# Platform Recommendation Algorithms, Niche Market Entry, and Quality Competition


Gaoyang Cai
Kellogg School of Management
Northwestern University
gaoyang.cai@kellogg.northwestern.edu

Xia Han
School of Management
University of Science and Technology of China
xhan0930@ustc.edu.cn

Grace Gu
***(Presenting author for the PlatStrat2025 Conference)***
Marshall School of Business
University of Southern California
gracegu@marshall.usc.edu

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## Abstract

As e-commerce platforms increasingly rely on recommendation algorithms to help consumers navigate a vast selection of products, regulation is often required to ensure fairness in algorithm recommendation and market competition. However, changes in recommendation algorithms aimed at improving market fairness and consumer welfare may also have unintended consequences on product variety and quality. We examine Amazon's binding commitment to comply with the U.K. Competition and Markets Authority's (CMA's) regulation, which prohibits Amazon from using Prime eligibility as a criterion for recommending the Featured Offer within a product market and its impacts on market outcomes. We find that, after the CMA's regulation, Amazon UK reduced the percentage of Prime-eligible offers in the default featured offers compared to before. Such an algorithmic change increases product clicks. However, the product markets' offer diversities declined, combined with worsened ancillary service qualities from the featured offers, leading to reduced consumer purchases and lower average product ratings. Mechanism analysis at the seller level reveals that the decline in product offer diversity is potentially due to sellers diverging in their responses to the algorithm change, with some concentrating their product portfolio more on core product markets and others shifting to long-tail product markets. Our findings provide implications for platform governance and optimizing regulatory policies to promote fair competition and enhance consumer welfare.



**Keywords:** recommendation algorithm, two-sided markets, niche market entry, platform regulation, cross-product-market competition

## Introduction

Given the wide availability of products and services online, consumers often incur substantial search costs in identifying suitable options and tend to operate within limited consideration sets (Chen and Yao 2017, Kim, Albuquerque, and Bronnenberg 2017, Donna, Pereira, Pires, and Trindade 2022, Greminger 2022, Donnelly, Kanodia, and Morozov 2023, Moraga-Gonzlez, Sndor, and Wildenbeest 2023a, 2023b, Greminger 2024). E-commerce platforms shape consumers' consideration, search, and purchase decisions by designing recommendation and ranking algorithms, which change the search costs of products or services (Kim, Albuquerque, and Bronnenberg 2010, Ursu 2018), and provide information on product qualities (Compiani, Lewis, Peng, and Wang 2024, Fong, Natan, and Pantle 2024).

However, an intermediary or platform business may have biased incentives in the recommendation, favoring first-party products and offers (Farronato, Fradkin, and MacKay 2023, Lam 2023, Lee and Musolff 2023, Reimers and Waldfogel 2023, Long and Amaldoss 2024) when they are competing with the third-party complementors (Foerderer, Kude, Mithas, and Heinzl 2018, Zhu and Liu 2018, Zhu 2019) or favoring third-party sellers who use the in-house fulfillment services of the intermediary (Scott Morton, Crawford, Crmer, Dinielli, Fletcher, Heidhues, Schnitzer, and Seim 2021, Gutirrez 2022, Raval 2022) at the expense of both consumer welfare and seller profits. Furthermore, sellers have incentives to compete for recommendations and enter the product market with better chances of being recommended (Armstrong and Zhou 2011, Athey and Ellison 2011, Castellini, Fletcher, Ormosi, and Savani 2023, Zhou and Zou 2023). Biases in recommendation algorithm may distort sellers' pricing and product quality enhancement strategies, as well as affect their entry and exit strategies across product markets (Armstrong, Vickers, and Zhou 2009, Dinerstein, Einav, Levin, and Sundaresan 2018, Teng 2022, Lee and Musolff 2023).

Given the central role of recommendation algorithms in shaping market dynamics, digital platforms act as gatekeepers with substantial control over consumer search and purchase, transaction outcomes, and the distribution of economic surplus. This raises important questions regarding regulating platform recommendation algorithms to mitigate recommendation bias, promote competitive fairness, and enhance social welfare. Regulatory responses have begun to materialize across different jurisdictions. For instance, on December 31, 2021, the Cybersecurity Administration of China (CAC) enacted the *Internet Information Service Algorithm Recommendation Management Regulations*. These regulations require algorithm operators to update their technologies to comply with specific auditing criteria, provide users access to and control over their data profiles, and prohibit anti-competitive practices, such as algorithm-based price discrimination.[1] In 2022, U.S. lawmakers updated the *Algorithmic Accountability Act*, aiming to mandate that companies evaluate the impacts of automated decision systems they develop and utilize, increase transparency, and empower consumers to make informed choices about the automation of critical decisions.[2] In 2023, U.S. lawmakers reintroduced the *Algorithmic Justice and Online Platform Transparency Act* to prohibit discriminatory uses of personal information in algorithmic processes and bolster transparency in algorithmic decision-making and content moderation.[3]

This paper investigates the impact of a regulatory policy change that imposes exogenous restrictions on the Amazon U.K. Store's recommendation algorithm to "guarantee all product offers[4] are treated equally when Amazon decides which will be featured in the 'Buy Box.'" The

[1] https://www.cac.gov.cn/2022-01/04/c_1642894606364259.htm
[2] https://www.wyden.senate.gov/imo/media/doc/Algorithmic%20Accountability%20Act%20of%202022%20Bill%20Text.pdf
[3] https://matsui.house.gov/sites/evo-subsites/matsui.house.gov/files/evo-media-document/matsui_030_xml.pdf
[4] On Amazon, a product *offer* refers to a purchase option provided by a seller within a given product market. A product is typically associated with multiple purchase offers offered by different sellers, with each seller providing a unique offer for a specific product; and a seller may offer different purchase options across different products. We treat each product as a *product market* because a product often attracts multiple sellers (i.e., multiple players), and the competing sellers within that product form the strategic players in the market. A *market niche*, defined officially by Amazon, is a collection of customer search terms and associated products that reflect a specific shopping need. Customers implicitly convey their underlying demand when they enter search queries on Amazon. Amazon organizes these queries by clustering search terms with similar purchase intent, forming distinct niches. Each niche includes

U.K. Competition and Markets Authority (CMA) has implemented explicit and verifiable restrictions on how Amazon selects which product offer to place in the 'Buy Box,' i.e., the Featured Offer within each product market. In particular, the regulatory policy forbids Amazon from using Prime eligibility or Prime labeling as relevant criteria for selecting the Featured Offer. The policy has been implemented across the entire Amazon U.K. Store since May 3rd, 2024, independent of both the buyer and seller strategies on the platform and the competitive landscape of product markets.

We collect comprehensive data on both the Amazon U.K. and Amazon U.S. Stores before and after the policy intervention at the aggregated consumer, seller, within-product market (offer), and cross-product market levels in major market niches defined officially by Amazon. By adopting a difference-in-differences (DID) approach, we analyze the average treatment effects of the platform recommendation algorithm change. We find that, on average, the recommendation algorithm change increases the consumer total clicks for a product market. Meanwhile, it decreases product sales and ratings at intensive margins and decreases offer varieties within a product market at extensive margins. Zooming in on product heterogeneities, we find that the number of offers decreases more in core product markets with high ratings, more clicks, and/or more sales. At the same time, such numbers increase in the remaining periphery product markets, reflecting heterogeneous treatment effects of the recommendation algorithm change across product markets.

Further analyzing the driving mechanisms of the product-level average treatment effects, we find that, at the seller level, the algorithm change incentivizes sellers to cut offer prices to

the top products that have received the majority of clicks and purchases in response to the associated search terms. In our dataset, a niche market consists of multiple related product markets, each supplied by various sellers offering different purchase options (i.e., offers). Our sample can be constructed from multiple perspectives, allowing for flexible aggregation at the level of niches, products, sellers, or individual offers. Our data structure supports cross-product and within-product analyses, depending on the research focus.

compete for recommendations, intensifying the competition within product markets. However, heterogeneous sellers employ divergent competition strategies; sellers with worse offer ranking positions before the recommendation policy change are more likely to exit core product markets and enter periphery product markets to diversify their offer portfolios, resulting in reduced offer varieties within the core product markets. By adopting such a product-market diversification strategy, those sellers mainly compete through offer price reduction for consumer reach at the expense of offer qualities in terms of the speed of delivery and restocking. On the other hand, sellers with better offer ranking positions before the policy change adopt a nearly converse strategy; they are more likely to remain in the core product markets while exiting the periphery markets. These sellers mainly compete for recommendations by enhancing offer quality and consolidating their competitive advantages in the core product markets.

Our research contributes to the growing literature studying regulations on platform recommendation or ranking algorithms that constrain platform monopoly power in designing algorithms and regulating platform self-preferencing (Gutierrez Gallardo 2022, Chen and Tsai 2024, Long and Amaldoss 2024, Waldfogel 2024) to promote competition fairness, and enhance consumer welfare (Witt 2022, Waldfogel 2024, Turcios 2025). We enrich this strand of the literature by studying how the platform recommendation algorithm affects market outcomes and differentiating the “competition for the market” from the “competition within the market.” By leveraging the Competition and Markets Authority’s (CMA) regulatory policy change that imposes exogenous shocks on the Amazon U.K. Store’s recommendation algorithms, we can separate the direct impact of the regulatory policy on the platform recommendation algorithm from the causal impact of the recommendation algorithm on the seller’s strategic responses and market outcomes, immune to the endogenous responses of platform recommendation algorithm to the unobserved market conditions. Furthermore, our research provides unique insights into the regulatory policy design by analyzing the platform recommendation algorithm change and the consequences on the market equilibrium.

Our findings provide meaningful managerial and regulatory implications. Regulation on platform algorithmic recommendations needs to assess the overall impact of platform recommendation algorithm changes (platform level) on seller competition (supply side) and consumer satisfaction (demand side). While restricting the platform's potential self-preferencing over its Prime services and Prime-eligible offers, it may be necessary to provide substitutable options that enable sellers with delivery and inventory management services of comparable quality to maintain consumer satisfaction as well as sellers' competitive advantages. In addition, from a platform design perspective, algorithmic regulations may cause the platform to shift away from recommending based on hidden product qualities (such as product durability, product return and complaint rates, supplier qualities, the reliability of delivery services, and the quality of after-sales services, etc.) to recommending based on publicly verifiable measures, such as prices, ratings, delivery time, and the change in offer stocks, etc. Although the algorithm that depends more explicitly on publicly verifiable metrics is more transparent and predictable, it also risks starkly incentivizing sellers to focus on only the narrow attributes emphasized by the recommendation algorithm and enter the product markets that have the most to gain from this strategic shift. Regulatory policies on recommendation algorithms that fail to take the platform and seller responses into account bear the risk of sellers racing to the bottom or strategically diversifying their product portfolios to game the recommendation system, which eventually distorts competition and decreases search efficiencies and consumer satisfaction.

## Research Context and Data Collection

**Research context.** In July 2022, the U.K. Competition and Markets Authority (CMA) opened an investigation into Amazon's U.K. business due to concerns that the company was abusing its strong market position by giving an unfair advantage to its own retail business and sellers who use its in-house fulfillment services over other third-party merchants on its marketplace. In response to the CMA's investigation, a policy imposed by CMA went into effect on May 3rd, 2024[5], with Amazon U.K. store making the following binding commitments:[6] 1) Ensure that Amazon does not use rival sellers' marketplace data to gain an unfair advantage over other sellers. 2) Guarantee that all product offers are treated equally when Amazon chooses the "Featured Offer." 3) Allow third-party businesses to negotiate their rates directly with independent providers on Prime delivery services so that customers can benefit from lower delivery costs. 4) Appoint an independent trustee to monitor the company's compliance with these commitments.[7] As a result, sellers whose product offers are not Prime eligible and sellers who do not use the Amazon fulfillment service should be able to compete for the Buy Box on an equal footing with FBA (Fulfilled by Amazon) and Prime-eligible sellers.[8]

We use the policy implementation as a natural experiment and set the 40 days before May 3rd, 2024, as the pre-treatment stage, when the platform still conditions recommendations on offers' Prime eligibility, and the 40 days after May 3rd, 2024, as the post-treatment stage. Throughout the two stages, we track the platform recommendation, product, seller, and aggregated consumer level data on both the Amazon U.K. and Amazon U.S. stores across major niche markets to identify the Amazon algorithm changes in response to the regulation policy and the treatment effects of the recommendation algorithm changes. We treat the Amazon U.K. Store as the treatment marketplace and the Amazon U.S. Store as the control marketplace, and we conduct our main analyses at a daily level.

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[5] https://sellercentral-europe.amazon.com/seller-forums/discussions/t/674418af-3917-4c07-bc31-2eb4f1fbc601.

[6] See: https://assets.publishing.service.gov.uk/media/6544cbaed36c91000d935d20/Non-confidential_decision_pdfa_4.pdf. and https://www.gov.uk/cma-cases/investigation-into-amazons-marketplace

[7] On February 5th, 2024, the CMA approved the appointment of Alcis Advisers by Amazon as Monitoring Trustee to monitor compliance with the binding commitments.

[8] https://channelx.world/2024/01/amazon-featured-offer-buy-box-eligibility-from-may-2024/

**Data collection.** Our data includes all market niches with a total number of consumer searches in the past 360 days greater than 10 million in the Amazon U.S. and greater than 2 million in the Amazon U.K., to ensure relevance of the data. This covers 80 market niches on both the U.K. and the U.S. Amazon marketplaces.[9] Then, we obtain the most clicked products within each niche market, which cover over 90% of total consumer clicks within the niche market using the official data source Amazon provides to third-party sellers.[10] To ensure comparability between the Amazon U.K. and Amazon U.S. marketplaces, we match the niche markets from each marketplace according to their names, products, and functionalities. This process yields matched niche markets comprising 74 from the Amazon U.K. marketplace and 78 from the Amazon U.S. marketplace. Secondly, we collect high-frequency, large-scale Amazon products, within-product offers, and seller-level data using an API for reliability and scalability.[11] In particular, we collect within-product offer rankings (including the offer that wins the Buy Box as shown in Figure A1 in the Online Appendix) as well as seller, product, and offer attributes data from Amazon.co.uk (U.K. stores) and Amazon.com (U.S. stores). Thirdly, we complement the API data with the historical data on product and offer attributes, product sales ranks, seller characteristics, and within-product offer stock changes from Keepa.[12]

## Identification, Variables, and Empirical Models

**Empirical design.** We adopt a difference-in-differences (DID) approach to identify the average treatment effects of the recommendation algorithm change. We leverage the exogenous changes in recommendation algorithms in Amazon U.K. as a natural experiment, with Amazon

[9] According to the United States Census Bureau, the total population of U.S. and U.K. by the year 2025 is 342.0 million and 68.8 million, respectively. See, https://www.census.gov/popclock/world/uk. We select a threshold number of consumer searches in each marketplace for niche market selection based on the population ratio of the U.S. and U.K.
[10] We obtain the Amazon official data on detailed niche markets categorization, major product markets within each niche market and the associated product click share and sales rank data in both the Amazon U.S. and U.K. marketplaces from the Amazon seller account we have opened.
[11] https://app.rainforestapi.com/
[12] https://keepa.com/#!

U.K. as the treatment market and Amazon U.S. marketplace as the control market. Secondly, we match the treatment products in Amazon U.K. with similar products in Amazon U.S. and compare the treatment products in Amazon U.K. with their corresponding "counterfactual" control counterparts in Amazon U.S. for each niche market. The main DID analysis is firstly conducted at the product level, then zooms in on the within-product offer level, and is finally conducted at the seller level.

To verify that the regulatory policy is implemented in the market, we first conduct a series of validity checks to identify the direct impact of the CMA regulatory policy on Amazon U.K.'s Featured Offer recommendations. Results are described in detail in the Online Appendix. In sum, we observe that the composition of the recommended Featured Offer changes significantly following the implementation of the regulatory policy on Amazon U.K. product markets, with the recommendation duration and the recommendation share of non-Prime-eligible offers significantly increased, compared with those of the Amazon U.S. product markets.

We also examine whether the Prime eligibility criteria changed due to either the CMA's investigation or the change of recommendation algorithms. The evidence in the Online Appendix shows that the determinants of Prime eligibility in either the Amazon U.K. or U.S. marketplaces do not change significantly after the recommendation algorithm changes. These tests help us identify the changes to the recommendation algorithm due to the exogenous regulatory policy shock and isolate the impacts of these algorithm changes on market outcomes.

**Main variables**

**Product-level dependent variables.** We focus on the impacts of recommendation algorithm changes on product performance. From an intensive margin perspective, we first construct a measure based on product clicks as the dependent variable, *Product clicks(log)*, to examine how the recommendation algorithm changes impact consumer engagement behaviors. Second, we adopt the sales rank of a product market in its focal category recorded on Amazon as the dependent variable for measuring product sales performance, i.e., *Product sales rank(log)*. And the larger the value of the product sales rank, the worse the performance of the products in the category. *Product clicks(log)* and *Product sales rank(log)* provide aggregated outcome measures of consumer search and purchase within each product market, respectively. The coefficient term of *Post Algorithm Change*Treatment Market* indicates how the altered recommendation algorithms affect the attractiveness of the products. Third, we test the impact of changes in product ratings (i.e., *Product ratings*), which indicate the changes in consumers' perception and evaluation of the quality of the recommended offers in the Amazon U.K. product markets.

To further evaluate the quality of the recommended offer in a product market, we use four key measures: (1) whether the offer provides free delivery ("Free Delivery Service"), (2) the change of offer delivery days across time, reflecting the change of the offer delivery speed ("Delivery Speed"), (3) whether the offer can be delivered within five days ("Fast Delivery Service"), and (4) the number of days required to restock after the product runs out of stock ("Restock Days"). In addition to these quality measures, we also examine the price changes of the recommended offers. The coefficient term of *Post Algorithm Change*Treatment Market* indicates how the new recommendation algorithm changes the average qualities and prices of offers in the Amazon U.K. product markets compared to the Amazon U.S. product markets.

From an extensive margin perspective, we count the number of offers provided by different sellers within each product market at each time point and set the dependent variable as *Product total offers(log)* to measure the impact of the recommendation algorithm change on offer varieties within product markets.

**Seller-level dependent variables.** We perform seller-level analyses to test the driving mechanisms. The first variable is the log of the seller's offer price for each product, representing the price the sellers set in the market at any given time, i.e., *Offer price(log)*. The second variable is the log of the seller's delivery days for each product, reflecting the average delivery time the sellers could provide in the product market, i.e., *Delivery days(log)*. Changes in these variables capture the sellers' direct responses to changes in the recommendation algorithm.

We then construct a set of dependent variables that capture sellers' overall quality adjustments following changes in the recommendation algorithm from the intensive margin perspective. The first quality measure focuses on delivery service. We assign a value of 1 to the *Free Delivery Service* variable when a seller offers free delivery in the product market and 0 otherwise. Similarly, we define *Fast Delivery Service* as 1 if a seller can deliver within five days and 0 otherwise. The second quality measure assesses a seller's stock management capability. We calculate the number of days it takes for a seller to restock after running out of stock and then take the logarithm of this duration as our primary variable, i.e., *Restock days(log)*. A shorter restocking period indicates a higher ability to fulfill demand promptly and adjust flexibly to the changing market demand. We also examine the extensive margin effects of recommendation algorithm changes from the seller's perspective by tracking the number of products each seller lists in each niche market over time (i.e., the number of products sellers sell in each niche) and analyzing changes in this metric to quantify sellers' entry and exit effects.

**Moderating variables.** We construct two moderators to examine potential heterogeneities of the main treatment effects at the product level and their driving mechanisms. The first moderator is based on product ratings, while the second focuses on seller ranking positions. For product heterogeneity, we categorize products into different groups based on product ratings and analyze the heterogeneous treatment effects of the algorithm change on these products. We also compute the average rating for each product market before the algorithm change (referred to as Product rating pre-treatment) and construct a three-way interaction term, i.e., *Post Algorithm*

*Change*Treatment*Product rating pre-treatment* to assess the moderating effects of the product rating heterogeneity.

For seller heterogeneity, we categorize sellers into subsamples of Top sellers, Middle sellers, Bottom-up sellers, and Bottom sellers, based on their ranking positions to analyze the heterogeneous responses to the recommendation algorithm change of these sellers. Additionally, we set *Top-position sellers* as one when sellers rank in the top 15 positions on average across different product markets before the algorithm change and zero otherwise. We construct three-way interaction terms, i.e., *Algorithm Change*Treatment*Top sellers, Algorithm Change*Treatment*Middle sellers, Algorithm Change*Treatment*Bottom-up sellers*, and *Algorithm Change*Treatment*Top-position sellers*, to assess the moderating effects of seller ranking position heterogeneity.

**Control variables.** To control for the differences in product attributes. we construct product-level control variables including the product price, which is measured as the natural logarithm of the listed price on the Amazon product listing page (*Product price(log)*); the product rating, defined as the average star rating given by past customers, reflecting the consumer satisfactions and the perceived product qualities (*Product rating*); and the number of product reviews left by past consumers, captured in logarithmic form of review volumes (*Product review counts (log)*), serves as a proxy for the product's popularity and credibility through social proof.

In addition, we construct seller-level control variables to capture the seller attributes. The seller rating refers to the average ratings a seller receives across transactions, signaling the seller's reliability and service quality, such as timely delivery, responsiveness, after-sales services, etc. (*Seller rating*). The number of seller reviews reflects the total volume of feedback the seller has accumulated (*Seller review counts(log)*), which helps measure the seller experience and reputation on the platform.

**Empirical models**

**Product-level analyses.** We test the product-level treatment effects using the following empirical model,

$Y_{it} = \beta_0 + \beta_1 * (Treatment\ market_i * Post\ Algorithm\ Change_t) + \beta_2 * X_{it} + \varphi_i + \psi_t + \epsilon_{it}$ (Product level) (1)

Where $Y_{it}$ is the outcome variable (e.g., product sales, clicks, entry margin) for product $i$ at time $t$. $Treatment\ market_i$ is a dummy variable equal to 1 if the product $i$ is in the Amazon U.K. marketplace and 0 otherwise. $X_{it}$ is a vector of control variables that may affect the outcome variable (e.g., product attributes, seasonal effects). $\varphi_i$ is a product fixed effect to control for unobserved heterogeneity across products. $\psi_t$ is a time-fixed effect used to control temporal trends. The coefficient $\beta_1$ captures the average treatment effect of the recommendation algorithm change for products on the Amazon U.K. marketplace compared with products in the Amazon U.S. marketplace. Positive $\beta_1$ indicates positive treatment effects at the product level.

**Seller-level analyses.** We also conduct analyses at the seller level using two models: the first is constructed at the seller-product level, and the second is at the seller-niche level.

$Y_{sit} = \gamma_0 + \gamma_1 * (Treatment\ market_{si} * Post\ Algorithm\ Change_t) + \gamma_2 * X_{sit} + \varphi_{si} + \psi_t + \epsilon_{sit}$ (Seller-product level) (2)

$Y_{snt} = \delta_0 + \delta_1 * (Treatment\ market_{sn} * Post\ Algorithm\ Change_t) + \delta_2 * X_{snt} + \omega_{sn} + \psi_t + \epsilon_{snt}$ (Seller-niche level) (3)

Where $Y_{sit}$ is the outcome variable for Seller $s$ in product market $i$ at time $t$, including seller's offer price in the product, seller's delivery service provided for the offer in the product, and seller's restock days for the offer in the product; $Treatment\ market_{si}$ is a dummy variable equal to 1 if Seller $s$ operates in the product market $i$ is in the Amazon U.K. marketplace and 0 otherwise. $X_{sit}$ is a vector of control variables that may affect the outcome variable, including the seller and seller offer attributes within each product market. $\varphi_{si}$ is a seller-product dyad fixed effect to control for unobserved heterogeneity across seller-product dyads. $\psi_t$ is a time-fixed effect used to control temporal trends. The coefficient $\gamma_1$ captures the effect of the recommendation algorithm change on sellers operating in product markets in the Amazon U.K. marketplace compared to sellers operating in the Amazon U.S. marketplace. A positive $\gamma_1$ indicates positive effects on the seller (-product) level.

We analyze data at the seller-niche level primarily to capture seller entry effects. Where $Y_{snt}$ is the outcome variable, including the number of products in niche market $n$ where seller $s$ operates at time $t$. $Treatment\ market_{sn}$ is a dummy variable equal to 1 if the seller $s$ operates in niche market $n$ is in the Amazon U.K. marketplace and 0 otherwise. $X_{snt}$ is a vector of control variables that may affect the outcome variable, including the seller and seller offer attributes within each product market. $\varphi_{sn}$ is a seller-niche dyad fixed effect to control for unobserved heterogeneity across seller-niche dyads. $\psi_t$ is a time-fixed effect used to control temporal trends. The coefficient $\delta_1$ captures the average treatment effect of the recommendation algorithm change on sellers in the Amazon U.K. marketplace compared with those in the Amazon U.S. marketplace. A positive $\delta_1$ indicates positive effects on the seller (-niche) level.

## Empirical Results

### Paralleling Trend Test

A key assumption of DID research design is that the product markets in the treatment and control groups are comparable before policy treatment. We first examine the covariate balance between the treatment and control groups before the CMA's regulatory policy. We do not observe significant differences in the main variables across the two groups of product markets in the pre-policy stage at each daytime point, including product prices, product ratings, product review counts, product clicks, product sales ranks, and the total offers in the products, suggesting a high level of balance and comparability between the two groups of products. Results are shown in Online Appendix Table A1

**Product-level average treatment effects**

***Product performance: Consumer clicks, product sales, and ratings (intensive margins).***

In response to the U.K. Competition and Markets Authority's (CMA) regulatory policy change, as offer recommendations in the Amazon U.K. market become less biased towards Prime-labeled offers, consumers are more likely to obtain either products with low prices or high observable qualities at the Featured Offer position (Wan et al. 2024), which saves them search costs of finding out and comparing across different offers within or across product markets, and potentially increase consumer surplus (Li et al. 2022). Furthermore, consumers may trust the recommendation algorithm more when they search for products with incomplete information as the platform shifts toward recommending low-price or high-observable-quality offers at the Featured Offer position. As a result, consumers are more likely to click on a product page to learn more about the product offers, such as the detailed descriptions, the delivery speed, the product return policy, product durability, and the product reviews revealing other dimensions of product qualities, etc. (the search margin).

However, as the platform reduces recommendations based on Prime eligibility, sellers may be incentivized to compete primarily by lowering prices. This may be because adjusting prices is easier and faster in response to changes in the recommendation algorithm compared to enhancing product qualities, especially for sellers lacking development capabilities. Furthermore, since Prime-eligible offers often possess higher observable or unobservable quality attributes, reducing the recommendation weight on Prime-eligible offers may lead to an overall decline in the quality of Featured Offers. Consumers sensitive to product quality may find fewer desirable offers based on observable factors such as ratings or delivery speed after clicking on the product page, resulting in lower purchase likelihood (reduced sales margins). Additionally, customers may experience lower satisfaction due to hidden quality issues, such as poor performance, low durability, or inconvenience of use, which could subsequently lead to reduced product ratings (rating margins).

**Table 1. Product Performance: Intensive Margins**

| | (1) DV: Product clicks(log) | (2) DV: Product sales rank(log) | (3) DV: Product ratings |
|---|---|---|---|
| Post Algorithm Change*Treatment Market | 0.009*** | 0.026*** | -0.001*** |
| | (0.003) | (0.002) | (0.000) |
| Product price(log) | -1.442*** | 0.110*** | -0.001 |
| | (0.015) | (0.007) | (0.001) |
| Product rating | 0.576*** | 0.068*** | |
| | (0.024) | (0.011) | |
| Product review counts(log) | 0.000 | -0.075*** | 0.022*** |
| | (0.003) | (0.002) | (0.001) |
| Constant | 7.470*** | 3.864*** | 3.691*** |
| | (0.100) | (0.046) | (0.006) |
| Product FE | Yes | Yes | Yes |
| Day Time FE | Yes | Yes | Yes |
| Adjusted R2 | 0.932 | 0.980 | 0.999 |
| Observations | 548,221 | 553,524 | 553,524 |

Notes: Robust standard errors are reported in parentheses, ***p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

We first test these potential treatment effects on product performance using a two-way fixed effects model with product and time-fixed effects included. We set the dependent variable as the number of clicks products obtain each week, and the regression results in Column 1 of Table 1 indicate that products in the Amazon U.K. marketplace obtain 0.9% more daily clicks at a 1% significance level compared with the products in the Amazon U.S. marketplace with no recommendation algorithm change. The regression results reported in Column 2 of Table 1 show that the sales ranks of treatment product markets decreased by about 2.6% at a 1% significance level due to the algorithm change. Furthermore, in Column 3 of Table 1, we report the impacts of the recommendation algorithm changes on product ratings within each product market. We find that the product ratings in treatment product markets decrease by about 0.1% at a 1% significance level after the recommendation algorithm changes compared with the products in the control marketplace. The results combined indicate that, despite the increasing clicks on the treatment product markets their sales ranks and ratings decreased due to the decreasing consumer purchases and satisfaction.

***Product prices and quality of the recommendation: Prices, delivery speed, free delivery service, and stock management.***

In accordance with the regulatory policy, Amazon shifted the recommendation weights of its recommendation criteria away from Prime eligibility and toward observable attributes such as lower offer prices and higher offer quality—specifically, faster delivery and improved restock management. In response, sellers can either reduce their offer prices or invest in enhancing observable quality.

Therefore, we examine how recommended offers' prices and quality metrics adjust within each product market following the algorithm change. We find that the prices of recommended offers in treated product markets decline by approximately 0.3% at a 1% significance level (Column 1 of Table 2). Then, we measure the offer's service quality from the following perspectives: delivery speed, free delivery service or fast shipping service defined as delivery within five days, and the number of days required to restock an offer once the inventory runs out. Compared to the control product markets, all the observed offer qualities in the treatment product markets deteriorate after the recommendation algorithm change. In particular, as is shown in Columns 2-5 of Table 2, the delivery speed of offers in the treatment product markets decreases by approximately 0.5%, and the fraction of recommended (Buybox) offers that provide free delivery and fast delivery services in treatment product markets decreases by approximately 0.2% and 1.4%, respectively. Additionally, the average number of days for restocking offers increases by about 2.3% for recommended offers in treatment markets compared to those in control markets (Column 5 of Table 2).

**Table 2. Product Prices and Quality: Intensive Margins**

| | (1) DV: Product prices(log) | (2) DV: Delivery speed(log) | (3) DV: Free delivery service (0, 1) | (4) DV: Fast delivery service (0, 1) | (5) Restock days (log) |
|---|---|---|---|---|---|
| Post Algorithm Change*Treatment Market | -0.003*** | -0.005** | -0.002*** | -0.014*** | 0.023*** |
| | (0.000) | (0.002) | (0.001) | (0.001) | (0.006) |
| Product price(log) | | 0.028*** | -0.022*** | 0.104*** | -1.499*** |
| | | (0.009) | (0.003) | (0.006) | (0.033) |
| Product rating | -0.001 | -0.002 | 0.005* | 0.003 | -0.028 |
| | (0.001) | (0.011) | (0.003) | (0.006) | (0.031) |
| Product reviews(log) | -0.000 | -0.001 | -0.001*** | 0.005*** | 0.026*** |
| | (0.000) | (0.002) | (0.000) | (0.001) | (0.005) |
| Constant | 2.096*** | 0.079* | 1.024*** | 0.086*** | 5.961*** |
| | (0.005) | (0.046) | (0.012) | (0.026) | (0.139) |
| Product FE | Yes | Yes | Yes | Yes | Yes |
| Day Time FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.999 | 0.100 | 0.397 | 0.812 | 0.752 |
| Observations | 553,524 | 528,438 | 528,438 | 553,524 | 553,524 |

Notes: Robust standard errors are reported in parentheses, ***p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

***Within-product offer varieties (extensive margins).***

For the extensive margins at the product level, we count the number of offers within each product market at each time as the dependent variable and have product-fixed effects, time-fixed effects, and necessary product-level variables controlled, the number of offers supplied by different sellers significantly decreases by about 0.5% in product markets in Amazon U.K. marketplace compared with product markets in Amazon U.S. marketplace. The result is reported in Column 5 of Table 3. We further study the moderating effects of product ratings and find that it is the products with high ratings (4.5 or above) that drive the average treatment effect above in the extensive margin, i.e., treatment product markets with high ratings experience a significant decrease in the total number of offers after the recommendation algorithm change (Column 4 in Table 3). However, product markets with rates below 4.5 experience a significant increase in the total number of offers (Columns 1, 2, and 3 in Table 3). The former effect dominates as the number of products with ratings higher than 4.5 exceeds that of the remaining product markets.

The results from the subsample analyses and the moderating effects in the full-sample analyses (Columns 5, 6, and 7 in Table 3) confirm each other. As a robustness check, we classify products alternatively based on product clicks and sales ranks. Table A7 shows that the number of offers decreases in product markets with more consumer clicks and/or higher sales ranks while increases in product markets with fewer clicks and/or lower sales ranks. The findings suggest that the offer variety in the core product market decreases. At the same time, it increases in other periphery product markets, and the results are robust across different product metrics, including product ratings, product consumer clicks, and product sales ranks.

**Table 3. Product-level ATE & HTE: Extensive Margins**

| DV: No. of offers (log) | (1) Sample: Tail products | (2) Sample: Middle products | (3) Sample: Second top products | (4) Sample: Top products | (5) Full sample | (6) Full sample | (7) Full sample |
|---|---|---|---|---|---|---|---|
| | Product rating<=3 | Product rating=3.5 | Product rating=4 | Product rating>=4.5 | | | |
| Post Algorithm Change*Treatment Market | 0.114*** | 0.024*** | 0.016*** | -0.009*** | -0.005*** | 0.093*** | 0.120*** |
| | (0.009) | (0.008) | (0.002) | (0.001) | (0.001) | (0.014) | (0.009) |
| Post Algorithm Change*Treatment*Product rating pre-treatment | | | | | | -0.022*** | |
| | | | | | | (0.003) | |
| Post Algorithm Change*Treatment*Top products | | | | | | | -0.129*** |
| | | | | | | | (0.009) |
| Post Algorithm Change*Treatment*Second top products | | | | | | | -0.104*** |
| | | | | | | | (0.009) |
| Post Algorithm Change*Treatment*Middle products | | | | | | | -0.103*** |
| | | | | | | | (0.012) |
| Post Algorithm Change*Product rating pre treatment | | | | | | 0.020*** | |
| | | | | | | (0.002) | |
| Post Algorithm Change*Top products | | | | | | | 0.104*** |
| | | | | | | | (0.007) |
| Post Algorithm Change*Second top products | | | | | | | 0.086*** |
| | | | | | | | (0.007) |
| Post Algorithm Change*Middle products | | | | | | | 0.058*** |
| | | | | | | | (0.009) |
| Product price(log) | 0.354** | -0.453*** | -0.156*** | -0.065*** | -0.078*** | -0.078*** | -0.079*** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (0.175) | (0.072) | (0.017) | (0.005) | (0.005) | (0.005) | (0.005) |
| Product rating | 0.055$^{***}$ | -0.086$^{***}$ | -0.069$^{***}$ | -0.044$^{***}$ | -0.050$^{***}$ | -0.049$^{***}$ | -0.049$^{***}$ |
| | (0.015) | (0.020) | (0.008) | (0.007) | (0.005) | (0.005) | (0.005) |
| Product review counts(log) | 0.019$^{***}$ | 0.041$^{***}$ | 0.006$^{***}$ | 0.007$^{***}$ | 0.007$^{***}$ | 0.007$^{***}$ | 0.008$^{***}$ |
| | (0.007) | (0.016) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) |
| Constant | 0.460$^{***}$ | 1.620$^{***}$ | 1.580$^{***}$ | 1.766$^{***}$ | 1.744$^{***}$ | 1.696$^{***}$ | 1.689$^{***}$ |
| | (0.095) | (0.091) | (0.040) | (0.030) | (0.023) | (0.024) | (0.023) |
| Product FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Day Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.949 | 0.931 | 0.947 | 0.969 | 0.968 | 0.968 | 0.968 |
| Observations | 3,016 | 8,014 | 76,389 | 466,105 | 553,524 | 553,524 | 553,524 |

Notes: Robust standard errors are reported in parentheses, ***p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

## Mechanism tests: Seller strategic responses to the recommendation algorithm changes

***Seller pricing and delivery service adjustment strategies.***

Table 4 shows seller-level analyses to examine how sellers adjust their pricing and delivery strategies following the recommendation algorithm change. On average, sellers operating in treatment product markets significantly reduce their offer prices by about 0.3% compared to those operating in control product markets (Column 3 of Table 4). Additionally, sellers in the treatment markets decrease their delivery speed by about 3.1% compared to control markets (Column 7 of Table 4). When accounting for seller heterogeneity, we find that top sellers in terms of their offer ranking positions before the recommendation algorithm change are less likely to decrease offer prices in the treatment markets compared to their counterparts in the control markets (Columns 1-2 of Table 4). While both types of sellers decrease their offer delivery speed after the algorithm change (Columns 5 - 6 of Table 4), top-ranked sellers decrease less in the offer delivery speed compared to lower-ranked sellers (Column 8 of Table 4).

**Table 4. Seller Strategic Responses to the Recommendation Algorithm Changes**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | DV: Offer price(log) | | | | DV: Delivery speed(log) | | | |
| | Sample: Non-Top sellers | Sample: Top sellers | Full sample | Full sample | Sample: Non-Top sellers | Sample: Top sellers | Full sample | Full sample |
| Post Algorithm Change*Treatment Market | -0.010$^{***}$ | -0.001$^{***}$ | -0.003$^{***}$ | -0.010$^{***}$ | -0.037$^{***}$ | -0.027$^{***}$ | -0.031$^{***}$ | -0.038$^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.002) |
| Post Algorithm Change*Treatment* Top-position sellers | | | | 0.009$^{***}$ | | | | 0.010$^{***}$ |
| | | | | (0.000) | | | | (0.002) |
| Post Algorithm | | | | -0.002$^{***}$ | | | | -0.012$^{***}$ |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Change* Top-position sellers | | | | | | | | |
| | | | | (0.000) | | | | (0.001) |
| Seller rating | -0.006*** | -0.003*** | -0.004*** | -0.004*** | 0.003 | 0.005** | 0.004*** | 0.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.003) | (0.002) | (0.002) | (0.002) |
| Seller review counts(log) | 0.001*** | 0.001*** | 0.001*** | 0.001*** | -0.001 | 0.005*** | 0.003*** | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) |
| Product rating | -0.019*** | 0.011*** | 0.006*** | 0.006*** | -0.037*** | -0.018** | -0.021*** | -0.022*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.014) | (0.008) | (0.007) | (0.007) |
| Product review counts(log) | -0.001*** | -0.002*** | -0.001*** | -0.001*** | -0.001 | -0.002** | -0.001 | -0.001 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) |
| Constant | 4.372*** | 3.886*** | 4.008*** | 4.008*** | 0.412*** | 0.245*** | 0.276*** | 0.285*** |
| | (0.008) | (0.008) | (0.007) | (0.007) | (0.062) | (0.033) | (0.029) | (0.029) |
| Seller-product FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Daytime FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.998 | 0.996 | 0.997 | 0.997 | 0.359 | 0.213 | 0.248 | 0.249 |
| Observations | 969,739 | 2,487,563 | 3,457,302 | 3,457,302 | 969,739 | 2,487,563 | 3,457,302 | 3,457,302 |

Notes: Robust standard errors are reported in parentheses, ***p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

***Seller quality adjustment strategies.***

In Table 5, we analyze sellers' offer quality adjustment strategies in product markets. On average, sellers in the treatment marketplace enhance their delivery service quality by offering more free delivery options and faster shipping services (offers that can be delivered within five days). Notably, these improvements are concentrated among top-ranked sellers regarding their offer ranking positions before the algorithm changes. In contrast, low-ranking sellers exhibit little to no improvement in delivery service quality. Another key aspect of quality enhancement is offer stock management. To measure this, we examine the number of days sellers take to restock an offer after running out of inventory. Our findings indicate that, on average, the offer restock time increases following the policy change for sellers in the treatment marketplace compared to those in the control marketplace. However, further conducting heterogeneity analysis, we find that top-ranked sellers significantly improve their stock management efficiency. It is the lower-ranked sellers that deteriorate in stock management after the recommendation algorithm change and drive the result of the increase in the average offer restock time.

**Table 5. Seller Divergent Strategic Responses to the Recommendation Algorithm Changes**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DV: Free delivery service (0, 1) | | | | DV: Fast delivery service (0, 1) | | | | DV: Restock days(log) | | | |
| | Sample: Non-Top sellers | Sample: Top sellers | Full sample | Full sample | Sample: Non-Top sellers | Sample: Top sellers | Full sample | Full sample | Sample: Non-Top sellers | Sample: Top sellers | Full sample | Full sample |
| Post Algorithm Change*Treatment Market | -0.004*** | 0.003*** | 0.001*** | -0.005*** | -0.013*** | 0.007*** | 0.002*** | -0.013*** | 0.012*** | -0.002* | 0.005*** | 0.012*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Post Algorithm Change*Treatment* Top-position sellers | | | | 0.007*** | | | | 0.020*** | | | | -0.014*** |
| | | | | (0.000) | | | | (0.001) | | | | (0.002) |
| Post Algorithm Change*Top-position sellers | | | | 0.002*** | | | | -0.005*** | | | | 0.021*** |
| | | | | (0.000) | | | | (0.001) | | | | (0.001) |
| Seller rating | -0.008*** | -0.001* | -0.002*** | -0.002*** | -0.000 | -0.001 | -0.001 | -0.001 | -0.013*** | 0.010*** | 0.001 | 0.001 |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.002) | (0.001) | (0.001) | (0.001) | (0.003) | (0.003) | (0.002) | (0.002) |
| Seller review counts(log) | 0.014*** | 0.001*** | 0.004*** | 0.004*** | 0.002*** | -0.001*** | -0.000 | -0.000 | -0.003** | -0.002 | -0.002** | -0.003** |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) | (0.002) | (0.001) | (0.001) | (0.001) |
| Product rating | 0.005*** | 0.005*** | 0.004*** | 0.005*** | 0.038*** | 0.031*** | 0.031*** | 0.031*** | 0.025 | -0.032*** | -0.024** | -0.021** |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.011) | (0.005) | (0.005) | (0.005) | (0.019) | (0.011) | (0.010) | (0.010) |
| Product review counts (log) | 0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.005*** | 0.001** | -0.000 | -0.000 | 0.009*** | 0.010*** | 0.009*** | 0.010*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Constant | 0.586*** | 0.861*** | 0.786*** | 0.781*** | 0.044 | 0.252*** | 0.201*** | 0.200*** | 4.398*** | 4.306*** | 4.396*** | 4.374*** |
| | (0.009) | (0.006) | (0.005) | (0.005) | (0.050) | (0.022) | (0.021) | (0.021) | (0.082) | (0.047) | (0.041) | (0.041) |
| Seller-product FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Daytime FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.986 | 0.949 | 0.968 | 0.968 | 0.556 | 0.687 | 0.672 | 0.672 | 0.908 | 0.930 | 0.927 | 0.927 |
| Observations | 969,739 | 2,487,563 | 3,457,302 | 3,457,302 | 969,739 | 2,487,563 | 3,457,302 | 3,457,302 | 679,638 | 1,376,298 | 2,055,936 | 2,055,936 |

Notes: Robust standard errors are reported in parentheses, ***p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

These findings suggest that sellers adopt divergent strategies in response to the recommendation algorithm changes. High-ranked sellers mainly enhance their offer qualities, while lower-ranked sellers struggle to adapt, mainly decreasing offer prices at the expense of their offer qualities.

***Seller entry and exit strategies.***

In Table 6, we further examine how sellers strategically adjust their product portfolios within each niche market in response to the recommendation algorithm changes to link seller strategic responses across related product markets within a niche. First, we find that, on average, sellers in the treatment marketplace increase the total number of products they operate within each niche market by approximately 1.3% at a 1% significance level after the policy change, compared to sellers in the control marketplace (Column 5 in Table 6). The moderating effects of seller rankings reveal distinct strategic responses. As sellers' average offer ranking positions before the recommendation algorithm change goes up, they operate in fewer product markets within the same niche (Columns 6 and 7 in Table 6). However, further conducting the heterogeneity analysis shows that the top-ranked sellers decrease the number of product markets they operate after the algorithm change (Column 4 in Table 6). In contrast, sellers with lower offer rankings before the change strategically expand into product markets with fewer competitors, seeking more exposure and recommendation opportunities in response to the algorithm change (Columns 1, 2, and 3 in Table 6).

Furthermore, the results remain robust when we use the indicator of whether a seller is selling in a product market at each point in time as the dependent variable to track sellers' entry and exit behaviors in each product market. We analyze the average and the heterogeneous treatment effects at the seller-product dyad level, including both the seller- and product-level fixed effects. Results in Table A8 in the Online Appendix suggest that, on average, sellers enter more product markets in the treatment marketplace than in the control marketplace. However, the low-ranked sellers enter more product markets to compete for recommendations and seek more exposure in the periphery product markets with lower product ratings, fewer consumer clicks, and lower sales ranks.

**Table 6. Seller Strategic Responses to the Recommendation Algorithm Changes: Entry Margins**

| DV: No. of product markets in the focal niche | (1) Sample: Bottom sellers | (2) Sample: Bottom-up sellers | (3) Sample: Middle sellers | (4) Sample: Top sellers | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Seller average position>=20 | Seller average position>=10&<20 | Seller average position>=3&<10 | Seller average position<3 | Full sample | Full sample | Full sample |
| Post Algorithm Change*Treatment Market | 0.056*** | 0.023*** | 0.009*** | -0.030*** | 0.013*** | 0.055*** | 0.041*** |
| | (0.003) | (0.002) | (0.001) | (0.002) | (0.001) | (0.003) | (0.002) |
| Post Algorithm Change*Treatment*Top sellers | | | | | | -0.085*** | |
| | | | | | | (0.003) | |
| Post Algorithm Change*Treatment*Bottom-up sellers | | | | | | -0.046*** | |
| | | | | | | (0.003) | |
| Post Algorithm Change*Treatment*Middle sellers | | | | | | -0.032*** | |
| | | | | | | (0.003) | |
| Post Algorithm Change*Treatment*Top-position sellers | | | | | | | -0.037*** |
| | | | | | | | (0.002) |
| Post Algorithm Change*Top sellers | | | | | | 0.030*** | |
| | | | | | | (0.001) | |
| Post Algorithm Change*Bottom-up sellers | | | | | | 0.015*** | |
| | | | | | | (0.001) | |
| Post Algorithm Change*Middle sellers | | | | | | 0.007*** | |
| | | | | | | (0.001) | |
| Post Algorithm Change* Top-position sellers | | | | | | | 0.014*** |
| | | | | | | | (0.001) |
| Seller Product price | -0.008 | -0.034*** | -0.036*** | -0.042*** | -0.032*** | -0.032*** | -0.032*** |
| | (0.005) | (0.004) | (0.003) | (0.004) | (0.002) | (0.002) | (0.002) |
| Seller Product ratings | 0.042*** | 0.058*** | 0.054*** | 0.034*** | 0.049*** | 0.049*** | 0.049*** |
| | (0.003) | (0.003) | (0.002) | (0.003) | (0.001) | (0.001) | (0.001) |
| Seller Product reviews | 0.015*** | 0.006*** | 0.004*** | 0.012*** | 0.008*** | 0.008*** | 0.008*** |
| | (0.002) | (0.002) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) |
| Constant | 0.853*** | 0.985*** | 0.954*** | 0.948*** | 0.951*** | 0.943*** | 0.946*** |
| | (0.031) | (0.022) | (0.015) | (0.023) | (0.011) | (0.011) | (0.011) |
| Seller-niche FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Daytime FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.955 | 0.947 | 0.940 | 0.944 | 0.946 | 0.946 | 0.946 |
| Observations | 165,559 | 221,613 | 354,100 | 150,975 | 892,247 | 892,247 | 892,247 |

Notes: Robust standard errors are reported in parentheses, ***p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

Finally, we further analyze heterogeneous sellers' cross-product-market responses within a niche by defining a new measure using the ratio of core products to the total number of products each seller operates within the niche market at each time. A higher ratio indicates that the seller is more focused on operating in the core product markets. We examine changes in this ratio due to the recommendation algorithm change to quantify how sellers adjust their operation focus across different product markets within each niche; these results are presented in Table 7. Our findings indicate that, on average, sellers in the treatment marketplace increase their entry into core product markets compared to sellers in the control marketplace (Column 5 in Table 7). However, the sellers with better offer rankings before the algorithm changes drive the result. On the contrary, sellers with lower offer rankings tend to shift towards operating in periphery product markets as a response to the recommendation algorithm change (Column 1 in Table 7). The evidence is consistent with our above seller-niche and seller-product level analyses.

**Table 7. Seller Strategic Responses to the Recommendation Algorithm Changes: Entry Margins**

| DV: No. of core products/total products | (1) Sample: Bottom sellers | (2) Sample: Bottom-up sellers | (3) Sample: Middle sellers | (4) Sample: Top sellers | (5) Full sample |
|---|---|---|---|---|---|
| Post Algorithm Change*Treatment Market | -0.004*** | -0.000 | 0.003*** | 0.002** | 0.001** |
| | (0.001) | (0.001) | (0.000) | (0.001) | (0.000) |
| Seller Product price | 0.038*** | 0.006*** | 0.008*** | 0.008*** | 0.012*** |
| | (0.002) | (0.001) | (0.001) | (0.002) | (0.001) |
| Seller Product ratings | 0.017*** | 0.009*** | 0.018*** | 0.012*** | 0.014*** |
| | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) |
| Seller Product reviews | 0.032*** | 0.013*** | 0.008*** | 0.008*** | 0.013*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) |
| Constant | 0.172*** | 0.164*** | 0.064*** | 0.052*** | 0.120*** |
| | (0.015) | (0.010) | (0.008) | (0.012) | (0.005) |
| Seller-niche FE | Yes | Yes | Yes | Yes | Yes |
| Daytime FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.985 | 0.985 | 0.977 | 0.967 | 0.982 |
| Observations | 165,559 | 221,613 | 354,100 | 150,975 | 892,247 |

Notes: Robust standard errors are reported in parentheses, ***p<0.01, **p<0.05, *p<0.10 (two-tailed tests).

The combined results suggest that sellers with better offer rankings before the recommendation algorithm change adopt a focused strategy, concentrating their efforts on improving offer qualities in fewer core product markets and competing for recommendations within them. At the same time, the other sellers pursue a diversification strategy to differentiate the profit foci from top-ranked sellers by entering more periphery product markets, increasing exposures, and mitigating the risks associated with operating in a single market.

## Conclusions and Discussions

Leveraging an exogenous regulation policy change that imposes objectively verifiable restrictions on the platform recommendation algorithm, this study identifies the platform recommendation algorithm change and analyzes its impacts on both the supply-side seller price and quality competitions within product markets, seller entry and exit strategies across product markets, and the demand-side consumer search and purchase behaviors, as well as their satisfaction. Our research provides insights to policymakers designing regulation policies on platform recommendation algorithms, the platform owner optimizing the algorithms, and third-party sellers competing within and across markets.

For regulators, law, and policymakers, regulating the platform's monopoly power in algorithm design is vital in maintaining recommendation fairness, promoting competition, and enhancing consumer welfare. Platform owners with misaligned incentives with consumers and sellers may design recommendation systems biased towards certain features, e.g., price, quality, or measures tied to platform revenues, which fail to incentivize balanced competition or maximize consumer welfare. A platform selling privately labeled products has additional incentives to engage in self-preferencing, which may simultaneously harm consumers and third-party sellers (Zhu and Liu 2018, Dub 2022, Farronato et al. 2023, Long and Amaldoss 2024, Waldfogel 2024).

However, to evaluate the regulation policy on the platform recommendation algorithm, the regulators must consider the platform's algorithm change in response to the policy. Objective verifiable or observationally fair recommendation algorithms regarding the length or probability of recommendations may not lead to balanced or fair competition. Depriving the recommendation algorithm of selecting based on hidden qualities and other unobservable factors that contribute to consumer surplus may distort seller competition for the recommendation within markets and distort their entry and exit strategies across product markets, decreasing consumer surplus and social welfare. Furthermore, seller strategic responses to the recommendation algorithm change may cause inefficiencies in both the extensive (entry and exit) margins and intensive (price and quality) margins. The regulators must combine the platform and seller-level responses to evaluate both a regulatory policy's short-run and long-run impacts.

From the platform owner's perspective, there are trade-offs between maximizing short-term and long-term revenues and conflicts between maximizing revenues and promoting fair competition or maximizing consumer fairness (Zhu and Liu 2018, Liu et al. 2022). Leveraging Amazon's verifiable binding commitment to the Markets Authority's (CMA's) regulation, we find that Amazon responds to the regulation by reducing recommendation weights on Prime eligibility. The altered recommendation algorithm incentivizes sellers to engage in short-run price competition. As a result, although offer prices fall and consumers are more likely to click on products in the treatment markets, the deteriorating offer qualities make consumers less likely to purchase an offer conditional on search, pay higher search costs, and be less satisfied after purchase. It suggests that the platform optimizing recommendation algorithms has to balance the short-term benefits, profiting from increasing search and purchases and complying with the regulation policy, with the long-term benefits derived from incentivizing sellers to invest and enhance product qualities and engaging in balanced competition to serve consumers in different segments. A platform that fails to consider the equilibrium impacts of the recommendation policy change on both the supply and demand sides risks its prosperity or survival.

Third-party sellers who intend to maximize profits face the trade-off between decreasing offer prices at the expense of decreasing offer qualities and enhancing offer qualities while increasing prices. The optimal response depends on both a seller's ability to enhance quality and the competitive position of the seller's offer in the price-quality space of a product market. Furthermore, as market entry and exit are costly, it would be beneficial for sellers to form accurate expectations on the platform recommendation algorithm and learn the algorithm adjustment fast to optimize both the pricing and quality adjustment strategies for competition within a market and the entry and exit strategies for competition across markets.

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