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 their own products and services. In this paper, 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 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.

*First Version: April 2021. I would like to thank X for their comments on this paper. Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the Federal Trade Commission, or its Commissioners. All work was conducted using the author's personal (i.e. non-work) time and resources.

1 Introduction

Policymakers are very concerned about the market power of large online platforms. The US antitrust agencies have now sued Google and Facebook for monopolization, while both the UK and EU are introducing new rules for the regulation of major online platforms. In a recent executive order, President Biden stated that "today a small number of dominant Internet platforms use their power to exclude market entrants [and] to extract monopoly profits" and encouraged the Federal Trade Commission (FTC) to write rules concerning unfair practices on major internet marketplaces.[1]

Regulators express particular concern that platforms that "run the marketplace while also competing in it" steer consumers to their own products and services over those of competitors. For example, the EU's proposed Digital Markets Act prohibits a gatekeeper platform from preferencing its own services over rivals. Biden's executive order specifically mentions harm to small businesses that depend on Internet platforms for their survival.

Amazon's treatment of third party sellers on its platform has come under concern, as the recent House Antitrust Subcommittee report (Nadler and Cicilline, 2020) states:

> 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

[1] See https://www.whitehouse.gov/briefing-room/presidential-actions/2021/07/09/executive-order-on-promoting-competition-in-the-american-economy/.

third-party sellers, and a seller in that same marketplace, creates an inherent conflict of interest.

In this article, I examine how Amazon determines the default seller in the Amazon Buy Box. While many merchants may list offers to sell the same product on Amazon's platform, the vast majority of consumers purchase from the default merchant for that product by clicking on the "One Click" button in the Amazon Buy Box. An estimated 80% of Amazon sales go through the Buy Box, with higher rates for mobile devices.[2]

Because Amazon picks the default merchant, it has the ability to steer consumers to a first party offer sold by its retail arm ("Amazon Retail") over third party offers. In addition, it may favor either first party or third party offers shipped by its fulfillment arm (Fulfilled by Amazon or "FBA") over third party offers using other shipping options ("Fulfilled by Merchant" or FBM). Such steering could then force sellers to ship using Amazon Fulfillment over alternatives in order to win the Buy Box and so reach consumers. In Congressional testimony, former Amazon CEO Jeff Bezos defends 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]

However, because Amazon does not disclose how its algorithm works, we do not know

[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.

whether Amazon favors first party offers by Amazon Retail over third party FBA offers, both of which are Prime-eligible, or how large Amazon's thumb on the scale is for either Amazon Retail or FBA. I provide evidence on these questions.

In order to do so, I gather data on the set of offers available for about a million products selling on Amazon across several countries. I focus on a sample of about eight hundred thousand products sold in four countries – the US, UK, Germany, and France – and 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 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, which allows me to examine how Amazon trades off its retail and fulfillment services against the product price. The model includes several publicly known features of the algorithm including 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. The estimated model correctly predicts the Buy Box winner 88% of the time for all products, and 80% of the time for products with multiple offers.

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. Using data from the US, UK, Germany, and France, 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 seller receiving a penalty equivalent to a 61% price increase, and a perfect FBM seller receiving a penalty equivalent to a 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, Amazon Retail's share of the Buy Box falls by 7.2 percentage points and Amazon Fulfillment's share of the Buy Box falls by 10.6 percentage points. On average, the Buy Box price falls by 0.6% with a 2.1% decrease for products where Amazon Retail previously won the Buy Box. I find very large changes in media categories; the share of Amazon Retail and Amazon Fulfillment for the Books and CD categories falls by 30 percentage points.

This paper is related to the recent debate on vertical integration and self-preferencing of large online platforms. Khan (2016) argues that Amazon has exploited its market power to privilege its own products, and that Amazon's preference towards FBA on its platform is a form of anti-competitive tying; Khan (2019) discusses how structural separation can remedy competitive harms from such integration. 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, for common demand functions, Amazon's incentives align with consumers. Hagiu et al. (2021) find that policies that prevent self-preferencing by Amazon are better for consumer welfare than preventing Amazon from acting as both a merchant and platform.

Empirically, Zhu and Liu (2018) find 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. Chen and Tsai (2021) is the closest paper to my own; they show that Amazon tends to recommend products sold by Amazon

Retail to consumers over products sold by third party retailers, and that this steering is inconsistent with Amazon promoting consumer welfare.

In addition, this paper informs debates on the adoption of algorithms in markets. One strand of the literature has focused on whether the adoption of pricing algorithms leads to supra-competitive prices by learning to collude (Asker et al., 2021; Calvano et al., 2020) or moving away from symmetric Bertrand-Nash equilibrium (Brown and MacKay, 2020; Leisten, 2021). Empirically, Assad et al. (2020) find that adoption of algorithmic pricing by gasoline stations tends to increase prices after both stations in a market adopt. Another strand of the literature examines how to detect and remove algorithmic biases against protected groups (Lambrecht and Tucker, 2019; Obermeyer et al., 2019; Rambachan et al., 2020).

Section 2 provides background details on the Amazon Buy Box and the Buy Box algorithm and Section 3 provides details on the data I use. Section 4 estimates the degree of self-preferencing for Amazon Retail and Amazon Fulfillment in the Buy Box algorithm, and Section 5 concludes.

2 Background

2.1 Sellers on Amazon

While Amazon.com began life as purely an online retailer, it became the *platform* we see today when it launched Amazon Marketplace in 2000. Amazon Marketplace allowed third-party sellers to sell directly on product pages along with Amazon itself in return for a pre-specified revenue share of third party sales.[4]

Figure 1 provides a diagram of the different sellers that operate on Amazon's marketplace. First, Amazon itself sells on the platform. In addition, independent third party merchants may sell on the platform through three different approaches. First, under the "Fulfillment by Amazon" or FBA program launched in 2006, 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.

Finally, in "Seller Fulfilled Prime", Amazon has conditions under which third party merchants can do their own shipping and achieve Prime Status. However, these conditions are quite onerous, and have become more so, which make it very difficult to obtain Prime

[4] Amazon Marketplace launched after two previous failed attempts to allow sellers on Amazon's platform, Amazon Auctions and z-Shops. See https://press.aboutamazon.com/news-releases/news-release-details/amazon-marketplace-winner-customers-sellers-and-industry.

Status without using FBA. As Nadler and Cicilline (2020) state[5]:

> On August 18, 2020, Amazon informed sellers of changes to Seller Fulfilled Prime which render it an entirely impractical option for most sellers. Even before this change, only a very small percentage of sellers could meet the onerous eligibility requirements for Seller Fulfilled Prime. This means FBA is functionally the only way for sellers to get the Prime badge for their product listings.

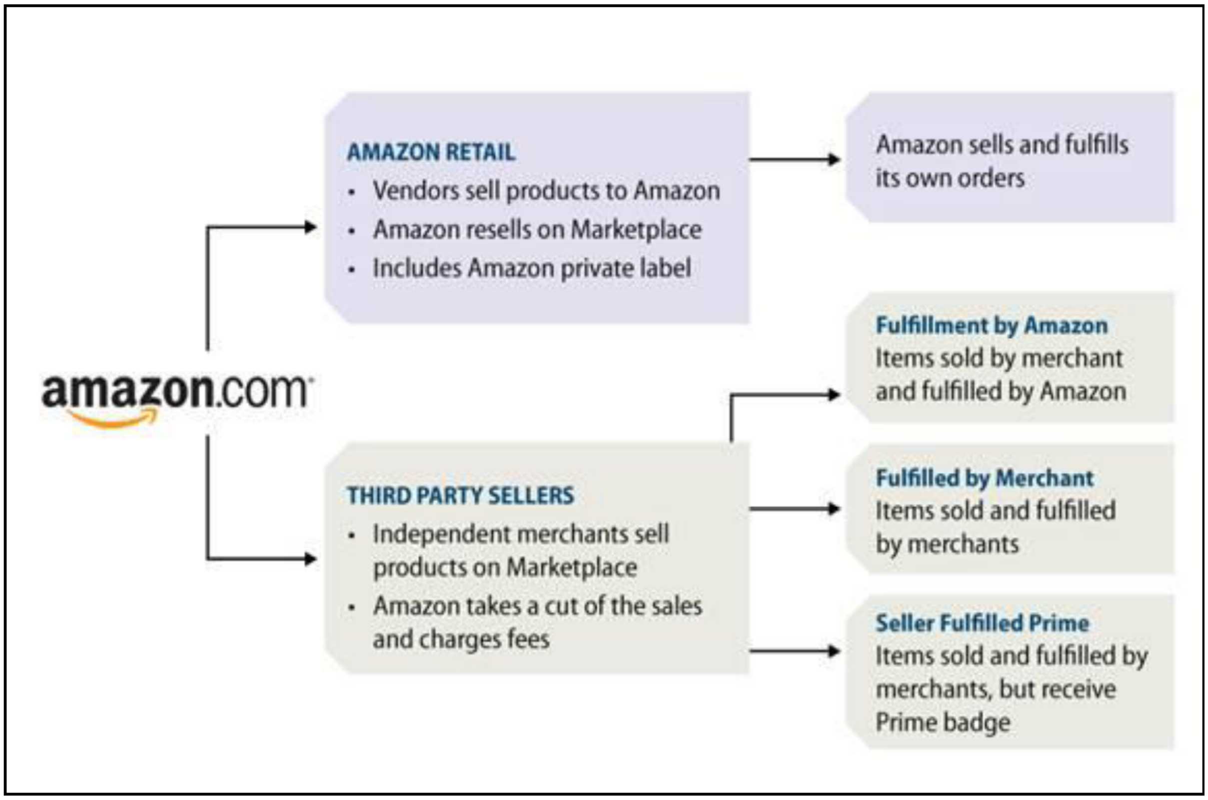
2.2 Buy Box

Figure 2 provides an example of how consumers purchase a product which has multiple competing sellers on Amazon's marketplace. Figure 2a depicts a product detail page for an Amazon product. For this product, the area in 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 area in the green box is the Buy Box; clicking "Buy Now" buys the product from the Buy Box winner. Finally, the area in the blue box allows consumers to click through to see other buying options.

Figure 2b shows some of these alternative offers. In particular, for this example, the Buy Box winner in the red box, Amazon Retail, is not the lowest price product. A Fulfilled by Merchant Offer in the blue box has a price of $24.97 for the same product, and a FBA offer

[5] These changes included requiring Saturday delivery and warehouses across the country to achieve Prime status; Nadler and Cicilline (2020) mention that only 200 sellers in the US could achieve Seller Fulfilled Prime status before the changes.

Figure 1 Types of Sellers on Amazon.com and Shipping Options



Note: See page 251, Nadler and Cicilline (2020).

in the green box has a price of $24.99. Notably, while the FBM offer has a much longer shipping time of March 15-19, the FBA offer has the same shipping guarantee as the Buy Box winner (March 9) and is also Prime eligible.

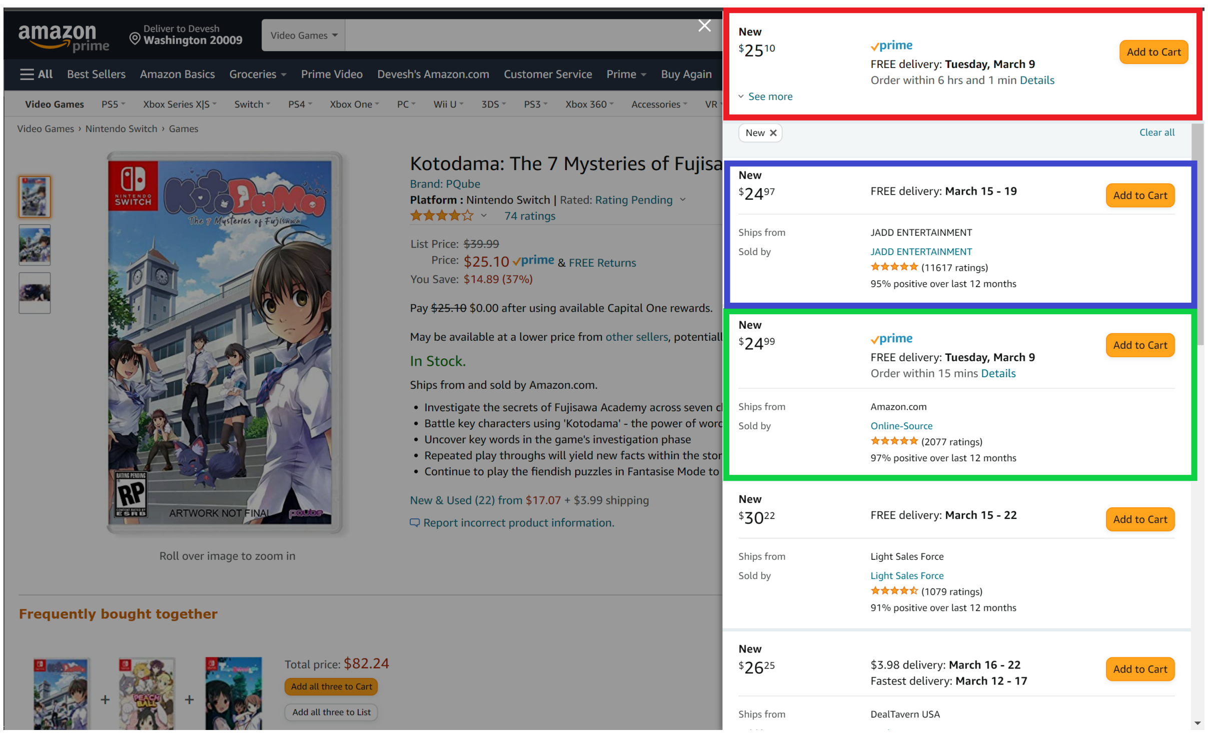
While consumers can click through to examine multiple offers, as shown above, most consumers purchase from the Buy Box winner. Feedvisor (2020) report that 80% of sales come through the Buy Box, with an even higher proportion of mobile sales coming through the Buy Box. The mobile screen has less "real estate" and so it is likely 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". Figure 3 provides an example of a product with no Buy Box winner. In Figure 3a, the area in the red box does not provide a price, unlike Figure 2a, and just states "Available from these Sellers". Similarly, the Buy Box located in the green box does not have a one click button, although one can click through to see offers. Figure 3b depicts the offers available; inside the green box is a FBA offer with a 2 day delivery time for $29.99.

2.3 Buy Box Algorithm

Amazon does not publically reveal its algorithm for determining the Buy Box winner. It does provide information to its sellers on what factors are important. Amazon singles out four such factors: price ("Price your items competitively"), shipping speed and shipping price ("Offer faster shipping and free shipping"), customer service ("Provide great customer

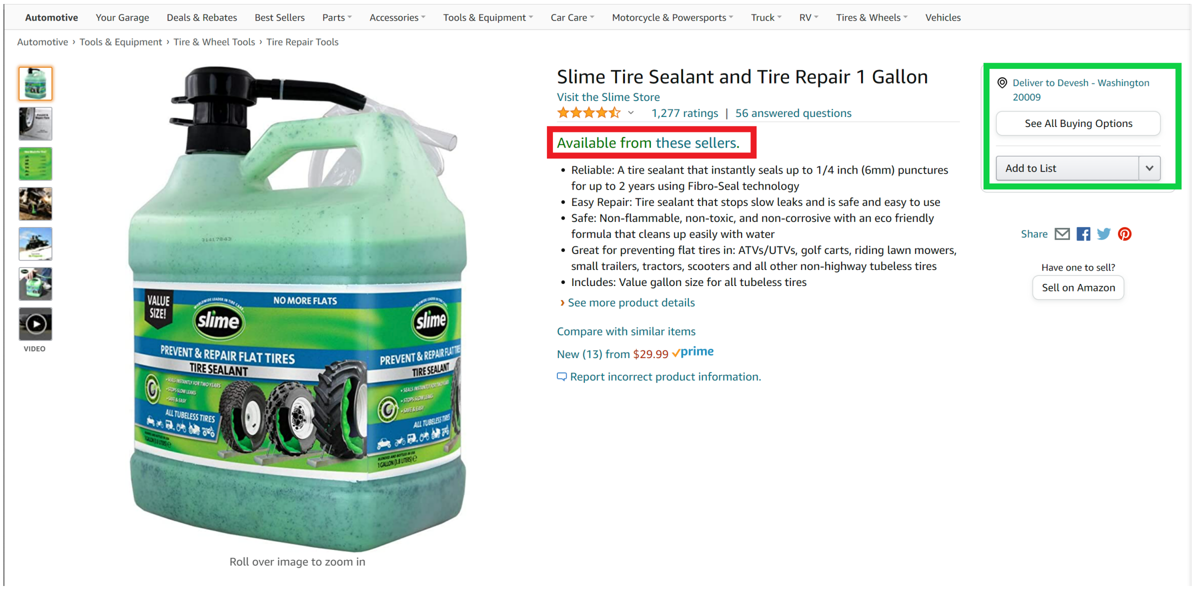
(a) Product Detail Page



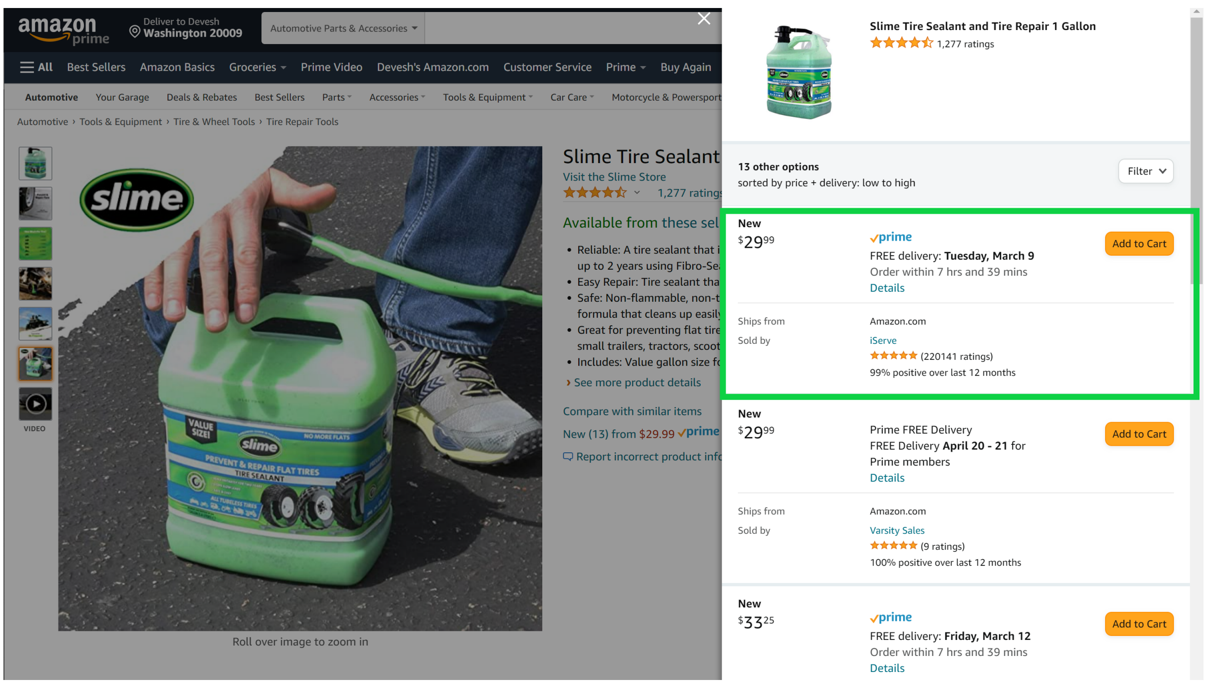
(b) Product Offers

Figure 2 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.



(a) Product Detail Page



(b) Product Offers

Figure 3 Example: Product With No Buy Box Winner

Note: Example of Product Detail Page and Offers for "Slime Tire Sealant and Tire Repair 1 Gallon" (ASIN B013J2RRFQ), taken on March 7, 2021.

service"), and being in stock ("Keep stock available").[6] However, consulting firms that assist Amazon sellers provide more details on how Amazon determines the Buy Box winner. I rely on Feedvisor (2020) for the information below.

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 80, 90, or 100% of the time. 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.[7] Third, Amazon determines an offer's rank in terms of several different metrics. Of eligible sellers, the most important criterion ("very high impact") according to Feedvisor (2020) is Fulfillment Method, with FBA offers prioritized over FBM. This suggests substantial self-preferencing towards Amazon Fulfillment in the algorithm.

The next three criteria in importance ("high impact") are whether the product is in stock, the product price including shipping, and the shipping time. Finally several criteria 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, and several metrics related to shipping such as late shipment rate, on-time delivery rate, order defect rate, and

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

[7] Nadler and Cicilline (2020) mention allegations that sellers found to sell products on other platforms for a lower price than on Amazon can be made ineligible to win the Buy Box.

whether consumers are given delivery tracking information.

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.

2.4 Previous Evidence

Several anecdotes have documented Amazon prioritizing Amazon Retail and FBA offers over offers of FBM third party sellers in the Buy Box. The Wall Street Journal, for example, describe a seller of Pillow Pets who lost the Buy Box to Amazon Retail once Amazon Retail began selling the same product at the same price. The seller's sales fell by nearly 80% after Amazon Retail's entry.[8] ProPublica examined 250 frequently purchased products over several weeks in 2016. They found that the Buy Box winner was not the lowest price most of the time; Amazon or FBA offers won the Buy Box over cheaper offers 75% of the time.[9] In addition, consumer purchasing all 250 products would pay 20% more when buying from the Buy Box over the cheapest available merchant.

[8] See https://www.wsj.com/articles/SB10001424052702304441404577482902055882264. In addition, Nadler and Cicilline (2020) describe a seller who had to repeatedly change his business model after Amazon repeatedly took over the Buy Box from his offers. See page 279 of Nadler and Cicilline (2020). Nadler and Cicilline (2020) also describe a seller who had both FBA and FBM offers and found that the FBA offer would win the Buy Box even if the FBM offer was 7% cheaper.

[9] See https://www.propublica.org/article/amazon-says-it-puts-customers-first-but-its-pricing-algorithm-doesnt.

3 Data

I first select a sample of products for a set of countries and product categories. I then obtain data on offers in the Buy Box for these products from Keepa, a third party API for Amazon data.

3.1 Sampling

I collect data from several countries and product categories between December 9, 2020 and January 29, 2021. For each country and product category, I first extract a list of the top 500,000 products based on their Amazon sales rank, where products are defined by their Amazon Standard Identification Number (ASIN). For a given product category, I 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 (if any) of the Buy Box.

My primary dataset is data for a set of 18 categories, listed in Table I, for the US, UK, Germany, and France. Table I lists the US category name as well as an abbreviation I use in the paper; for other countries, I match to the closest product category in that country. Table V and Table VI contain the category name for each country. For most of these

Table I Samples by Category and Country Set

Category	US, UK, DE, FR	JP, CA, IT, ES, MX
Automotive (Auto)	1	0
Baby Products (Baby)	1	0
Beauty & Personal Care (Beauty)	1	0
Books	1	0
CDs & Vinyl (CD)	1	0
Movies & TV (DVD)	1	1
Electronics	2	1
Patio, Lawn, & Garden (Garden)	1	0
Grocery & Gourmet Food (Grocery)	1	0
Health & Household (Health)	1	0
Home & Kitchen (Home)	2 (1 for US)	1
Industrial & Scientific (IndustrialScientific)	1	0
Office Products (Office)	2	1
Pet Supplies (Pet)	1	0
Sports & Outdoors (Sports)	1	0
Tools & Home Improvement (Tools)	1	0
Toys & Games (Toys)	2	1
Video Games	2	1

categories, I collect data for one sample at the category-country level. 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. Finally, as a secondary dataset, I collect data from six product categories – DVD, Electronics, Home, Office, Toys, and Video Games – for Japan, Canada, Italy, Spain, and Mexico.[10] Table I lists the number of samples by category and country set.

For each offer, the API records the price and shipping cost of the offer, whether the seller is Amazon, whether the seller is FBA, whether the seller is Prime, and whether the offer is immediately shippable (i.e. not out of stock). In addition, I have the seller ID of the

[10]For CA Video Games and MX Office and Video Games, there are less than 25,000 products. I thus only collect a sample of 7,500 products for these samples, excluding the "tail" sample of 2,500 products with a sales rank greater than 25,000.

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 number of feedback ratings that the seller has, and the average rating (ranging from 0% to 100%) of the seller.

Before any analysis, I conduct some data cleaning on the offers. For each sample, I remove products without any offers as well as all used offers. The Buy Box winner is identified based on the seller ID recorded for the Buy Box winner.[11] The API's record of the average Buy Box price over the previous year is also included; I remove products for which no such average Buy Box price was 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. Including all countries, the dataset has 1,092,467 products and 4,417,310 offers.[12]

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 other categories, I separate estimates by product category. I depict these

[11] 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 use 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).

[12] The API provides data on up to 100 (new and used) offers in order of their price, where price includes shipping cost. 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.

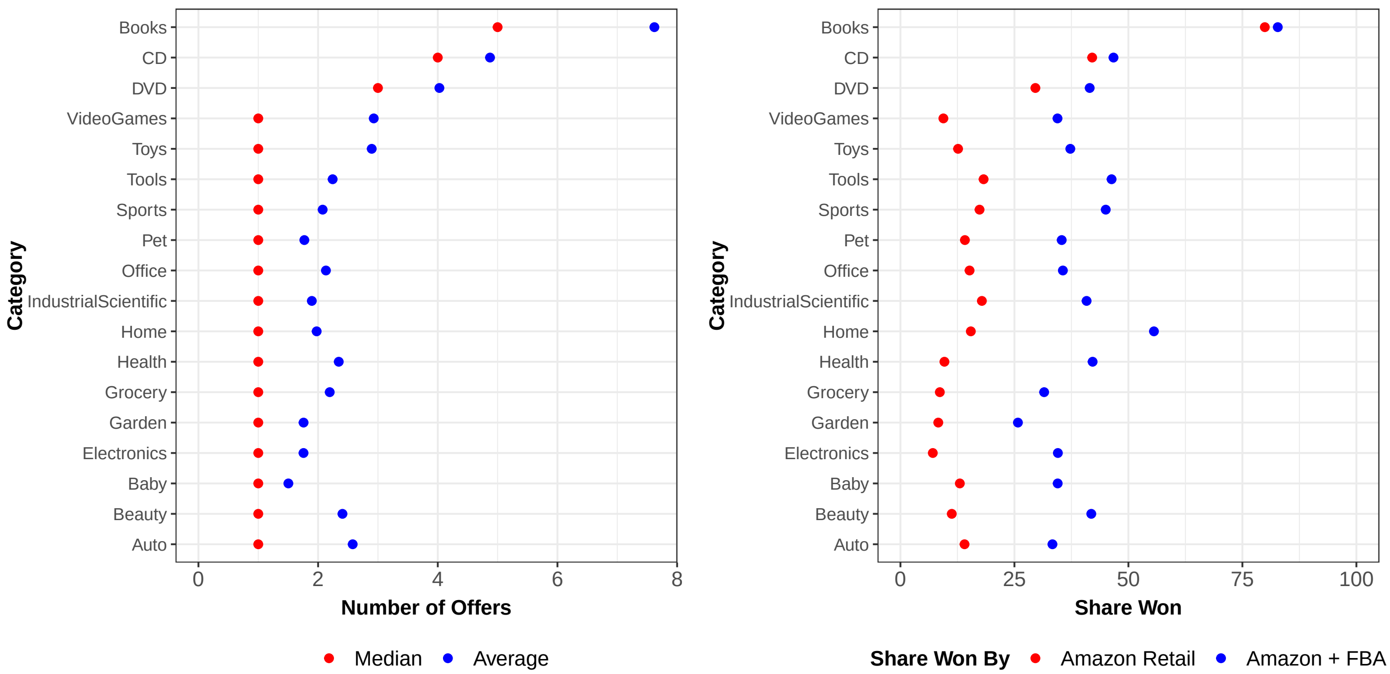
descriptive statistics in graphs, ordering categories by their value of one of the variables.

In Figure 4a, 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 4b, 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!

The share of Buy Box winners for which Amazon ships the product – i.e. 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 for shipping.

Next, I examine how often the Buy Box winner is not the lowest price offer in Figure 5a for all products (in red) and for products with multiple offers (in blue). I only consider offers



(a) Number of Offers

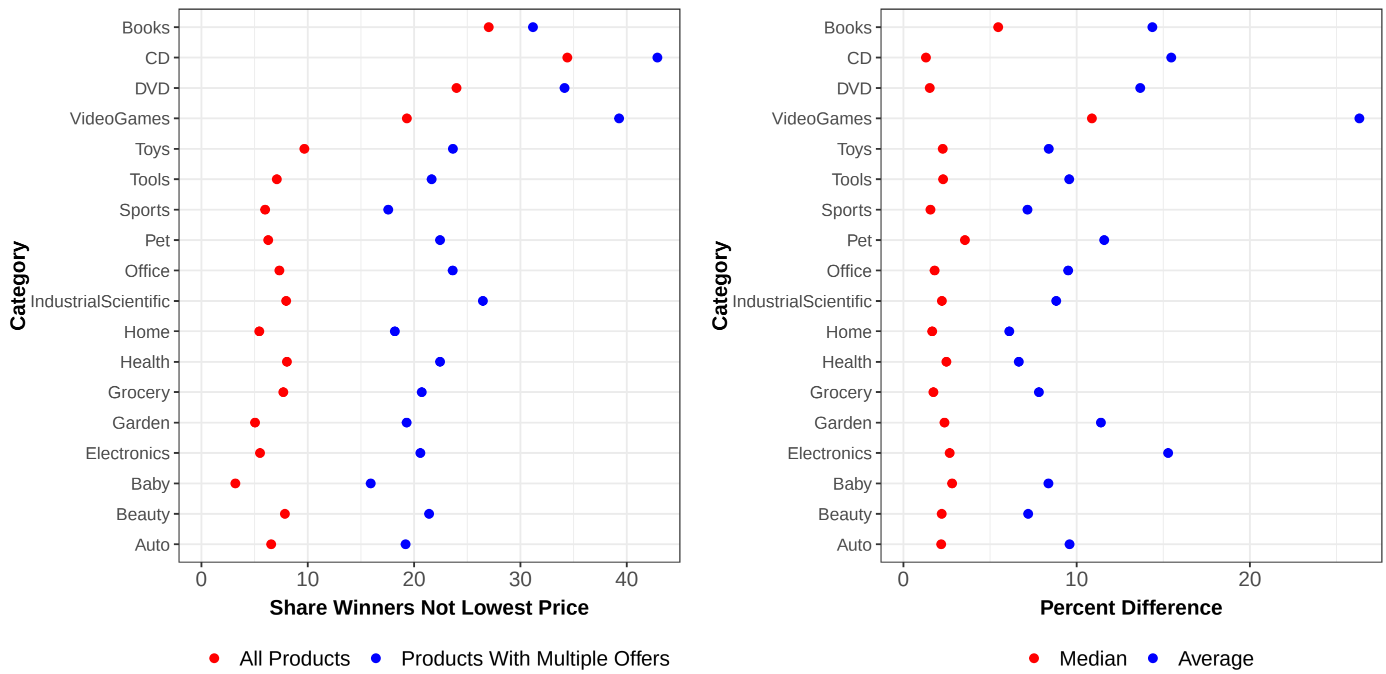
(b) Buy Box Winner

Figure 4 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.

when the product is immediately shippable, to avoid low price offers that are not selected because the product is temporarily out of stock. For all products, 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. Only including 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, defined as the difference between the Buy Box price and lowest price divided by the lowest price. Figure 5b 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 winner is not the lowest price.



(a) Winner Not Lowest Price (b) Percent Price Difference if Winner Not Lowest Price

Figure 5 Price Differences From Buy Box Winner by Product Category

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

4 Results

4.1 Empirical Model

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

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

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.[13] By normalizing by the average Buy Box price over the past year, I allow Amazon to penalize offers that are "price gouging" by being high relative to the typical Buy Box price. As in Figure 3, 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, α, a constant, will separate the value of having an offer win the Buy Box from no winner.

I then include three terms that depend upon the fulfillment type of the offer $f(o)$, so estimates are different for FBA and FBM offers. These terms are all zero for Amazon Retail. First, $\gamma_{f(o)}$ are constants for Fulfilled by Amazon and Fulfilled by Merchant offers. Second,

[13] The price I use includes shipping costs. I set the shipping cost to zero for Amazon and FBA offers, as would be true for Prime members. Consumers without Prime have to buy at least $25 to avoid shipping costs, and would receive slower shipping.

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 implies that Amazon Retail is equated to a seller with one million feedback ratings, and that δ should be positive if more feedback implies a better offer. 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.

Third, r_s iss the feedback rating of the seller; I include it subtracting 100. This normalization implies that Amazon Retail is equated to a seller with a 100% rating, and that 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 is meant to capture both the potential 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 characteristics of the seller or offer observed by Amazon but not by the econometrician.

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, it does not have information on shipping speed as the API did not record information on shipping speed. The Amazon and FBA offers should have the same shipping speed (Amazon two day shipping for Prime members), but shipping speed will both be longer and more variable for FBM offers. Thus, the difference between Amazon and FBA on the one hand, and FBM on the other, will reflect both differences in shipping speed and Amazon self-preferencing its fulfillment service.

This model also does not include Seller Fulfilled Prime separately, as the API stopped tracking Seller Fulfilled Prime (SFP) at the same time that Amazon made it much more difficult to receive SFP status (see the discussion in Section 2.1). Because very few sellers have SFP, this is unlikely to affect the estimates, but it would understate the FBM coefficient as SFP sellers would wrongly be classified as FBM.

4.2 Estimates

I first estimate (1) for all products in the primary sample, as well as for each country separately. Table II 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 or shippable 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.

In order to interpret the estimates, I normalize the effect of each variable using the price coefficient.[14] Thus, a offer being in stock is equivalent to a 16% reduction in price for the entire sample. Increasing the number of feedback ratings from 1,000 to 100,000 is akin to a

[14] Formally, the normalized value for coefficient ξ is $\exp(\xi/\beta) - 1$.

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 significant self-preferencing in favor of Amazon Retail and Amazon Fulfillment.

I find a similar hierarchy – a substantial 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, because Amazon might vary its algorithm across product categories for several reasons. First, consumer sensitivity to price may vary across categories – for example, consumers might be more price sensitive in categories with expensive products. Second, Amazon might want

Table II 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.

to incentivize merchant entry in some categories more than others; for example, Amazon may have a catalogue of all books or DVDs but rely on third party merchants for product discovery in categories like electronics where no such catalogue exists. Finally, Amazon's market power is likely stronger in some categories like Books compared to others.

Figure 6 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 the five highest categories for both the price premium over FBA and price premium 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.

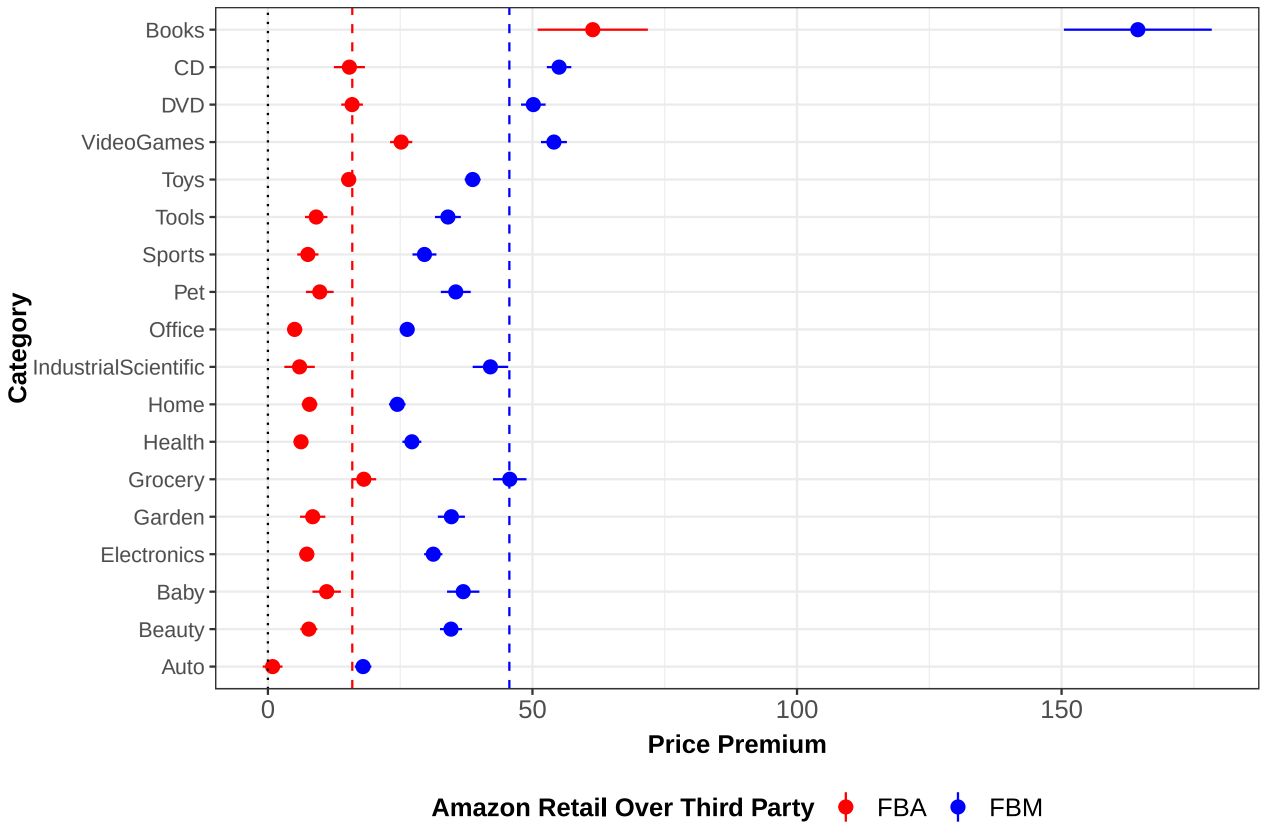


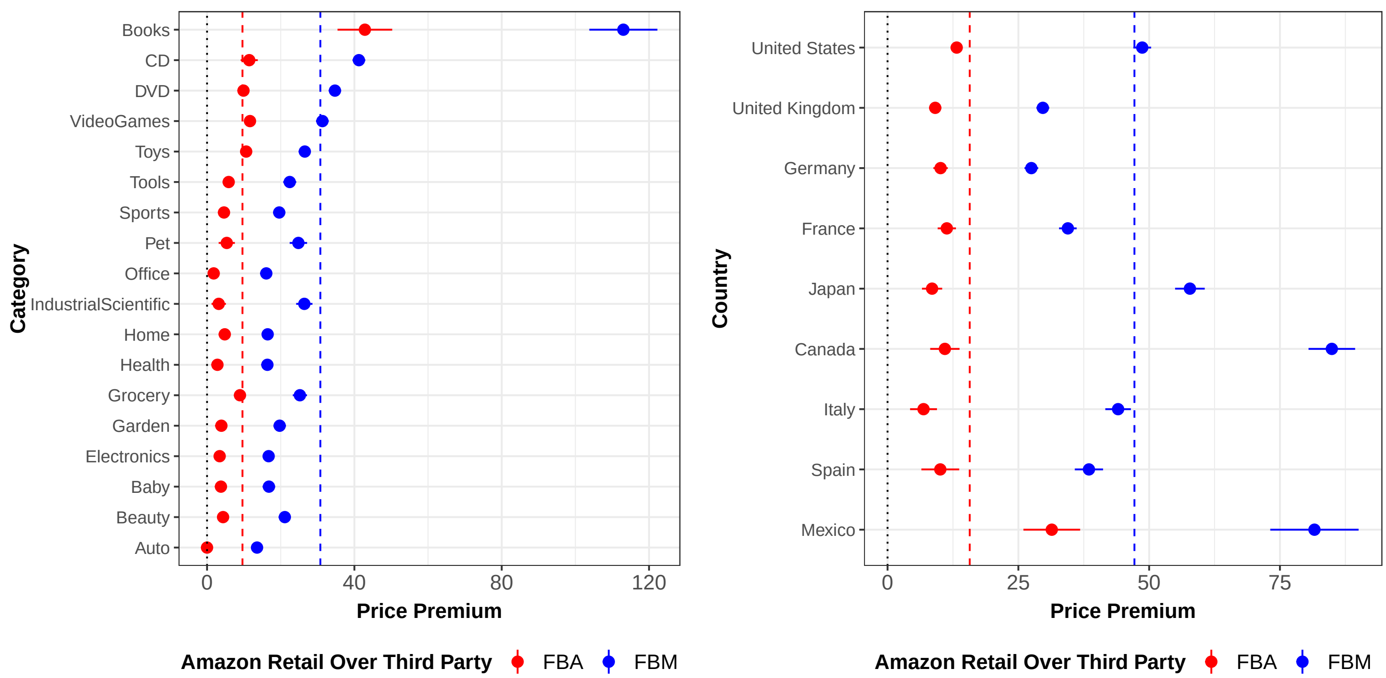
Figure 6 Buy Box Price Premia for Amazon Retail by Product Category

Note: The figure reports estimates of the "Is FBA" and "Is FBM" coefficients in (1) divided by the price coefficients, based upon products in the primary sample. Each row represents a product category and depicts the point estimate and 95% Confidence Interval. The red dashed vertical line depicts the estimate for Amazon Retail over FBA for the entire primary sample, and the blue dashed vertical line depicts the estimate for Amazon Retail over FBM for the entire primary sample.

I examine two further specifications in Figure 7. First, part of the self-preferencing estimates reported above likely reflect Amazon often leaving the Buy Box closed when there are third party offers but no Amazon offer. I thus examine estimates including only products with a Buy Box winner, and removing the outside option. 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 10% and over FBM 31%, compared to 15% and 38% earlier.

In Figure 7a, I depict estimates by product category after only including products with a Buy Box winner. Estimated price premia for Amazon Retail over FBA are between 2% and 12% for most products, and for Amazon Retail over FBM between 13% and 30%. Books remains a substantial outlier with a price premium of 43% for Amazon Retail over FBA and 113% for Amazon Retail over FBM, while Auto has no price premium for Amazon Retail over FBA. Thus, Amazon's option to close the Buy Box does not fully explain estimates of self-preferencing effects.

Second, I examine a larger set of countries by including data from Japan, Canada, Italy, Spain, and Mexico in the dataset and estimating the model at the country level. Here, I restrict products to those in the DVD, Electronics, Home, Office, Toys, and Video Games categories so that estimates for each country are based on the same categories. As Figure 7b shows, I find substantial self-preferencing effects for Amazon Retail over FBA and Amazon Retail over FBM for 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.



(a) Only Products With Buy Box Winner

(b) All Countries

Figure 7 Additional Specifications

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 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 but restricts the estimation to products with a Buy Box winners. The right figure examines all countries but restricts to the DVD, Electronics, Home, Office, Toys, and Video Games categories.

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. For this section, I use estimates of the empirical model estimated at the category level. Overall, the model correctly predicts the Buy Box offer 88% of the time across all categories, and 80% of the time for just products with multiple offers.[15] I examine prediction accuracy in more detail in Appendix A.1.

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 fixedincluding 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

[15] 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.

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. Table III provides estimates of these counterfactual changes. Just changing the preference for FBA has modest effects on the Buy Box winner and Buy Box price. After treating a perfect FBA seller as the same as Amazon Retail, Amazon Retail's share of the Buy Box falls by 0.52 percentage points, while the share of Amazon Retail and FBA together rises by 0.65 percentage points. Perhaps intuitively, 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 (defined by averaging the change in price divided by the baseline Buy Box price across products) 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 0.6% 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 8, I examine the change in Buy Box share for Amazon Retail, and for Amazon

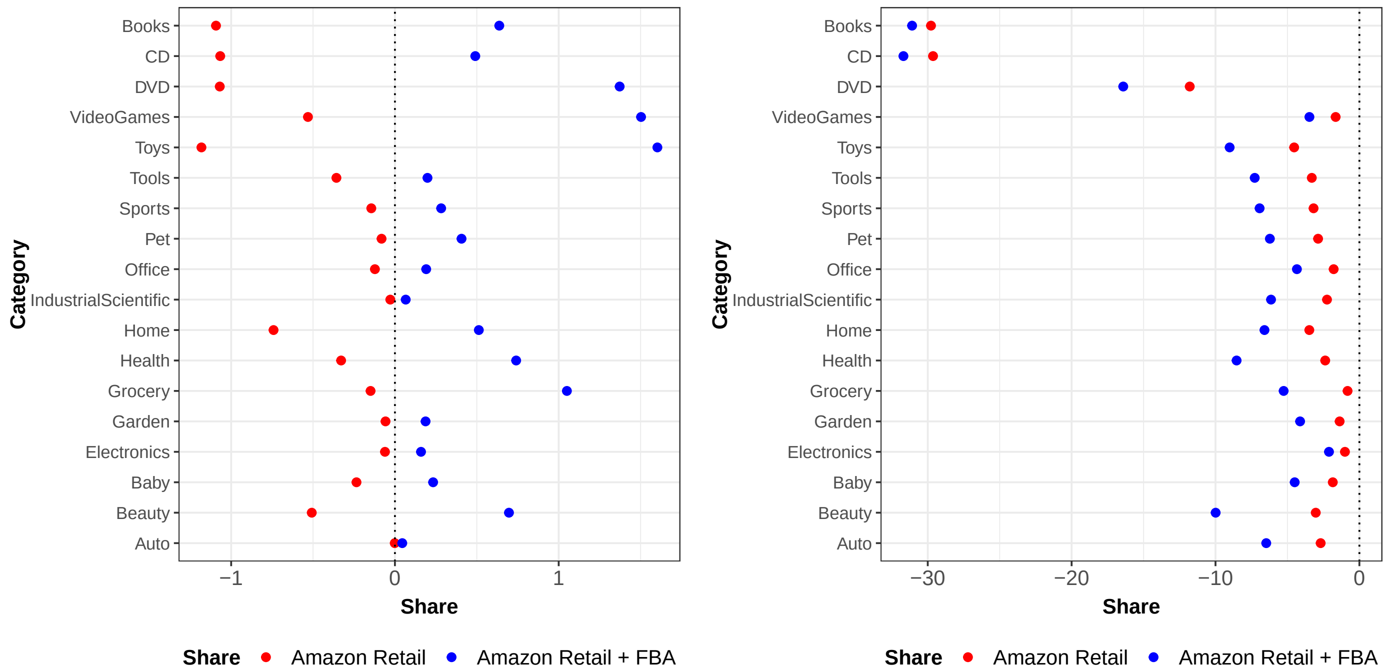
Table III Effects of Counterfactual Changes to Buy Box Algorithm

Measure	Amazon Retail = "Perfect FBA"	Amazon Retail = "Perfect FBM"
Amazon Share of Buy Box	-0.52%	-7.17%
Amazon + FBA Share of Buy Box	0.65%	-10.62%
Average Change in Buy Box Price	0.12%	-0.62%
Average Change in Buy Box Price, Amazon Retail Baseline Winner	-0.10%	-2.14%

Note: All estimates based on the primary sample of products in the US, UK, Germany, and France, and use sample weights. The first column examines a counterfactual in which Amazon Retail and a "perfect" (100% rating score and 1 million ratings) FBA seller receive the same preference in the algorithm. The second column examines a counterfactual in which Amazon Retail, a "perfect" (100% rating score and 1 million ratings) FBA seller, and a perfect FBM seller receive the same preference in the algorithm.

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 do not include many of the changes from removing self-preferencing as they keep the set of offers the same. In reality, changes to the algorithm will likely change the prices that sellers set. They will also affect whether sellers choose to use FBA or FBM for fulfillment; without a substantial preference for FBA in the Buy Box algorithm, many FBA



(a) Amazon Retail = "Perfect FBA"

(b) Amazon Retail = "Perfect FBM"

Figure 8 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.

sellers would likely switch to FBM. Finally, and most importantly, 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 guarantee winning the Buy Box, and so might receive smaller quantity discounts from vendors. And Amazon might decide to increase the revenue share it charges third party retailers after the changes, which would raise prices, or even foreclose them entirely by moving away from being a dual platform.

5 Discussion and Conclusion

Policymakers are now considering how to treat platform self-preferencing. For example, Khan (2019) contrasts two potential remedies for platform self-preferencing: a non-discrimination regime (i.e. a ban on self-preferencing) and structural separation. Other alternatives are also possible, such as changes to the user interface of the platform to reduce the salience of the "default" choice.

This work helps to demonstrate why a non-discrimination regime would be difficult to implement in practice. Take, for example, the self-preferencing I document in favor of

Amazon Retail over FBA sellers. Because Amazon does not allow reviews of itself, it would be difficult for a regulator to assess whether Amazon Retail itself is a "perfect seller", or how its quality compares to third party sellers. In addition, while consumers prefer high quality sellers, only Amazon would have the data available to examine how consumers trade off price and seller quality. Amazon could easily disguise self-preferencing by inflating its own quality in the algorithm, or by overestimating how much consumers value seller quality. On the other hand, a regulator that did not account for quality in the algorithm could lead to a platform flooded with poor quality sellers.

These problems are even more severe with self-preferencing over merchants using their own fulfillment services. Here, a regulator would also have to distinguish whether any preference for Amazon fulfillment reflected accounting for the shipping time guarantees provided by Amazon fulfillment, or harmful self-preferencing by the platform. Again, only Amazon would have the data to assess how much consumer value better shipping, as well as how merchants compare in their shipping quality. Shipping quality depends on several metrics that Amazon both determines and estimates for all sellers.

In contrast, structural separation that separated Amazon the platform, Amazon the retailer, and Amazon the fulfillment service would naturally remove any incentive for the platform to prefer the retailer or fulfillment service unless doing so improved the consumer experience. Such separation would not require a regulator to regularly assess Amazon's algorithms. In addition, a separated platform might allow non-Amazon fulfillment services such as UPS and FedEx to brand their own services on the Amazon platform and compete with Amazon fulfillment for sellers. However, structural separation would remove any efficiencies generated from vertical integration, which could lead to higher prices or worse quality for consumers.

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A Appendix

A.1 Predictive Accuracy

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. For this section, I use estimates of the empirical model estimated at the category level.

Table IV examines prediction accuracy by comparing model predictions to the actual winner of the Buy Box. The first column of the table is the actual share of products by winner type, and the first row of the table is the predicted share of products by winner type. Overall, the model predicts aggregate shares of each type of offer fairly well, except for the share where there is no Buy Box winner. The model overpredicts Amazon Retail's share of Buy Box winners by 2.5 percentage points, with a predicted share of 32.2% compared an actual share of 29.7%, and overpredicts FBA's share by 0.9 percentage points, with a predicted share of 38.5% compared to an actual share of 37.4%. The model underpredicts FBM's share by 2.3 percentage points (26.8% predicted compared to 29.1% actual) and underpredicts the share with no Buy Box winner by 1.5 percentage points (2.4% predicted compared to 3.9% actual).

The next four rows and columns of Table IV report the share predicted of each winner type given the actual winner of the Buy Box. The model predicts Amazon Retail wins the Buy Box 99.1% of the time when it does, and that FBA wins the Buy Box 97.4% of the time when it does. The model performs slightly worse for FBM offers – it predicts FBM wins the Buy Box 85% when an FBM offer wins the Buy Box, predicting Amazon Retail 7.4% of the time, FBA 4.6% of the time, and No Winner 3.0% of the time. Finally, the model performs much worse when no offer wins the Buy Box. The model predicts that no one wins the Buy Box 36% of the time when there is no winner, predicting that FBA wins 15% of the time and that FBM wins 49% of the time.

Next, I examine how often the empirical model predicts the correct offer as the Buy Box winner across product categories. Overall, the model correctly predicts the Buy Box offer 88% of the time across all categories, and 80% of the time for just products with multiple offers. Figure 9 depicts these estimates by product category for all products as well as just products with multiple offers. The model best predicts Books, with the Buy Box winner predicted correctly 95% of the time for both all products and products with multiple offers. The model performs the worst for Video Games, predicting 75% of Buy Box winners correctly for all products and 65% for products with multiple offers. For the median category, the model predicts 90% of all products correctly and 80% of products with multiple offers correctly.[16]

A.2 Category Names

Table V and Table VI provide the category names for each category by country.

[16]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.

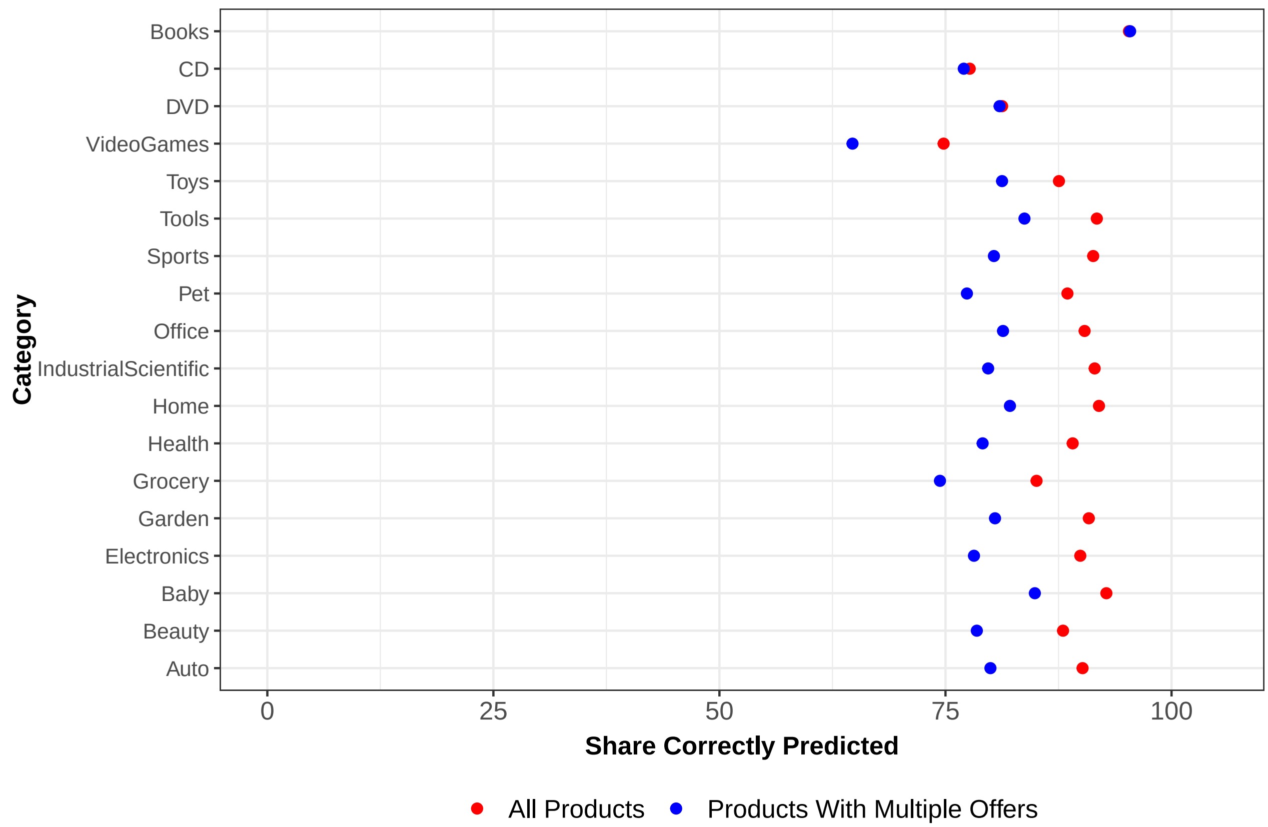

Figure 9 Percent Correctly Predicted by Product Category

Note: The figure depicts estimates of the share correctly predicted by category. Predicted winners based on the offer with the maximum probability among offers for a product, using estimates of the empirical model at the category level.

Table IV Prediction Accuracy of Empirical Model

		Predicted Winner			
Winner	Share	Amazon Retail	FBA	FBM	No Winner
Share Predicted		32.2%	38.5%	26.8%	2.4%
Amazon Retail	29.7%	**99.1%**	0.5%	0.3%	0.1%
FBA	37.4%	1.9%	**97.4%**	0.4%	0.2%
FBM	29.1%	7.4%	4.6%	**85.0%**	3.0%
No Winner	3.9%	0.2%	15.1%	48.6%	**36.1%**

Note: Predicted winners based on the offer with the maximum probability among offers for a product, using estimates of the empirical model at the category level. I examine four offer types – Amazon Retail, FBA, FBM, and no Buy Box winner. The first row is the share predicted for each offer type, while the first column is the actual share for each offer type. The next four rows and columns provide the share of the predicted offer type of the Buy Box winner for each actual Buy Box winner's offer type. For example, Amazon Retail is the predicted Buy Box winner 99.1% of the time when Amazon Retail wins the Buy Box, and FBA is the predicted Buy Box winner 0.5% of the time.

Table V Category Names by Country for Primary Dataset

Category	US	UK	DE	FR
Auto	Automotive	Automotive	Auto & Motorrad	Auto et Moto
Baby	Baby Products	Baby Products	Baby	Bébé et Puériculture
Beauty	Beauty & Personal Care	Beauty	Beauty	Beauté et Parfum
Books	Books	Books	Bücher	Livres
CD	CDs & Vinyl	CDs & Vinyl	Musik-CDs & Vinyl	CD et Vinyles
DVD	Movies & TV	DVD & Blu-ray	DVD & Blu-ray	DVD et Blu-ray
Electronics	Electronics	Electronics & Photo	Elektronik & Foto	High-Tech
Garden	Patio, Lawn & Garden	Garden & Outdoors	Garten	Jardin
Grocery	Grocery & Gourmet Food	Grocery	Lebensmittel & Getränke	Epicerie
Health	Health & Household	Health & Personal Care	Drogerie & Körperpflege	Hygiène et Santé
Home	Home & Kitchen	Home & Kitchen	Küche, Haushalt & Wohnen	Cuisine et Maison
IndustrialScientific	Industrial & Scientific	Business, Industry & Science	Gewerbe, Industrie & Wissenschaft	Commerce, Industrie et Science
Office	Office Products	Stationery & Office Supplies	Bürobedarf & Schreibwaren	Fournitures de bureau
Pet	Pet Supplies	Pet Supplies	Haustier	Animalerie
Sports	Sports & Outdoors	Sports & Outdoors	Sport & Freizeit	Sports et Loisirs
Tools	Tools & Home Improvement	DIY & Tools	Baumarkt	Bricolage
Toys	Toys & Games	Toys & Games	Spielzeug	Jeux et Jouets
VideoGames	Video Games	PC & Video Games	Games	Jeux vidéo

Table VI Category Names by Country for Additional Countries

Category	JP	CA	IT	ES	MX
DVD	DVD	Movies & TV	Film e TV	Películas y TV	Películas y Series de TV
Electronics	家電＆カメラ	Electronics	Elettronica	Electrónica	Electrónicos
Home	ホーム＆キッチン	Home & Kitchen	Casa e cucina	Hogar y cocina	Hogar y Cocina
Office	文房具　オフィス用品	Office Products	Cancelleria e prodotti per ufficio	Oficina y papelería	Oficina y Papelería
Toys	おもちゃ	Toys & Games	Giochi e giocattoli	Juguetes y juegos	Juguetes y Juegos
VideoGames	ゲーム	Video Games	Videogiochi	Videojuegos	Videojuegos