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AMAZON SELF-PREFERENCING IN THE SHADOW OF THE DIGITAL MARKETS ACT

Joel Waldfogel

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ABSTRACT

Regulators around the world are discussing, or taking action to limit, self-preferencing by large platforms. This paper explores Amazon's search rankings of its own products as the European Union's Digital Markets Act (DMA) was coming into effect. Using data on over 8 million Amazon search results at 22 Amazon domains in the US, Europe, and elsewhere, I document three things. First, conditional on rudimentary product characteristics, Amazon's own products receive search ranks that are 24 positions better on average throughout the sample period. Second, the Amazon rank differential is large in comparison with the differential for 142 other popular brands. Third, shortly after the EU designated Amazon a "gatekeeper" platform in September 2023, the Amazon rank differential fell from a 30 position advantage to a 20 position advantage, while other major brands' rank positions were unaffected. The changed Amazon search rankings appear in both Europe and other jurisdictions.

Joel Waldfogel
Frederick R. Kappel Chair in Applied Economics
3-177 Carlson School of Management
University of Minnesota
321 19th Avenue South
Minneapolis, MN 55455
and NBER
jwaldfog@umn.edu

1 Introduction

Regulators around the world have grown concerned about major platforms giving preferential treatment to their own products relative to those of their suppliers. European regulators passed the Digital Markets Act (DMA), forbidding "gatekeeper platforms" from ranking "services and products offered by the gatekeeper itself more favourably ... than similar services or products offered by third parties."[1] US lawmakers have raised similar concerns. The proposed American Innovation and Choice Online Act would prohibit "large online platforms ... from engaging in specified acts, including giving preference to their own products on the platform."[2]

The arrival of regulation in Europe, along with the threat of regulation elsewhere, has made it necessary for gatekeeper platforms to come into compliance with rules against self-preferencing. Yet, policy makers and researchers lack clear definitions of self-preferencing, so it is unclear how gatekeepers can, or will, comply with the new rules. With this in mind, this paper has asks three questions. First, using data on over 8 million Amazon search listings in response to 100 common search queries, I estimate a simple measure of Amazon self-preferencing, the Amazon product search ranking differential, conditional on a small set of product characteristics (Jürgensmeier and Skiera, 2023; Farronato et al., 2023). Second, I compare the Amazon rank differential with other brands' rank differentials. Finally, I measure the effect of the DMA, from the date of Amazon's gatekeeper designation, on the Amazon rank differential.

I have three findings. First, conditional on star ratings, prices, and a few other characteristics, Amazon gives its own products search ranks that are on average 24 positions

[1] See `https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/digital-markets-act-ensuring-fair-and-open-digital-markets_en`.

[2] See `https://www.congress.gov/bill/117th-congress/senate-bill/2992`. Senator Elizabeth Warren has advocated structural separation of retailing from production, arguing that "You can be an umpire or you can own teams... But you can't be an umpire and own one of the teams that's in the game." See `https://www.nytimes.com/2019/03/13/technology/elizabeth-warren-tech-companies.html`.

better than expected over the entire sample period. Second, while inherent limitations of the approach make it hard to designate the Amazon rank differential self-preferencing, the Amazon rank differential is large in comparison with the analogous brand effects for 142 other brands. Third, after the EU's designation of Amazon as a "gatekeeper" platform, the rank of Amazon products in Amazon search results changed substantially: the Amazon rank differential fell from a 30, to a 20 rank advantage, while other brands' search ranks did not change. Regulation appears to have had a substantial effect: Amazon has substantially worsened the search ranks for its own products. The change in Amazon's rank differential appears in both the EU and elsewhere.

2 Background

2.1 Policy context

Over the past few years regulators around the world have focused growing attention on large platforms's treatment of their suppliers and, in particular, on potential self-preferencing behavior of platforms selling their own products alongside those of their suppliers.

The European Union's Digital Markets Act "entered into force" on November 1, 2022 with the establishment of a "High-level group to provide advice and expertise on implementing the DMA." Beginning May 2, 2023, gatekeeper "obligations and prohibitions" took effect "subject to further specifications." The European Commission then designated six firms (Alphabet, Amazon, Apple, ByteDance, Meta, Microsoft) as gatekeepers on September 6, 2023.[3] The firms had six months – until March 2024 – to come into "compliance with obligations and prohibitions."[4]

US regulators, too, have taken action to curb Amazon's power. In September 2023

[3] See https://ec.europa.eu/commission/presscorner/detail/en/ip_23_4328.

[4] See https://www.europarl.europa.eu/RegData/etudes/ATAG/2022/739226/EPRS-AaG-739226-DMA-Application-timeline-FINAL.pdf.

the FTC sued Amazon, arguing that it "is a monopolist that uses a set of interlocking anticompetitive and unfair strategies to illegally maintain its monopoly power."[5] The FTC argued that "Amazon's illegal, exclusionary conduct makes it impossible for competitors to gain a foothold." Among the FTC concerns is a claim that Amazon biases its "search results to preference Amazon's own products over ones that Amazon knows are of better quality."

The evolving regulatory landscape raises the question of how Amazon might adjust its search algorith to bring its degree of self promotion into compliance with the DMA. A March 2024 Amazon compliance report explained that its ranking "processes operate in an unbiased manner, using objective inputs and weighing them neutrally to facilitate the best possible customer choice irrespective of whether a product is offered by Amazon Retail or Sellers" and declared Amazon's search rankings to be "in compliance with Article 6(5) of the DMA."[6]

2.2 Relevant literature

This study is relevant to three strands of literature. First, there is a theoretical literature offering reasons why platforms might bias their rankings (Bourreau and Gaudin, 2022; Hagiu et al., 2022). Second, there are direct attempts to measure bias in promotion at Amazon or other platforms (Jürgensmeier and Skiera, 2023; Farronato et al., 2023; Raval, 2022; Chen and Tsai, 2019; Aguiar et al., 2021). Third, there are attempts to model platform rankings and possible bias (Ursu, 2018; Lam, 2021; Lee and Musolff, 2021; Compiani et al., 2021;

[5] "The FTC and its state partners say Amazon's actions allow it to stop rivals and sellers from lowering prices, degrade quality for shoppers, overcharge sellers, stifle innovation, and prevent rivals from fairly competing against Amazon." See `https://www.ftc.gov/news-events/news/press-releases/2023/09/ftc-sues-amazon-illegally-maintaining-monopoly-power`.

[6] The report also stated that "The Store designs its shopping and discovery experience to feature the items customers want to purchase. That is the Store's primary goal when ranking results in response to a search query on the product search results page. Our ranking models do not differentiate on the basis of whether the product is sold by Amazon Retail or a Seller or whether it is an Amazon product or a third-party product. The Store has no incentive to do otherwise—maintaining trust is at the heart of what we do at Amazon, and we would not risk our reputation with customers by making it difficult for them to find the products they look to buy, nor our trust with Sellers who help maintain the wide selection in our Store for the benefit of our customers." See `https://assets.aboutamazon.com/d6/09/381147c54c478a7917faee4b2059/amazon-dma-public-compliance-report.pdf`.

Reimers and Waldfogel, 2023; Gutierrez, 2021). This study, by contrast, documents changes to Amazon's self promotion as new regulations were coming into effect.

Measuring self-preferencing is difficult, for both conceptual and data availablity reasons. Some observers question whether platform self-preferencing warrants attention or concern, pointing to the common retail practice of selling store brands (Dubé, 2022). Nowithstanding those objections, lawmakers in the EU have moved ahead, outlawing self-preferencing by dominant platforms. Even if one understands self-preferencing to warrant attention, its definition and identification are not straightforward. In principle, self-preferencing is portrayal of one's own products in way that is better than is warranted. This just begs the question of what degree of promotion is warranted.

Reimers and Waldfogel (2023) present a framework in which platforms can rank products to maximize a weighted sum of consumer and producer surplus. Rankings that deviate from this frontier reflect platform bias. Implementing their framework requires data on both product characteristics and rankings, as well as the product-level sales consequences of the rankings. This is in general difficult, as platforms do not generally share quantity data.

Some studies quantify self-preferencing using publicly available data on search rankings and product characteristics, regressing search rankings on product characteristics presumed relevant to the products' appropriate ranking, as well as an indicator for whether the product is the platform's own (Jürgensmeier and Skiera, 2023; Farronato et al., 2023). While one can be concerned that the coefficient on the platform indicator reflects a combination of platform bias and unobserved characteristics of platform products, this approach has the great virtue of feasibility. Moreover, if the unobserved appeal of each brand's product evolves slowly over time, it is reasonable to view changes in Amazon-brand rank differentials as reflections of changes in self-preferencing.

3 Data

The data for this study consist of roughly 10 million product listings in Amazon search results at 22 Amazon domains between late June 2023 and March 2024. For this study I chose 100 commonly-used search terms (Table A.1).[7] Using ASIN Data API (`https://app.asindataapi.com/`), I searched each of these terms weekly at each of 22 Amazon country domains.[8] I kept the first three pages of each search result, delivering an average of roughly 150 ranked listings j per search term $\times$ country $\times$ time search.

For each listing, I observe the product title (from which I infer its brand, e.g. whether it is an Amazon product), the price, the number of ratings the product has received, the average Amazon stars, whether the product is Prime-eligible, the date and domain of the search, the search term entered, and whether the listing is sponsored. Including only observations with valid data for all variables, I have 8,221,729 listings. Table 1 describes the sample. The average listing has 4.37 Amazon stars and 3,479 user ratings. Just over a third of the listed products are eligible for Amazon Prime, and 4.5 percent of the listings are sponsored. Just 1.5 percent of listings are for Amazon-brand products.

Amazon and non-Amazon products have systematically different search ranks. The median for Amazon products is 31, compared with 76 for non-Amazon products. The inter-quartile range for Amazon-brand product ranks runs from 11 to 77, while the inter-quartile range for non-Amazon products runs from 38 to 115.

[7] These terms were collected from `https://www.semrush.com/blog/most-searched-items-amazon/`, `https://conversion.ag/blog/most-searched-keywords-on-amazon/`, and `https://www.incubeta.com/insights/the-top-10-most-searched-keywords-on-amazon-in-europe-and-the-uk-june-2022/`.

[8] The included countries are United Arab Emirates (amazon.ae), Canada (CA), China (CN), Japan (JP), United Kingdom (UK), United States (com), Austria (AT), Belgium (BE), Brazil (BR), Mexico (MX), Turkey (TR), Germany (DE), Egypt (EG), Spain (ES), France (FR), India (IN), Italy (IT), Netherlands (NL), Poland (PL), Saudia Arabia (SA), Sweden (SE), and Singapore (SG).

4 Empirical strategy

In this study I would like to document how the rank differential for Amazon products varies across contexts and over time. To this end, I estimate variants of the following equation:

$$r_{jcst} = X_{jt}\beta + \alpha\delta_j^{Amazon} + \mu_{cst} + \epsilon_{jcst}, \tag{1}$$

where r_{jcst} is the search rank of product j in country c for a search involving search term s on date t; X_{jt} contains product j characteristics at time t, including its price, the number of ratings it has received from consumers, its average Amazon star rating, and indicators for whether the product is Prime-eligible and whether the search result is sponsored; δ_j^{Amazon} is an indicator for whether product j is an Amazon product (e.g. Amazon Basics brand); μ_{cst} is a search fixed effect, so that identification occurs within results for particular week and country-specific searches; and ϵ_{jcst} is an error term.

If X_{jt} contained all of the variables relevant to product j's appropriate ranking, then α would provide a measure of Amazon self-preferencing. It is difficult to know whether X meets this criterion. Hence, I refer to α as a "rank differential" rather than as a measure of bias. It will be of interest to see how α varies across contexts. If the unobserved appeal of Amazon products evolves slowly over time, then abrupt changes in the rank differential will reflect changes in the extent of self-preferencing.

5 Results

I present results in five parts. Section 5.1 present the Amazon-branded products' rank differential. Section 5.2 compares the Amazon rank differential to other brands. Section 5.3 shows how Amazon's rank differential evolves over time. Section 5.4 presents estimates of the effect of gatekeeper designation on ranks and prices. Section 5.5 compares the evolution

of Amazon's rank differential to the differential for other brands.

5.1 Overall Amazon rank differential

Table 2 presents an estimate of Equation (1), and coefficients conform the expectation that more appealing products receive better ranks. That is, the rankings appear to be broadly consistent with giving better ranks to products that are more appealing to consumers. All but one of the 22 domain-specific price parameters are positive, and 19 have t-statistics above 1.96. This indicates that products with higher prices have higher (worse) rankings. On the other hand, products with better star ratings and more customer ratings have lower (better) rankings. Products that are Prime-eligible receive better rankings. Finally, sponsored search results receive better rankings, presumably because Amazon is compensated for these products' ranking positions.

After accounting for these factors (along with a $c \times s \times t$ fixed effect), Amazon-branded products receive search ranks that are 24.3 (standard error = 0.83) positions lower (better).[9] See column (1) of Table 2. This is consistent with either Amazon self-preferencing, or it indicates that Amazon branded products have substantial appeal beyond what is implied by the variables in X. I also estimate a variant in which I allow all of the Xs to have domain-specific coefficients:

$$r_{jcst} = X_{jt}\beta^c + \alpha\delta_j^{Amazon} + \mu_{cst} + \epsilon_{jcst}.$$

This approach, in column (2) of Table 2, yields a nearly identical estimate of α, of -24.5 (0.77).

[9] I cluster standard errors, here and in the remainder of the paper, on search term × Amazon domain × brand.

5.2 Amazon vs other brands

Amazon's branded products are of course not the only branded products appearing in the Amazon search results. I identify commonly-appearing brands, and I estimate brand-specific α coefficients (for 142 brands appearing at least 5,000 times in the data) via:

$$r_{jcst} = X_{jt}\beta + \Sigma_{b \in B}\alpha^b \delta_j^b + \mu_{cst} + \epsilon_{jcst},$$

where b denotes a particular brand and B is the full set of brands.

Figure 1 shows the resulting distribution of brand-specific α coefficients, with a vertical line at the Amazon estimate. Amazon has one of the largest negative coefficients.[10] It is possible that Amazon has a brand that is highly appealing, conditional on X, or that Amazon is engaged in self-preferencing.

5.3 Amazon's rank differential over time

The sample, which runs from July 2023 to March 2024, covers the period following the September 2023 designation of gatekeepers and the following six-month period when designated gatekeepers, such as Amazon, were to come into compliance with the DMA's prohibition on self-preferencing.

The left panel of Figure 3 shows the Amazon-brand share of search listings over time, and it falls sharply – and by about a third – after the designation of gatekeepers. The right panel of Figure 3 shows the average search ranks of Amazon and non-Amazon products. The average Amazon rank worsens from 45 to 55 around November, 2023. Figure 4 shows the distribution of Amazon products across search ranks before and after the gatekeeper designation in September of 2023. Prior to September, there is a bulge in the distribution

[10] Other brands with large negative coefficients include INIU, KLEENEX, BONTEC, SONY, UTOPIA, BRITA OPTIMUM NUTRITION, DURACELL, and JACK & JONES.

for rank positions 1-25. This bulge disappears after the designation. It appears that Amazon worsened the ranks of its own-brand products and, in particular, substantially reduced the Amazon-brand shares of products ranked better than 25.

I also explore the evolution of Amazon's treatment of its products through the rank differential α. I estimate a variant of Equation (1) in which α varies by week, and Figure 5 shows the results. Roughly two months after Amazon's gatekeeper designation, Amazon's ranking of its own products, conditional on X, changed substantially: Estimated α was roughly -30 between July and the end of October 2023. It then abruptly jumped to -20, where it remained through the end of the sample period.

It is of interest to know whether this change in ranking occurred only in regions governed by the European Union. Figure 6 compares the evolution of the α coefficients in EU and non-EU countries. Both show similar patterns. Hence, whatever gives rise to the changed rankings of Amazon products is not specific to the EU. This is perhaps not surprising in light of the evolving regulatory climate in the US, including the FTC lawsuit against Amazon in September 2023. It is also possible the DMA is an example of a European regulation with extra-territorial impact (Bradford, 2020).

Figure 2 compares the distribution of brand effects before and after the gatekeeper designation in September 2023. Prior to the change, Amazon had the greatest rank differential; after the gatekeeper designation, Amazon's rank differential declined slightly, from the top to the 98^{th} percentile of the distribution.

5.4 Effect of gatekeeper designation

I estimate an explicit effect of gatekeeper designation using

$$r_{jcst} = X_{jt}\beta + \alpha\delta_j^{Amazon} + \psi\delta_j^{Amazon}\delta_t^{post} + \mu_{cst} + \epsilon_{jcst}, \tag{2}$$

where δ^{post} is an indicator that is 1 after Amazon's gatekeeper designation. Column (1) of Table 3 reports estimates: the Amazon rank differential was -31.9 (0.94) prior to the gatekeeper designation, and the differential fell by 10.6 (0.68) rank positions afterwards. This shows that the gatekeeper designation led the Amazon products in the search results to have a smaller rank differential. The second column explores whether the Amazon effect operates within product or via the set of products included. That is, I add an ASIN (Amazon standard identification number) $\times$ search term $\times$ domain fixed effect, so that the coefficient on $\delta_j^{Amazon}\delta_t^{post}$ reflects the change in rank for a particular product, search term, and domain. The resulting coefficient is 1.97 (0.44), or roughly one fifth as large as the effect of gatekeeper status on the ranks of included Amazon products. This indicates that most of the overall Amazon effect operates through the selection of products included in the search results.

Columns (3) and (4) explore impacts of Amazon's gatekeeper designation on Amazon-brand product prices relative to other products. While Amazon-brand products are less expensive, there is no detectable change in Amazon product prices relative to others, either overall (column (3)) or within product (column (4)) following the gatekeeper designation and the associated worsening of Amazon-brand products' search ranks. This is perhaps surprising, given the theoretical possibility that a changed ranking algorithm could alter pricing incentives.

Columns (5) and (6) investigate effects on the Amazon-brand rank differential in EU countries relative to the others. Column (5), which includes search term $\times$ domain $\times$ week fixed effects, shows that the Amazon rank differential changed only negligibly differently in EU countries, by 0.70 rank positions (1.31). Column (6), which also includes ASIN $\times$ search term $\times$ domain fixed effects, shows that the worsening of particular Amazon-brand products' ranks in non-EU countries (2.69, with a standard error of 0.58) is largely offset in the EU countries (-2.02, se = 0.87). If there is any EU-specific effect of the policy, it is to mitigate the within-ASIN rank changes experienced outside of the EU.

5.5 Amazon vs other brands over time

The change in Amazon's rank differential documented in Figure 5 may not be specific to Amazon; it may instead reflect general changes to Amazon's ranking algorithms, with effects on many brands. To explore this, I estimate time patterns of αs for the most frequently-appearing brands in the sample. Figure 7 reports the results. Brands differ in their α levels. For example, Ziploc averages roughly 5, while Logitech averages roughly -10. Amazon is an outlier in two senses. First, the level of its α is unusually high (in absolute value), particularly before September 2023. Second, its coefficient is unusual in that it changes substantially during the sample while the others remain roughly constant. The comparison of α_t^b across brands makes it seem very likely that Amazon changed its treatment of its own brands in search results.

In March 2024, Amazon argued that their search results "operate in an unbiased manner, using objective inputs and weighing them neutrally to facilitate the best possible customer choice irrespective of whether a product is offered by Amazon Retail or Sellers, and therefore are in compliance with Article 6(5) of the DMA." If Amazon's rankings of its own products were unbiased in March 2024 but had been more favorable to Amazon prior to September 2023, then Amazon's March 2024 description indicates that they were engaged in self-preferencing prior to their gatekeeper designation. Either way, it appears that the extent of Amazon self-preferencing changed after their gatekeeper designation.

6 Conclusion

Regulatory action around the world – and particularly in Europe – has sought to limit the extent of self-preferencing at Amazon. While it is difficult to identify whether particular brand rank differential constitutes self-preferencing, a change in Amazon's rank differential absent a change in the appeal of the products would reflect a changed extent of self-preferencing.

The search rankings of Amazon-brand products in searches at Amazon changed substantially and abruptly shortly after Amazon's gatekeeper designation, while Amazon was to come into compliance with the DMA. Hence, it appears that the DMA (along, potentially, with other regulatory actions, such as the FTC lawsuit) has affected the extent of self-preferencing at Amazon. There is a separate question of whether these changes have improved welfare, and that remains an important topic for further research.

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7 Figures and Tables

Table 1: Summary statistics

variable	average	s.d
price	570.68	3569.4
stars	4.37	0.51
# ratings	3,479.00	19616.6
% Prime	38.10	48.6
% sponsored	4.50	20.8
% Amazon	1.50	12.1

Note: The sample contains 8,211,571 search listings from weekly searches on 100 search terms at 22 Amazon domains between June 2023 and March 2024.

Table 2: Amazon rank differential

	(1) search rank	(2) search rank
Amazon-brand product	-24.343***	-24.526***
	(0.825)	(0.773)
stars	-5.387***	
	(0.166)	
# ratings	-0.000***	
	(0.000)	
sponsored	-3.369***	
	(0.377)	
Prime-eligible	-0.766***	
	(0.260)	
Observations	8211571	8211571

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Note: Regressions include search term × domain × week fixed effects. The first column includes domain-specific price coefficients. The second column includes domain-specific coefficients on all variables except the Amazon product indicator. Standard errors are clustered by search term × Amazon domain × product brand.

Table 3: Rank and price differentials and gatekeeper designation

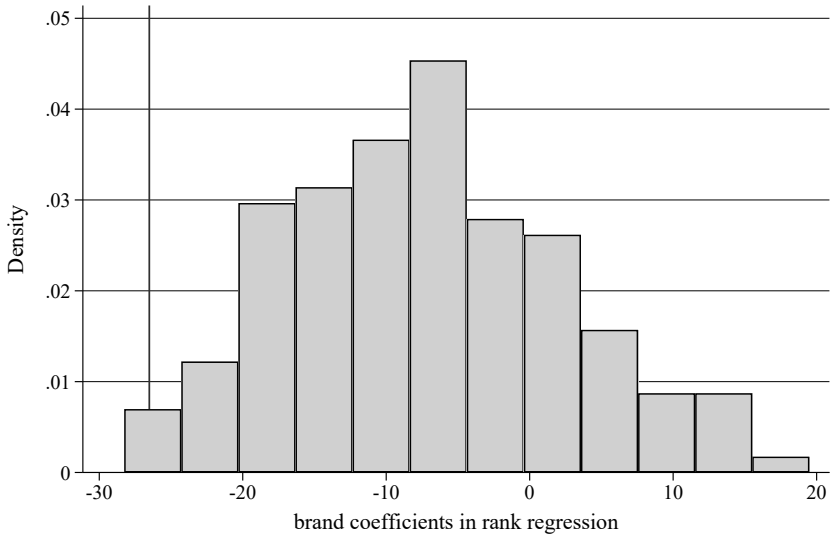
	(1) rank	(2) rank	(3) ln(price)	(4) ln(price)	(5) rank	(6) rank
Amazon-brand product	-31.932***		-0.192***		-28.962***	
	(0.935)		(0.024)		(1.265)	
Amazon-brand product × dpost	10.608***	1.972***	-0.010	0.001	10.248***	2.690***
	(0.681)	(0.439)	(0.013)	(0.003)	(0.951)	(0.575)
Amazon-brand product × dEU					-8.108***	
					(1.753)	
Amazon-brand product × dpost × dEU					0.696	-2.023**
					(1.314)	(0.867)
search term × domain × week FE	yes	yes	yes	yes	yes	yes
ASIN × search term × domain FE	no	yes	no	yes	no	yes
Observations	8211571	7654237	9866103	9091208	8211571	7654237

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

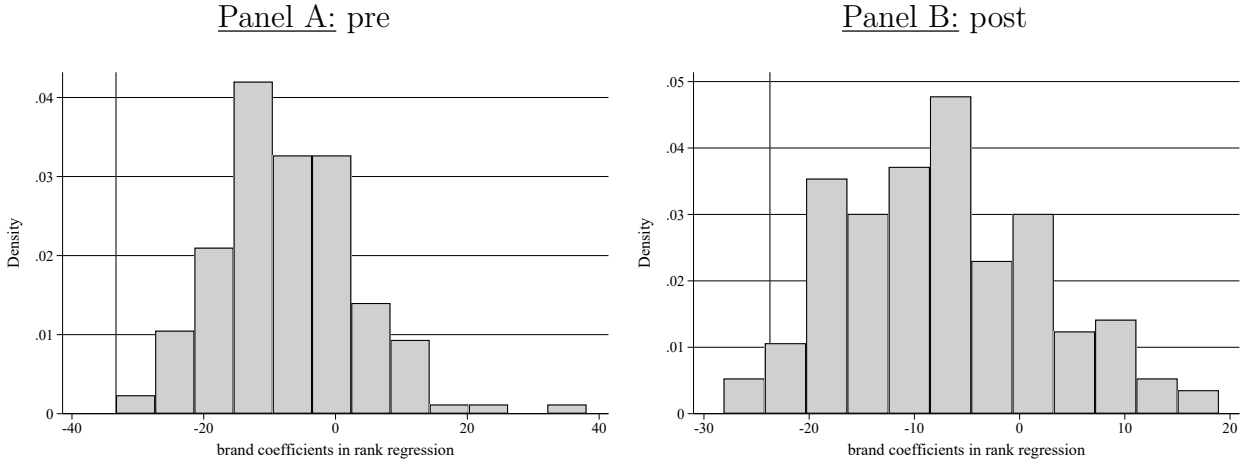
Note: Regressions include search term × domain × week fixed effects. The variable "dpost" refers to the period following gatekeeper designation. Regressions in columns (2), (4), and (6) also include ASIN × search term × domain fixed effects. The rank regressions also include domain-specific price coefficients as well as the other variables in Table 2. Standard errors are clustered by search term × Amazon domain × product brand.

Figure 1: Brand rank differential distribution



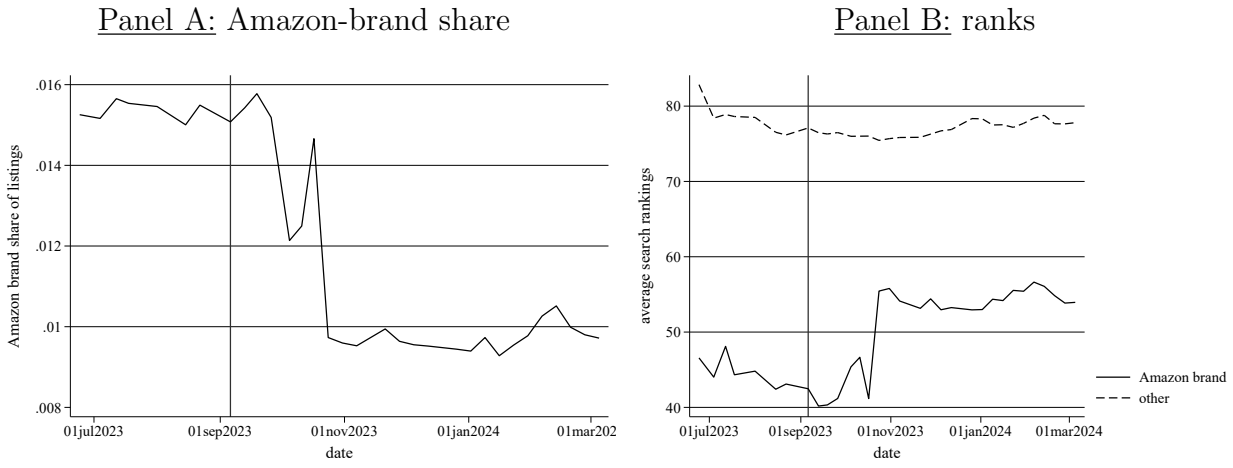
Notes: Coefficients on brand indicators in regression of search rank on product characteristics (price, # of ratings, Amazon star rating, whether Prime eligible, whether sponsored). The Amazon brand coefficient is at the vertical line.

Figure 2: Brand rank differential distribution: pre and post



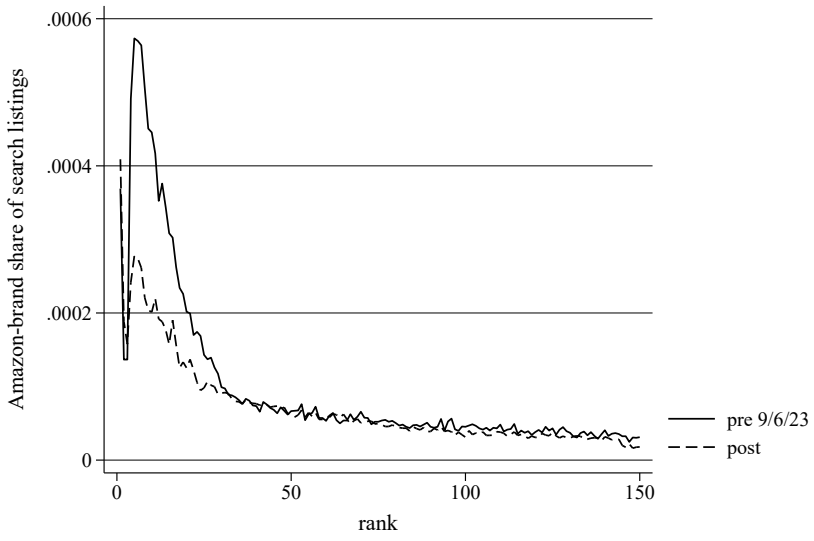
Note: As in Figure 1 except that the left panel includes data until the gatekeeper designation in September 2023, while the right panel includes the period after September 6, 2023.

Figure 3: Amazon ranks and share over time



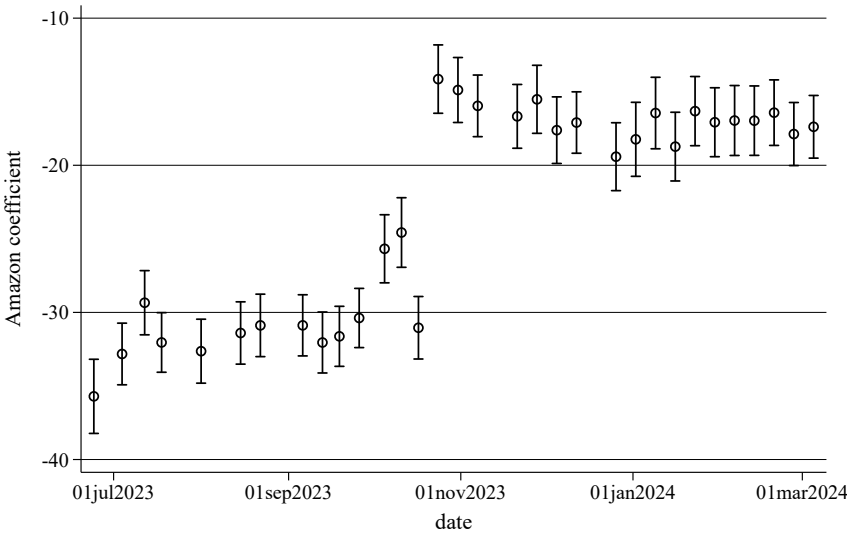
Note: The left panel shows the Amazon-brand product share of search listings. The right figure shows the average ranks, by week, for Amazon and non-Amazon-brand products. The vertical line marks Amazon's gatekeeper designation.

Figure 4: Amazon rank distribution before and after gatekeeper designation



Notes: Rank distributions for Amazon-brand products before and after Septemeber 6, 2023.

Figure 5: Amazon rank diffenential (α) over time

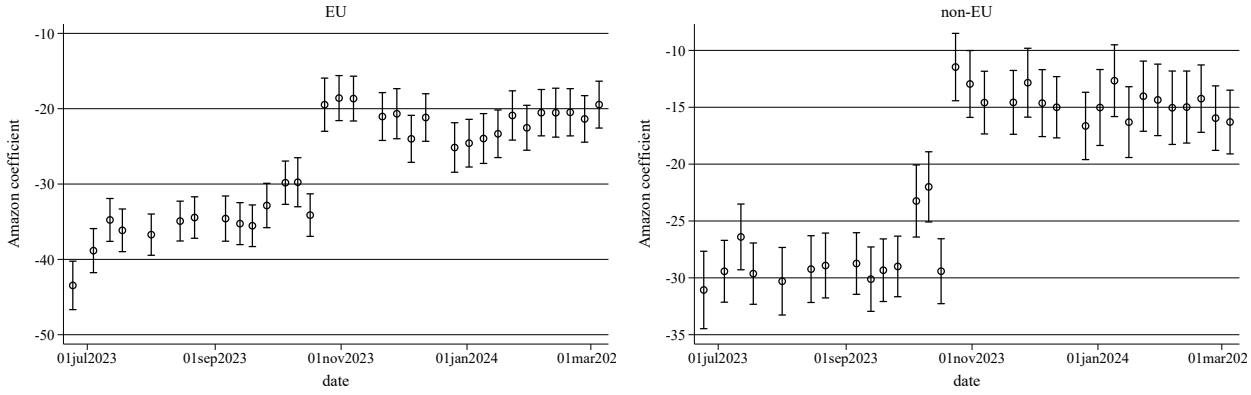


Notes: Coefficients from interaction of an Amazon product indicator and week effects in a regression of search ranks on product characteristics.

Figure 6: Amazon rank differentials (α) for EU and non-EU countries

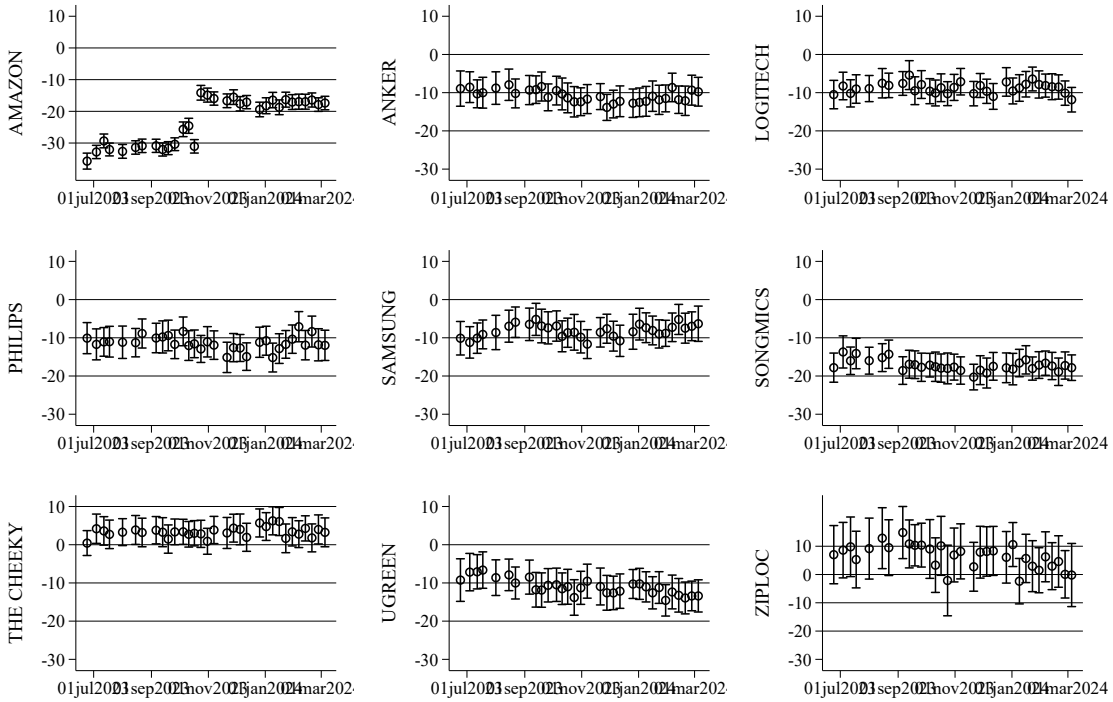
Panel A: EU

Panel B: non-EU



Note: As in Figure 5, except that the left panel includes only EU countries (AT, BE, DE, ES, FR, IT, NL, PL, and SE) while the right panel includes the remainder (US, CA, CN, JP, UK, IN, SA, and SG).

Figure 7: Rank differential for various brands over time



Notes: Each of the panels is analogous to Figure 5 but for separate brands. The Figure includes Amazon (top left) as well as the other eight most frequently-appearing brands in the sample.

A Appendix

Table A.1: Search terms

AA batteries	mens underwear
Desk	micro sd card
Office Chair	mirror
Weighted blanket	mouse pad
baby wipes	mouthwash
backpack	necklace
bath towel	nuts
bed frame	outdoor rug
bed sheets	paper towels
bluetooth speaker	patio furniture
chocolate	pillow
coconut oil	power bank
coffee	printer paper
coffee maker	protein powder
computer desk	razors for men
diapers	rice
dishwasher pods	robe
dog bed	salt
dog food	sandals for women
dresses	shelf
dumbbells	shoe rack
dutch oven	shoes
earrings	shower curtain
extension cord	sleeping bag
face mask	socks
fan	solar lights outdoor
file folders	storage bins
fish oil	summer dresses for women
gaming chair	sunglasses for women
gift card	swimsuit
hand soap	tablet
hdmi cable	tank tops for women
headphones	tea
hoodie	toaster
ibuprofen	toilet paper
immersion blender	trash bags
iphone 11 case	trash can
iphone charger	tv stand
jeans	umbrella
keyboard	usb c cable
kids clothes	vacuum cleaner
knife	vitamin d
laptop bag	watch
led light bulb	water bottle
lingerie for women	water filter
long sleeve t shirt men	wine glasses
luggage	winter coats
mattress	wireless earbuds
maxi dresses for women	wireless mouse
melatonin	yoga mat
	ziploc bags