with $\geq$ 4 active days per month (Nov 2022 - Oct 2023)
2. **Intermediate sample**: 74,940 individuals
3. **LLM Adoption Definition**: 3 consecutive weeks of $\geq$1 URL calls to main LLM chatbots; adoption is first week
4. **Final sample**: 2,041 LLM adopters, data aggregated to weekly level

Why This Adoption Criteria?

- Focus on users who eventually adopt (similar ex-ante propensity)
- Avoid systematic differences with never-adopters
- Ensure sustained rather than experimental usage

Users Mostly Active During Entire Observation Window

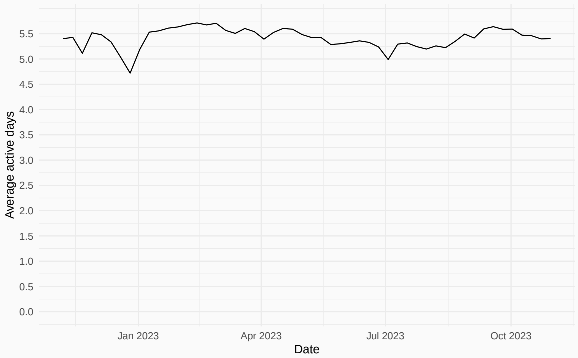

Figure 1: Average number of active days per week demonstrates consistent usage

Summary Statistics: Pre-Adoption 1/2

Category	Variable	Mean	SD	Median
Search	All search	32.7	84.1	9
	Google	17.7	41.2	1
	Questions	3.8	12.0	0
	Navig. only	0.8	3.0	0
	Navig. + other	1.5	6.6	0
	Long	6.6	20.5	1
	Short	5.0	16.4	1
Website traffic	All websites	4,325.1	14,576.4	1,495
	Top 1,000 websites	3,219.9	13,477.5	985
	non-Top 1,000 websites	1,105.2	3,369.4	297
	Top 25%	831.6	4,396.4	249
	Bottom 25%	1,154.3	3,435.1	309
Referred traffic	All referred	21.7	101.3	6
	Bottom 25%	4.9	10.5	1

Summary Statistics: Pre-Adoption 2/2

Category	Variable	Mean	SD	Median
Ads	All ads [Google, Yieldmo]	211.6	1,516.8	21
	Google ads: display	161.1	1,399.7	8
	Google ads: search	14.7	35.2	0
	Google ads: video	4.0	41.0	0
	Yieldmo	31.9	375.0	0
Control	All control	648.9	2,310.4	73
	Email	378.4	1,273.9	20
	Retail	208.1	1,515.4	3
	News	62.5	818.6	0
Education	All education	169.7	712.7	0
	Variety of URL calls	1.3	3.3	0
	Wikipedia	13.9	322.7	0
	Stack Overflow	0.9	5.1	0
	Reddit	14.4	126.5	0

LLM Adoption Patterns

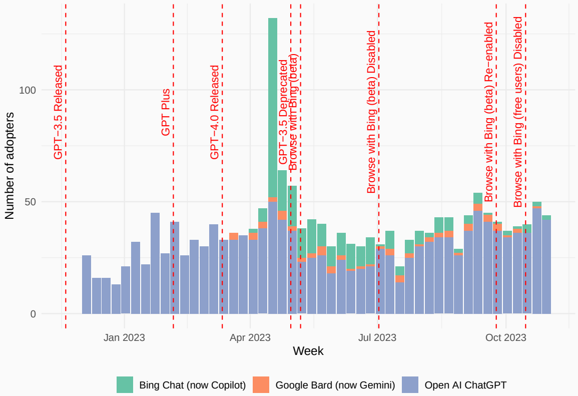

Figure 2: Adoption per week (first week of three consecutive weeks of usage)

On average, users made 35.1 calls to LLM per week post-adoption (SD=139.1)

Data Coverage by Time Since Adoption

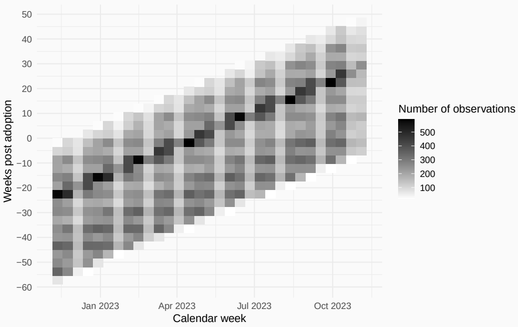

Figure 3: Observations by calendar week and weeks since adoption

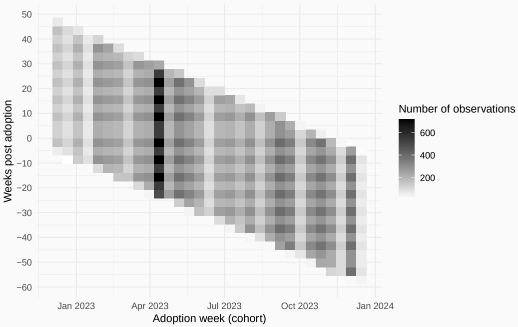

Figure 4: Observations by adoption cohort and weeks since adoption

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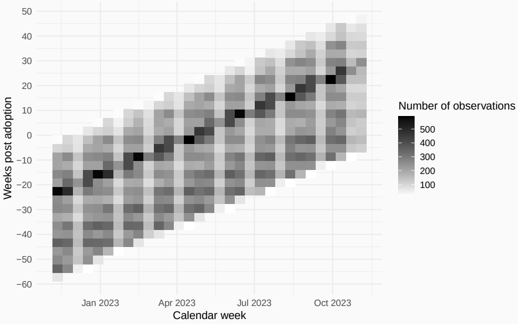

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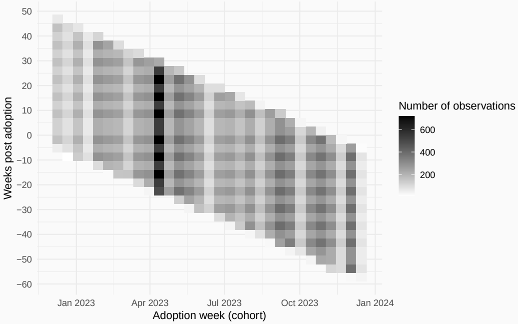

Figure 4: Observations by adoption cohort and weeks since adoption

To have in mind when looking at the results...

Estimates become less precise 35+ weeks post-adoption due to fewer observations

Identification Challenge

Standard TWFE Problems

- Staggered adoption with heterogeneous treatment effects (over cohorts and time)

  ▸ LLM usage across cohorts

- Using already-treated units can contaminate estimates (De Chaisemartin & D'Haultfœuille, 2020)

Estimate Staggered Diff-in-Diff following Callaway & Sant'Anna (2021)

- Cohort- and time-specific Average Treatment Effects on Treated (ATT)
- Use only not-yet-treated units as controls
- Account for treatment effect heterogeneity across time and cohorts
- Control for overall web activity using retail/news/email activity

Estimation

Individual i, adoption week g and calendar time t where:

- $Y_{i,t}$, $Y_{it}(g)$: Observed and potential outcomes (as function of adoption week g)
- $G_{i,g} = 1$: If individual i adopted in week g
- $D_{i,t} = 1$: If individual i has adopted by week t

Cohort- and Time-specific Average Treatment Effect on the Treated

$$\begin{aligned}
\mathrm{ATT}_{g,t} &= \mathbb{E}[Y_{i,t}(g) - Y_{i,t}(0) \mid G_{i,g} = 1] \\
&= \mathbb{E}[Y_{i,t} - Y_{i,g-1} \mid G_{i,g} = 1] - \mathbb{E}[Y_{i,t} - Y_{i,g-1} \mid D_{i,t} = 0, G_{i,g} = 0].
\end{aligned}$$

We aggregate effects at the event time $e = t - g$

Assumptions

Conditional Parallel Trends Assumption

For all $t \geq g$ and all groups g and g' with $g \neq g'$:

$$\mathbb{E}[Y_{i,t}(0) - Y_{i,g-1}(0)|G_{i,g} = 1, X_i] = \mathbb{E}[Y_{i,t}(0) - Y_{i,g-1}(0)|G_{i,g'} = 1, X_i]$$

In the absence of treatment, all cohorts would have experienced parallel trends

No Anticipation Assumption

For all $t < g$ and all g:

$$\mathbb{E}[Y_{i,t}(g)] = \mathbb{E}[Y_{i,t}(0)]$$

Units do not change behavior in anticipation of future treatment

- Pre-treatment outcomes unaffected by knowledge of future adoption timing

What is our approach robust to?

1. Calendar time shocks (e.g., seasonality, holidays)

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The Effect of LLM Adoption on: Search

Effect on Online Search

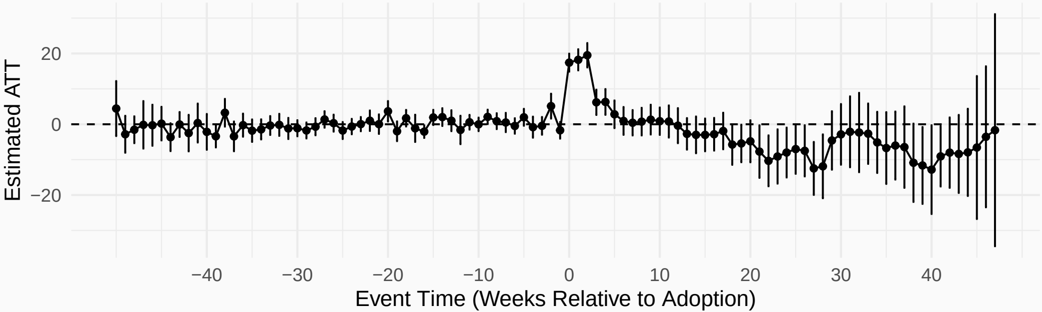


Figure 5: Effects on All Search

Statistical Power Considerations

- 100,000+ total observations spread across 52 weeks $\times$ 48 cohorts
- Results in 2,448 individual ATT parameters (51 weeks x 48 cohorts)
- Each estimate uses only subset of data (treated cohort + not-yet-treated)
- Precision decreases for long-term effects when there are few cohorts, e.g. with 35+ weeks post-adoption

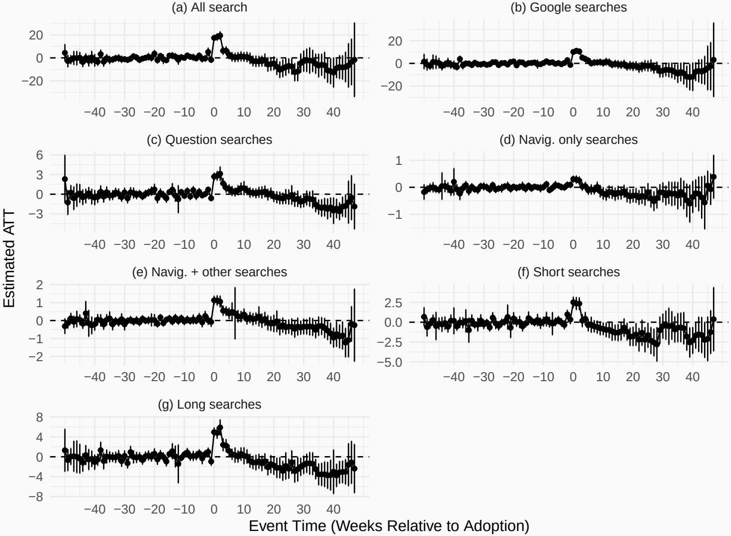
Effect on Online Search: Broken by Search Type

	All search	Google	Questions	Navig. only	Navig. + other	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ATT (weeks: 20-47)	-7.079^{**}	-5.568^{*}	-1.256^{***}	-0.242	-0.407^{**}	-1.467^{**}	-2.466^{***}
	(3.517)	(3.224)	(0.469)	(0.160)	(0.170)	(0.668)	(0.795)
Pre-adoption avg.	32.669	17.680	3.779	0.800	1.500	5.030	6.630

Note: N = 106,132; Panelists = 2,041; Weeks = 52; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

- **21.7%** decrease in total searches (weeks 20-47)
- **31.5%** decrease in Google searches specifically
- Contrasting effects for question searches vs. navigational searches

Effect on Online Search



The Effect of LLM Adoption on: Browsing Activity

Overall Browsing Behavior

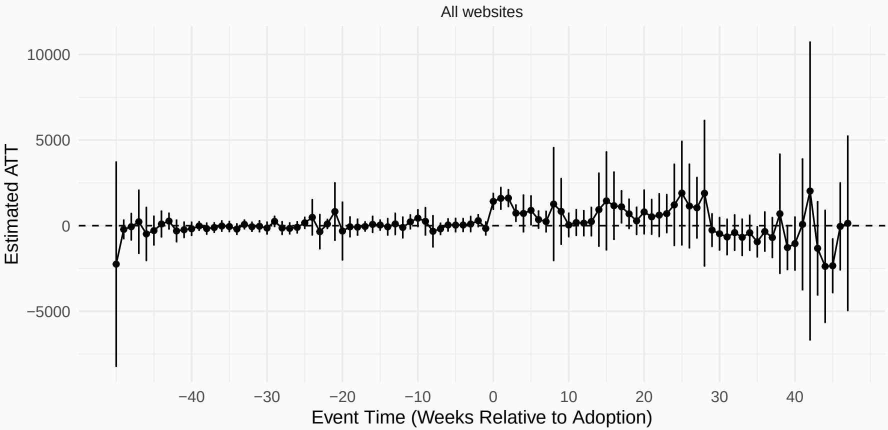


Figure 7: Effects on total traffic

Browsing Results

		Top 1,000 websites		Quartiles of traffic[a]	
	All websites	Top	not-Top	Top 25%	Bottom 25%
	(1)	(2)	(3)	(4)	(5)
ATT (weeks: 20-47)	-17.752	470.449	-488.201^{**}	102.276	-482.310^{**}
	(561.734)	(490.040)	(212.767)	(103.300)	(211.224)
Pre-adoption avg.	4,325.075	3,219.854	1,105.221	831.576	1,154.265
Websites	4,533,082	1,000	4,532,082	7	4,532,215

Notes: N = 106,132; Panelists = 2,041; Weeks = 52

*p<0.1; **p<0.05; ***p<0.01

- No effect on top websites by amount of traffic
- Effect on less-frequently visited websites

See Plots

a : Quartiles defined using all panelists (adopters and non-adopters) to avoid bias on selection of low/high traffic pre-adoption.

Overall Browsing Behavior

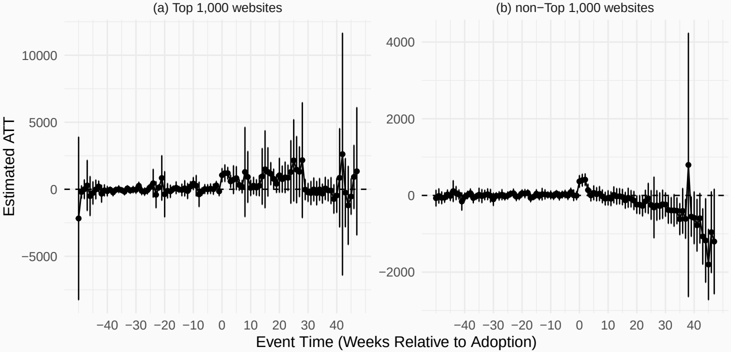


Figure 8: Effects on traffic for top 1,000 websites vs. other websites

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Top websites = Top 1000 websites in visits; e.g., Google, Google Docs, YouTube, Facebook, Bing, etc...

Traffic Referred from Search

	All referred	Top 25%	25%-50%	50%-75%	Bottom 25%
	(1)	(2)	(3)	(4)	(5)
ATT (weeks: 20-47)	-0.078	0.142	2.204	-1.403	-1.021^{*}
	(5.513)	(0.904)	(5.348)	(0.983)	(0.566)
Pre-adoption avg.	21.723	4.749	6.869	5.158	4.947
Note:					*p$<$0.1; **p$<$0.05; ***p$<$0.01

- Effect on less-frequently visited websites
- No effect on larger websites consistent with navigational search being unaffected (e.g., searching "amazon" and clicking on amazon.com)

Note: Quartiles defined using all panelists (adopters and non-adopters) to avoid bias on selection of low/high traffic pre-adoption.

The Effect of LLM Adoption on: Advertising

Effect on Advertising Exposure

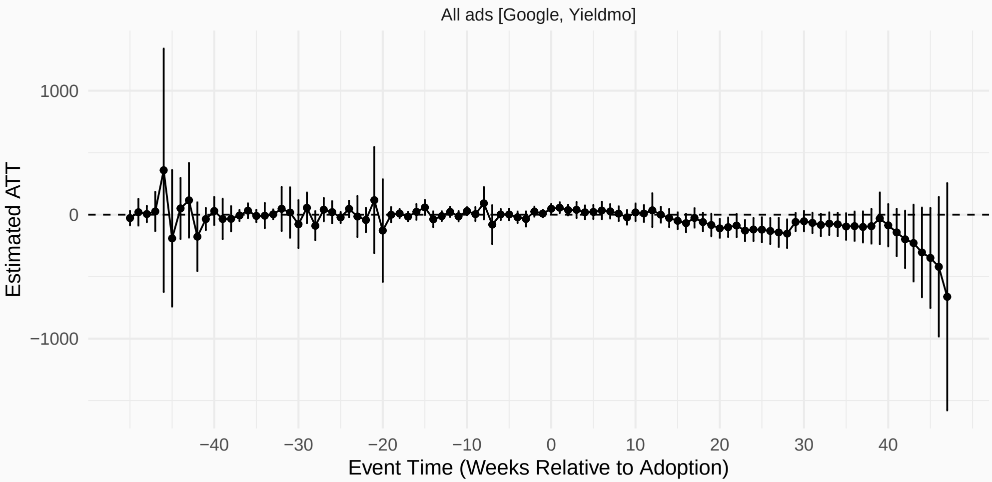


Figure 9: Effects on advertising exposure by type

Advertising Exposure: Google

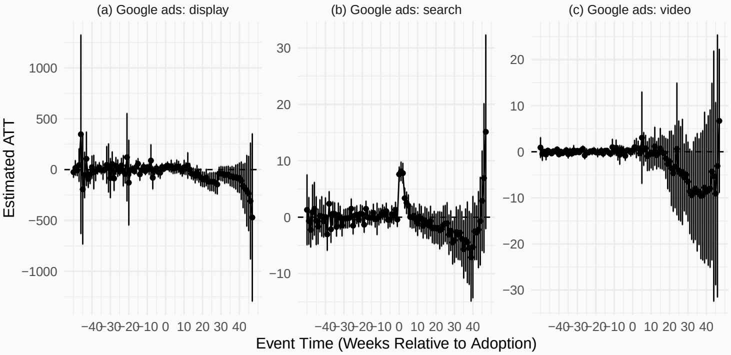


Figure 10: Effects on Google Ads exposure

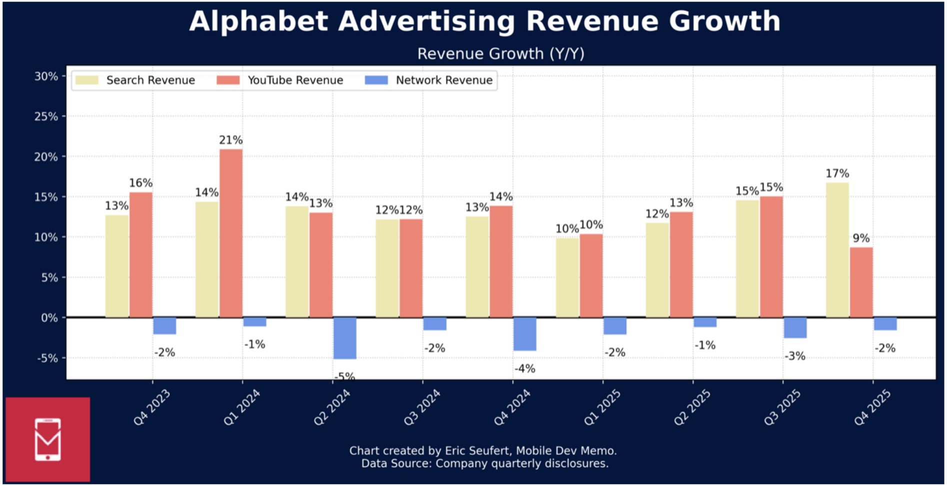
Advertising Exposure

	All ads	Google ads			Yieldmo
	[Google, Yieldmo]	Display	Search	Video	
	(1)	(2)	(3)	(4)	(5)
ATT (weeks: 20-47)	-154.213^{**}	-122.217^{*}	-1.914	-5.798	-24.284
	(73.299)	(73.479)	(1.978)	(6.485)	(32.310)
Pre-adoption avg.	211.606	161.092	14.686	3.952	31.876
Note:	N = 106,132; Panelists = 2,041; Weeks = 52;				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

- Significant drop in total ad impressions: Particularly strong on Google display ads
- No significant effect on Google search ads or video ads
- Suggests substituted searches were less monetizable

▸ See Google Ads Plots

Our results are consistent with Financial Reports



Heterogeneity by Retail Activity

- Classify users based on their pre-adoption average level of retail activity
- Measure weekly URL calls to retail domains: low $[0, 13.5]$, mid to $[13.5, 75.1]$, high $[75.1, \infty]$
- Estimate separate regressions

Heterogeneity by Retail Activity

	All ads [Google, Yieldmo]			Google ads: display		
	Low	Mid	High	Low	Mid	High
	(1)	(2)	(3)	(4)	(5)	(6)
ATT (weeks: 20-47)	34.650	-9.113	-561.285^{**}	22.493	12.079	-448.582^{*}
	(66.737)	(34.557)	(234.000)	(61.866)	(32.213)	(243.936)
Pre-adoption avg.	106.885	166.582	364.512	85.641	124.363	275.721

Note: N = 35,360/35,360/35,412; Panelists = 680/680/681; Weeks = 52; *p<0.10; **p<0.05; ***p<0.01

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$\Longrightarrow$ **High retail activity users** show the largest drops in ad exposure - consumers that are most to advertisers – and likely publishers – are most affected

The Effect of LLM Adoption on: Specific Domain Types

Types of Websites

- Education
  - By Platform Type
  - By Monetization
- User-Generated Content Platforms
  - Wikipedia
  - StackOverflow
  - Reddit
  - Social Media

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Education Websites

Why Education Websites?

- Students were early ChatGPT adopters (30% used for schoolwork)[1]
- Educational tasks easily completed with LLMs
- Clear substitution potential for homework, explanations, summaries

Sample

- 1,886 users who visited education websites $\geq$10 times
- Average: 170 URL calls per week to education domains
- Covers learning management systems, online platforms, other educational content

[1] https://www.intelligent.com/one-third-of-college-students-used-chatgpt-for-schoolwork-during-the-2022-23-academic-year/, Accessed May 12, 2025

Education: All Education Websites

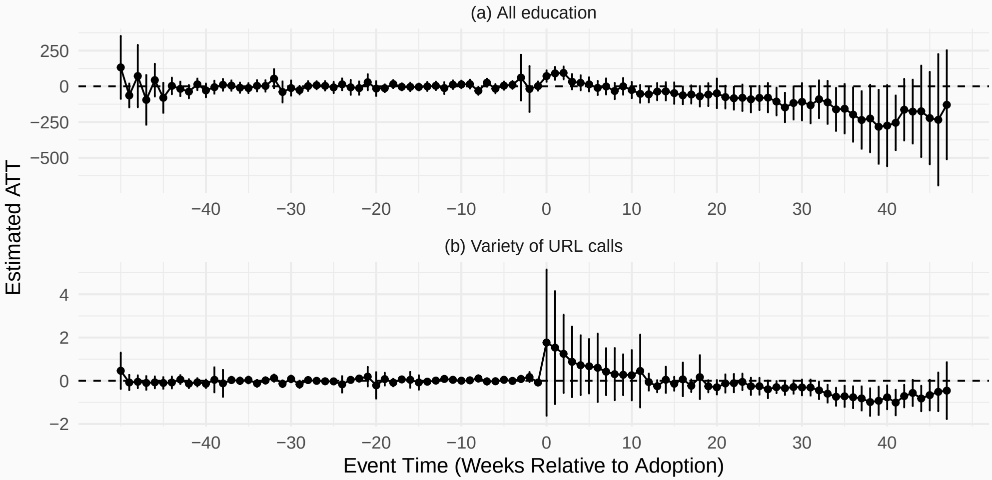

Figure 11: Effects on all education websites

Education: By Platform Type

	All education	Variety of URL calls	Learning management system	Online learning platform
	(1)	(2)	(3)	(4)
ATT (weeks: 20-47)	-151.532^{**}	-0.520^{***}	-23.124^{*}	-123.794^{**}
	(65.729)	(0.166)	(14.049)	(54.269)
Pre-adoption avg.	169.688	1.290	62.199	55.785

Note: N = 98,072; Panelists = 1,886; Weeks = 52
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

- **Learning Management Systems**: Canvas, Blackboard (institutional platforms)
- **Online Learning Platforms**: Cengage, Edgenuity (content providers)
- Effect on less-frequently visited websites

See Plots

Education: By Monetization Strategy

	Ads	Subscription	Purchase	B2B
	(1)	(2)	(3)	(4)
ATT (weeks: 20-47)	-20.084	-109.946^{**}	-59.846	-124.665^{**}
	(20.363)	(55.582)	(41.389)	(58.473)
Pre-adoption avg.	20.111	53.556	49.790	125.892

Note: N = 98,072; Panelists = 1,886; Weeks = 52
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

- **Subscription platforms**: Significant drop
- **B2B revenue sites**: Significant drop
- Multiple revenue streams simultaneously threatened

See Plots

Types of Websites

- Education
  - By Platform Type
  - By Monetization
- User-Generated Content Platforms
  - Knowledge-sharing platforms
    - Wikipedia (“factual” information)
    - StackOverflow (complex technical questions)
    - Reddit (subjective and experience-based questions and discussions)
  - Social Media (social interactions)

User-Generated Content Platforms

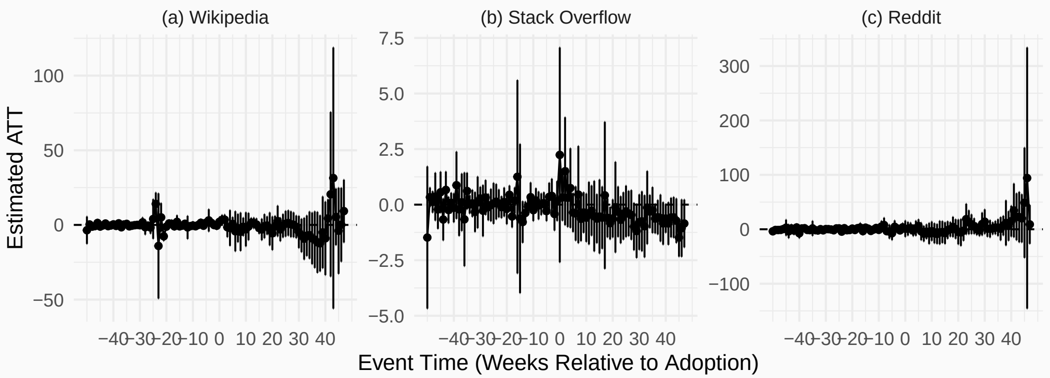

Figure 12: Effects on Stack Overflow, Reddit and Wikipedia

User-Generated Content Platforms

	Wikipedia	Stack Overflow	Reddit
	(1)	(2)	(3)
ATT (weeks: 20-47)	−1.104	−0.649*	12.736
	(5.668)	(0.345)	(12.172)
Pre-adoption avg.	13.878	0.944	14.384
Panelists	1634	287	1488
Weeks	52	52	52
Observations	84,968	14,924	77,376
Note:			*p<0.1; **p<0.05; ***p<0.01

- **Stack Overflow**: Significant decrease in URL calls
- **Reddit** and **Wikipedia**: No significant change
- Stack Overflow and Reddit results confirm prior research

Social Media

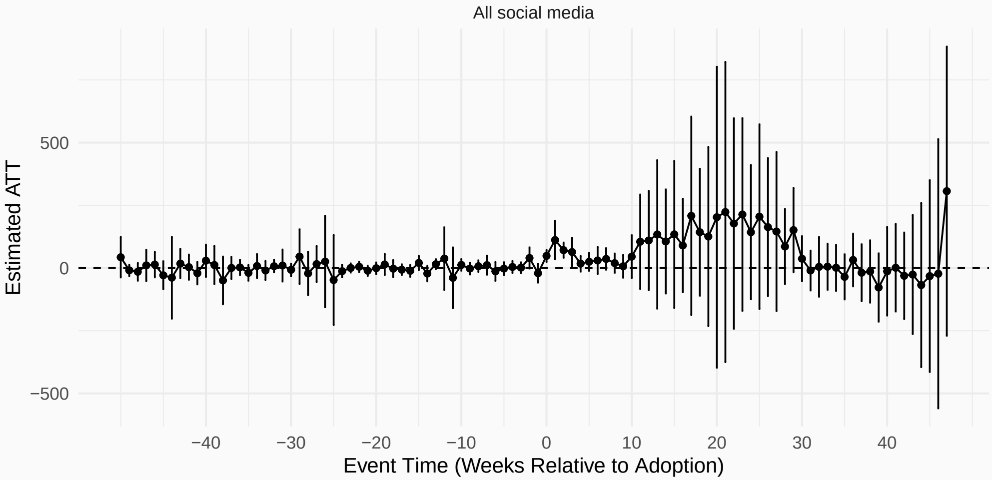

Figure 13: Effects on All Social Media

Social Media

	All social media	Facebook	Instagram	X	Discord	LinkedIn	TikTok
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ATT (weeks: 20-47)	62.431	14.590	−14.437	−2.121	−3.151	22.949	45.717
	(75.321)	(18.726)	(46.566)	(18.080)	(4.206)	(30.431)	(69.720)
Pre-adoption avg.	179.690	85.804	40.296	18.088	11.004	9.465	7.518

Note: *p<0.1; **p<0.05; ***p<0.01

$\Longrightarrow$ No effect on social media

See Plots

Why the Difference Across Platforms (One Potential Explanation)

- **Wikipedia**: Provides comprehensive insights, added value of LLMs limited
- **Stack Overflow**: Complex "objective" Q&A more easily substituted by LLMs
- **Reddit**: Ambiguous/subjective/social content less substitutable
- **Social Media**: Social interactions less substitutable
- Suggests that LLMs excel at providing definitive answers to complex technical questions but less so in more personal/subjective/social contexts

We cannot rule out alternative explanations

Implications & Discussion

Key Findings

- **LLMs shift how users access information; from about 20 weeks post-adoption**
  - Decrease in search activity
  - No effect on frequently visited websites but drop in activity on less frequently visited websites
  - Drop in ad exposure, especially for high-retail-activity users
  - Decrease in activity on education-related websites
  - Among UGC platforms, Stack Overflow affected, Wikipedia, Reddit, and Social Media unaffected
- **Patterns suggest that LLMs act as substitutes, not complements, to traditional online activities**

Thank You!

Working paper on SSRN

Appendix

References i

Athey, S., Mobius, M., & Pal, J. (2021). ***The impact of aggregators on internet news consumption* (tech. rep.).** National Bureau of Economic Research.

Brynjolfsson, E., Li, D., & Raymond, L. (2025).**Generative ai at work.** *The Quarterly Journal of Economics*, qjae044.

Burtch, G., Lee, D., & Chen, Z. (2024).**The consequences of generative ai for online knowledge communities.** *Scientific Reports*, *14*(1), 10413.

Calzada, J., & Gil, R. (2020).**What do news aggregators do? evidence from google news in spain and germany.** *Marketing Science*, *39*(1), 134–167.

Chiou, L., & Tucker, C. (2017).**Content aggregation by platforms: The case of the news media.** *Journal of Economics & Management Strategy*, *26*(4), 782–805.

Cui, Z. K., Demirer, M., Jaffe, S., Musolff, L., Peng, S., & Salz, T. (2024).**The effects of generative ai on high skilled work: Evidence from three field experiments with software developers.** *Available at SSRN 4945566*.

Demirci, O., Hannane, J., & Zhu, X. (2025).**Who is ai replacing? the impact of generative ai on online freelancing platforms.** *Management Science*.

Fradkin, A. (2025).**Demand for llms: Descriptive evidence on substitution, market expansion, and multi-homing.** *Working Paper*.

Gans, J. S. (2024). ***Copyright policy options for generative artificial intelligence* (tech. rep. No. w32106).** National Bureau of Economic Research. https://www.nber.org/papers/w32106

Goldberg, S., & Lam, H. T. (2025). ***Generative ai in equilibrium: Evidence from a creative goods marketplace* (tech. rep. No. SSRN 5152649).** Stanford Graduate School of Business. https://ssrn.com/abstract=5152649

Humlum, A., & Vestergaard, E. (2025).**The unequal adoption of chatgpt exacerbates existing inequalities among workers.** *Proceedings of the National Academy of Sciences*, *122*(1), e2414972121.

Lambrecht, A., & Misra, K. (2017).**Fee or free: When should firms charge for online content?** *Management Science*, *63*(4), 1150–1165.

Li, X., & Kim, K. (2024).**Impacts of generative ai on user contributions: Evidence from a coding q &a platform.** *Marketing Letters*, 1–15.

Lyu, L., Siderius, J., Li, H., Acemoglu, D., Huttenlocher, D., & Ozdaglar, A. (2025).**Wikipedia contributions in the wake of chatgpt.** *arXiv preprint arXiv:2503.00757*.

References iii

Oberholzer-Gee, F., & Strumpf, K. (2007). **The effect of file sharing on record sales: An empirical analysis.** *Journal of political economy*, *115*(1), 1–42.

Pattabhiramaiah, A., Sriram, S., & Manchanda, P. (2019). **Paywalls: Monetizing online content.** *Journal of marketing*, *83*(2), 19–36.

Rob, R., & Waldfogel, J. (2007). **Piracy on the silver screen.** *The Journal of Industrial Economics*, *55*(3), 379–395.

Seamans, R., & Zhu, F. (2014). **Responses to entry in multi-sided markets: The impact of craigslist on local newspapers.** *Management Science*, *60*(2), 476–493.

Shorakaei, H., Zhang, M., Bayley, T., & Begen, M. A. (2025). **Empowering or eroding contributions? how generative ai impacts user-generated content across diverse communities.** *How Generative AI Impacts User-Generated Content Across Diverse Communities (March 24, 2025)*.

Sun, M., & Zhu, F. (2013). **Ad revenue and content commercialization: Evidence from blogs.** *Management Science*, *59*(10), 2314–2331.

Yang, S. A., & Zhang, A. H. (2024). **Generative ai and copyright: A dynamic perspective.** *arXiv preprint arXiv:2402.17801*. https://arxiv.org/abs/2402.17801

Sample Characteristics

Variable	Main	Education	Wikipedia	Stack Overflow	Reddit	Social media
Unique panelists	2,041	1,886	1,634	287	1,488	2,034
Weeks in data	52	52	52	52	52	52
Total observations	106,132	98,072	84,968	14,924	77,376	105,768
Pre-adoption	64,543	59,706	51,120	8,246	46,245	64,282
Post-adoption	41,589	38,366	33,848	6,678	31,131	41,486

Require a user to have at least 10 URL calls in the entire observation window on the relevant main DV

Cohort heterogeneity

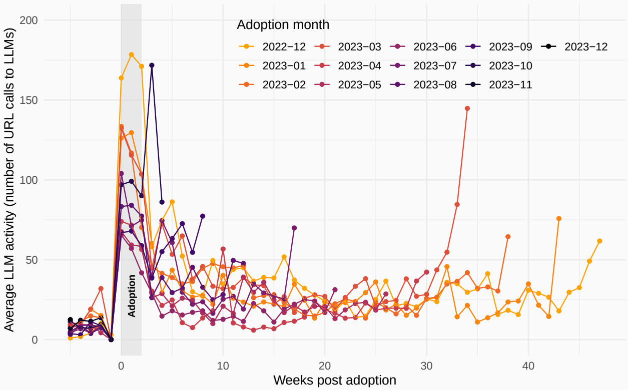

Figure 14: Average number of URL calls to LLMs per post-adoption week by adoption month.

Back to Identification

Control Variables

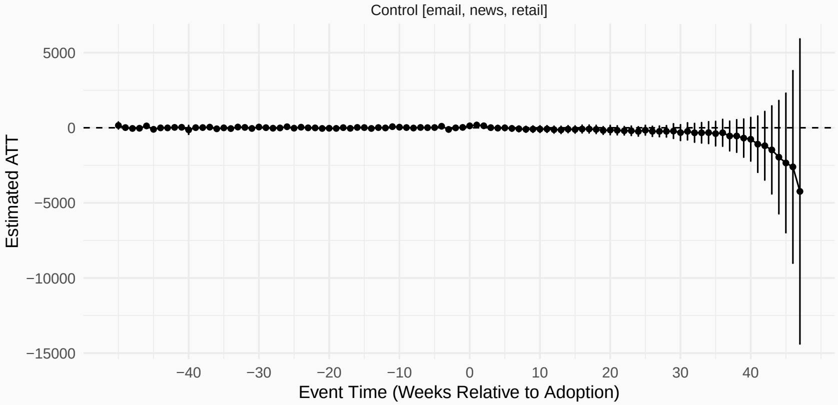

Figure 15: Validation: No effect on control categories (email, news, retail)

Back to Identification

Control Variables

	Dependent variable:
	Control [email, news, retail]
ATT (weeks 00-02)	148.064*
	(81.733)
ATT (weeks 03-19)	−83.958
	(114.006)
ATT (weeks 20-47)	−777.914
	(825.146)
Pre-adoption avg.	648.945
Panelists	2041
Weeks	52
Observations	106,132
Note:	*p<0.1; **p<0.05; ***p<0.01

Back to Identification

Overall Browsing Behavior

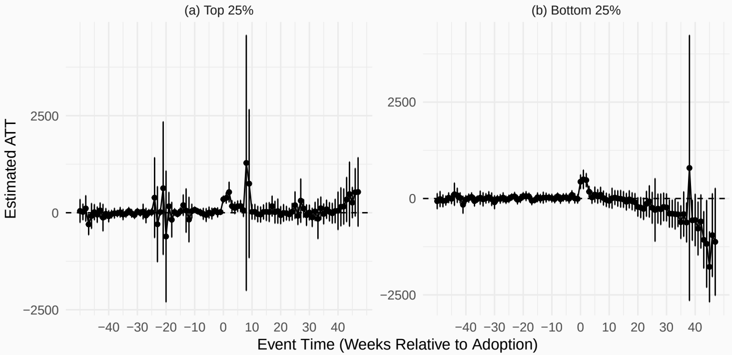

Figure 16: Effects on traffic for websites belonging to top 25% and bottom 25% of traffic

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Advertising Exposure: Google

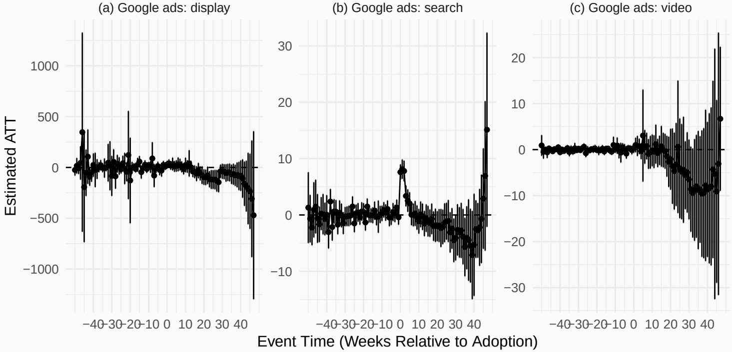

Figure 17: Effects on Google Ads exposure

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Education: By Platform Type

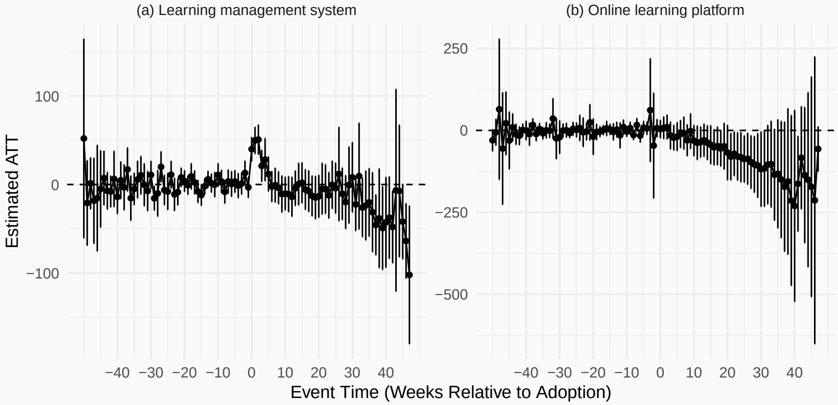

Figure 18: Effects on education websites by category

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Education: By Monetization Strategy

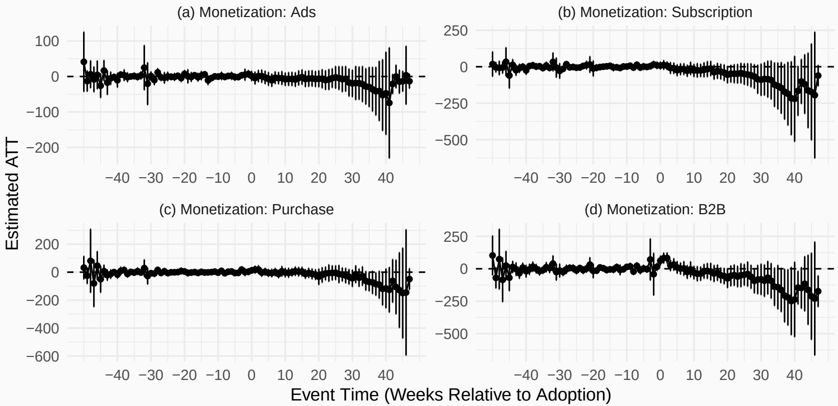

Figure 19: Effects on education websites by monetization

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Social Media

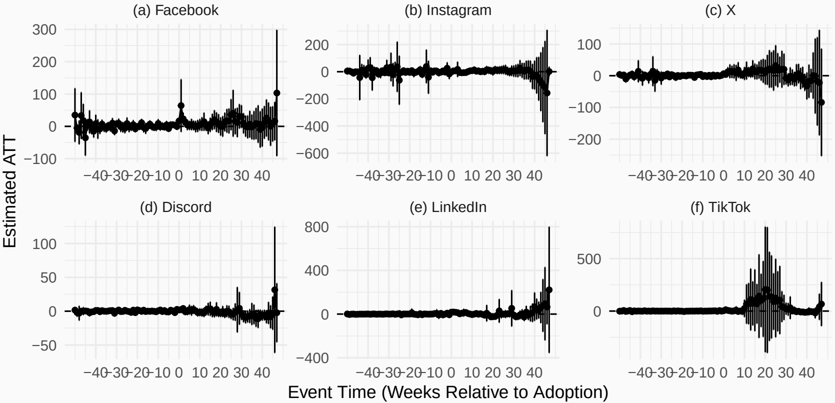

Figure 20: Effects on Social Media, by Website

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Backup: Robustness Checks

Sample Sensitivity

- Results robust to different activity thresholds ($\geq$3, $\geq$5, $\geq$15 URL calls)
- Alternative adoption definitions (2-4 consecutive weeks)
- Consistent patterns across specifications
- Effects hold with different control variable combinations

Alternative Specifications

- Results similar without control variables (wider confidence intervals)
- Inverse hyperbolic sine vs. log transformation
- Different aggregation windows (bi-weekly, monthly)
- Seasonal controls yield consistent results

Robustness Checks: Activity Inclusion Criteria

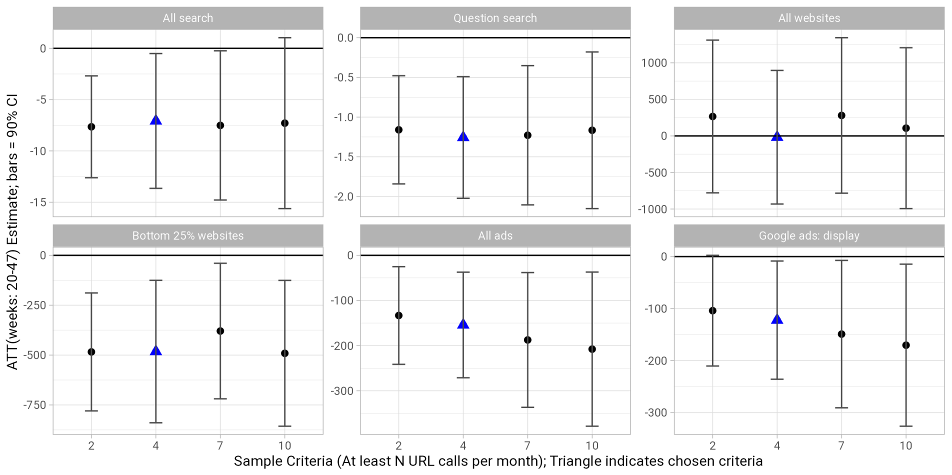

Figure 21: Sensitivity to overall sample criteria.

Robustness Checks: LLM Adoption Criteria

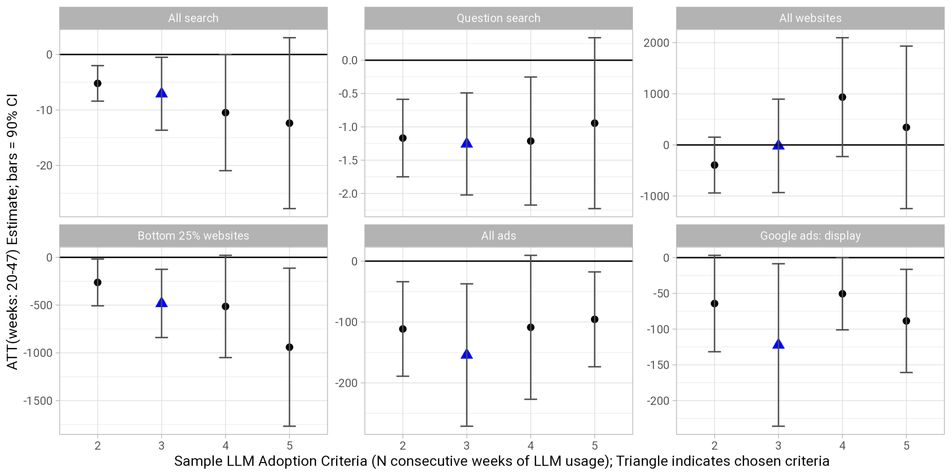

Figure 22: Sensitivity to LLM adoption sample criteria.

Robustness Checks: Model Specification

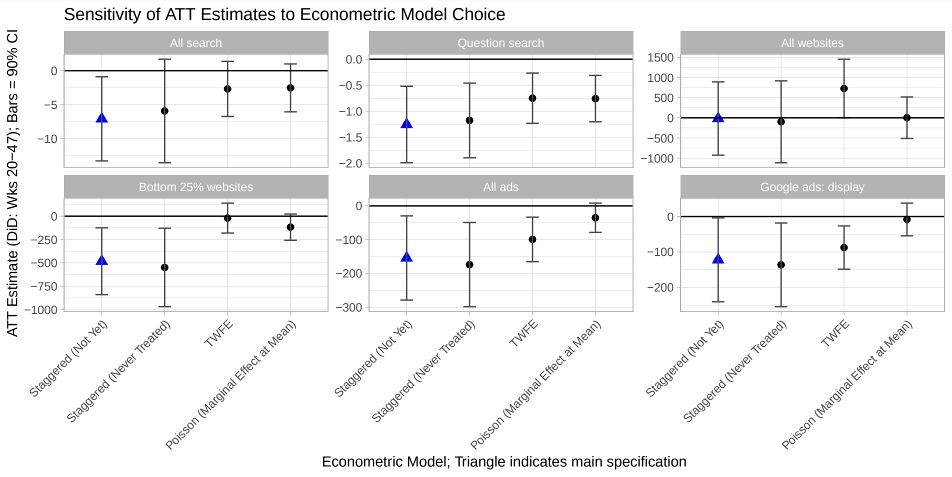

Figure 23: Sensitivity to Model Specification

Robustness Checks: Anticipation

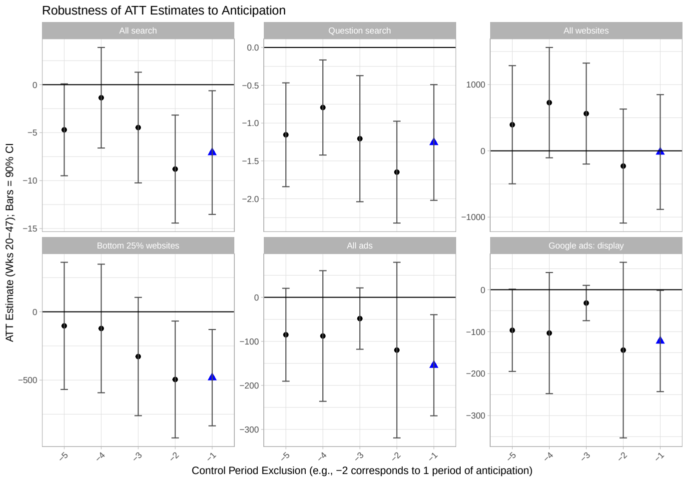

Figure 24: Sensitivity to Anticipation periods

Cohort Heterogeneity: Search

	ATT (weeks 20-47)						
	All search	Google	Questions	Navig. only	Navig. + other	Short	Long
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cohort (weeks: 4-15)	-6.406	-7.004	-1.413^{***}	-0.304	-0.419^{**}	-1.240^{*}	-2.257^{**}
	(4.531)	(4.297)	(0.537)	(0.199)	(0.169)	(0.731)	(0.914)
Cohort (weeks: 16-21)	0.124	-4.751	-0.234	0.042	-0.273	0.061	-0.602
	(6.380)	(3.758)	(0.742)	(0.228)	(0.324)	(1.034)	(1.351)
Cohort (weeks: 22-28)	-18.803^{***}	0.236	-0.721	-0.322	-0.281	-4.554^{**}	-4.528^{**}
	(6.139)	(2.741)	(0.765)	(0.253)	(0.338)	(1.814)	(1.829)
Cohort (weeks: 29-48)	1.770	0.419	-0.517	0.145	0.122	0.628	-0.762
	(5.033)	(4.032)	(0.763)	(0.240)	(0.308)	(0.826)	(1.288)
Pre-adoption avg.	32.669	17.680	3.779	0.800	1.500	5.030	6.630

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Cohort Heterogeneity: Referred Traffic

	ATT (weeks 20-47)				
	All referred	Top 25%	25%-50%	50%-75%	Bottom 25%
	(1)	(2)	(3)	(4)	(5)
Cohort (weeks: 4-15)	−0.017	0.247	2.106	−1.249	−1.121*
	(4.913)	(0.829)	(4.248)	(1.101)	(0.630)
Cohort (weeks: 16-21)	−4.571	−0.276	−0.208	−2.765	−1.322
	(13.472)	(2.450)	(13.170)	(3.601)	(0.979)
Cohort (weeks: 22-28)	0.202	−2.143	3.466	−0.740	−0.381
	(4.386)	(2.217)	(3.065)	(0.968)	(0.657)
Cohort (weeks: 29-48)	5.136	6.817	−1.359	−0.311	−0.011
	(12.342)	(11.173)	(3.881)	(1.179)	(0.990)
Pre-adoption avg.	21.723	4.749	6.869	5.158	4.947

Note: *p<0.1; **p<0.05; ***p<0.01

Cohort Heterogeneity: Ads

	ATT (weeks 20-47)				
	All ads [Google, Yieldmo]	Google ads: display	Google ads: search	Google ads: video	Yieldmo
	(1)	(2)	(3)	(4)	(5)
Cohort (weeks: 4-15)	−133.492	−100.197	−2.574	−5.711	−25.010
	(84.338)	(82.071)	(2.339)	(4.668)	(38.611)
Cohort (weeks: 16-21)	−22.099	−7.145	−3.358	−3.960	−7.638
	(40.855)	(38.944)	(2.596)	(5.500)	(10.657)
Cohort (weeks: 22-28)	−275.374***	−264.413**	−0.906	−3.697	−6.358
	(105.341)	(105.693)	(2.465)	(7.150)	(17.651)
Cohort (weeks: 29-48)	−18.435	−7.686	−2.302	−5.038	−3.410
	(34.451)	(29.204)	(3.077)	(8.042)	(24.169)
Pre-adoption avg.	211.606	161.092	14.686	3.952	31.876

Note: *p<0.1; **p<0.05; ***p<0.01

Cohort Heterogeneity: Education

	ATT (weeks 20-47)			
	All education	Variety of URL calls	Learning management system	Online learning platform
	(1)	(2)	(3)	(4)
Cohort (weeks: 4-15)	-176.342^{**}	-0.616^{***}	-23.051^{*}	-146.631^{**}
	(84.972)	(0.195)	(13.441)	(72.547)
Cohort (weeks: 16-21)	-29.101	0.031	5.492	-40.445
	(62.685)	(0.210)	(23.213)	(49.219)
Cohort (weeks: 22-28)	-90.154	-0.377	-34.869	-58.493
	(61.597)	(0.274)	(28.419)	(40.619)
Cohort (weeks: 29-48)	-91.794	-0.697^{**}	-38.216	-33.077
	(91.110)	(0.284)	(62.419)	(44.839)
Pre-adoption avg.	169.688	1.290	62.199	55.785

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Backup: Additional Heterogeneity

User Characteristics

- Early vs. late adopters show similar long-term patterns
- Effects consistent across different adoption cohorts
- High-activity users show stronger responses

Platform-Specific Analysis

- ChatGPT vs. Bing Chat users show similar patterns
- Effects concentrated among sustained (vs. experimental) users
- Intensity of LLM usage correlates with substitution effects

Backup: Methodological Details

URL Call Classification

- Includes direct website visits and background calls
- Ad impressions identified through known ad network domains:
  - adservice.google.com (Google Display)
  - imasdk.googleapis.com (Google Video)
  - ads.yieldmo.com (Yieldmo)
- Search queries captured in URL parameters (content masked)
- Educational websites manually verified for accuracy (top 107 domains)

Estimation

Individual i, adoption week g and calendar time t where:

- $Y_{i,t}$, $Y_{it}(g)$: Observed and potential outcomes (as function of adoption week g)
- $G_{i,g} = 1$: If individual i adopted in week g
- $D_{i,t} = 1$: If individual i has adopted by week t

Cohort- and Time-specific Average Treatment Effect on the Treated

$$
\begin{aligned}
\mathrm{ATT}_{g,t} &= \mathbb{E}[Y_{i,t}(g) - Y_{i,t}(0) \mid G_{i,g} = 1] \\
&= \mathbb{E}[Y_{i,t} - Y_{i,g-1} \mid G_{i,g} = 1] - \mathbb{E}[Y_{i,t} - Y_{i,g-1} \mid D_{i,t} = 0, G_{i,g} = 0].
\end{aligned}
$$

Assumptions

Conditional Parallel Trends Assumption

For all $t \geq g$ and all groups g and g' with $g \neq g'$:

$$\mathbb{E}[Y_{i,t}(0) - Y_{i,g-1}(0)|G_{i,g} = 1, X_i] = \mathbb{E}[Y_{i,t}(0) - Y_{i,g-1}(0)|G_{i,g'} = 1, X_i]$$

In the absence of treatment, all cohorts would have experienced parallel trends

No Anticipation Assumption

For all $t < g$ and all $g' \geq g$:

$$\mathbb{E}[Y_{i,t}(g)] = \mathbb{E}[Y_{i,t}(0)]$$

Units do not change behavior in anticipation of future treatment

- Pre-treatment outcomes unaffected by knowledge of future adoption timing

What is our approach robust to?

1. Level differences across cohorts due to unobservables (e.g., early adopters have systematically higher/lower outcome levels)

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2. Stronger effects for those joining earlier/later
   - We estimate cohort-level effects $ATT_{g,t}$
3. Declining activity over time
   - We have evidence of users being active through the observation window
   - We control for plausibly unaffected behaviors (retail, news, email) ▸ Control regressions