Steering in One Click: Platform Self-Preferencing in the Amazon Buy Box*

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Abstract

Online platforms can strongly influence consumer behavior through default options, creating incentives to steer consumers to the platform's own products and services. I examine how Amazon determines which merchant is the default option on the Amazon Buy Box. Using data on hundreds of thousands of products and several countries, I show that the Amazon platform substantially prioritizes its retail arm and fulfillment arm in the recommendation algorithm. Amazon's preference for its fulfillment arm has much larger effects on the default platform price and share of third party merchants winning the Buy Box than its preference for its retail arm.

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1 Introduction

Policymakers are concerned about online platforms' market power, including that platforms that "run the marketplace while also competing in it" steer consumers to their own products and services over competitors. In the Digital Markets Act, for example, the European Union bans a gatekeeper platform from such self-preferencing.

Amazon's treatment of third party sellers on its platform has come under particular criticism. The European Commission investigated Amazon and found that "Amazon's rules and criteria for the Buy Box and Prime unduly favour its own retail business, as well as marketplace sellers that use Amazon's logistics and delivery services."[1] Similarly, the House Antitrust Subcommittee report (Nadler and Cicilline, 2020) found:

> The company's control over and reach across its many business lines enable it to self-preference and disadvantage competitors in ways that undermine free and fair competition. ... Amazon's dual role as an operator of its marketplace that hosts third-party sellers, and a seller in that same marketplace, creates an inherent conflict of interest.

While many merchants list offers to sell the same product on Amazon's platform, the vast majority of consumers purchase from the default merchant featured in the "One Click" button in the Amazon Buy Box. An estimated 80% of Amazon sales go through the Buy

[1] See https://ec.europa.eu/commission/presscorner/detail/en/ip_22_7777.

Box, with higher rates for mobile devices.[2]

Because Amazon picks the default merchant, it can steer consumers to a first party offer sold by its retail arm ("Amazon Retail") over third party offers. In addition, it may favor third party offers shipped by its fulfillment arm (Fulfilled by Amazon or "FBA") over those using other shipping options (Fulfilled by Merchant or "FBM"). Such steering could force sellers to ship using Amazon Fulfillment to win the Buy Box and reach consumers. Former Amazon CEO Jeff Bezos defended Amazon's self-preferencing as in the consumer interest: "I think the Buy Box does favor products that can be shipped with Prime. ... The Buy Box was trying to pick the offer that we predict the customer would most like."[3]

Because Amazon does not disclose its algorithm, we do not know whether Amazon favors Amazon Retail offers over third party FBA offers, both of which are Prime-eligible, or how large a preference Amazon places on Amazon Retail or FBA.

I provide evidence on these questions by gathering data on the set of offers available for more than a million products selling on Amazon across several countries. I focus on a primary sample of about eight hundred thousand products sold in four countries – the US, UK, Germany, and France – across eighteen categories. The Buy Box winner is often not the lowest price offer. For products with multiple offers, the Buy Box does not have the lowest price offer between 15% to 27% of the time in non-media categories, and between 30% to

[2]See the Amazon Buy Box Playbook (Feedvisor, 2020), available at https://feedvisor.com/resources/e-commerce-strategies/the-amazon-buy-box-playbook-for-sellers-and-retailers/.

[3]See https://www.rev.com/blog/transcripts/big-tech-antitrust-hearing-full-transcript-july-29.

45% of the time for media categories.

I then estimate a multinomial logit model that predicts which offer Amazon chooses to win the Buy Box. The model includes the price of an offer, whether Amazon or a third party provides the offer, whether Amazon or a third party fulfills the offer, whether the product is in stock, as well as controls for a third party's merchant rating and number of ratings. The model does not include shipping time, which will vary between products fulfilled by Amazon and those fulfilled by merchants; thus, estimated premia over FBM potentially includes shipping time differences.

To measure Amazon's self-preferencing, I compare Amazon Retail to a "perfect" third party seller – a hypothetical merchant with a million ratings and a 100% rating score. In my primary sample, a perfect FBA seller receives a penalty equivalent to a 16% increase in price over an Amazon Retail offer, while a FBM offer for the same seller receives a penalty equivalent to a 46% increase in price over an Amazon Retail offer. These self-preferencing effects are quite similar across countries.

Examining product categories separately, I find statistically significant self-preferencing for Amazon Retail over FBA sellers in 17 out of 18 categories, and for Amazon Retail over FBM sellers in all categories. The Books category has much larger self-preferencing for Amazon Retail than any other category, with a perfect FBA (FBM) seller receiving a penalty equivalent to a 61% (164%) price increase.

I then examine counterfactual changes to the Buy Box algorithm to remove Amazon's estimated preference towards Amazon Retail and Amazon Fulfillment. In the first counterfactual, I treat Amazon Retail as equivalent to a perfect FBA seller. This change decreases Amazon Retail's share of the Buy Box by a half a percentage point, but increases Amazon Fulfillment's share of the Buy Box by 0.65 percentage points. The Buy Box price increases by 0.1% on average, but decreases by 0.1% for products where Amazon Retail previously won the Buy Box.

Removing self-preferencing towards Amazon Fulfillment has much larger effects. In the second counterfactual, I treat Amazon Retail as equivalent to both a perfect FBA seller and perfect FBM seller. Here, the share of the Buy Box for Amazon Retail and Amazon Fulfillment falls by 7.2 and 10.6 percentage points, respectively. On average, the Buy Box price declines by 0.6% with a 2.1% decrease for products where Amazon Retail previously won the Buy Box. Media categories have the largest changes, with the share of Amazon Retail and Amazon Fulfillment for the Books and CD categories falling by 30 percentage points.

This paper is related to the recent debate on vertical integration and self-preferencing of large online platforms; Etro (2022) summarizes the literature. Khan (2016) argues that Amazon has exploited its market power to privilege its own products, and that Amazon's preference towards FBA is anti-competitive tying; Khan (2019) discusses how structural separation can remedy competitive harms. De Corniere and Taylor (2019) find that a platform's self-preferencing can benefit or hurt consumer welfare depending upon how consumer and seller profits align. Etro (2021) argues that Amazon's incentives align with consumers for common demand functions. Hagiu et al. (2021) find that policies that ban self-preferencing by Amazon are better for consumer welfare than preventing Amazon from acting as both a merchant and platform. Bar-Isaac and Shelegia (2022) examine the conditions where a platform would prefer to steer consumers through its algorithm as opposed to use auctions to allocate demand. Zhu and Liu (2018) document that Amazon Retail tends to enter into high quality, popular products sold by third party merchants, and that Amazon Retail's entry tends to lower prices and lead to the exit of third party sellers.

Several recent papers empirically examine Amazon's self-preferencing. Chen and Tsai (2021) show that Amazon tends to recommend products sold by Amazon Retail over products sold by third party retailers, and that this steering lowers consumer welfare. Hunold et al. (2022) find that Amazon is more likely to have no Buy Box winner when prices are lower on competing platforms and the only offers are from third party sellers and not Amazon. Gutierrez (2022) models how Amazon sets fees for third parties and finds that structural separation or a ban on having Amazon as a seller lowers welfare. Lam (2023) develops a graph based model for consumer search behavior on Amazon and finds that Amazon does preference itself in search, but removing self-preferencing reduces welfare. Finally, Lee and Musolff (2021) examines data on offers for Amazon Fashion products and fins the Buy Box recommendation algorithm boosts Amazon Retail over third party offers, and that such preferencing improves consumer welfare as consumers prefer Amazon offers.

This article also informs debates on the adoption of algorithms in markets, including whether the adoption of pricing algorithms leads to supra-competitive prices by learning to collude (Asker et al., 2021; Assad et al., 2020; Calvano et al., 2020) or moving away from symmetric equilibria (Brown and MacKay, 2020; Leisten, 2021). Others examine algorithmic biases against protected groups (Lambrecht and Tucker, 2019; Obermeyer et al., 2019; Rambachan et al., 2020).

2 Background

2.1 Sellers on Amazon

Amazon Marketplace allows third-party sellers to sell directly on product pages along with Amazon itself in return for a revenue share of third party sales. Under the "Fulfillment by Amazon" or FBA program, third party sellers use Amazon to store and ship items after paying additional fees to Amazon. FBA offers are given Prime status, just as Amazon Retail offers are, which provides Amazon Prime members with free two-day shipping of the product. Sellers can also do their own shipping, known as "Fulfillment by Merchant" or FBM, but their offers will not receive Prime status.[4]

[4]In "Seller Fulfilled Prime", third party merchants can do their own shipping and achieve Prime Status. However, Amazon's conditions to enter this program are quite onerous, and have become more so, which mean that "FBA is functionally the only way for sellers to get the Prime badge for their product listings." (Nadler and Cicilline, 2020).

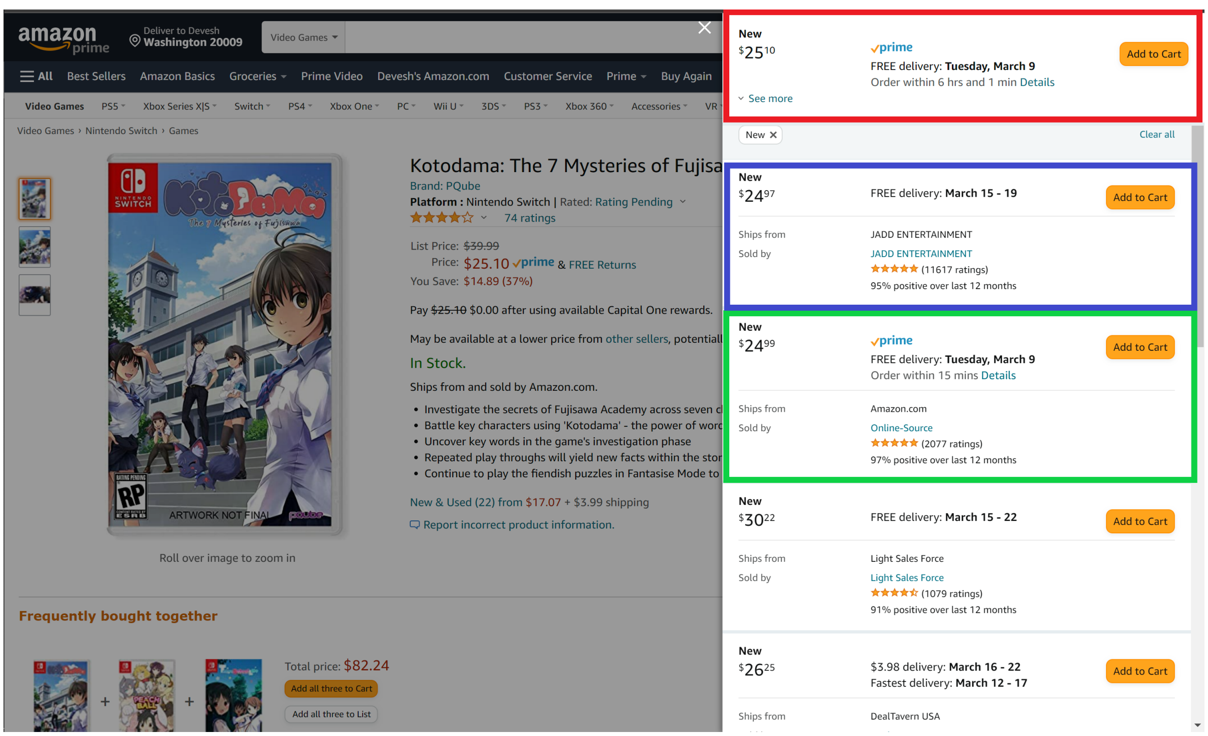
2.2 Buy Box

Figure 1 provides an example of how consumers purchase a product which has multiple competing sellers on Amazon's marketplace. Figure 1a depicts a product detail page for an Amazon product. For this product, the red box depicts information on the Buy Box winner, which is the default option among competing sellers. Here, Amazon Retail sells the product for $25.10. the green box is the Buy Box; clicking "Buy Now" buys the product from the Buy Box winner. Finally, the blue box allows consumers to click through to see other buying options.

Figure 1b shows these alternative offers. The Buy Box winner in the red box is Amazon Retail and is not the lowest price product. A FBM offer in the blue box has a price of $24.97, and a FBA offer in the green box has a price of $24.99, compared to $25.10 for the winner. While the FBM offer has a much longer shipping time than the winner, the FBA offer is Prime eligible with the same shipping guarantee as the Buy Box winner.

While consumers can click through to examine multiple offers, most consumers purchase from the Buy Box winner. Feedvisor (2020) report that 80% of sales come through the Buy Box. A higher proportion of mobile sales come through the Buy Box because the smaller mobile screen makes it more difficult to discover offers beyond the default option. Amazon may also not allow any seller to win the Buy Box and so leave it "empty", in which case there is no default seller of the item. Figure A.1 provides an example of a product with no

(a) Product Detail Page



(b) Product Offers

Figure 1 Example: Product Where Buy Box Winner is Not Lowest Price

Note: Example of Product Detail Page and Offers for "Kotodama: The 7 Mysteries of Fujisawa – Nintendo Switch" (ASIN B07Q847Z67), taken on March 7, 2021.

Buy Box winner.

2.3 Buy Box Algorithm

Amazon does not disclose its algorithm for determining the Buy Box winner, but it singles out four factors of importance: price ("Price your items competitively"), shipping speed and price ("Offer faster shipping and free shipping"), customer service ("Provide great customer service"), and being in stock ("Keep stock available").[5]

Feedvisor, which assists Amazon sellers, provides more details on how Amazon determines the Buy Box winner (Feedvisor, 2020). First, the Buy Box operates as a "rotation", where Amazon assigns different sellers a share of Buy Box wins. For example, two equally ranked sellers might split the Buy Box 50-50, whereas a seller significantly better than its competitors could win much more frequently. Second, Amazon deems only certain sellers as qualified to win the Buy Box, and may deem a seller unqualified if it has poor performance metrics and an offer unqualified if its price exceeds the product's list price. Third, Amazon determines an offer's rank in terms of several different metrics. The most important criterion ("very high impact") according to Feedvisor (2020) is Fulfillment Method, with FBA offers prioritized over FBM. This factor suggests the algorithm preferences Amazon Fulfillment.

The next three criteria in importance ("high impact") are whether the product is in stock, the product price including shipping, and shipping time. Several criteria related to

[5] See https://sellercentral.amazon.com/gp/help/external/201687550?language=en-US&ref=efph_201687550_cont_200418100.

seller quality are given “medium impact”, including the number of feedbacks the seller has received, its feedback rating, how long it takes for the seller to respond to consumers, as well as several metrics related to shipping quality.

Finally, Amazon Retail and Amazon Fulfillment are considered to have “perfect” scores on many of these criteria; that is, an offer from Amazon Retail is considered equivalent to a perfect seller.

3 Data

3.1 Sampling

I collect data from several countries and product categories between December 9, 2020 and January 29, 2021 from Keepa, a third party API for Amazon data (Keepa, 2020-2021). For each country-category, I first extract a list of the top 500,000 products based on their Amazon sales rank. Products are defined by a unique Amazon Standard Identification Number (ASIN). I then sample all of the top 5,000 products, 2,500 of products ranked between 5,001 and 25,000, and 2,500 products ranked below 25,000. This sampling strategy ensures that I have data on all of the “head” products with the most sales, as well as samples of the “torso” and “tail” ASINs. I then collect data from the API for all offers for each product at a point in time, as well as the winner of the Buy Box.

My primary dataset consists of four countries – the US, UK, Germany, and France, and

18 categories: Auto, Baby, Beauty, Books, CD, DVD, Electronics, Garden, Grocery, Health, Home, IndustrialScientific, Office, Pet, Sports, Tools, Toys, and VideoGames. For most of these categories, I collect data for one sample at the category-country level.[6] In additional specifications, I use data from six product categories – DVD, Electronics, Home, Office, Toys, and Video Games – for Japan, Canada, Italy, Spain, and Mexico. Section A.3 provides more information on the number of samples and categories used.

For each offer, the API records the price and shipping cost of the offer, whether the seller is Amazon, FBA, and/or Prime, and whether the offer is immediately shippable. In addition, I have the seller ID of the Buy Box winner, and statistics at the product level such as the average Buy Box price of the product over the past year. I then match each seller to information on the seller's number of feedback ratings and average rating ranging from 0% to 100% positive.

I remove products without any offers as well as all used offers. The Buy Box winner is identified based on seller ID.[7] I also remove products for which the API's record of the average Buy Box price over the previous year was not recorded. About 91% of the original set of products remains after this data cleaning. In total, the primary dataset of the US, UK, Germany, and France has 833,667 products and 3,456,837 offers, while the entire dataset has

[6]For five categories – Electronics, Home, Office, Toys, and Video Games – I collect two samples of data for these four countries, with the second sample collected weeks later.

[7]In cases where a seller that won the Buy Box has more than one offer (for example, an FBA and non-FBA offer), I identify the winning offer using information on the price, shipping cost, FBA status, and Prime status of the winner. In a few cases, I exclude products for which the API reported that it could not record a Buy Box winner (as opposed to no Buy Box winner).

1,092,467 products and 4,417,310 offers.[8]

3.2 Descriptive Statistics

I then examine descriptive statistics for the primary sample of products sold in the US, UK, Germany, and France. Because media categories such as Books, CD, and DVD are quite different from non-media categories, I separate estimates by product category.

In Figure 2a, I depict the median (red) and average (blue) number of offers for a given product. The median number of offers is one for all categories except Books, CD, and DVD, with a median of 3 for DVD, 4 for CD, and 5 for Books. The average number of offers is about 2 for most categories, with an average of about 2.9 for Toys and Video Games, 4 for DVD, 4.8 for CD, and 7.6 for Books.

In Figure 2b, I depict the share of products with a Buy Box winner where the winner is Amazon Retail (red) or either Amazon Retail or a FBA third party offer (blue). Other than Books, CD, and DVD, the share of products with a Buy Box winner where the winner is Amazon Retail ranges from 7% to 18%; the lowest value is Electronics at 7%. Amazon Retail is the Buy Box winner 30% of the time for CD products, 42% of the time for DVD products, and an astounding 80% of the time for Books. Separating Books by country, Amazon is the Buy Box winner 100% of the time for UK Books!

[8]The API provides data on up to 100 new and used offers in order of their total price. This limit is reached for 2,321 products included in the final sample, of which 53% are in US Books and 78% are in US products in general.

The share of Buy Box winners for which Amazon ships the product – either Amazon Retail or third party FBA offers – is substantially higher. For most categories, the share of Buy Box winners for which Amazon ships the product ranges between 25% and 50%. Here, too, Books is an outlier, with 83% of Buy Box winners using Amazon Fulfillment.

Next, I examine how often the Buy Box winner is not the lowest price offer in Figure 2c for all products in red and for products with multiple offers in blue across all instock offers. In most categories, the Buy Box winner is not the lowest price offer 3% to 10% of the time. The Buy Box winner is not the lowest price much more often in media categories, at 19% for Video Games, 24% for DVD, 27% for Books, and 34% for CD. For UK Books, the Buy Box winner is not the lowest price about half the time. For products with multiple offers, the Buy Box winner is not the lowest price between 15% to 27% of the time in non-media categories, and between 30% to 45% of the time for media categories.

I then document the percentage difference in price when the Buy Box winner is not the lowest price.[9] Figure 2d depicts the median (in red) and average (in blue) percentage difference in price by category. At the median, the Buy Box price is between 1% and 4% greater than the lowest price for almost all categories, with the two highest differences for Books at 5.5% and Video Games at 11%. The average percentage price difference is much higher, ranging between 6% and 15% across categories. It is the highest for Video Games, where on average the Buy Box price is 26% greater than the lowest price when the Buy Box

[9] This is defined as the difference between the Buy Box price and lowest price divided by the lowest price.

winner is not the lowest price.

4 Results

4.1 Empirical Model

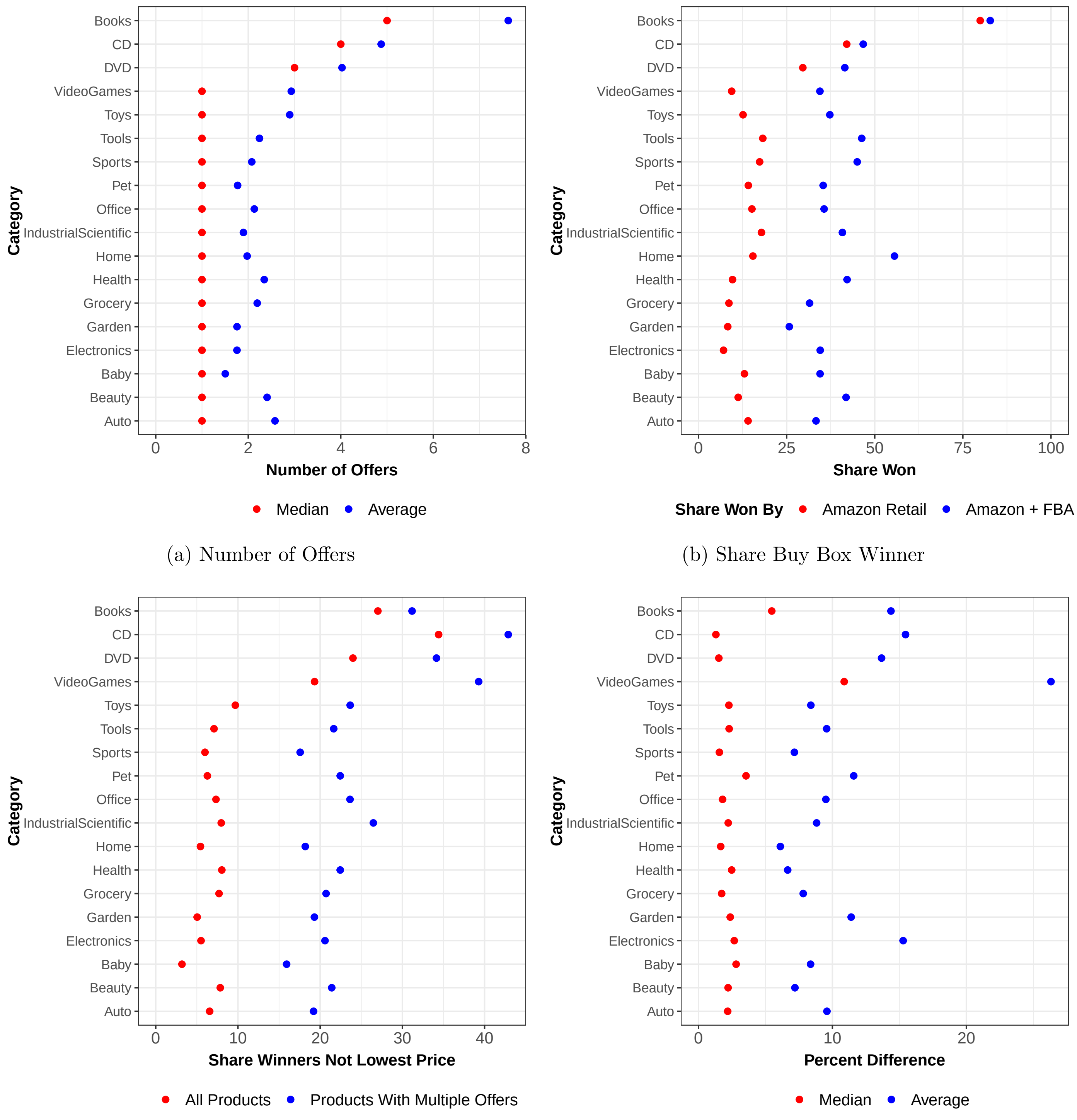
I model Amazon's choice of the default seller through a multinomial logit model. The value of a given offer V_{ios} for product i, offer o, and seller s is:

$$V_{ios} = \alpha + \beta[\log(p_{ios}) - \log(p_i^{365})] + \gamma_{f(o)} + \delta_{f(o)}[\log(c_s) - \log(1,000,000)] + \rho_{f(o)}(r_s - 100) + \varepsilon_{ios} \quad (1)$$

I include the log price of the offer $\log(p_{ios})$ minus the log average Buy Box price over the past year $\log(p_i^{365})$; β measures how sensitive the offer value is to price. The price includes shipping costs, which are zero for Amazon and FBA offers. By normalizing by the average Buy Box price over the past year, I allow Amazon to penalize offers that are high relative to the average Buy Box price.

Amazon may not allow any seller to win the Buy Box. Because I include an outside option of no Buy Box winner that is normalized to zero, the constant α measures the value of having an offer win the Buy Box.

Three terms depend upon the fulfillment type of the offer $f(o)$. These terms are different for FBA and FBM offers and zero for Amazon Retail. First, $\gamma_{f(o)}$ are constants for FBA and



(a) Number of Offers

(b) Share Buy Box Winner

(c) Share Winner Not Lowest Price

(d) Percent Price Difference if Winner Not Lowest Price

Figure 2 Buy Box Offers by Product Category

Note: All estimates based on the primary sample of products in the US, UK, Germany, and France, and use sample weights. Categories are ordered based on the median number of offers in the primary sample.

FBM offers. Second, c_s is the number of lifetime feedback ratings of the seller; I include the number of lifetime feedbacks in log form, subtracting the log of one million feedbacks. This normalization equates Amazon Retail to a seller with one million feedback ratings; δ should be positive if more feedback implies a better offer.[10]

Third, r_s is the feedback rating of the seller; I include it subtracting 100. This normalization equates Amazon Retail to a seller with a 100% rating; ρ should be positive if a higher rating implies a better offer.

The error ε_{ios} is distributed Type I extreme value. The econometric error captures both the randomness in Amazon's algorithm described in Section 2.3, as multiple sellers may "share" the Buy Box with a better offer having a larger share of the Buy Box, as well as offer or seller characteristics observed by Amazon but not by me.

This model controls for the main elements in Amazon's algorithm detailed in Section 2.3, including the price, fulfillment method, whether the seller is in stock, and multiple measures of seller quality. Unfortunately, the API did not record information on shipping speed. The Amazon and FBA offers both use Amazon's fulfillment network and so should have the same shipping speed (Amazon two day shipping for Prime members), but shipping speed will be longer and more variable for FBM offers. Thus, the difference between Amazon and FBA on the one hand, and FBM on the other, reflects both differences in shipping speed and Amazon self-preferencing its fulfillment service.

[10] Out of hundreds of thousands of sellers with offers in the primary sample, only 8 US, 5 UK, 3 German, and 2 French sellers have more than 1 million feedbacks.

4.2 Estimates

I first estimate (1) for all products in the primary sample, as well as for each country separately. Table I contains these estimates. The estimates of each variable accord with intuition for the full sample and each country separately – higher prices lower the value of an offer, an instock offer increases the value of an offer, and more feedback ratings and a higher rating score increase the value of the offer for both FBA and FBM offers. Both FBA and FBM offers for a perfect seller, defined as 1 million ratings and a 100% score, are lower value than an Amazon offer, with FBA offers of higher value than FBM offers.

For ease of interpretation, I estimate the price change required to yield the same change in utility as the change in a given variable, calculated for coefficient ξ as $\exp(\xi/\beta) - 1$. For the entire sample, an offer being in stock provides the same increase in utility as a 16% reduction in price. Increasing the number of feedback ratings from 1,000 to 100,000 is akin to a 5.1% decrease in price for a FBA seller and a 3.5% decrease in price for a FBM seller. An increase in average rating from 80% to 100% is equivalent to a 1.5% decrease in price for a FBA seller, and a 2.5% decrease in price for a FBM seller.

Amazon Retail offers enjoy a substantial price premium over third party offers. A FBA offer for a seller with 1 million feedbacks and a 100% rating is equivalent to a 16% increase in price over an Amazon Retail offer, while a FBM offer for the same seller is equivalent to a 46% increase in price over an Amazon Retail offer. These estimates are statistically significantly different from zero, and indicate self-preferencing in favor of Amazon Retail and Amazon Fulfillment.

I find a preference for Amazon Retail over third party FBA offers, and an even larger preference for Amazon Retail over third party FBM offers for each country separately. The estimated price premium for Amazon Retail over FBA is quite similar across countries; I estimate a price premium of 11.3% for Amazon Retail over FBA for the US, 11.3% for the UK, 14.6% for Germany, and 10.0% for France. The estimated price premium for Amazon Retail over FBM is higher for the US, at 52.4%, than the European countries, at 33.1% for the UK, 34.6% for Germany, and 39.6% for France.

Next, I examine heterogeneity in self-preferencing in the algorithm across categories. Amazon might vary its algorithm across product categories because of differences in consumer sensitivity to price, the value to the platform of additional merchants, or Amazon's market power.

Figure 3 depicts the price premia by category after estimating the empirical model at the category level. I estimate a positive and substantial price premium for Amazon Retail over FBA for every category except Auto; these premia are all statistically significantly different from zero after accounting for multiple hypothesis testing using a Bonferroni correction. The price premia for Amazon retail over FBM are positive for all categories and are always substantially and significantly larger than the price premium over FBA.

Across categories, the highest estimated price premia are in media categories. Four of

Table I Buy Box Model Estimates

	(1) All	(2) US	(3) UK	(4) DE	(5) FR
Log Price Difference	-8.371	-8.374	-8.912	-9.791	-7.068
	(0.022)	(0.048)	(0.045)	(0.050)	(0.039)
Is Offer	5.452	4.485	5.494	6.110	5.507
	(0.012)	(0.028)	(0.022)	(0.025)	(0.024)
Is FBA	-1.239	-0.893	-0.955	-1.331	-0.677
	(0.017)	(0.027)	(0.035)	(0.042)	(0.046)
Is FBM	-3.147	-3.527	-2.547	-2.912	-2.358
	(0.013)	(0.027)	(0.025)	(0.030)	(0.031)
Is Shippable	1.416	2.513	0.999	0.868	0.334
	(0.012)	(0.024)	(0.025)	(0.031)	(0.031)
Log Feedback Difference, FBA	0.092	0.132	0.079	0.052	0.057
	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
Log Feedback Difference, FBM	0.063	0.126	0.047	0.089	0.030
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Rating Difference, FBA	0.006	0.013	0.003	0.006	0.005
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Rating Difference, FBM	0.011	0.013	0.014	0.003	0.010
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4,290,504	1,273,859	995,395	1,197,940	823,310
Pseudo R^2	0.692	0.720	0.640	0.728	0.698

Note: The table reports estimates of (1) for all products in the primary sample, in the first column, and each country separately, in the next four columns. Standard errors are in parentheses.

the five highest categories for both the price premium over FBA and over FBM are Books, CD, DVD, and Video Games. For most categories, Amazon's price premium over a "perfect" FBA seller ranges between 5% and 15%, and its price premium over a "perfect" FBM seller ranges between 25% and 50%.

Books are a notable outlier – the price premium over FBA for Books is 61%, higher than the premium for FBM in all other categories. The price premium over FBM for Books is an astonishing 164%. These large estimates likely reflect UK Books, for which Amazon Retail won the Buy Box nearly 100% of the time and for which the Buy Box winner was not the lowest price about half the time. However, Books had the highest share of Amazon Retail winning the Buy Box across categories for all four countries.

I examine how well my empirical model approximates the Buy Box algorithm by comparing the actual winners of the Buy Box to the empirical model's predictions. For each product, I predict the Buy Box winner as the offer with the maximum probability of being chosen based on category level estimates. The model correctly predicts the Buy Box offer 88% of the time across all categories, and 80% of the time for products with multiple offers.[11] Appendix A.2 examines prediction accuracy in more detail.

In Figure 3b, I examine a larger set of countries by estimating the model at the country level including data from Japan, Canada, Italy, Spain, and Mexico. I restrict products to those in the DVD, Electronics, Home, Office, Toys, and Video Games categories so that esti-

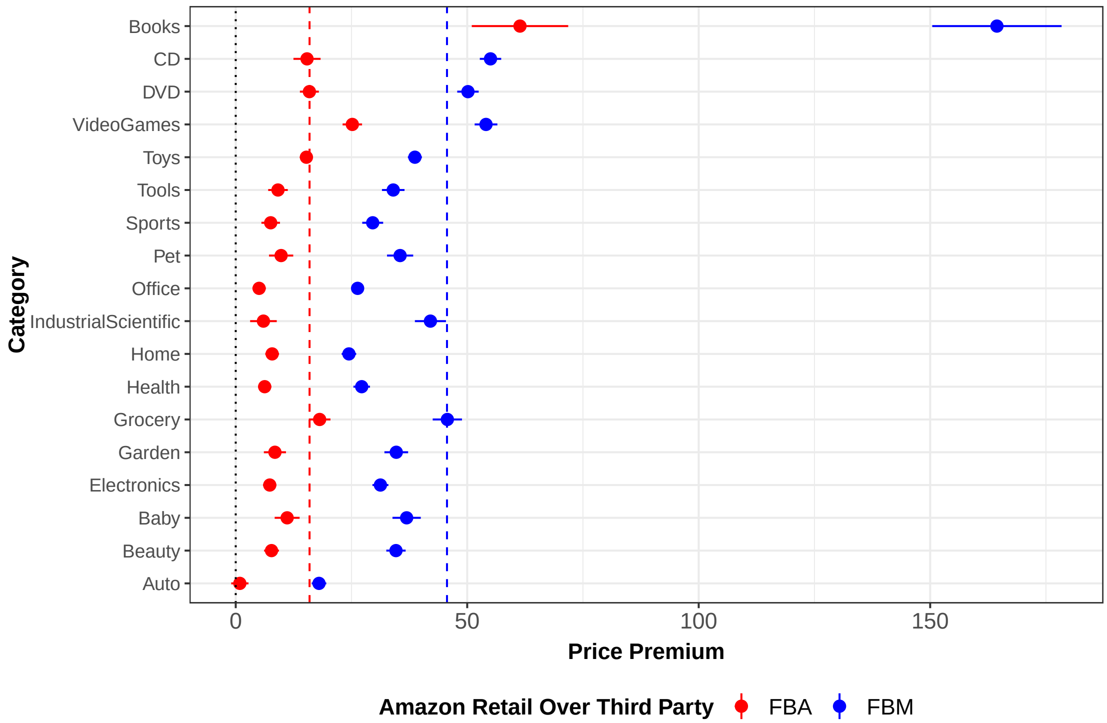
[11]These estimates are quite high compared to empirical demand estimation. For example, Raval et al. (2021) document that demand models predict 40% to 44% of choices correctly for a set of hospital markets.

mates for each country are based on the same categories. I find substantial self-preferencing effects in all countries. Except for Mexico (at 31%), the price premium for Amazon Retail over FBA ranges between 7% and 13% across countries. The estimated premium for Amazon Retail over FBM is between 25% and 60% for most countries, with Canada and Mexico as outliers at about 80%. Thus, the Buy Box algorithm prioritizes Amazon Retail and Amazon Fulfillment across a wide range of countries.

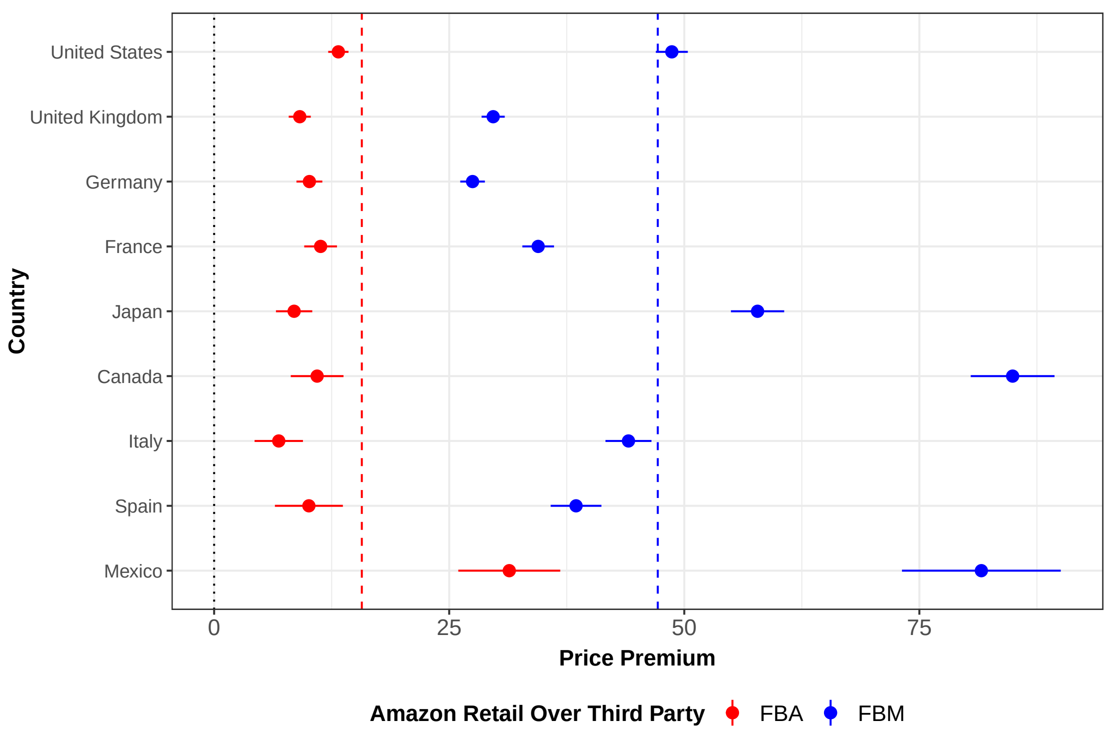
The estimates reported above may reflect Amazon closing the Buy Box when there are third party offers but no Amazon offer (Hunold et al., 2022). I thus allow the outside option to be treated differently than other offers by estimating a nested logit model that includes the outside option in a separate nest than merchant offers. I continue to find substantial self-preferencing on behalf of Amazon Retail, but the estimates are somewhat smaller. Using all products in the primary sample, Amazon Retail's estimated price premium over FBA is 11% and over FBM 32%, compared to 15% and 38% in the baseline specification.[12]

Estimated price premia for Amazon Retail over FBA are between 3% and 15% for most products, and for Amazon Retail over FBM between 15% and 35%. Books remains a substantial outlier with a price premium of 57% for Amazon Retail over FBA and 150% for Amazon Retail over FBM. Figure A.2a depicts the category-level estimates. Thus, Amazon's decisions to close the Buy Box do not explain most of the estimated self-preferencing effects.

[12] I find similar self-preferencing estimates with a multinomial logit model dropping the outside option and products with a closed Buy Box.



(a) By Product Category



(b) By Country

Figure 3 Buy Box Price Premia for Amazon Retail

Note: The figures report estimates of the "Is FBA" and "Is FBM" coefficients in (1) divided by the price coefficients. Each row represents a product category or country and depicts the point estimate and 95% Confidence Interval. The red dashed vertical line depicts the estimate for Amazon Retail over FBA, and the blue dashed vertical line depicts the estimate for Amazon Retail over FBM. The left figure examines the primary sample. The right figure examines all countries but restricts to the DVD, Electronics, Home, Office, Toys, and Video Games categories.

Another potential concern is that Amazon might not allow certain low quality offers to compete in the Buy Box. If this was the case, my estimates would overstate self-preferencing by not including these measures of quality or excluding disqualified offers. To account for this issue, I estimate a multinomial logit model including only offers that the API records as having *ever* won the BuyBox in its scans of each product. I find similar estimates of self-preferencing as in the baseline specification. Using all products in the primary sample, Amazon Retail's estimated price premium over FBA is 14% and over FBM 41%, compared to 15% and 38% at baseline. Figure A.2b depicts the category-level estimates. These results are inconsistent with unobserved quality differences explaining the estimated self-preferencing effects.

4.3 Counterfactuals

I now examine two counterfactual changes to the Buy Box algorithm that remove some of Amazon's self-preferencing of its retail and fulfillment arms. As I discuss below, these counterfactuals hold many factors fixed including the set of offers for a product. In the first counterfactual, I set the fixed effect for FBA in (1) (γ_{FBA}) to zero. Thus, this counterfactual change gives FBA sellers with a million feedback ratings and a 100% rating score the same preference in the algorithm as Amazon Retail. In the second counterfactual, I set the fixed effects for FBA and FBM in (1) (γ_{FBA} and γ_{FBM}) to zero. Here, both FBA and FBM sellers with a million reviews and a 100% rating receive the same preference as each other, and as Amazon Retail. These counterfactuals remove the self-preferencing for Amazon Retail and/or Amazon Fulfillment, but continue to consider Amazon Retail as a "perfect" seller and discriminate against lower quality third party sellers. Thus, for example, Amazon will always win the Buy Box with the same price as a third party seller in these counterfactuals.

I then examine counterfactual changes by comparing predictions of the model under the baseline estimates to predictions of the model under each counterfactual, using estimates of the model at the category level.

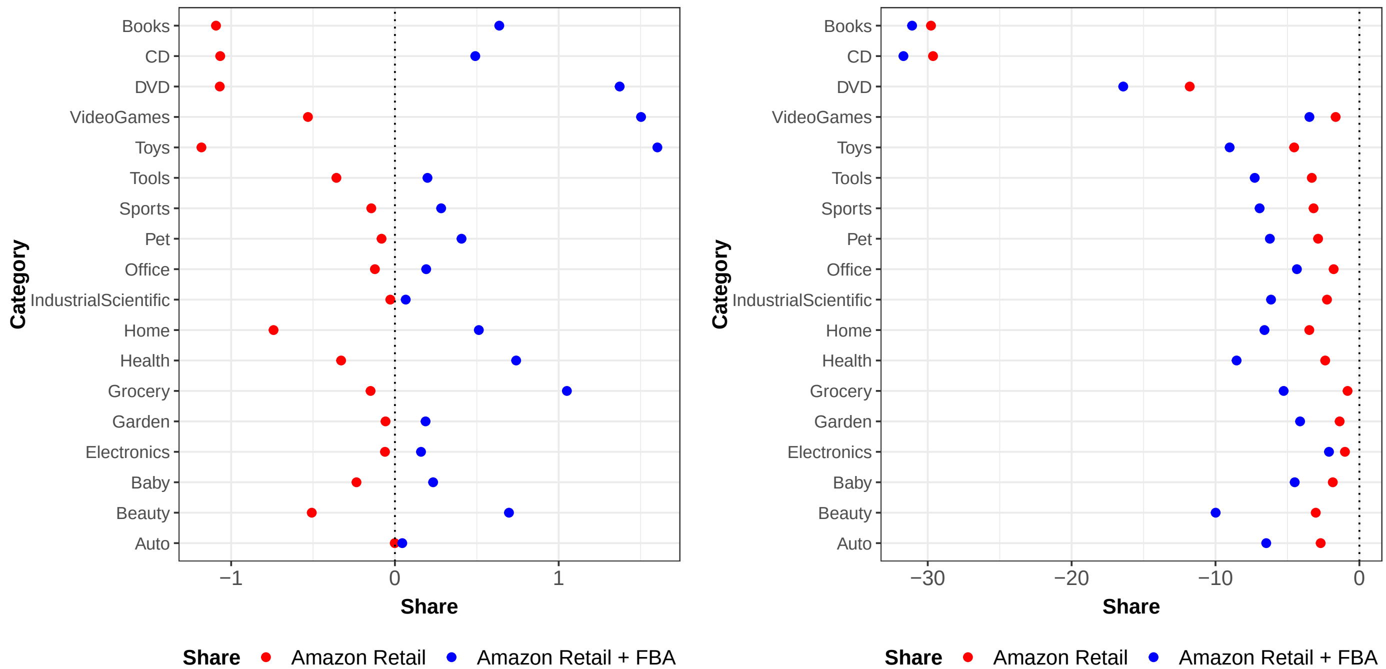
Changing the preference for FBA alone has modest effects on the Buy Box winner and price. After treating a perfect FBA seller as the same as Amazon Retail, Amazon Retail's share of the Buy Box falls by 0.54 percentage points, while the share of Amazon Retail and FBA together rises by 0.65 percentage points. Lower price FBA sellers displace Amazon Retail in the Buy Box but higher price FBA sellers displace FBM sellers. Thus, the average change in Buy Box Price (the average change in price divided by the baseline Buy Box price) is a 0.12% *increase*, while the average change in Buy Box price for products where Amazon Retail previously won the Buy Box is a 0.10% decrease.

Treating a perfect FBA and perfect FBM seller as the same as Amazon has much larger effects. Amazon's share of the Buy Box falls by 7.2 percentage points, while the share of Amazon Retail and FBA falls by 10.6 percentage points. The average change in the Buy Box price is a 0.62% decrease in price, while the average change in price for products where Amazon Retail previously won the Buy Box is a 2.1% decrease in price.

In Figure 4, I examine the change in Buy Box share for Amazon Retail, and for Amazon Fulfillment, separately by category. The left figure examines removing self-preferencing of Amazon Retail over FBA; the largest reductions in Amazon's share, in media categories and Toys, are just larger than 1 percentage point; similarly, the largest increases in the share of Amazon Fulfillment are about 1.5%. The right figure examines removing self-preferencing of Amazon Retail over FBA and FBM, which results in much larger changes. In particular, the share of Amazon Retail and Amazon Fulfillment drop by about 30 percentage points for Books and CD, and by 12 and 16 percentage points respectively for DVD. Across most categories, the share of Amazon Retail falls between 1 and 4 percentage points, and the share of Amazon Fulfillment between 5 and 10 percentage points.

These counterfactuals keep the set of offers the same. Changes to the algorithm will likely change how sellers set prices and whether sellers choose to use FBA or FBM for fulfillment. Without a substantial preference for FBA in the Buy Box algorithm, many FBA sellers would likely switch to FBM. Finally, these counterfactuals do not account for entry; removing self-preferencing for Amazon in the Buy Box would likely lead to entry of third party sellers on products where Amazon currently wins the Buy Box.

In addition, Amazon might change its prices and fees after removing self-preferencing. If Amazon Retail or Amazon Fulfillment exhibit returns to scale, a reduction in the share of either could increase Amazon Retail's prices, and Amazon's FBA fees if increased costs are passed on to retailers. Without self-preferencing, Amazon Retail might be unable to guar-



(a) Amazon Retail = "Perfect FBA"

(b) Amazon Retail = "Perfect FBM"

Figure 4 Change in Buy Box Share with Counterfactual Changes to Buy Box Algorithm by Product Category

Note: All estimates based on the primary sample of products in the US, UK, Germany, and France, and use sample weights. Each figure examines the change in the share of Amazon Retail (in red) and the share of Amazon Retail and FBA (in blue) in the Buy Box by category. The left figure examines a counterfactual in which Amazon Retail and a "perfect" (100% rating and 1 million ratings) FBA seller receive the same preference in the algorithm. The right figure examines a counterfactual in which Amazon Retail, a "perfect" (100% rating and 1 million ratings) FBA seller, and a perfect FBM seller receive the same preference in the algorithm.

antee winning the Buy Box, and so might receive smaller discounts from vendors. Finally, Amazon might decide to increase the revenue share it charges third party retailers after the changes or foreclose them entirely by moving away from being a dual platform.

5 Conclusion

I have examined whether Amazon preferences its retail and fulfillment arms in its choice of the default seller on the Amazon Buy Box. I have found substantial self-preferencing in favor of both Amazon Retail and Amazon Fulfillment across countries and almost all product categories. The largest self-preferencing effects are for Books, where Amazon arguably has the greatest market power. In counterfactuals holding offer terms fixed, removing the self-preference effects for Amazon Fulfillment from the algorithm would substantially reduce Amazon's Buy Box share and the average Buy Box price.

The European Union recently settled its investigation into Amazon's Buy Box conduct by requiring Amazon to include multiple competing offers in the Buy Box and not preference its own offers, as well as to allow competing fulfillment services to qualify for Prime shipping. Reports indicate that the US Federal Trade Commission will soon sue Amazon over issues related to third party sellers.[13] Thus, antitrust enforcement may result in a rapid change in the competitive environment on Amazon's platform in the coming years.

[13] See https://www.bloomberg.com/news/articles/2023-06-29/amazon-major-ftc-antitrust-case-expected-in-coming-weeks.

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