Amazon self-preferencing in the face of heightened antitrust scrutiny*

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Abstract

Using data on over 8 million Amazon search results at 22 Amazon domains in the US, Europe, and elsewhere, I document a sharp, worldwide change in the extent of Amazon self-preferencing in October 2023, as Amazon faced heighted antitrust scrutiny in the US and Europe. The Amazon rank differential fell by more than ten rank positions, while other major brands' rank positions were unaffected. Roughly three quarters of the effect operates through Amazon's choice of products to include in the displayed search rankings (among those still on offer at Amazon); the remainder reflects changed search ranks within products.

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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 Federal Trade Commission sued Amazon in September of 2023, claiming that Amazon biases its "search results to preference Amazon's own products over ones that Amazon knows are of better quality."[3] The arrival of regulation in Europe, along with threats of regulation and litigation elsewhere, has made put pressure on gatekeeper platforms to come into compliance with rules against self-preferencing.

Yet, policy makers and researchers lack either clear definitions of self-preferencing or workable approaches to testing for its presence. Because platform-brand products may have important unobservable characteristics, an obvious testing approach – regressing search ranks on a platform dummy and product characteristics – may not provide convincing evidence of platform bias (Jürgensmeier and Skiera, 2023; Farronato et al., 2023). Despite the difficulty of measuring the *level* of self-preferencing, it feasible to measure *changes* in self-preferencing, provided that unobservable product characteristics do not change abruptly. Accordingly, this paper explores the evolution of Amazon self-preferencing in its search results over a period of

[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`.

[3]See `https://www.ftc.gov/news-events/news/press-releases/2023/09/ftc-sues-amazon-illegally-maintaining-monopoly-power`.

heightened antitrust scrutiny around the work, between mid-2023 and early 2024. Using data on over 8 million Amazon search listings in response to 100 common search queries executed weekly at 22 Amazon domains, I estimate the time-varying Amazon rank differential in three kinds of models: linear models of the ranks among the top three pages, or roughly 150, listed search results for each search term, week, and domain, linear probability models of the tendency for particular products to be included among the top 150 search listings, and censored models in which products still available at Amazon but not among the results are understood to have worse ranks than the ranked products.

I have five findings. First, the Amazon search rank differential, the Amazon product coefficient in a regression of search ranks on product characteristics, became about 10 rank positions less favorable to Amazon's products in October 2023, one month after the EU's designation of Amazon as a "gatekeeper" platform and shortly after the FTC lawsuit's filing. Second, about one quarter of the changed Amazon rank differential operated within product; the remainder reflects change in the Amazon-brand products included in the top 150 search results. Third, while Amazon stopped selling some Amazon-brand products in Fall of 2023, the withdrawal does not explain the changed Amazon rank differentials, as the models of the choice of products to feature in the search rankings include only ongoing Amazon products. Fourth, the change in the Amazon-brand product rank differential is not accompanied by changes in the rank differentials for other commonly-occurring brands, indicating that changes in the ranking algorithm are specific to Amazon house brand products. Fifth, the changed Amazon rank differential appears in the EU, the US, and elsewhere, indicating that Amazon's changed self-preferencing is not a targeted response to regulatory pressures in the US and the EU.

2 Background

2.1 Policy context

Over the past few years, regulators around the world have focused growing attention on large platforms' 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.[4] The firms had six months – until March 2024 – to come into "compliance with obligations and prohibitions."[5]

US regulators, too, have taken action to curb Amazon's power. In September 2023 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."[6] 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 algorithm 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

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

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

[6] "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.

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."[7]

In August 2023, the Wall Street Journal was reported that Amazon had eliminated "dozens of its house brands and that Amazon had "discussed offering to exit from the [private label] business as a concession to the FTC."[8] While this may itself be a response to heightened antitrust scrutiny, it is useful to distinguish possible self-preferencing among available products from effects operating through product withrawal. Hence, in modeling the products included in Amazon search results, it is important to include only products still for sale and therefore at risk for inclusion in search results. I do this in the models of which products to include in the search results and in the censored models which include both top-150 ranked products and products whose ranks I do not observed but which are still for sale and at risk of being included.

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

[7]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.

[8]See https://www.wsj.com/articles/amazon-cuts-dozens-of-house-brands-as-it-battles-costs-regulators-3f6ad56d.

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; 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. More to the point for the present exercise, 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 over 8 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).[9] Using ASIN Data API (`https://app.asindataapi.com/`), I searched each of these terms weekly at each of 22 Amazon country domains.[10] 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 directly ranked observations with valid data for all variables, I have 8,221,729 listings; and I refer to this as the "direct rankings" sample. The Amazon house-brand products in the sample are sold under many names, including Amazon Brand, Amazon Basics, Amazon Essentials, Pinzon, Solimo, Amazon Aware, Vedaka, Presto!, Umi, INKAST, Nora Nico, Amfit Nutrition, and others.

The search rankings that I observe include only a subset of the products available to be ranked. I also employ a second approach in which I treat products which are still available at Amazon, but which do not appear in a week's search results, as though they were ranked worse than the lowest-ranked search result. This requires construction of a list of products for possible inclusion for each country c and search term s in each week. One intuitive approach to constructing the risk set would be to include any product that has already appeared in a

[9]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/`.

[10]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).

result for search term s in Amazon domain c and which will appear again during the sample. Without further refinement, this approach has the shortcoming that the risk set would grow as products have had more time to have appeared in a past search ranking; and it would shrink as the end of the sample approaches. I avoid this problem with a rolling window. That is, I choose an interval of, say, k days, and include a product j in the week-t risk set if it has appeared in the last k days and will appear again in the next k days. I choose k=30 but also verify that results arise with $k = 60$ and $k = 90$.

The rolling window sample raises two complications. First, to be included in a rolling window sample, a product must appear repeatedly in the sample. Hence, the basic sample is not a proper subset of of the rolling window sample. Second, because I do not observe the at-risk products in weeks when they do not appear among the search ranks, I do not see their time-varying characteristics (ratings, whether sponsored, etc.). Hence, I estimate models of inclusion in the ranks without the time-varying product characteristics.

Table 1 describes the samples. The direct rankings sample has 8.7 million observations with valid data on all variables. The average listing has 4.37 Amazon stars and 3,404 user ratings. Just over a third of the listed products are eligible for Amazon Prime, and 4.36 percent of the listings are sponsored. Just 1.47 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. The 30-day-window sample includes 12.1 million observations of products at risk of inclusion in a search in a week. Of those, 56.73 percent are included in the search rankings.

The raw ranks – and search inclusion probabilities – for Amazon and non-Amazon products over time provides a preview of the major findings. During the initial sample period, Amazon products have an average rank of roughly 40. During October of 2023, the average rank of Amazon-brand products rises to nearly 50 and remains there for the remainder of the sample period. Non-Amazon products have an average rank of 70, and this is stable throughout the sample period. The propensity for search listings to include Amazon products provides a further preview. Using the 30-day-window sample, nearly 55 percent of currently-available Amazon products are included in the search results, while roughly 57 percent of the non-Amazon products appear in the search results each week. The non-Amazon share is steady throughout the sample period, while the Amazon share falls in October, to roughly 45 percent.

Figure A.1 shows that the ranking of Amazon products changed in October, and the change operates through two possible mechanisms: ranks of particular products may change; and different products may appear in the top-150 results.

4 Empirical strategy

I am interested in documenting the change in the Amazon rank differential over time as antitrust enforcement from various authorities around the world are giving Amazon greater scrutiny for self-preferencing. I do so in a way that allows for both changes in ranks and changes in the tendency for products to appear in the top-150 search results.

First, I am interested in the evolution of the Amazon search rank differential conditional on product characteristics – and among observed (top-150) listings – which I explore via the following regression:

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

where X_{jt} includes product characteristics (the price, the average rating, the number of ratings, whether the product is sponsored and whether it is eligible for Amazon Prime), δ_j^{Amazon} is an indicator for an Amazon-brand product, and μ_{cst} is a fixed effect for the search (a search is defined by a search term s in a domain c during a week t). The coefficients α_t show the evolution of the Amazon search rank differential, conditional on characteristics. These coefficients are affected by both any possible within-product change in ranking as well as any changed tendency for Amazon to include products among those that are ranked.

I isolate possible within-product changes in rankings by adding a fixed effect for the product j in the search term s and the domain c, or via:

$$r_{jcst} = X_{jt}\beta^{'} + \alpha^{'}_t \delta^{Amazon}_j + \mu^{'}_{jcs} + \mu^{'}_{cst} + \epsilon^{'}_{jcst}, \tag{2}$$

where $\mu^{'}_{jcs}$ is a $j \times c \times s$ fixed effect. Here, the evolution of $\alpha^{'}_t$ reflects the change in the ranking of product j when included in a search on term s in domain c. Both equations (1) and (2) are estimated on the data included in the ranks (where the ranks are observed).

Second, I explore the tendency for Amazon to include products in the ranking. Define δ^{r}_{jcst} as an indicator that equals 1 if product j is included among the ranked products for a search on s in c during week t. Because I directly observe the time-varying product characteristics only during weeks when they are included in the search results, I exclude these variable from these regressions. I estimate this model two ways: including a search ($c \times s \times t$) fixed effect and also including a product ($j \times c \times s$) fixed effect.

Third, I measure composite (rank and inclusion) effects by estimating censored regression models of the search ranks in which I assume that a product at risk of inclusion but not included this week has a search rank worse than the worst observed rank for that search, domain, and week. As with the inclusion regressions, I cannot include time-varying product characteristics. Moreover, I do not include the fixed effects μ_{jcs} nor μ_{cst} in the equations. These specifications show the evolution of the overall rank. I compare the resulting time patterns of α coefficients with rank regressions that also lack time-varying product characteristics and fixed effects.

Finally, I estimate variants of the models above separately for other commonly-appearing brands. That is, I estimate separate sets of α_t^b not only for Amazon-brand products but also for other brands b. This indicates whether the changes in the search ranks observed for Amazon products are specific to Amazon or part of a more general change in ranking algorithms.

5 Results

I present regression results in five parts. Section 5.1 presents the evolution of the Amazon search rank differential, among products included in the search rank, with and without product fixed effects. Section 5.2 documents the evolution of the inclusion differential for Amazon-brand products in the search results, among the products still for sale at Amazon and therefore at risk of inclusion. Third, Section 5.3 shows how the Amazon rank differential evolves in censored models treating the unranked but at risk products as if their ranks were worse than the ranked products. Section 5.4 compares the evolution of the Amazon brand rank differential with other commonly-occurring brands. Finally, Section 5.5 presents some discussion of Amazon's statement of compliance with the EU's DMA, along with evidence about how the effects I document operate around the world.

5.1 Amazon rank differential among search results

I begin by exploring the evolution of the Amazon rank differential α_t based on an estimate of Equation (1), which includes product characteristics and search (i.e. $s \times c \times t$) but not product fixed effects.[11] The left panel of Figure 1 shows α_t coefficients describing the evolution of the Amazon search rank differential. After averaging roughly -30, the rank differential moves

[11]The correlates of product search rank levels, while not the focus of this study, are "sensible": Products with lower prices, better ratings, or more ratings receive better search results, as do sponsored listings and Prime-eligible products.

substantially, to -20 or by roughly ten positions, in October, 2023.

Although these negative Amazon search rank differentials are consistent with Amazon self-preferencing, they are also consistent with the presence of unobservable product characteristics. I do not interpret the levels of these coefficients as evidence of Amazon self-preferencing. Rather, I interpret the changes in these coefficients as changes in self-preferencing.

The right panel of Figure 1 reports analogous estimates of the $\alpha_t^{'}$ from a model that adds the product fixed effect (specifically, μ_{jcs}), normalized to zero on October 17, 2023. The within-product component of the change in the Amazon rank differential is roughly a quarter of the overall change in α_t in the left panel of Figure 1. The two figures differ because some part of the change in the Amazon search differential stems from ranking the same products differently (when included in a search in a domain). The remainder stems from changed inclusion of products and in particular the removal of products with particularly large Amazon rank differentials.

5.2 Amazon product inclusion in search results

Next, I explore the evolution of an Amazon differential in the tendency for products to be included among the top 150 search listings. Using the 30-day window sample, I regress the indicator δ_{jcst}^{r} for whether a product is included among search results on the Amazon product indicator and various fixed effects. The left panel of Figure 2 reports the Amazon inclusion differential from a specification including a search fixed effect, and the right panel of Figure 2 reports the differential from a model that also includes the product fixed effect. I normalize coefficients to zero on October 17, 2023. As Figure 2 shows, the tendency for Amazon-brand products to be included in the search results falls distinctly during October of 2023 by roughly 8 percentage points, or by more than a tenth.

It is worth noting that a change in the probability of including Amazon products in the search results cannot alone explain a change in the rank differential. Removing Amazon-brand products from the search results at random does not change the search rank differential identified above in Section 5.1. The distributions Amazon product rank is similar before vs after the gatekeeper designation for ranks worse than about 30. At better ranks, the number of Amazon products falls by about half. See Figure A.2.

5.3 Rank effects from censored models

My data include the first three pages of search results and therefore about 150 listings per search. Products that Amazon continues to sell, but which do not appear in a search result for a particular week, are therefore ranked below the lowest-ranked product that I observe for that search. I use this insight to estimating a censored model of the rank using the 30-day-window sample, which includes no time-varying product characteristics. For comparison I also estimate the same specification using OLS on the observed ranks. Both specifications show a substantial worsening in Amazon products ranks, which is roughly 10 rank positions in the OLS model and larger – roughly 20 – in the censored model. Figure A.3 compares the coefficient patterns.

5.4 Amazon vs other major brands

The change in Amazon's rank differential documented in various ways above 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 the α_t coefficients for the most frequently-appearing brands in the sample. First, I estimate models of the rank including a search ($s \times c \times t$), not a product ($\jmath \times s \times c$), fixed effect. Second, I report the analogous inclusion regression (with δ^r_{jcst} as the dependent variable). Figure 3 reports the results. Brands differ in their rank differentials. 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. The right panel of Figure 3 reports the evolution of brand differentials in inclusion. Again, the Amazon coefficient has a sharp change, while the others do not.

5.5 Discussion

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.

Figure 4 reports the results of three separate regressions analogous to the right panel of Figure 1 for the EU countries, the US, and remaining countries. The same time pattern of Amazon rank differentials appears in all three areas. While Amazon's changed rankings may be a response to pressure from antitrust regulators, the changes are not specific to the European Union.

6 Conclusion

Regulatory action around the world has sought to limit the extent of self-preferencing at Amazon. While it is difficult to identify whether a particular brand rank differential constitutes self-preferencing, a change in Amazon's rank differential absent a change in the appeal of the products reflects *changed* self-preferencing. And in a period when antitrust scrutiny was growing, Amazon's self-preferencing changed substantially. Both in raw data and conditional on rudimentary product characteristics, the Amazon rank differential become more than 10 rank positions less favorable to Amazon's own products. About a quarter of this change is within product, while the remainder reflects Amazon's changed tendency to include its own still-available products among the top 150 products in the ranking. While the rank differential for Amazon products changed, the analogous rank differential for other commonly-appearing brands was stable. Finally, the change in the extent of Amazon's self-preferencing appears not only in the EU and the US but also in other regions. There is a separate question of whether these changes have improved welfare. The approach in this paper does not speak to whether the Amazon rank differentials either before or after the change were appropriate. It is possible, for example, that the appeal of Amazon's products to its consumers warranted the initial search rank differential and that the changes have made consumers worse off. Measuring the welfare effects of self-preferencing – and changes in self-preferencing – remains an important topic for further research.

References

Aguiar, L., J. Waldfogel, and S. Waldfogel (2021): "Playlisting favorites: Measuring platform bias in the music industry," *International Journal of Industrial Organization*, 78, 102765.

Bourreau, M. and G. Gaudin (2022): "Streaming platform and strategic recommendation bias," *Journal of Economics & Management Strategy*, 31, 25–47.

Chen, N. and H.-T. Tsai (2019): "Steering via algorithmic recommendations," *Available at SSRN 3500407.*

Compiani, G., G. Lewis, S. Peng, and W. Wang (2021): "Online search and product rankings: A double index approach," *Available at SSRN 3898134.*

Dubé, J.-P. (2022): "Amazon Private Brands: Self-Preferencing vs Traditional Retailing," *Available at SSRN 4205988.*

Farronato, C., A. Fradkin, and A. MacKay (2023): "Self-preferencing at Amazon: evidence from search rankings," Tech. rep., National Bureau of Economic Research.

Gutierrez, G. (2021): "The welfare consequences of regulating Amazon," Tech. rep., mimeo, New York University.

Hagiu, A., T.-H. Teh, and J. Wright (2022): "Should platforms be allowed to sell on their own marketplaces?" *The RAND Journal of Economics*, 53, 297–327.

Jürgensmeier, L. and B. Skiera (2023): "Measuring Fair Competition on Digital Platforms," *arXiv preprint arXiv:2303.14947.*

Lam, H. T. (2021): "Platform search design and market power," *Job Market Paper, Northwestern University.*

Lee, K. H. and L. Musolff (2021): "Entry into two-sided markets shaped by platform-guided search," *Job Market Paper, Princeton University.*

Raval, D. (2022): "Steering in One Click: Platform Self-Preferencing in the Amazon Buy Box," *Unpublished manuscript.*

Reimers, I. and J. Waldfogel (2023): "A Framework for Detection, Measurement, and Welfare Analysis of Platform Bias," Tech. rep., National Bureau of Economic Research.

Ursu, R. M. (2018): "The power of rankings: Quantifying the effect of rankings on online consumer search and purchase decisions," *Marketing Science*, 37, 530–552.

7 Figures and Tables

Table 1: Summary statistics

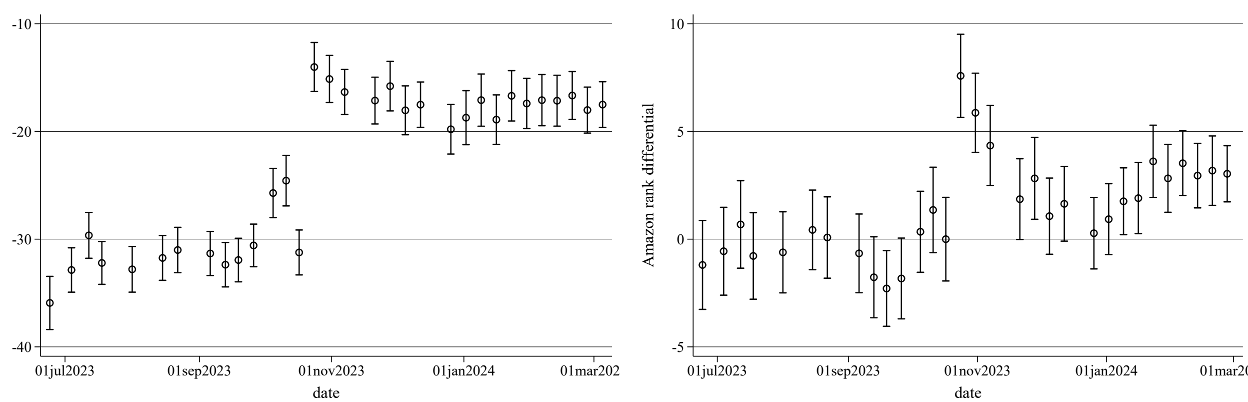
	ranked		30-day-window	
	N	mean	N	mean
% ranked			12,136,683	56.73%
rank	8,716,505	74.06	6,884,613	68.68
price	8,716,505	612.22		
stars	8,716,505	4.37		
# ratings	8,716,505	3404.13		
% Prime-eligible	8,716,505	36.95%		
sponsored	8,716,505	4.36%		
Amazon-brand product	8,716,505	1.47%	12,136,683	1.59%

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. Prices are in cents.

Figure 1: Amazon ranks differential over time

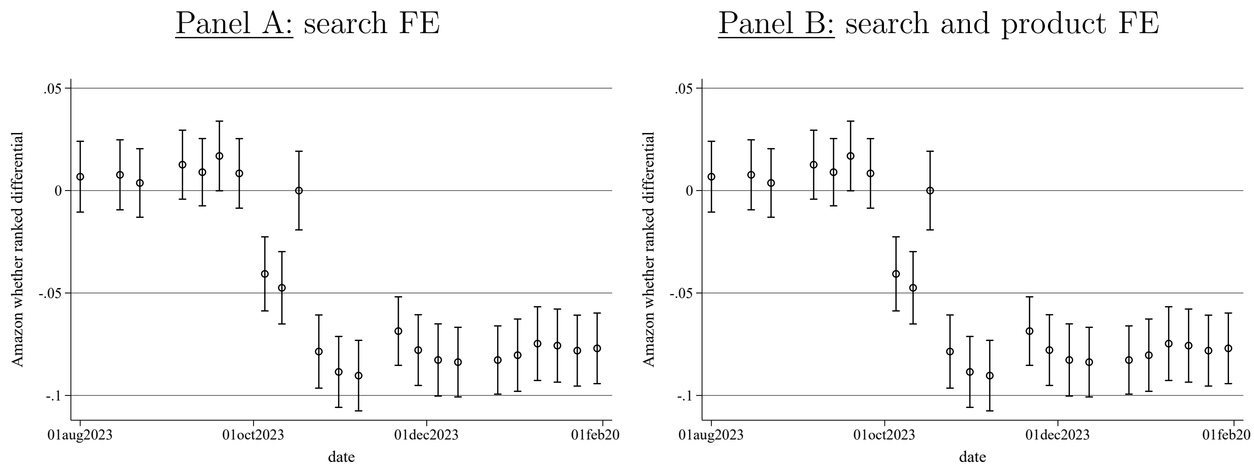
Panel A: search FE

Panel B: search and product FE



Note: Figures show the Amazon rank differential, the coefficient on the Amazon-brand product indicator (α_t) from a regression of search ranks on product characteristics, fixed effects, and the Amazon indicator. The left panel shows α_t from a regression with product characteristics (X_{jt}) and search ($s \times c \times t$) FE. The right panel's regression adds product ($\jmath \times c \times s$) FE.

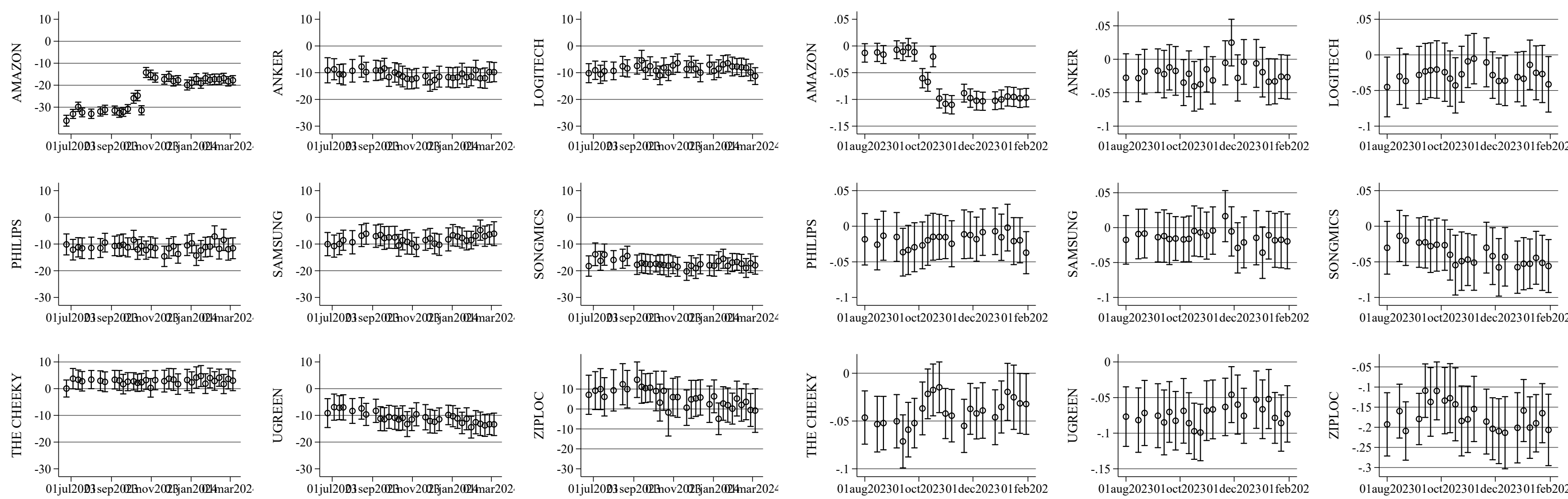
Figure 2: Amazon inclusion differential over time



Note: Figures show the Amazon inclusion differential, the coefficient on the Amazon-brand product indicator (α_t) from a regression of an indicator for inclusion in the search results on fixed effects, and the Amazon indicator. The left panel shows the Amazon-brand inclusion differential from a regression with search ($s \times c \times t$) FE. The right panel's regression adds product ($\jmath \times c \times s$) FE. Both figures use the 30-day-window sample.

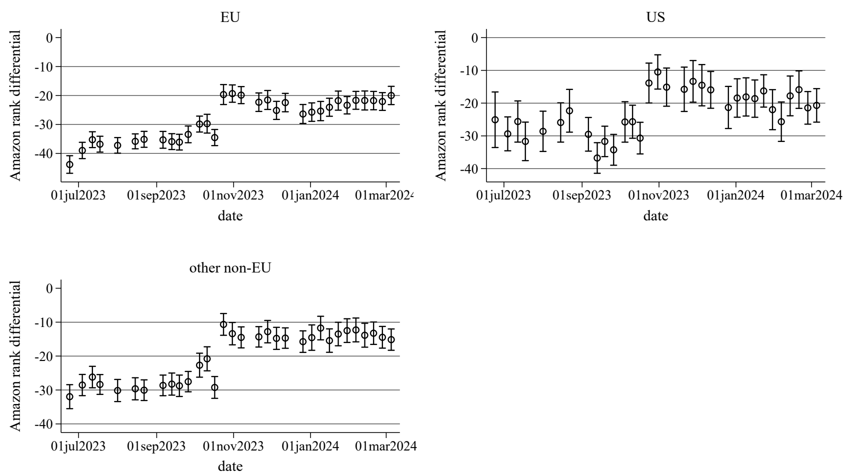
Figure 3: Amazon vs other brands

Panel A: ranks Panel B: inclusion



Note: Figures show the Amazon inclusion differential, the coefficient on the Amazon-brand product indicator (α_t) from a regression of an indicator for inclusion in the search results on fixed effects, and the Amazon indicator. The left panel shows the Amazon-brand inclusion differential from a regression with search ($s \times c \times t$) FE. The right panel's regression adds product ($\jmath \times c \times s$) FE. Both figures use the 30-day-window sample.

Figure 4: Amazon rank differentials (α) for EU and non-EU countries



Notes: Amazon rank differentials from regressions with product characteristics and search ($s \times c \times t$) fixed effects. Separate regressions for EU countries, the US, and the remaining non-EU countries.

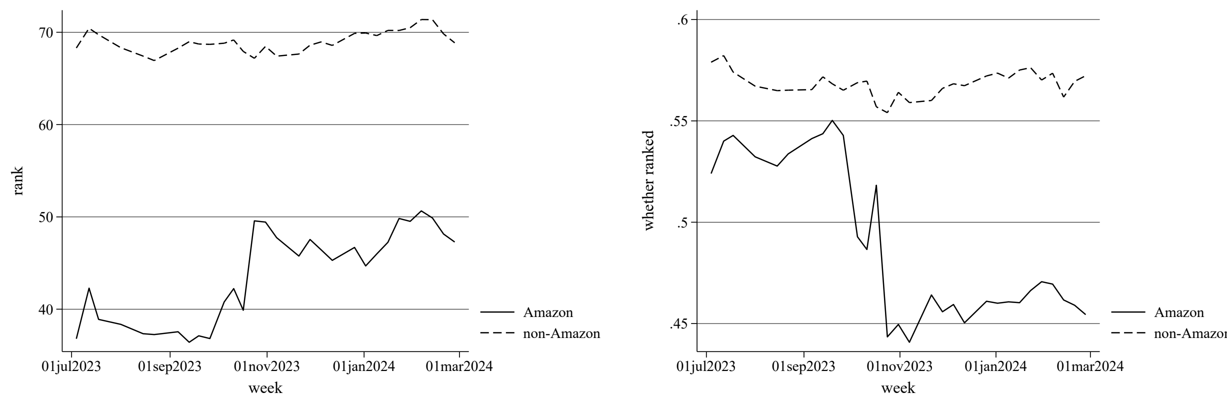
A Online Appendix

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

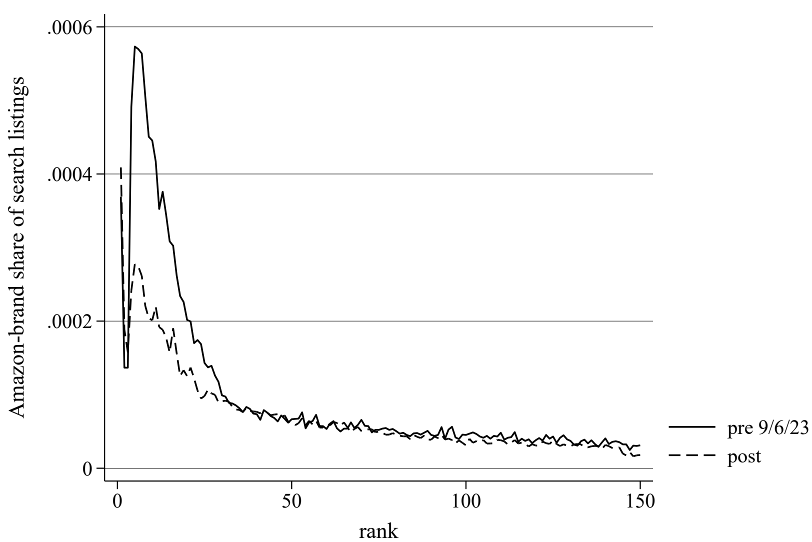
Figure A.1: Ranks, and ranking inclusion, for Amazon and other products

Panel A: ranks   inclusion



Note: The left figure shows the average search ranks for Amazon and non-Amazon products. The right figure shows the share of available Amazon and non-Amazon products appearing in the search results each week. A product is available in a week if the product will appear in Amazon search results again within the next 30 days. The figures are weekly searches on 100 terms in each of 22 Amazon domains.

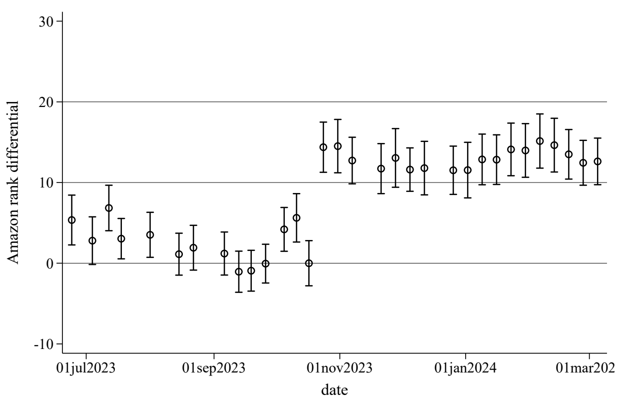
Figure A.2: Amazon rank distribution before and after gatekeeper designation



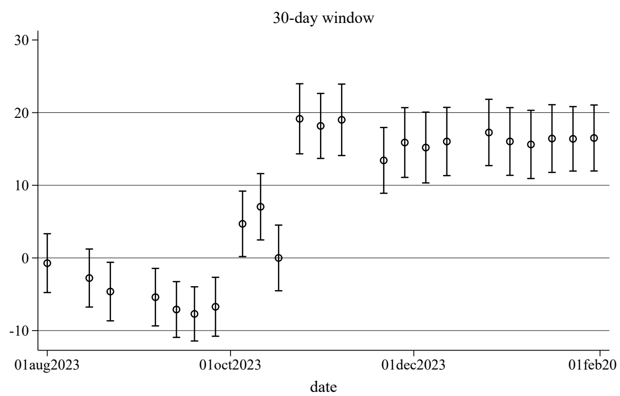
Notes: Rank distributions for Amazon-brand products before and after Septemeber 6, 2023.

Figure A.3: Amazon rank differential: OLS vs interval regression

Panel A: OLS



Panel B: interval regression



Note: Figures show the Amazon rank differential from OLS and interval regression models without fixed effects nor time-varying observables. The left panel includes only observations with ranks; the right panel uses the 30-day-window sample.