ABSTRACT

Title of Dissertation:	THE COMPETITION IN ONLINE MARKETPLACES
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This dissertation examines competition in online marketplaces using data from the largest online marketplace in the U.S., Amazon.com.

The first essay studies direct sales competition between a marketplace operator and third parties that sell their products on the marketplace and examines factors that third-party sellers may use to avoid direct competition with the marketplace operator. I find that third-party sellers can best avoid competing directly with Amazon by selling unbranded products and by marketing products that are fulfilled by Amazon.

The second essay investigates competitive results between the marketplace operator and third-party sellers. I find that despite inherent competitive disadvantages, third-party sellers may increase their likelihood of winning the sales competition against the marketplace operator when they offer a lower price than the marketplace operator and when they use the marketplace operator's fulfillment services. In addition, a third-party seller using direct fulfillment is less likely to outcompete a seller using

operator-managed fulfillment services, but it can be more competitive when it offers lower prices and when it sells low-priced products.

The third essay investigates how employment of the marketplace's store banner impacts sales performance for both private label products and non-private label products on an online marketplace. I find that directly branding private labels and using store banners on non-private label products are both associated with greater sales performance. In addition, lower-priced products and non-private label products may achieve greater benefits from store banners.

The findings contribute to the online marketplace literature by empirically testing the impact of direct sales, fulfillment services, and store banner use on competition between a marketplace operator and third-party sellers. The findings also contribute to important antitrust considerations.

THE COMPETITION IN ONLINE MARKETPLACES

by

Hao Su

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Dedication

This dissertation is dedicated to my beloved wife Chengcheng Ji, my father Zhi Su, my mother Ling Jia, my father-in-law Hua Ji, and my mother-in-law Huiming Ma. The endless love and the unconditional support that I have received from my family has helped me pursue my dream. I love you and owe you everything.

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Chapter 1: Overview

This dissertation is developed over three essays and examines competition on online marketplaces. Specifically, the first essay studies factors that may allow third-party sellers to avoid directly competing with the marketplace operator. The second essay investigates competitive results between the marketplace operator and third-party sellers, while the third essay examines how the employment of the marketplace's store banner impacts product sales performance.

The first essay examines the direct sales decisions of the marketplace operator. In direct sales competition between a marketplace operator and third parties that sell their products on the marketplace, the third parties are likely to lose due to information and cost advantages possessed by the marketplace operator. Consequently, third-party sellers may choose to offer products that do not directly compete with products offered by the marketplace operator. Therefore, I examine factors that predict the marketplace operator's decision to directly sell a product on its marketplace.

In addressing my research questions, I use data from Amazon, the largest marketplace operator in the U.S. The results show that the marketplace operator is more likely to directly sell a product: (1) when the product is not carried by third-party sellers that use Amazon fulfilment services, (2) when the product is a well-known brand, and (3) when the product is part of a brand that offers a large number of other branded products on the marketplace. Therefore, third-party sellers can better avoid competing directly with Amazon by selling unbranded products and marketing products that tend to be fulfilled by Amazon.

The second essay studies the competitive results under two different scenarios: (1) when the marketplace operator and third-party sellers compete by selling the same product, and (2) when third-party sellers using operator-managed fulfillment services compete with third-party sellers using their own direct fulfillment services. I focus on factors that influence the winners of these sales competitions.

I find that the marketplace operator is more likely to win the competition against third-party sellers. The likelihood of a third-party seller winning the competition against the marketplace operator may increase: (1) when there is a higher number of the sellers that use operator-managed fulfillment services, and (2) when the third-party sellers offer a lower price than the marketplace operator.

In addition, the results show that between the third-party seller using operator-managed fulfillment services and third-party sellers using direct fulfillment, the competition favors sellers using operator-managed fulfillment services. However, the likelihood of a third-party seller that uses direct fulfillment winning the competition increases: (1) if it offers a lower price, and (2) when the product price is low. The findings suggest that third-party sellers may try to avoid direct competition with the marketplace operator unless they can offer lower prices. Moreover, they can increase their chances of a sale by using operator-managed fulfillment services. As the marketplace operator determines the competitive results, my findings also contribute to important antitrust considerations.

The third essay investigates how using the marketplace's store banner impacts product sales performance for products sold on an online marketplace. Marketplace operators may use store banners on both private label products to reveal ownership of

the products, and on non-private labels as advertisements. I address the following three research questions: (1) Is using a store banner associated with better sales performance for a product on an online marketplace? (2) How does this performance vary between directly branded private-label products and non-private-label products using a banner as an advertisement? (3) How does the impact of using store banners vary for products at different price levels?

The study takes advantage of Amazon's sales of private labels that contain the Amazon name (i.e., are store banner branded) and other Amazon private label products that are not store banner branded, as well as the sales of non-private-label products with the Amazon store banner (i.e., "Amazon Exclusive") offered by Amazon and third-party retailers. The results of my empirical analysis show that both directly branding private labels and using store banners on non-private labels as advertisements are positively associated with sales performances. In addition, the positive relationship between using a store banner as an advertisement and sales performance diminishes as product price increases, suggesting that lower-priced (less than $12) non-private label products benefit most from the connection with the marketplace store brand. Therefore, marketplace operators may consider directly branding their private labels using store banners. Manufacturers or brand owners may contract with the marketplace operator for permission to use the store banner on their products, especially low-priced products, as an advertisement to improve sales performance.

Chapter 2: Direct Sales Competition from Marketplace Operators

Introduction

Marketplaces play a crucial role in the digital economy, matching buyers and sellers, facilitating transactions, and providing an institutional infrastructure (Bakos, 1998). But in many marketplaces, the operators compete directly with "third-party" sellers.[1] This direct competition can overwhelmingly favor the marketplace operator. Therefore, a viable strategy for third-party sellers is to avoid directly competing with the marketplace operator. For this reason, I investigate factors associated with the decision by marketplace operators to market a product in direct competition with third-party sellers. Based on my results, I provide recommendations to third-party sellers for avoiding competition with the marketplace operator.

Retailers traditionally operate in a *pure* direct sales mode when they purchase products from suppliers at a wholesale price, determine retail prices, and then sell their products directly to consumers. Online retailers can also act as marketplace operators, relying solely on "third-party sellers" (i.e., *pure* marketplace mode). Wish, eBay, and Etsy are examples of pure marketplace retailers. Between these two extremes, there is a *hybrid* mode. In this mode, firms, such as Amazon, Walmart, Target, and Newegg, directly sell to end users and also operate marketplace services enabling third-party sales (Hagiu & Wright, 2015; Tian et al., 2018). I focus on how third-party sellers can compete with the marketplace operator in this hybrid mode.

[1] On an online marketplace, the marketplace operator is considered as the first party, consumers are considered as the second party, the independent sellers are considered as the third party.

Marketplace operators compete with third-party sellers if they sell the same (or similar) products. In this competition, a marketplace operator is likely to win (i.e., make the sale) for the following reasons: First, the marketplace operator can monitor the behavior of third-party sellers and react to competitive strategies undertaken by the sellers (e.g., by adjusting prices). Second, third-party sellers cannot avoid the double marginalization problem because they must share revenue with the marketplace operator in the form of service fees or commissions.[2] Third, the marketplace operator generally has lower costs due to greater scale, relative to third-party sellers (Hagiu & Wright, 2015).

However, marketplace operators will often compete on only a fraction of products sold through the marketplace. The overall success of the marketplace depends on making an array of products available to attract consumers. Third-party sellers can contribute to this product assortment (Knee, 2018; Parker et al., 2017; Zhu & Liu, 2018). For example, third-party sales through Amazon Marketplace, at $175 billion, were nearly double the $83 billion in Amazon's direct retail sales in 2018 (Marketplace Pulse, 2018). Moreover, the cost and difficulty of managing and distributing products increases with the number of products directly sold (Tian et al., 2018). Therefore, from an operational perspective, it may be efficient for the operator to only sell a subset of products on the marketplace. Finally, antitrust concerns may arise when a firm

[2] Double marginalization refers to the additional profits, reflected in higher prices to consumers, when two firms operate within a supply chain (see e.g., Dellarocas, 2012). For this case, the third-party sales price incorporates profits earned by both the third-party seller and the retailer, whereas the retailer's sales price reflects only its own profits.

simultaneously operates a marketplace and directly competes with third-party sellers.[3] Therefore, to avoid government action, it may be beneficial for the marketplace operator to provide competitive space for third-party sellers.

The objective of this study is to examine factors that predict the marketplace operator's decision to directly sell a product. Specifically, I address the following research question: What factors predict direct sales of a product by a hybrid marketplace operator? The goal is to provide relevant information to third-party sellers as they choose products to sell and attempt to avoid competing directly against the marketplace operator.

The literature suggests several attributes that lead a marketplace operator to directly sell a product. High sales (or demand) is the most widely determined factor (e.g., Anderson, 2008; Brynjolfsson et al., 2003, 2011; Hagiu & Wright, 2015; Jiang et al., 2011; Zhu & Liu, 2018). Using analytical models, Hagiu and Wright (2015) suggest additional product attributes that the marketplace operator may use to determine direct sales, including information advantage and product spillover effects (e.g., marketing activities). Zhu and Liu (2018) empirically examine Amazon's operations and find that Amazon is more likely to sell successful products (i.e., products with a high percent of positive reviews, high sales, and a large number of sellers) and is less likely to sell products that require greater efforts to improve sales performance.

This study draws on the literature from information asymmetry (Akerlof, 1970; Arrow, 1963; Jensen & Meckling, 1976) and distribution intensity (Frazier & Lassar,

[3] For instance, the United States (Tracy et al., 2020), Canada (Vieira, 2020) and the European Union (Pop & Schechner, 2020) have opened investigations into Amazon over its competition with third-party sellers.

1996; Lusch et al., 1990; Pegram, 1965) to analyze product-level data from the largest hybrid marketplace in the U.S., Amazon.com. Building on prior literature, I investigate attributes that lead to direct sales by the marketplace operator. I find that Amazon is more likely to offer to directly sell a product: (1) when the product is not carried by third-party sellers that use Amazon fulfilment services, (2) when the product is a well-known brand, and (3) when the product is part of a brand that offers a large number of other branded products on the marketplace. Therefore, third-party sellers can better avoid competing directly with Amazon by selling unbranded products and choosing products that tend to be fulfilled by Amazon. With these latter products, Amazon already earns fulfillment fees from the third-party sellers, so may deem it less advantageous to compete on these products.

The rest of the study proceeds as follows. The next section reviews related literature and develops the hypotheses. I then describe the data. Thereafter, the analyses and estimation results are discussed. A final section presents a summary, theoretical contributions, practical implications, and limitations to this study.

Literature Review and Hypothesis Development

In this section, the extant studies on the motivations of marketplace operators to compete with third-party sellers are reviewed. A successful marketplace needs to have not only a large base of consumers, but also third-party sellers offering a selection of products on the marketplace (D. S. Evans et al., 2008; Hagiu & Spulber, 2012).

How does a marketplace operator determine which products to directly sell? The first factor identified in the literature, as outlined in the Introduction section, is sales revenues. It has been well documented that marketplace operators choose

products to sell directly based on sales (or demand) (e.g., Anderson, 2008; Brynjolfsson et al., 2003, 2011; Hagiu & Wright, 2015; Jiang et al., 2011; Zhu & Liu, 2018).

Operators may also be motivated to directly sell products to increase the health of the marketplace. For example, Intel introduced its own hardware devices (i.e., microprocessors) to compete with third-party sellers on its platform. Intel's primary goal was not necessarily to increase its own sales, but to stimulate third parties to provide more innovative products (Gawer & Cusumano, 2002). Wang, Li, and Singh (2018) find evidence that Google chose to compete with third-party developers on a flashlight app given consumer concerns over privacy with similar apps developed by third parties. Moreover, retailers may offer direct sales of some products to address counterfeit issues. A case study by Zhu and Sun (2019) supports this motivation in its investigation of products offered by one of China's largest e-commerce marketplaces, JD.com.

Based on analytical modeling, Hagiu and Wright (2015) suggest additional product attributes that the marketplace operator can use to make decisions on products to directly sell. The authors propose that the operator should directly sell a product: (1) when it has an information advantage *vis a vis* third-party sellers, and (2) when pricing and marketing activities for the product have large spillovers onto other products (Hagiu & Wright, 2015).

In summary, extant literature suggests that marketplace operators directly offer products based on the motivations for capturing higher sales, improving consumer satisfaction in the marketplace products, maintaining the health of marketplace, and when there are inherent advantages to selling the products.

To build on the existing literature, I propose three new attributes that may be associated with direct sales by the marketplace operator: (1) the number of third-party sellers that do not use operator-managed fulfillment service, (2) the popularity of the brand being sold, and (3) cross-product spillover effects. The literatures on information asymmetry and distribution intensity are adopted as the theoretical foundations for my proposed hypotheses.

Direct vs. Operator-managed Fulfillment Services

In economic transactions, information asymmetries between the buyer and seller may be present, with the seller often possessing greater product knowledge than the buyer. This asymmetry leads to two potential problems: adverse selection (e.g., sellers hide or offer false information on products and services) and moral hazard (e.g., sellers reduce the promised quality of product and service) (Akerlof, 1970; Arrow, 1963; Jensen & Meckling, 1976). In traditional brick-and-mortar transactions, consumers can mitigate information asymmetry by "kicking the tires", but this option is infeasible in online retailing settings. Moreover, this information asymmetry is reinforced by adding an additional party—the marketplace operator—that may also lack information about the quality of products and services offered by third-party sellers. Consequently, two additional problems may arise on online marketplaces: "blame shifting" and "complaint mishandling".

First, consumers may not differentiate between the marketplace operator and the third-party sellers. When consumers buy products from third-party sellers on Amazon.com for example, they may blame Amazon—the marketplace operator—for product or delivery problems, even if the sales are through Amazon Marketplace with

distribution by the third parties. Therefore, shoddy product and service quality offered by third-party sellers may reduce consumer satisfaction with marketplaces and tarnish the operator's reputation.

Second, marketplace operators may find it difficult to handle consumers' post-purchase complaints. After consumers place orders on marketplaces, third-party sellers may directly ship products to consumers, without additional input from the marketplace operator. Thus, the operator may not detect product or delivery problems until a consumer provides feedback or complains about a sale. Therefore, the operator may need to institute policies and practices to discourage poor or dishonest third-party sellers.

One method used by marketplace operators to differentiate among third-party sellers is to disclose the identity of the third-party sellers and establish seller evaluations visible to buyers. The evaluations may motivate sellers to provide higher-quality products and services, and in turn alleviate the "blame shifting" problem. However, marketplace operators may lack direct information or evidence on the quality of products and services offered by third-party sellers and may still experience the problem of "complaint mishandling". Active involvement in the sale of a product may offer a more direct resolution to the complaint problems faced by operators.

Marketplace operators may try to ascertain information on the quality of products sold by third-party sellers via inspection/authentication services. However, these services require high investments; for example, in training inspectors, and increase transaction costs for both third-party sellers and consumers (e.g., higher commission or service fees) on the marketplaces. Therefore, these

inspection/authentication services may only be used for specific marketplaces; for example, online luxury goods marketplaces (Choi, 2019). For most other marketplaces, this option may be infeasible.

Marketplace operators may, however, be able to monitor third-party seller quality if the third-party sellers opt to have the marketplace operator distribute their products. After the marketplace operator receives a shipment, it can inspect the products before shipping them to end users. Conversely, to maintain the integrity of products sold on the marketplace, the operator may choose to directly sell a product if third-party sellers do not distribute the product through the operator's distribution centers. Similarly, studies have shown that vertical integration is a preferred governance choice when there is difficulty in ascertaining the quality of products produced by partners (e.g., Bresnahan & Levin, 2013; Caves & Bradburd, 1988; Leiblein & Miller, 2003; Oxley, 1997).

The satisfaction of marketplace customers hinges on how well online orders are fulfilled (Boyer & Hult, 2005; Nguyen et al., 2019; Rabinovich & Bailey, 2004; Rabinovich & Evers, 2003; Rao, Goldsby, et al., 2011). When orders are not delivered within expected timeframes, consumers may consider the transaction as a service failure (Rao, Griffis, et al., 2011). Since customers may not differentiate between the marketplace operator and third-party sellers, the reputation of the marketplace operator could be diminished due to poor fulfillment outcomes from third-party sellers. Therefore, as a risk reduction strategy, a marketplace operator may choose to directly sell products that are fulfilled by third-party sellers and do not pass through the operator's distribution centers.

Based on these arguments, the first hypothesis is the following:

H1. The fulfillment of a product by third-party sellers is positively associated with direct sales of the product by a marketplace operator.

Brand

Brand-name manufacturers are more likely to care about the quality of their distribution channels than are the manufacturers of unbranded products since their brand reputations can be negatively impacted by poor distribution outcomes (Lusch et al., 1990; Pegram, 1965). Kim, Kim, and Lee (2010), based on a survey from the Korean luxury fashion industry, suggest that distribution channels impact a consumer's evaluation of brand values. Therefore, brand-name manufacturers may prefer distribution channels with strong reputations. These findings are supported by Frazier and Lassar (1996) based on a survey of U.S. manufacturers in the consumer electronics industry (i.e., stereo speakers). Brand-name manufacturers may prefer products be sold directly by marketplace operators to better ensure distribution quality.

Furthermore, brand-name manufacturers have raised concerns about third parties selling counterfeit products. These sales can damage the brand's reputation and reduce consumer satisfaction with retailers. Using game theoretic models, Cho, Fang, and Tayur (2015) evaluate anticounterfeit strategies adopted by manufacturers.[4] They find that authorizing specific retailers to directly sell their products can help reduce

[4] The anticounterfeit strategies that Cho, Fang, and Tayur (2015, p. 274) evaluated include "(i) quality strategy that alters the quality of brand-name products against a counterfeiter, (ii) pricing strategy that alters the price of brand-name products against a counterfeiter, (iii) marketing campaign that educates consumers about the dangers of counterfeits, (iv) enforcement strategy that increases the chances to seize the production of counterfeits, and (v) technology strategy that makes the brand-name product more difficult to counterfeit" (Cho et al., 2015, p. 274).

counterfeit sales in licit channels. At the same time, marketplace operators have been plagued by counterfeit sales (Khan, 2019). Therefore, offering direct sales of brand-name products may help operators protect the reputation of their businesses.

These arguments support the second hypothesis:

H2. The strength of a product's brand is positively associated with direct sales of the product by a marketplace operator.

Spillover Effects

Offering direct sales requires marketplace operators to invest in sourcing, marketing, and distributing the products. These efforts may have cross-product spillover effects. When the marketplace operator promotes a product, consumers may also be attracted to complementary products. For example, if the marketplace sells an action figure for a Disney character, consumers may also be attracted to buy accessories for the figure, a related book, a related movie, and/or a related action figure. Therefore, marketplace operators may be more willing to offer an item if there is a greater chance for related sales. The mathematical model by Haigu and Wright (2015) suggests that direct selling by a marketplace operator will be preferred for products that have positive spillovers onto other products. Since products carrying the same brand identification may share common features and have similar consumer bases, there may be spillover purchases from one branded item to another item from the same brand.

As a result, the final hypothesis is summarized as follows:

H3. The number of products of the same brand sold on the marketplace is positively associated with direct sales of the product by a marketplace operator.

Other product characteristics (e.g., demand/sales, product ratings, and number of sellers) that impact a marketplace operator's direct sales decision have been examined previously. I do not build hypotheses for these characteristics but include these factors as controls in my analysis. Readers can refer to related studies for details (e.g., Hagiu & Wright, 2015; Jiang et al., 2011; Zhu & Liu, 2018).

Data

To test my hypotheses, I collect data from a third-party firm that monitors product information on Amazon.com. Data are collected on products under the category "Toys & Games". Based on a 30-day average sales ranking, I picked the 3,000 best-selling products[5] from six subcategories: building toys, dolls & accessories, play vehicles, puzzles, stuffed animals & plush toys, and toy figures & playsets.

Data for all products in these subcategories were collected between 12:00 p.m. and 4:00 p.m. daily from September 18, 2019 to October 15, 2019. The unit of analysis in this study is product-date and refers to the situation for a given product on a given date within the timeframe of my study. After removing observations with missing values, the sample includes an unbalanced panel dataset of 327,112 listings (i.e., product-date observations) for 15,585 products over 28 days.

[5] Amazon Standard Identification Numbers (ASINs)—the unique blocks of 10 letters and/or numbers that identify items—are used to define a product in my data set.

Empirical Analysis

Econometric Model

To examine the attributes that lead the marketplace operator to directly sell a product, I construct a dichotomous dependent variable to measure whether Amazon offers a product directly, namely "Amazon Sell". The value, 1, indicates that Amazon directly sells the product. In this scenario, a consumer can find Amazon on the list of sellers for the product.[6] The value, 0, indicates that Amazon does not directly sell the product but leaves sales to third-party sellers. Consumers will not find Amazon on the list of sellers for these products, so all the sellers will be third-party sellers.

To test H1– a positive link between third-party sellers that directly distribute a product and the marketplace operator's direct sales decision, I take advantage of two classes of third-party sellers, those that use the Fulfill-By-Amazon (FBA) program and those that conduct their own fulfillment activities, known as fulfillment by merchant "FBM". After joining the FBA program, third-party sellers can send their products to Amazon's fulfillment centers, and Amazon will pick, pack, ship, and handle returns for these products (Amazon, 2022b). If a third-party seller decides not to join the FBA program, then it will fulfill its orders and handle returns without using Amazon's distribution network; that is, FBM.

Comparing FBA with FBM sellers, I argue that the product and service quality of FBA sellers will be easier for Amazon to ascertain since Amazon undertakes the

[6] Amazon may or may not face competition from third-party sellers. I re-estimate all of the models with the subset of observations where there is at least one third-party seller. The results are similar to those with the full sample, indicating that this issue may not impact the robustness of the results in this study.

fulfillment services (i.e., picking, packing, shipping, and returns). Therefore, I expect that the number of FBM offers for a product to be positively correlated with direct selling by Amazon, after controlling for total number of offers.

To test H2 – the positive association between brand strength and the marketplace operator's decision to directly sell a product, I assess brand strength by the total number of product reviews for a brand (namely "Reviews per Brand"). The total number of reviews is used as a proxy to measure brand visibility and familiarity. According to Amazon, brand is "a unique and identifiable symbol, association, name, or trademark that serves to differentiate competing products or services. It can apply to a single product, an entire product line, or even a company" (Amazon, 2021). Since the number of product reviews for a brand may be proportional to sales for products within the brand, I control for product-level sales and the number of branded products in my model.

To test H3 – the positive association between the number of products of a given brand on the marketplace and the decision by the marketplace operator to directly sell a product within that brand, I construct a variable to measure the total number of products for each brand, namely "Products per Brand". I argue that the greater the number of products from a brand carried on the marketplace, the larger the potential spillover to other products, and the more likely the marketplace operator will choose to directly sell the products.

Given previous findings in extant studies (e.g., Hagiu & Wright, 2015; Jiang et al., 2011; Zhu & Liu, 2018), I control for the following variables in my analysis:

"Sales Rank" – I use a product's sales rank in the main category (i.e., "Toys & Games") as a proxy for actual sales of the product. Previous studies (e.g., Chevalier & Goolsbee, 2003; M. Sun, 2011) have found a log-linear relationship between sales ranking and actual sales.

"Product Rating" – I include the overall (star) rating of a product, ranging from 1 to 5, to measure perceived quality of the product. The higher the rating of a product, the more satisfied consumers are with the product. Product rating is independent of a retailer's rating.

"Total Offers" – I include the total number of offers for a product (third-party seller plus marketplace operator offers). Zhu and Liu (2018) note that greater numbers of sellers for a product may suggest that it is a profitable product to sell, which may motivate the marketplace operator to sell the product directly. On the other hand, a large number of sellers may be an indication of intense competition, which could discourage the marketplace operator from offering direct sales.

"FBA Fees" – I use the FBA fees for a product to measure the extra cost for sellers for distributing that product through Amazon's fulfillment services. Amazon sets a product-specific rate for its FBA service, and the third-party sellers using the service will be charged the FBA fee for each sale. The main determination of the FBA fee is package size and weight of the product. Fee determination is independent of the sales price of a product or the popularity of the product.

Descriptive Statistics

Tables 1 and 2 provide descriptive statistics (e.g., means, standard deviations, minimums, and maximums) and correlations between variables in my analysis.

The dichotomous variable "Amazon Sell" assesses Amazon's decision to sell a product. In my sample, Amazon does directly sell products 53% of the time (173,473 out of 327,112 observations). This number is reasonably consistent with the statistics for the entire Amazon marketplace, with Amazon providing a direct listing for 58% of all marketplace products in 2018 (Eadicicco, 2019).

Table 1: Descriptive Statistics

(N = 327,112)

Variable	Mean	Std. Dev.	Min.	Max.
Amazon Sell	0.53	0.50	0.00	1.00
FBM Offers	5.35	5.16	0.00	84.00
Reviews per Brand	117.70	130.04	0.14	2,539.00
Products per Brand	208.79	389.94	1.00	1,409.00
Sales Rank	50,758.54	50,924.76	1.00	1,235,017.00
Product Rating	4.39	0.47	1.00	5.00
Total Offers	14.10	15.80	1.00	177.00
FBA Fees	5.08	3.50	2.41	144.11
Price	24.55	28.59	1.31	734.60
Package Dimension	6,331.38	11,814.61	1.00	400,833.00
Package Weight	612.34	1,163.84	5.00	32,219.00

The dichotomous variable “Amazon Sell” assesses Amazon’s decision to sell a product. In my sample, Amazon does directly sell products 53% of the time (173,473 out of 327,112 observations). This number is reasonably consistent with the statistics for the entire Amazon marketplace, with Amazon providing a direct listing for 58% of all marketplace products in 2018 (Eadicicco, 2019).

A product’s sales rank in the category of “Toys & Games” ranges from 1 to 1,235,017. The average product rating is 4.39 out of 5. This rating may indicate that consumers are generally satisfied with the products on Amazon Marketplace, at least for products sold in the category of “Toys & Games”. A relatively high average product rating may also suggest that Amazon’s consumers have a high expectation benchmark for product quality. On average, a product has 14 offers from different sellers, and 5, on average, are from FBM sellers. Third-party sellers need to pay an average of $5.08 per sale for FBA service fees. A brand has an average of 209 products that are sold on the Amazon Marketplace, with an average of 118 reviews for each brand. On average, the package dimension (weight) of a product is 6,331.38 cubic centimeters (612.34 grams).

The correlation between the package dimension (weight) and “FBA Fees” is 0.94 (0.78) while the correlation between the package dimension (weight) and the dependent variable “Amazon Sell” is relatively low at 0.06 (0.05), indicating that these instruments are strong.

Table 2: Correlations Matrix of Variables

(N = 327,112)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Amazon Sell	1.00										
(2) FBM Offers	0.21***	1.00									
(3) Reviews per Brand	0.11***	0.03***	1.00								
(4) Products per Brand	0.02***	0.26***	-0.00	1.00							
(5) Sales Rank	-0.19***	0.02***	-0.13***	-0.07***	1.00						
(6) Product Rating	0.06***	0.07***	0.05***	0.17***	-0.12***	1.00					
(7) Total Offers	0.09***	0.47***	-0.03***	0.40***	-0.08***	0.10***	1.00				
(8) FBA Fees	0.07***	-0.01***	0.08***	0.05***	-0.01**	-0.03***	-0.06***	1.00			
(9) Price	-0.09***	0.07***	0.02***	0.29***	0.05***	0.02***	0.04***	0.57***	1.00		
(10) Package Dimension	0.06***	-0.01***	0.08***	-0.00	-0.02***	-0.01***	-0.05***	0.94***	0.52***	1.00	
(11) Package Weight	0.05***	-0.02***	0.06***	0.02***	-0.01**	-0.04***	-0.07***	0.78***	0.56***	0.78***	1.00

*** p<0.01, ** p<0.05, * p<0.1

Estimation Strategy

To examine the factors that are correlated with the marketplace operator's directly sales (i.e., H1 through H3), I estimate a probit regression model. However, potential endogeneity and simultaneity issues for the following variables may be a concern in my analysis.

"Sales Rank" is potentially endogenous, as the marketplace operator's direct sales decision may improve the product's sales ranking. This simultaneous impact was shown by Zhu and Liu (2018). Moreover, "FBA Fees" is potentially endogenous as Amazon's decision to sell directly may motivate it to increase this fee to make third-party sellers less competitive.[7]

To address endogeneity issues, three-stage least squares (3SLS) is used (Zellner & Theil, 1962). Since, "Amazon Sell", my main dependent variable, is dichotomous, regular 3SLS estimation, where all equations are estimated via ordinary least squares (OLS), is not feasible. Instead, I adopt the conditional mixed-process (CMP) modeling framework that allows individual equations to have non-continuous dependent variables (e.g., binary, ordered, categorical, censored, etc.) (Roodman, 2011).

Specifically, the following equations are estimated:

[7] "Product Rating" may also be endogenous as the operator's decision to sell a product directly could help improve the product's rating. However, Zhu and Liu (2018) did not find this impact. Therefore, endogeneity for this variable may not be a concern.

$$Amazon\ Sell_{it} = \beta_0 + \beta_1\ ln(Sales\ Rank)_{it} + \beta_2\ ln(FBM\ Offers)_{it} + \beta_3\ ln(Reviews\ per\ Brand)_{it} + \beta_4\ ln(Products\ per\ Brand\ Products)_{it} + \beta_5\ Product\ Rating_{it} + \beta_6\ ln(Total\ Offers)_{it} + \beta_7\ ln(FBA\ Fees)_i + \varepsilon_{it} \quad (1)$$

$$ln(Sales\ Rank)_{it} = \beta_0 + \beta_1\ Amazon\ Sell_{it} + \beta_2\ Product\ Rating_{it} + \beta_3\ ln(Total\ Offers)_{it} + \beta_4\ ln(Price)_{it} + u_{it} \quad (2)$$

$$ln(FBA\ Fees)_{it} = \beta_0 + \beta_1\ ln(Package\ Volume)_{it} + \beta_4\ ln(Package\ Weight)_{it} + v_{it} \quad (3)$$

In Equations (1) through (3), *i* represents a product and *t* a day in my database.

Similar to the three-stage procedure, the CMP model estimation is as follows:

In the first step, the instrumented value for each endogenous variable is estimated. For each of the three equations, the unique independent variables among the system are used as the instrumental variables to predict the endogenous variable(s). In Equation (1), "FBM Offers", "Reviews per Brand", "Products per Brand" and "FBA Fees", are used as the instrumental variables for "Amazon Sell". Similarly, in Equation (2), "Price" is used as the instrumental variable for "Sales Rank". I use a product's Buy Box winning price as a proxy for sales price.[8] An offer featured by the Buy Box indicates that the retailer recommends this offer as the best offer, and that consumers need not search for a better offer. As such, the price offered by the seller winning

[8] Prices can be set by Amazon, FBA sellers or FBM sellers. Prices include shipping fees, if assessed.

placement in the Buy Box becomes the most likely sales price for an order.[9] Finally, in Equation (3), package volume in cubic centimeters and the package weight in grams are used to estimate FBA Fees.

In Step 2, the residuals from the estimations in Step 1 are used to determine the covariance matrix of the equation disturbances. In the final step, a maximum likelihood approach is adopted to simultaneously estimate Equations (1) and (2) as a system.[10] The covariance matrix estimated in the second stage is used, and the endogenous variables are replaced by the instrumented values estimated in the first stage.

All of the above procedures are implemented using Stata's *cmp* command (Roodman, 2011). Cluster–robust standard errors are calculated as they allow observations for the same product to potentially correlate.

In summary, I simultaneously estimate Equations (1) and (2) using the CMP model, including the fitted value for FBA Fee. For both equations, I log all continuous variables to reduce the potential impact from outlying observations.

Estimation Results

The results of the CMP model are reported in Table 3. Models (1) (2) and (3) show the estimations for Equation (1) (2) and (3), respectively.

The coefficients for "Sales Rank" ($\gamma = 0.8419$; $p < 0.01$) and "Amazon Sell" ($\gamma = 1.1466$; $p < 0.01$) are positive and significant at the 0.01 level in Models (1) and (2), respectively. These

[9] When there is no Buy Box for a product, the retailer does not recommend an offer, and consumers need to conduct their own search for the best offer. In this case, I use the lowest price among all offers as a proxy for the sales price.
[10] Equation (3) is not estimated in Stage 3 since FBA Fees is not dependent on any of the endogenous variables.

results show that the product's sales rank has a positively significant effect on the retailer's decision to sell directly while the reverse also holds, indicating the existence of a bidirectional relationship between the two variables. These results confirm the findings by Zhu and Liu (2018) that Amazon targets successful products (i.e., better ranked products) to offer direct sales and the product's sales rank increases after the retailer decides to sell the product directly.

The coefficients for "Product Rating" are significant at the 0.01 level in both Models (1) and (2). Its direction shows a positive ($\gamma = 0.2992$; $p < 0.01$) relationship with "Sales Rank" in Model (2) and a negative ($\gamma = -0.2512$; $p < 0.01$) relationship with "Amazon Sell" in Model (1). These results suggest that after controlling for the impact of sales rank, Amazon may directly sell products with which consumers are less satisfied, possibly to improve consumer experience and maintain the health of marketplace. At the same time, products with higher perceived quality have higher sales rankings.

The coefficient for "Total Offers" is insignificant in both Models (1) and (2). These results suggest that increasing the number of sellers may not improve the sales rank of a product, and the total number of sellers is not associated with Amazon's decision to sell the product directly.

In Model (2), the coefficient for "Price" is negative and significant ($\gamma = -0.0102$; $p < 0.01$). Therefore, on average, higher-priced products produce fewer sales than lower-priced products.

In Model (3), the coefficients of "Package Dimension" ($\gamma = 0.1353$; $p < 0.01$) and "Package Weight" ($\gamma = 0.2052$; $p < 0.01$) are positive and significant, suggesting that the determination of FBA fee is significantly related to package size and weight of the product.

Table 3: Estimation Results

	(1) Amazon Sell	(2) ln(Sales Rank)	(3) ln(FBA Fees)
Amazon Sell	-	1.1466***	-
		(0.0036)	
ln(Sales Rank)	0.8419***	-	-
	(0.0001)		
ln(FBM Offers)	0.0023***	-	-
	(0.0002)		
ln(Reviews per Brand)	0.0007***	-	-
	(0.0001)		
ln(Products per Brand)	0.0009***	-	-
	(0.0001)		
Product Rating	-0.2512***	0.2992***	-
	(0.0040)	(0.0047)	
ln(Total Offers)	0.0110	-0.0133	-
	(0.0079)	(0.0094)	
ln(Price)	-	-0.0102***	-
		(0.0003)	
ln(FBA Fees)	0.0144***	-	-
	(0.0004)		
ln(Package Dimension)	-	-	0.1353***
			(0.0037)
ln(Package Weight)	-	-	0.2052***
			(0.0034)
Constant	9.7285	-11.5643	-0.7681***
	(0.0000)	(0.0000)	(0.0215)
Observations		327,112	

*** p<0.01, ** p<0.05, * p<0.1

Cluster-Robust Standard Errors in Parentheses

The values of *ln(Sales Rank)* are reversed.

The logged value of *FBM offers* is set to -1 when the original value is 0.

Now, I focus on Model (1). In Model (1), the coefficient for "FBA Fees" is positive and significant ($\gamma = 0.0144$; $p < 0.01$), indicating that the products the marketplace operator offers directly are associated with higher FBA fees.

The coefficient for "FBM Offers" is positive and significant ($\gamma = 0.0023$; $p < 0.01$) after controlling for the total number of offers, supporting H1. This result suggests that the marketplace operator is more likely to directly sell a product when the product is offered by a higher number of third-party retailers that fulfill the orders by themselves, holding all other variables constant.

The coefficient for "Reviews per Brand" is positive and significant ($\gamma = 0.0007$; $p < 0.01$), supporting H2. Marketplace operators may be more likely to directly sell products for better-known brands.

Finally, the coefficient for "Products per Brand" is positive and significant ($\gamma = 0.0009$; $p < 0.01$), supporting H3. The marketplace operator is more likely to directly sell a product when there are higher numbers of products of the same brand offered on the marketplace. These results suggest that the operator may consider spillover effects within brands when choosing products to directly sell.

Overall, support for the three hypotheses is found. Consistent with the extant literature (Hagiu & Wright, 2015; Jiang et al., 2011; Zhu & Liu, 2018), the results confirm that marketplace operators are more likely to directly sell popular products. In addition, the results suggest that operators are more likely to offer direct sales, (1) when the products are offered by a higher number of third-party sellers that directly fulfill their own orders, (2) when the products are offered by well-known brands, and (3) when their brands offer a higher number of products on the retailer-owned marketplace.

To assess the accuracy of my predictions, I present the classification table for Model (1) in Table 4 using a cutoff of 0.5. The overall rate of correct classifications is 73.16%. The model is more accurate at predicting Amazon directly selling (accuracy rate is 78.57%) than it is at predicting Amazon not directly selling the product (accuracy rate is 67.05%).

Table 4: Classification Table (Full Sample)

Number of Observations		Observed "Amazon Sell"		Total
		Yes	*No*	
Predicted "Amazon Sell"	*Yes*	136,293	50,629	186,922
	No	37,180	103,010	140,190
	Total	173,473	153,639	327,112
	(Accuracy)	(78.57%)	(67.05%)	(73.16%)

As a further check on the accuracy of my predictions, I re-estimate my models using the observations from the first 14 days of my dataset (i.e., from September 18, 2019 to October 1, 2019), and use estimated results to classify the observations from the latter 14 days (i.e., from October 2, 2019 to October 15, 2019). Results for the classification table using a cutoff of 0.5 are reported in Table 5. The overall rate of correct classifications is 73.13%, with an accuracy rate of predicting Amazon selling (not directly selling) a product at 79.06% (66.65%). The results indicate that my model provide reasonable predictions for the marketplace operator's determination of products to sell.

Table 5: Classification Table (Holdout Sample)

Number of Observations		Observed "Amazon Sell"		Total
		Yes	*No*	
Predicted "Amazon Sell"	*Yes*	68,865	26,582	95,447
	No	18,244	53,136	71,380
	Total	87,109	79,718	166,827
	(Accuracy)	(79.06%)	(66.65%)	(73.13%)

As a further robustness check, I re-estimate the conditional mixed-process (CMP) model with the subset of observations that exclude observations with no third-party seller (i.e., those observations where Amazon is the only seller of the product). The results for Models (4) (5) and (6) are presented in Table 6. The results are consistent between the full sample (i.e., Table 3) and subsample (i.e., Table 6), indicating the robustness of my results.

Table 6: Robustness Test Results

	(4) Amazon Sell	(5) ln(Sales Rank)	(6) ln(FBA Fees)
Amazon Sell	-	1.1116***	-
		(0.0407)	
ln(Sales Rank)	0.8433***	-	-
	(0.0450)		
ln(FBM Offers)	0.0043***	-	-
	(0.0003)		
ln(Reviews per Brand)	0.0013***	-	-
	(0.0002)		
ln(Products per Brand)	0.0014***	-	-
	(0.0001)		
Product Rating	-0.2567***	0.3057**	-
	(0.0971)	(0.1314)	
ln(Total Offers)	0.0067	-0.0078	-
	(0.0211)	(0.0244)	
ln(Price)	-	-0.0178***	-
		(0.0011)	
ln(FBA Fees)	0.0252***	-	-
	(0.0006)		
ln(Package Dimension)	-	-	0.1343***
			(0.0037)
ln(Package Weight)	-	-	0.2048***
			(0.0033)
Constant	9.7509	-11.5791***	-0.7583***
	-	(0.6166)	(0.0217)
Observations	321,185		

*** p<0.01, ** p<0.05, * p<0.1

Cluster-Robust Standard Errors in Parentheses

The values of *ln(Sales Rank)* are reversed.

The logged value of *FBM offers* is set to -1 when the original value is 0.

Conclusions

In competition between third-party sellers and marketplace operators in hybrid marketplaces, all parties must consider which products to sell. However, this decision is most important for third-party sellers since they have a high probability of losing a sale when competing directly with the operator. Consequently, I examine the factors that predict the marketplace operator's decision to directly sell a product.

I examine three previously unexplored factors that may influence the direct sales decision: the number of third-party sellers that directly sell the product, the strength of the product's brand, and the impact of product spillover effects within the brand. The results suggest that marketplace operators are more likely to directly sell a product under the following conditions: (1) when the products are fulfilled directly by a greater number of third-party sellers, (2) when the products have strong brand recognition, and (3) when there are a great number of products on the marketplace offered under the same brand as the focal product. Moreover, I find that the products that Amazon sells directly are associated with higher FBA fees.

My results show that third-party sellers can avoid directly competing with Amazon on Amazon Marketplace by carefully considering their product offerings. Since Amazon is more likely to directly sell products with strong brands, third-party sellers may re-brand products or use private brands to avoid direct competition with the marketplace operator. If a third-party seller wishes to sell branded products, it may be advantageous to avoid directly competing with Amazon; for example, by creating unique offerings such as bundled products or specific quantities (e.g., 3-packs or 12-packs). Moreover, Amazon is less likely to directly sell a product if a high number of

third-party sellers use Amazon's FBA service. Since the fee for this service depends on product weight and size characteristics, and not on the product's price, third-party sellers may avoid using this service when product price is low relative to the Amazon fee.

Finally, although not explicitly investigated, my findings suggest important antitrust considerations. I find that products sold directly by third-party sellers and products with higher FBA fees are associated with direct sales by Amazon. These findings suggest that Amazon may strategically compete with retailers that are not sufficiently contributing to its marketplace revenues (i.e., FBM retailers) or may avoid competition when it collects alternate fulfillment fees (from FBA retailers). Both of these decisions suggest potential conflicts of interest between Amazon as a marketplace operator and Amazon as a retailer, raising antitrust concerns.

This study has several limitations. First, the study analyzes only one category of products, restricting its generalizability to other categories of interest. Further research can use a cross-category study. Second, all prices used in this study do not include sales tax. I do not include sales tax as a part of the price because collection policies vary across states and sellers. Further research can test whether the tax collection policies impact the competitiveness of third-party marketplace sellers. Third, as there are no privately branded products (e.g., Amazon Basics) in this study, the impacts of offering privately branded products are not examined. Future research can investigate how private brands influence competitive outcomes. Fourth, the study does not assess the impact of Amazon Prime service (a membership service offered by Amazon), a potential factor impacting sales choice. Although many FBA sellers participate in the Amazon Prime program, it is not universal for these sellers. Finally, since Amazon operates the largest marketplace in the U.S.,

comparing the findings from this study with results from other marketplaces could improve the external validity of this study.

Chapter 3: Competitive Results on Online Marketplaces

Introduction

On online marketplaces (e.g., Amazon Marketplace and Walmart Marketplace), marketplace operators may sell products directly to customers, while enabling third parties to sell products as well. Thus, there is direct competition between third-party sellers and the marketplace operator if they sell the same products on the marketplace.

A marketplace operator will likely win the competition (i.e., make the sale) when competing against third-party sellers based on four justifications: First, the marketplace operator designs the algorithm to determine competitive results. Fair competition between the marketplace operator and third-party sellers may exist only if the algorithm is fully transparent to all sellers. However, most marketplace operators do not fully disclose the functioning of their marketplaces, so the fairness of competition is an open question (Etumnu, 2022). Second, the marketplace operator can monitor the behavior of third-party sellers and react to competitive strategies undertaken by the sellers (e.g., by adjusting listed price). Third, third-party sellers may find it difficult to offer competitive prices since they must share revenue with the marketplace operator in the form of service fees or commissions. Lastly, the marketplace operator often has lower costs due to greater scale, relative to third-party sellers (Hagiu & Wright, 2015).

Despite inherent competitive disadvantages, third-party sellers may still directly compete with the marketplace operator, generating sales. The first objective of this study is to investigate competition between third-party sellers and the marketplace operator, and examine factors that may increase the likelihood of third-party sellers winning the competition.

As noted above that the competitive results are determined by the marketplace operator. The marketplace operator may make decisions on the winner based on its own interests (e.g., gain higher profits or higher customer satisfaction from third-party sales). For example, a marketplace operator may favor third-party sellers that use the operator's fulfillment services. These services generate additional revenues for the operator and allow the operator to better manage distribution quality. As a result, a marketplace operator may tilt the competitive results in favor of the third-party sellers that use the operator-managed fulfillment services. Therefore, the second objective of this study is to investigate the role that operator-provided fulfillment services play in determining the competitive winners on a marketplace.

Specifically, three competitive scenarios are investigated:

(1) Competition between the marketplace operator and third-party sellers when selling the same product,

(2) Competition between third-party sellers using operator-managed fulfillment services and third-party sellers using direct fulfillment when the marketplace operator is also competing but does not win the sale,

(3) Competition between third-party sellers using operator-managed fulfillment services and third-party sellers using direct fulfillment when the marketplace operator is not competing for the sale.

This study examines factors that determine the winners of these competitions.

The study draws on the literature from competition (e.g., Hagiu & Wright, 2015; Lai et al., 2022; L. Sun et al., 2020a, 2020b; Zhu & Liu, 2018) on online marketplaces to analyze product-level data from the largest online marketplace in the U.S., Amazon.com. Taking advantage of

Amazon's Buy Box recommendation,[11] this study investigates competition on Amazon Marketplace and assesses the influence of several factors—numbers of offers from sellers that use Amazon's fulfillment services (FBA sellers), price differences among Amazon, FBA sellers and sellers that fulfill their own products (FBM sellers), and product price—on the determination of the Buy Box winner.

My results show that when third-party sellers and the marketplace operator sell the same product, the marketplace operator is most likely to outcompete the third-party sellers. However, the likelihood of a third-party seller winning the Buy Box while competing against the marketplace operator increases when: (1) there is a higher number of the sellers that use operator-managed fulfillment services (holding the total number of sellers constant), and (2) third-party sellers offer lower prices than the marketplace operator.

In addition, third-party sellers using operator-managed fulfillment services are more likely to outcompete sellers that directly fulfill their own orders. The likelihood of a third-party seller that uses direct fulfillment winning the Buy Box against sellers that use operator-managed fulfillment services increases: (1) when sellers using direct fulfillment offer lower prices than sellers using operator-managed fulfillment services (with the winning chances increasing as the price gap increases), and (2) when the product's price is low.

The rest of the study proceeds as follows. The next section reviews related literature and develops the hypotheses. I then describe my research setting and data. Thereafter, the analyses and

[11] According to Amazon, "the Featured Offer (in the Buy Box) is the offer near the top of a product detail page, which customers can buy now or add to their shopping carts" (Amazon, 2022c). The seller winning the Buy Box placement is most likely to make the sale.

estimation results are discussed. A final section presents a summary, theoretical contributions, practical implications, and limitations to this study.

Literature Review and Hypothesis Development

The literature on online marketplaces has examined competition between the marketplace operator and third-party sellers. Most of these studies examine factors that motivate the marketplace operator to compete with third parties on its marketplace.

It has been documented that marketplace operators make decisions on products to direct sell in competition with third-party retailers based on several factors. Marketplace operators tend to sell popular, high-demand products (e.g., Anderson, 2008; Brynjolfsson et al., 2003, 2011; Hagiu & Wright, 2015; Jiang et al., 2011; Zhu & Liu, 2018) and products that require little effort to improve sales performance (e.g., products with strong brands) (Zhu & Liu, 2018). Hagiu and Wright (2015) suggest that the marketplace operator may directly sell products that have positive spillover impacts onto other products (e.g., may generate future sales).

Marketplace operators may also be motivated to offer products that help to maintain the overall success of the marketplaces. For example, marketplace operators may sell products that are believed to stimulate the introduction of innovative products from third parties (Gawer & Cusumano, 2002), overcome consumer concerns over privacy issues (Wang et al., 2018), or help to counteract the sale of counterfeit products (Zhu & Sun, 2019).

Recent literature has investigated competitive outcomes on online marketplaces (e.g., Chiu et al., 2021; Etumnu, 2022; Lai et al., 2022; L. Sun et al., 2020b). The literature suggests that marketplace operators are more likely to win sales competitions with third-party party sellers for

two major reasons: First, direct sales may help marketplace operators capture higher profits (and the operator largely determines who wins the sales). Second, product and service quality may be better ascertained by consumers when products are directly purchased from the marketplace operator rather than from a third-party seller.

Analyzing data on the sales of ground coffee (from Amazon in the US and Canada) and red wine (from Amazon in the UK), Etumnu (2022) compares sales ranks of products sold by Amazon to the sales ranks of products sold by FBA and FBM retailers. He found that the sales ranks of products offered by Amazon or FBA sellers may not differ significantly, but are generally higher than the ranks of products offered by FBM sellers, *ceteris paribus*.

Using game theoretical models, Lai et al. (2022) compared two substitutable products sold by Amazon and an FBA seller. They suggest that (1) using FBA services always benefits the third-party seller unless the cost of the FBA service is "too high"; and (2) when customer-perceived differences in fulfillment services between Amazon and FBA sellers is small, competition will be tilted in favor of the FBA seller since Amazon may factor the FBA fee into its profit calculations.

Studies by Sun et al. (2020b) and Chiu et al. (2021) focus on competition between sellers using different fulfillment services. Sun et al. (2020b) analyze data from a fast-fashion retailer selling baby dresses on Amazon and compare the performance of products before and after the seller switched from FBM services to FBA services. They found that using FBA services results in higher sales, but also more returns than using FBM services.

Chiu et al. (2021) compare price discounts offered by third-party sellers using Walmart fulfilment services (similar to FBA) to those offered by merchants using direct fulfillment. They find that on average, Walmart fulfillment retailers have higher discounts than direct fulfillment

retailers when selling products in three general product categories, electronics, houseware, and toys.

To build on this existing literature, I investigate three competitive scenarios that may apply to a broad range of products on an online marketplace:

(1) Competition between the marketplace operator and third-party sellers when they offer the same product;

(2) Competition between third-party sellers using operator-managed fulfillment services and third-party sellers using direct fulfillment, when the marketplace operator sells the same product but does not win the competition;

(3) Competition between third-party sellers using operator-managed fulfillment services and third-party sellers using direct fulfillment, when the marketplace operator does not sell the same product.

Under the first scenario, I propose that three attributes that may impact the likelihood of third-party sellers winning the competition against the marketplace operator: (1) the number of third-party sellers using operator-managed fulfillment, (2) price differences between the competitors, and (3) the price of the product. The latter two attributes may also apply to the scenarios (2) and (3).

Order Fulfillment Services

Customer satisfaction on online marketplaces depends in part on the quality of order fulfillment services (Boyer & Hult, 2005; Nguyen et al., 2019; Rabinovich & Bailey, 2004; Rabinovich & Evers, 2003; Rao, Goldsby, et al., 2011). Successful marketplaces, such as Amazon

and JD, have invested substantial resources to enhance their fulfillment systems. Moreover, many of these marketplaces allow third-party sellers to purchase fulfillment services from the marketplace operator (Lai et al., 2022; Qin et al., 2020; L. Sun et al., 2020a, 2020b).

When third-party sellers use operator-managed fulfillment services, customers may not distinguish between the service quality offered by the marketplace operator and the service quality of the third-party retailer (Etumnu, 2022). On the other hand, customers may be concerned about the quality of fulfillment services directly managed by third-party retailers. Therefore, the marketplace operator may favor third party sellers that use the operator's fulfillment services over third parties that manage their own fulfillment services when determining competitive results between third-party retailers.

Moreover, when third-party sellers use operator-managed fulfillment services, the marketplace operator earns fees from the provision of these services. As a result, the marketplace operator may favor third-party retailers that use operator-managed fulfillment services in an effort to maximize profitability.

Based on above arguments, I purpose the first hypothesis as follows:

H1. The likelihood of a third-party seller winning the sales competition against the marketplace operator increases as the number of the sellers use operator-managed fulfillment services increase, holding fixed the total number of third-party retailers.

Price Differences

Price-sensitive customers may choose products from retailers that offer low prices. On a marketplace, the marketplace operator may consider price as a key factor impacting a customer's

purchase decision. When third-party sellers offer lower prices than the marketplace operator, the third party increases their chance of winning the sales.

Moreover, the marketplace operator earns commissions from the third-party sales of products. Commissions are generally based on the sales price of products. The marketplace operator earns higher commissions for a higher-priced products sold by third parties. Therefore, with high sales commissions, marketplace operators may be able to earn greater profits on third-party sales of high-priced products than on direct sales of these products (Lai et al., 2022).

Based on above arguments, I purpose Hypotheses 2a and 2b as follows:

H2a. The likelihood of a third-party seller winning the sales competition against the marketplace operator on a product is higher when the third-party seller offers a lower price than the marketplace operator.

H2b. Given a lower price, the likelihood of a third-party seller winning the sales competition increases as the price difference becomes greater.

In addition, when third-party sellers use operator-managed fulfillment services, the marketplace operator earns fees for the services. In general, the fees for the fulfillment services are based on product characteristics (e.g., size and weight) rather than the sales price of the product. Therefore, when a customer purchases a product from a third-party seller that manages its own fulfillment, the marketplace operator's profit from the sale will only be a percentage of the product's sales price (i.e., the commission). On the other hand, when the seller uses operator-managed fulfillment services, the marketplace operator's revenues will be higher, reflecting the fulfillment fee as well as the commission (assuming the price charged is the same as the price charged by the direct fulfillment retailer).

The final prices charged by retailers using their own fulfillment services, compared to the prices charged by retailers using operator-managed fulfillment services, will depend, in part, on the cost to a retailer of fulfilling a product relative to the fees charged by the marketplace operator.

However, in general, one would expect Hypotheses 3a and 3b to hold:

H3a. The likelihood of third-party sellers that use direct fulfillment winning the sales competition against third-party sellers that use operator-managed fulfillment services increases when the direct-fulfillment sellers offer lower prices.

H3b. Given a lower price, the likelihood of a third-party sellers that use direct fulfillment winning the sales competition against third-party sellers that use operator-managed fulfillment services increases as the price difference becomes greater.

Product Price

Expectations for product and service quality will vary depending on the price of a product. As the price of a product increases, customers may have a higher-level uncertainty about product quality and expect higher quality service. When third-party sellers use operator-managed fulfillment services, the marketplace operator will manage the fulfillment channel. Consumers may find this management reassuring, especially for higher-priced products where the chance of loss due to poor quality fulfillment may be perceived as greater.

Therefore, the final hypothesis is as follows:

H4. The likelihood of third-party sellers that uses direct fulfillment winning the sales competition against sellers that use operator-managed fulfillment services increases, the lower the product price.

Data

Research Setting

My research setting is the largest online marketplace in the U.S., Amazon.com.

Amazon enables multiple sellers to offer products on its marketplace, often in competition with Amazon's own sale of the same products. Third-party retailers can be divided into two categories: FBA and FBM sellers. Amazon offers the FBA program to third-party sellers at an extra cost (i.e., service fee). After joining the FBA program, third-party sellers can send their products to Amazon's fulfillment centers, and Amazon will pick, pack, ship, and handle returns for these products (Amazon, 2022b). If third-party sellers decide not to join the FBA program, then they will directly fulfill the orders and handle returns on their own. Sales by non-FBA sellers are part of Amazon's FBM program.

Although consumers may manually pick their favorite seller/offer, most consumers choose to follow the Buy Box (a.k.a. Featured Offer) recommendations determined by Amazon's confidential algorithms. Amazon explains the Featured Offer in the Buy Box as follows:

"The Featured Offer is the offer near the top of a product detail page, which customers can buy now or add to their shopping carts. A key feature of the Amazon website is that multiple sellers can offer the same product. If more than one eligible seller offers a product, they may compete to become the Featured Offer for that product (as long as it can be shipped to the customer's address). To give customers the best possible shopping experience, sellers must meet performance-based requirements to be eligible to compete for Featured Offer placement. For many sellers, Featured Offer placement can lead to increased sales." (Amazon, 2022c)

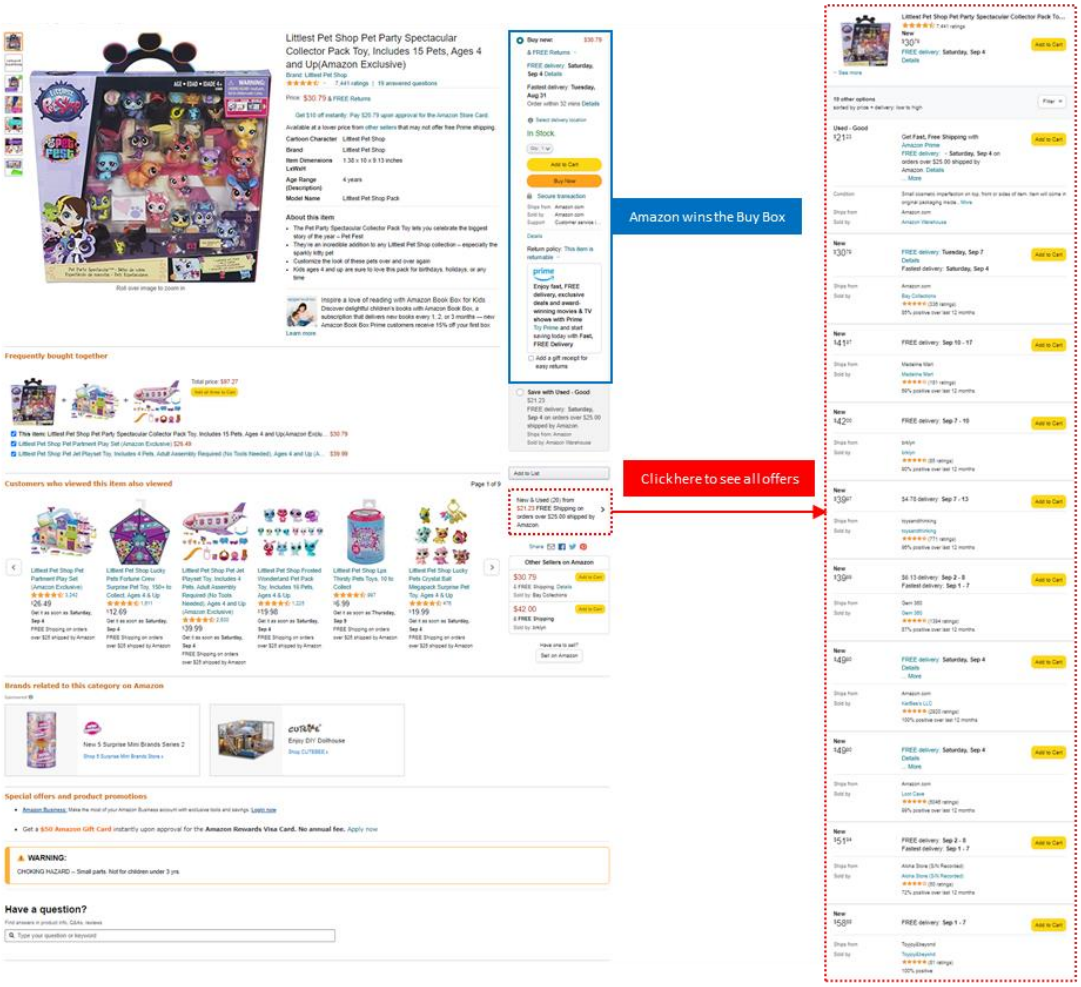
Based on Amazon-focused blogs and anecdotes:

"In fact, 82 percent of sales on Amazon go through the Buy Box. The number is even higher for sales on mobile devices, with many experts believing the total figure could be closer to 90 percent." (Tadrzak, 2022)

This study, therefore, uses Amazon's Buy Box recommendations as a proxy for the winner of the sales competition. Generally speaking, four types of the Buy Box recommendations may occur for a product: (a) Amazon wins the Buy Box, (b) an FBA seller wins the Buy Box, (c) an FBM seller wins the Buy Box, and (d) No Buy Box recommendation. Figures 1 through 4 demonstrate examples of each winner category.

When the Buy Box winner is shown as "Ships from Amazon.com" and "Sold by Amazon.com", it suggests a Type (a) recommendation, that is Amazon wins the Buy Box (Figure 1). When the Buy Box winner is shown as "Ships from Amazon.com" and "Sold by a third-party seller", this suggests a Type (b) recommendation, that is, an FBA seller wins the Buy Box (Figure 2). When the Buy Box winner is shown as "Ships from a third-party seller" and "Sold by a third-party seller", this suggests a Type (c) recommendation, that is, an FBM seller wins the Buy Box (Figure 3). When there is no Buy Box recommendation (Figure 4), this may suggest that none of the offers are eligible for a Buy Box recommendation and that consumers should click the button "See All Buying Options" and pick their favorite offer from the pop-up list. I focus on the first three Buy Box recommendations with a featured winner only in this study.

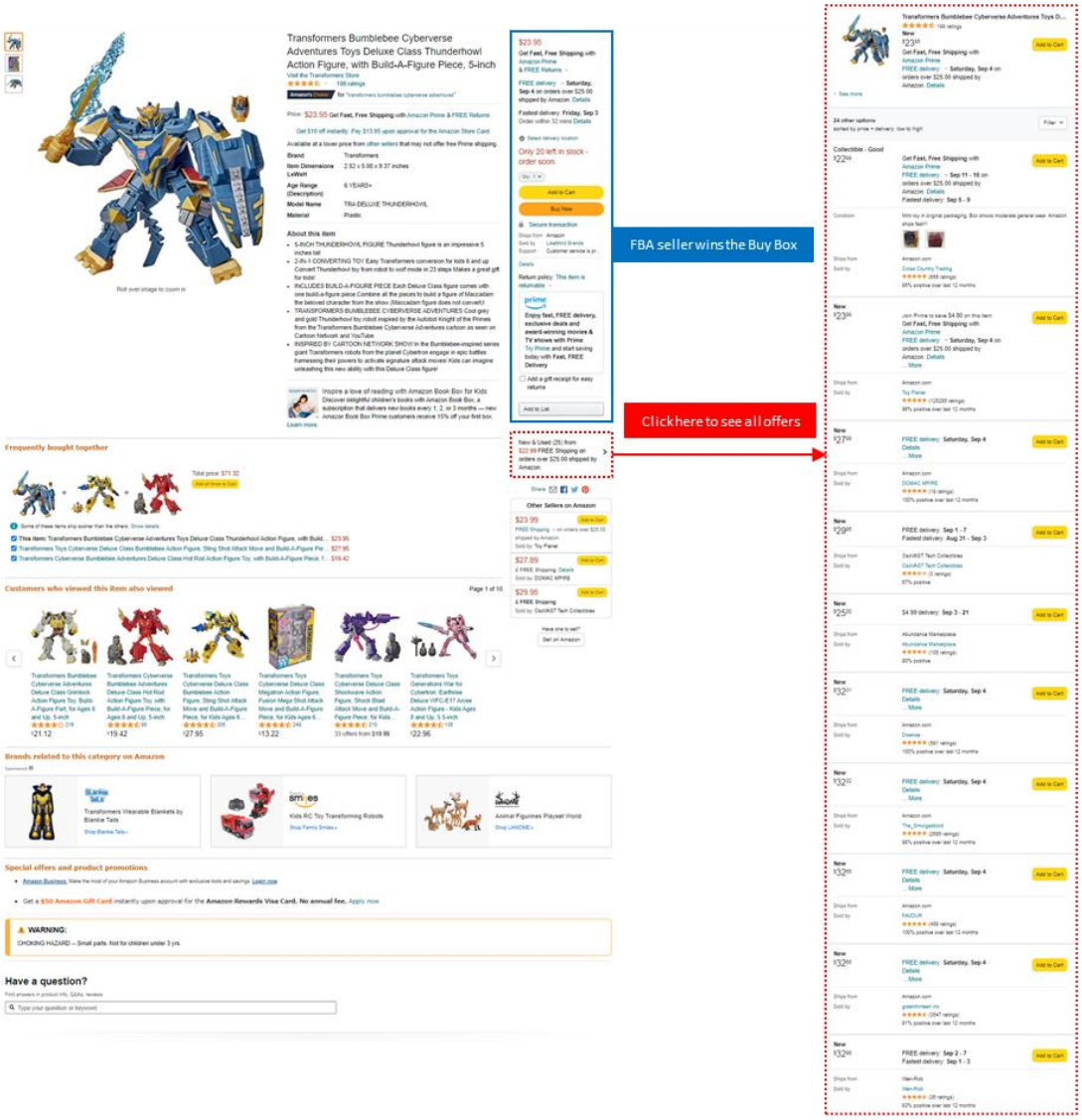
Figure 1: Example of "Amazon Winning the Buy Box"



Source: https://www.amazon.com/dp/B00Y8YOEU6/

Accessed August 30, 2021.

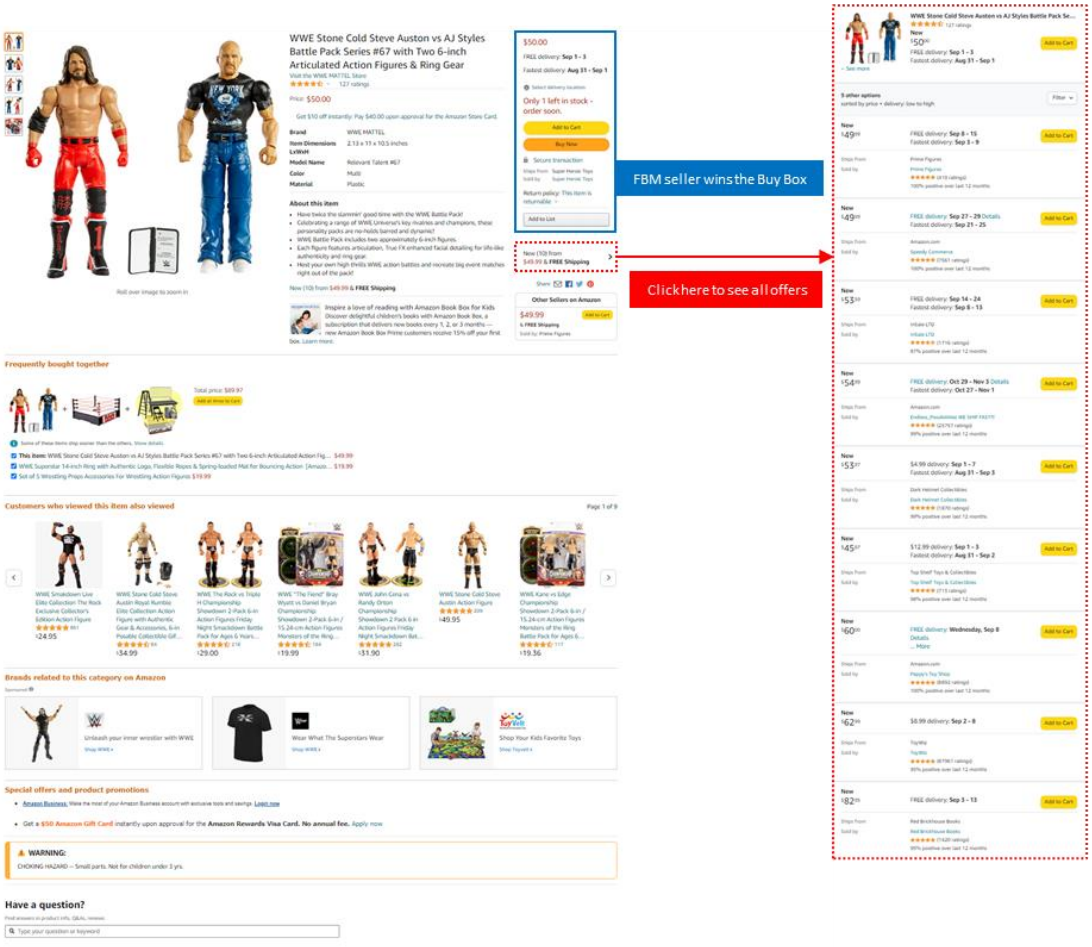
Figure 2: Example of “FBA Seller Winning the Buy Box”



Source: https://www.amazon.com/dp/B083VLVBZ4/

Accessed August 30, 2021.

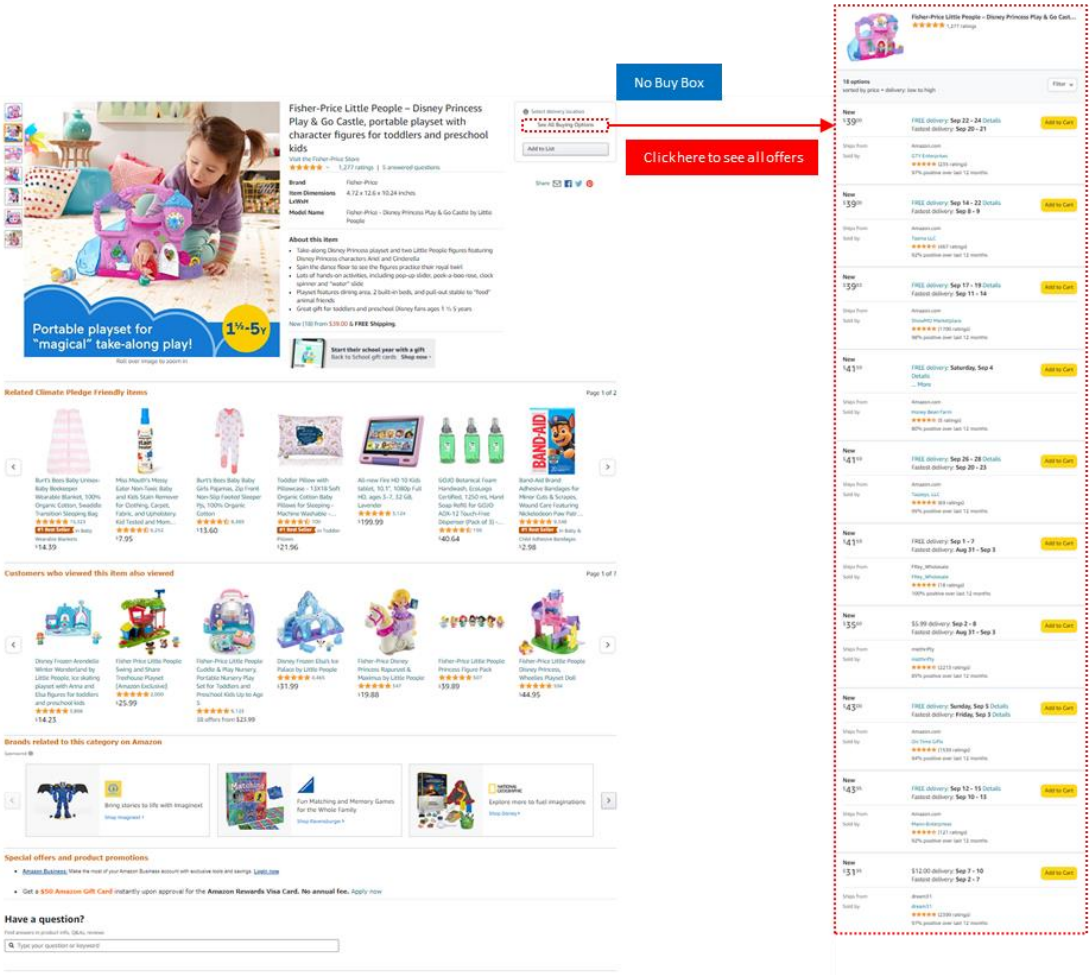
Figure 3: Example of "FBM Seller Winning the Buy Box"



Source: https://www.amazon.com/dp/B07Y92VQQW8M/

Accessed August 30, 2021.

Figure 4: Example of "No Buy Box"



Source: https://www.amazon.com/dp/B084P6W6NV/

Accessed August 30, 2021.

Data

The data consist of products from six subcategories under the category “Toys & Games” on Amazon.com: (1) building toys, (2) dolls & accessories, (3) play vehicles, (4) puzzles, (5) stuffed animals & plush toys, and (6) toy figures & playsets. According to the 30-day average sales rank on Day 1 of my data collection (i.e., September 18, 2019), I determined the 3,000 best-selling products from each of the six subcategories as my subjects. These best-selling products may not draw a complete picture of the categories but can represent a large portion of potential sales. The data on the 18,000 products from the six subcategories are derived from a third-party firm that monitors product information on Amazon.com. I retrieved data for the products between 12:00 p.m. and 4:00 p.m. Eastern Time (US) daily for 28 days (from September 18, 2019, to October 15, 2019). The unit of analysis for this study is product-date and refers to the situation for a given product on a given date within the timeframe of my study.

As discussed above, this study aims to investigate the competitive results (i.e., Buy Box winners determined by Amazon) in the following scenarios:

(1) Competition between the marketplace operator and third-party sellers when they offer the same product;

(2) Competition between third-party sellers using operator-managed fulfillment services and third-party sellers using direct fulfillment, when the marketplace operator sells the same product but does not win the competition;

(3) Competition between third-party sellers using operator-managed fulfillment services and third-party sellers using direct fulfillment, when the marketplace operator does not sell the same product.

For scenario (1), I build a sample (namely "Sample 1") with the observations in which all products are directly sold by Amazon as well as at least one FBA seller and one FBM seller. This sampling strategy allows me to observe the different competitive scenarios between Amazon and the third-party sellers (i.e., FBA and FBM sellers). The sample includes the observations in which either Amazon, or the lowest-priced FBA or FBM seller wins the Buy Box. Based on these criteria, the sample includes 100,658 observations.[12]

Table 7 summarizes the distribution of the Buy Box winners for Sample 1. As shown in Table 7, Amazon wins the Buy Box 89.81% (90,401 out of 100,658) of the time. For the remaining 10,257 (10.19%) observations, a third-party seller wins the Buy Box. Comparing the two types of third-party retailers, the lowest-priced FBA seller wins 9.75% (9,819 out of 100,658) of the time and the lowest-priced FBM retailer 0.44% (438 out of 100,658) of the time.

Table 7: Data Summary by Buy Box Winners (Sample 1)

(N = 100,658)

Buy Box Winner	Number of Observations	Percent
Amazon	90,401	89.81%
Lowest FBA	9,819	9.75%
Lowest FBM	438	0.44%
Total	100,658	100.00%

[12] Observations in which there is no Buy Box winner are excluded.

Scenario 2 analyzes Buy Box competition between the lowest-priced FBA and FBM sellers when Amazon competes but does not win. Clearly, Sample 2 is a subsample of Sample 1 and, includes the 10,257 observations in which either an FBA or FBM wins the Buy Box. Table 8 summarizes the distribution of the Buy Box winners for Sample 2. As shown in Table 8, the lowest-priced FBA seller wins the Buy Box 9,819 out of 10,257 times (95.73%), while the lowest-priced FBM seller wins the Buy Box 438 out of 10,257 (4.27%) times.[13]

Table 8: Data Summary by Buy Box Winners (Sample 2)

(N = 10,257)

Buy Box Winner	Number of Observations	Percent
Lowest FBA	9,819	95.73%
Lowest FBM	438	4.27%
Total	10,257	100.00%

For Scenario 3, I build a sample (namely "Sample 3") with the observations in which all products are sold only by third-party sellers (i.e., Amazon does not directly sell the products), and there is at least one FBA seller and one FBM seller among the sellers.[14] Sample 3 includes 64,328 observations. The distribution of the Buy Box winners for Sample 3 is summarized in Table 9. As shown in the table, FBA sellers win the Buy Box for 58,246 out of 64,328 observations (90.55% of the time), while FBM sellers wins the Buy Box for 6,082 out of 64,328 observations (9.45% of the time).

[13] In both Samples 2 and 3, the number of FBA sellers is nearly as many as the number of FBM sellers.
[14] Observations in which there is no Buy Box winner are excluded.

Table 9: Data Summary by Buy Box Winners (Sample 3)

(N = 64,328)

Buy Box Winner	Number of Observations	Percent
Lowest FBA	58,246	90.55%
Lowest FBM	6,082	9.45%
Total	64,328	100.00%

In summary, the statistics suggest that Amazon is likely to win the Buy Box in competition with FBA and FBM retailers. FBA sellers are likely to win the Buy Box in competition with FBM sellers. The empirical analysis, below, examines these scenarios in greater detail.

Empirical Analysis

Econometric Model

To test my hypotheses (H1 through H4), I model competitive results (i.e., the Buy Box winner) at the product-date level. At a given time on Amazon Marketplace, sellers, including Amazon, FBA retailers, and FBM retailers, compete to win the Buy Box recommendation. A large majority of purchasers follow the Buy Box recommendation. Therefore, I use the Buy Box recommendation to signify the winner of the sales competition. As well, the Buy Box price is used as a proxy for the selling price.

Hypotheses 1, 2a and 2b investigate competition between third-party sellers and the marketplace operator. I construct a binary dependent variable, namely “3PS Win”. The value, 0, indicates that Amazon wins the placement in the Buy Box. The value, 1, indicates that Amazon loses the Buy Box while a third-party seller (either the lowest-priced FBA or FBM seller) wins.

Hypotheses 3a, 3b and 4 investigate competition between FBA and FBM sellers. I use another binary dependent variable, namely "FBM Win", to signify an FBM retailer wins the Buy Box. "FBM Win" equals 0 if an FBA seller wins the Buy Box and equals 1 if an FBM seller wins.

To test H1 – the impact of third-party seller type on a third-party seller winning the Buy Box, I include the number of FBA offers for a product as an independent variable, namely "FBA Offers". I control for the total number of third-party offers, "Total 3PS Offers", in the model. I predict that Amazon is more likely to choose a third-party seller offer for the Buy Box (FBA or FBM), as the number of FBA offers increases, holding total 3rd party offers fixed, given that Amazon profits from providing fulfillment services for FBA sellers and that Amazon may believe that service provided by FBA sellers is more reliable than service provided by FBM sellers (since it provides the fulfillment services).

The variables "Total 3PS Offers" and "FBA Offers" may be highly correlated. As there are more offers available for a product, FBA offers, a component of all offers, will also likely increase. Although this high correlation may not be a theoretical concern, it may still need to be addressed in terms of statistical methodology. To address the collinearity issue, I include the ratio of "FBA Offers" to "Total 3PS Offers" (namely "FBA Offers Ratio") instead of "FBA Offers" in the analysis. For hypotheses H2a, H2b, H3a and H3b, I investigate the impact of price differences between Amazon, and the lowest-priced FBA and FBM sellers, on the Buy Box competitive results. For each product, I collect three prices: (1) the price offered by Amazon, (2) the lowest price offered by an FBA seller, and (3) the lowest price offered by an FBM seller.[15]

[15] Amazon and FBA sellers do not charge shipping fees to Prime members for orders, nor to customers for orders over $25. Therefore, most of the orders placed for Amazon direct sales and FBA sales do not include shipping fees.

For H2a and H2b, I examine the impact of the price difference between Amazon and the lowest-priced FBA and lowest priced FBM seller. Hence, I calculate the difference between the lowest FBA (FBM) price and the Amazon price, i.e., FBA (FBM) price minus Amazon price. The price differences can be positive, negative, or zero. When the price difference is positive (negative, or zero), the price offered by Amazon is lower than (higher than, or equal to) the lowest price offered by an FBA or FBM seller.

To capture distinct impacts from positive and negative values, I create spline variables for these price differences. When the price difference is positive (negative), the value of the positive price difference spline variable is greater than (less than) zero, with the value of the negative (positive) price difference for the spline variable set to zero (Scheer et al., 2003; Schoenherr et al., 2017). Therefore, a set of four independent variables for price differences is included in the analysis as follows:

(a) Price Diff.: FBA < Amazon

(b) Price Diff.: FBA > Amazon

(c) Price Diff.: FBM < Amazon

(d) Price Diff.: FBM > Amazon

For H3a and H3b, I test the impact of the price difference between the lowest-priced FBA and lowest-priced FBM seller when Amazon sells a product but does not win the Buy Box (i.e., Sample 2) and when Amazon does not sell a product (i.e., Sample 3). Similarly, I calculate the

The amount an FBM seller charges for shipping depends on its policies; however, the price listed from an FBM seller includes shipping fees. Therefore, the prices I compare among different types of retailers generally accounts for shipping.

difference between the lowest FBM and FBA prices, i.e., FBM price minus FBA price, and create spline variables for these price differences to capture distinct impacts from positive and negative values. As a result, another two independent variables, namely "Price Diff.: FBM < FBA" and "Price Diff.: FBM > FBA", are included in the analysis.

For H4, I investigate the impact of product price on the Buy Box competitive results between the FBA and FBM sellers. I use a product's Buy Box winning price as a proxy for product sales price, namely "Product Price". I expect that the FBM seller may be more likely to win the Buy Box against the FBA seller on lower-priced products holding the other factors constant.

I include control variables in my analysis.

As mentioned above, I control for the total number of third-party offers, "Total 3PS Offers". Moreover, the marketplace operator may be more likely to win the competition against third-party sellers on successful products (i.e., higher sales and better rated) that have the potential to generate greater profits. Thus, "Sales Rank" and "Product Rating" are included in my analysis.

I use a product's sales rank in the top-level category (i.e., "Toys & Games") as a proxy for actual sales, namely "Sales Rank". Previous studies (e.g., Chevalier & Goolsbee, 2003; M. Sun, 2011) have found a log-linear relationship between sales rank and actual sales, thus the logged values of "Sales Rank" is used in my analysis.

I include the overall star rating of a product, ranging from 1 to 5, to measure customer feedback on a product, namely "Product Rating". The higher the rating of a product, the more satisfied customers are with the product. Note that product rating is independent of a merchant's rating.

Descriptive Statistics

Tables 10, 11 and 12 provide descriptive statistics (e.g., means, standard deviations, minimums, and maximums) for Samples 1 through 3.

As reported in Table 10 for Sample 1, among the 100,658 observations, Amazon loses the Buy Box only 10% of the time. On average, a product has 6 offers from FBA sellers and 8 offers from FBM sellers. Generally, Amazon has a price advantage over the FBA and FBM sellers; its price $4.19 ($5.35) lower than the lowest price offered by an FBA (FBM) seller. When Amazon's price is lower than the lowest price offered by an FBA (FBM) seller, its price is $4.47 ($5.65) lower, on average. Whereas Amazon's price is only $0.27 ($0.30) higher than the lowest price offered by an FBA (FBM) seller when it does not have the lowest price.

The products in this sample have a range of prices between $1.50 and $799.95 with an average of $21,58. A product's sales rank in the category of "Toys & Games" ranges from 1 to 934,101. The average product rating is 4.45 out of 5. This rating may indicate that customers are generally satisfied with the products on Amazon Marketplace, at least for the category of "Toys & Games". A relatively high average product rating may also suggest that Amazon Marketplace's customers have high expectations for product and service quality.

Table 10: Descriptive Statistics (Sample 1)

(N = 100,658)

Variable	Mean	Std. Dev.	Min.	Max.
3PS Win	0.10	0.30	0.00	1.00
FBA Offers	5.72	5.04	1.00	71.00
Total 3PS Offers	13.32	6.38	2.00	99.00
FBA Offers Ratio	0.41	0.24	0.02	0.97
Price Diff: FBA - Amazon	4.19	11.81	-75.60	295.01
Price Diff.: FBA < Amazon	0.27	1.97	0.00	75.60
Price Diff.: FBA > Amazon	4.47	11.54	0.00	295.01
Price Diff.: FBM - Amazon	5.35	8.35	-75.85	246.28
Price Diff.: FBM < Amazon	0.30	1.79	0.00	75.85
Price Diff.: FBM > Amazon	5.65	7.95	0.00	246.28
Product Price	21.58	27.70	1.50	799.95
Sales Rank	35,596.93	40,193.01	1.00	934,101.00
Product Rating	4.45	0.42	1.00	5.00

As reported in Table 11 for Sample 2, when Amazon competes but does not win the Buy Box competition, the Buy Box is won by an FBM seller in only 4% of the 10,257 observations. On average, a product has 7 offers from either FBA or FBM sellers. The FBM seller that offers the lowest price among all FBM sellers generally has a price disadvantage, with its price $3.41 higher than the lowest price offered by an FBA seller, on average. When the FBM's price is lower than the lowest FBA price, the price is only $0.50 lower, on average. The sales ranks of the products sold by 3rd party retailers when Amazon loses the Buy Box range from 39 to 765,326. In this sample, the average product rating is 4.41 out of 5.

Table 11: Descriptive Statistics (Sample 2)

(N = 10,257)

Variable	Mean	Std. Dev.	Min.	Max.
FBM Win	0.04	0.20	0.00	1.00
FBA Offers	7.48	5.38	1.00	65.00
Total 3PS Offers	14.86	6.29	2.00	97.00
FBA Offers Ratio	0.49	0.24	0.05	0.95
Price Diff.: FBM - FBA	3.41	8.93	-99.87	246.28
Price Diff.: FBM < FBA	0.50	2.76	0.00	99.87
Price Diff.: FBM > FBA	3.92	8.26	0.00	246.28
Product Price	23.57	44.03	2.88	799.94
Sales Rank	53,777.63	45,927.89	39.00	765,326.00
Product Rating	4.41	0.42	1.00	5.00

As reported in Table 12 for Sample 3, when Amazon does not compete for the sale of a product, FBM (FBA) sellers win the Buy Box 9% (91%) of the time. On average, a product has 6 offers from FBA sellers and 7 offers from FBM sellers. The FBM seller that offers the lowest price among all FBM sellers has a price disadvantage over the FBA seller; its price is $2.12 higher than the lowest price offered by an FBA seller, on average. When the FBM price is lower than the FBA price, the price is only $1.37 lower, on average. The sales ranks of the products in this sample range from 21 to 934,074, with an average product rating of 4.36 out of 5.

Table 12: Descriptive Statistics (Sample 3)

(N = 64,328)

Variable	Mean	Std. Dev.	Min.	Max.
FBM Win	0.09	0.29	0.00	1.00
FBA Offers	6.16	4.86	1.00	76.00
Total 3PS Offers	12.75	7.00	2.00	85.00
FBA Offers Ratio	0.48	0.22	0.01	0.97
Price Diff.: FBM - FBA	2.12	10.05	-65.50	245.06
Price Diff.: FBM < FBA	1.37	3.86	0.00	65.50
Price Diff.: FBM > FBA	3.49	8.74	0.00	245.06
Product Price	28.08	34.36	2.67	499.99
Sales Rank	63,399.17	48,404.92	21.00	934,074.00
Product Rating	4.36	0.50	1.00	5.00

Tables 13, 14 and 15 provide correlation matrices for the variables for Samples 1, 2 and 3, respectively.

Table 13: Correlations Matrix of Variables (Sample 1)

(N = 100,658)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) 3PS Win	1.00									
(2) FBA Offers Ratio	0.11***	1.00								
(3) Total 3PS Offers	0.08***	0.19***	1.00							
(4) Price Diff.: FBA < Amazon	0.33***	0.07***	0.06***	1.00						
(5) Price Diff.: FBA > Amazon	-0.11***	-0.12***	-0.13***	-0.05***	1.00					
(6) Price Diff.: FBM < Amazon	0.27***	0.02***	0.08***	0.86***	-0.04***	1.00				
(7) Price Diff.: FBM > Amazon	-0.09***	0.13***	-0.21***	-0.06***	0.44***	-0.12***	1.00			
(8) Product Price	0.02***	-0.08***	0.01**	0.04***	0.35***	0.10***	0.30***	1.00		
(9) Sales Rank	0.15***	-0.13***	-0.11***	0.07***	-0.11***	0.08***	-0.11***	-0.03***	1.00	
(10) Product Rating	-0.03***	0.00	0.09***	-0.06***	0.01*	-0.06***	-0.03***	0.04***	-0.16***	1.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Correlations Matrix of Variables (Sample 2)

(N = 10,257)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) FBM Win	1.00							
(2) FBA Offers Ratio	-0.13***	1.00						
(3) Total 3PS Offers	0.00	0.18***	1.00					
(4) Price Diff.: FBM < FBA	0.50***	-0.12***	-0.02	1.00				
(5) Price Diff.: FBM > FBM	-0.10***	0.11***	-0.14***	-0.09***	1.00			
(6) Product Price	0.03**	-0.10***	-0.01	0.18***	0.38***	1.00		
(7) Sales Rank	0.02*	-0.08***	-0.04***	-0.01	-0.03**	-0.05***	1.00	
(8) Product Rating	-0.03**	0.01	0.02*	-0.01	-0.02*	0.01	-0.15***	1.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Correlations Matrix of Variables (Sample 3)

(N = 64,328)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) FBM Win	1.00							
(2) FBA Offers Ratio	-0.22***	1.00						
(3) Total 3PS Offers	0.02***	0.04***	1.00					
(4) Price Diff.: FBM < FBA	0.41***	-0.22***	0.11***	1.00				
(5) Price Diff.: FBM > FBA	-0.12***	0.14***	-0.27***	-0.14***	1.00			
(6) Product Price	0.01	-0.05***	0.10***	0.43***	0.04***	1.00		
(7) Sales Rank	0.08***	-0.15***	-0.02***	0.08***	-0.04***	0.05***	1.00	
(8) Product Rating	0.01*	-0.00	0.09***	0.06***	-0.06***	0.06***	-0.10***	1.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimation Strategy

My goals are to investigate the factors that (1) improve the likelihood of a third-party seller winning the Buy Box against Amazon (i.e., H1, H2a and H2b) and (2) improve the likelihood of an FBM seller winning the Buy Box against an FBA seller (i.e., H3a, H3b and H4) when Amazon does not win the Buy Box or is not a product seller. To examine these factors, I estimate logit regression models with cluster-robust standard errors for Samples 1 through 3.

To test the competitive results between Amazon and the third-party sellers, I estimate a logit regression model using data from Sample 1 with Equation (1) as follows:

$$\begin{aligned}(3PS\ Win)_{it} = {} & \beta_0 + \beta_1\,(FBA\ Offers\ Ratio)_{it} + \beta_2\,ln(Total\ 3PS\ Offers)_{it} \\ & + \beta_3\,ln(Price\ Diff.: FBA < Amazon)_{it} \\ & + \beta_4\,ln(Price\ Diff.: FBA > Amazon)_{it} \\ & + \beta_5\,ln(Price\ Diff.: FBM < Amazon)_{it} \\ & + \beta_6\,ln(Price\ Diff.: FBM > Amazon)_{it} \\ & + \beta_7\,ln(Product\ Price)_{it} + \beta_8\,ln(Sales\ Rank)_{it} \\ & + \beta_9\,(Product\ Rating)_{it} + \varepsilon_{it} \qquad (1)\end{aligned}$$

To test the competitive results between FBA and FBM sellers when Amazon does not win the Buy Box (Samples 2 and 3), I estimate a logit regression model with Equation (2) as follows:

$$(FBM\ Win)_{it} = \beta_0 + \beta_1\ (FBA\ Offers\ Ratio)_{it} + \beta_2\ ln(Total\ 3PS\ Offers)_{it} + \beta_3\ ln(Price\ Diff.: FBM < FBA)_{it} + \beta_4\ ln(Price\ Diff.: FBM > FBA)_{it} + \beta_5\ ln(Product\ Price)_{it} + \beta_6\ ln(Sales\ Rank)_{it} + \beta_7\ (Product\ Rating)_{it} + \varepsilon_{it} \quad (2)$$

In Equations (1) and (2), i denotes product, and t denotes time (date). As the dependent variables, "3PS Win" and "FBM Win", are dichotomous, logit regression analysis is appropriate. Using cluster-robust standard errors allows observations for the same product to potentially correlate. To reduce the impact from outlying observations, I log all the variables expect "FBA Offers Ratio" and "Product Rating" (since they are not skewed) in both models.

Estimation Results

Table 16 presents the estimation results for Models (1) through (3).

Model (1) is used to investigate the Buy Box competition between the marketplace operator—Amazon—and third-party sellers (i.e., H1, H2a and H2b). Models (2) and (3) are used to investigate the Buy Box competition between the lowest-priced FBA and FBM sellers (i.e., H3a, H3b and H4). Model (2) looks at the scenario in which Amazon sells the product but does not win the Buy Box. Model (3) examines the scenario in which Amazon does not sell the product.

Table 16: Estimation Results

	(1)	(2)	(3)
	3PS Win	FBM Win	FBM Win
FBA Offers Ratio	1.0383***	-0.6993	-1.1615***
	(0.1575)	(0.6487)	(0.2626)
ln(Total 3PS Offers)	0.2352***	-0.3970	-0.3965***
	(0.0751)	(0.3631)	(0.0670)
ln(Price Diff.: FBA < Amazon)	2.0907***	-	-
	(0.0872)		
ln(Price Diff.: FBA > Amazon)	-0.8554***	-	-
	(0.0638)		
ln(Price Diff.: FBM < Amazon)	0.3847***	-	-
	(0.1057)		
ln(Price Diff.: FBM > Amazon)	0.0010	-	-
	(0.0433)		
ln(Price Diff.: FBM < FBA)	-	3.1168***	2.1278***
		(0.3963)	(0.0807)
ln(Price Diff.: FBM > FBA)	-	-1.9919***	-0.6167***
		(0.5656)	(0.0905)
ln(Product Price)	-0.0473	-1.0686***	-1.2806***
	(0.0659)	(0.2864)	(0.0850)
ln(Sales Rank)	-0.4645***	0.1031	-0.1081**
	(0.0338)	(0.1503)	(0.0520)
Product Rating	0.1200	0.2796	-0.0568
	(0.0808)	(0.3718)	(0.1011)
Constant	-8.3507***	-0.5099	0.3738
	(0.6632)	(2.5881)	(0.7691)
Observations	100,658	10,257	64,328

*** p < 0.01, ** p < 0.05, * p < 0.1

Cluster-Robust Standard Errors in Parentheses

The values of *ln(Sales Rank)* are reversed.

The coefficient for "FBA Offers Ratio" is positive and significant at the 0.01 level in Model (1) ($\gamma = 1.0383$; $p < 0.01$), suggesting that the likelihood of a third-party seller winning the competition against Amazon increases when the number of FBA sellers is higher after controlling for the total number of sellers. This result supports H1.

Model (1) includes both pairs of the spline variables for differences between the prices offered by Amazon and the lowest prices offered by FBA and FBM sellers.

When the FBA sellers offer a lower price than Amazon, there is a positive and significant ($\gamma = 2.0907$; $p < 0.01$) impact on a third-party seller winning the Buy Box. The same is the case when the FBM seller's price is lower than the Amazon offer ($\gamma = 0.3847$; $p < 0.01$), suggesting an additional impact. When the FBA sellers' lowest price is higher than Amazon's price, the spline coefficient is negative and significant ($\gamma = -0.8554$; $p < 0.01$). Any additional impact from the FBM seller offering higher prices than Amazon is insignificant. These results indicate that the likelihood of a third-party seller winning the Buy Box against Amazon is higher when the third-party sellers offer a lower price than Amazon, and that the likelihood will increase as the price difference increases. Hence, H2a and H2b are supported.

Note that the coefficient for the spline variable, "FBA < Amazon" is greater than for the spline variable "FBA > Amazon". This asymmetry may suggest that FBA sellers have more to gain (i.e., by increasing their winning probability for the Buy Box) by offering a lower price than Amazon, than Amazon has to gain by offering a lower price than the FBA sellers.

Now, I focus on Models (2) and (3) that investigate competition between FBA and FBM sellers when Amazon does not win the Buy Box or does not sell the product (i.e., H3a, H3b and H4).

Models (2) and (3) include a pair of the spline variables for price differences between the lowest prices offered by FBA and FBM sellers. When Amazon does not win the Buy Box (Model 2), there is a positive and significant ($\gamma = 3.1168$; $p < 0.01$) impact on the FBM seller winning the Buy Box if the lowest FBM price is lower than the lowest FBA price. The same is the case when Amazon does not sell the product (Model 3) ($\gamma = 2.1278$; $p < 0.01$). If the lowest FBM price is higher price than the lowest FBA price, there is a negative influence on the FBM seller winning the Buy Box in Model 2 ($\gamma = -1.9919$; $p < 0.01$) and Model 3 ($\gamma = -0.6167$; $p < 0.01$). Hence, H3a and H3b are supported.

The coefficients for "Product Price" are negative and significant in both Models (2) ($\gamma = -1.0686$; $p < 0.01$) and (3) ($\gamma = -1.2806$; $p < 0.01$) suggesting the FBM seller is less likely to win the competition for higher-priced products. This negative relationship holds under both scenarios; that is when the marketplace operator is selling or not selling the product, supporting H4.

Regarding the control variables, the coefficient for "Sales Rank" is negative and significant in Models (1) and (3) but insignificant in Model (2), suggesting that the likelihood of a third-party seller or the FBM seller winning the competition may increase for the lower-sales products. The coefficients for "Product Rating" are insignificant in all the models suggesting that product rating after controlling for product's sales rank may not significantly change the Buy Box outcome. The

coefficient for “Product Price” is insignificant in Model (1), suggesting that product price does not determine the Buy Box competition between Amazon and third-party sellers. The coefficient for “FBA Offers Ratio” is negative and significant in Model (3), but insignificant in Model (2), suggesting that in direct competition between third party sellers (without Amazon competing), fewer FBA offers increases the chance of an FBM seller winning the Buy Box.

Overall, all my hypotheses are supported. The results suggest the following:

(1) The marketplace operator is more likely to win the Buy Box competition against third-party sellers.

(2) Third-party sellers using operator-managed fulfillment services are more likely to win the Buy Box competition against the sellers that manage their own fulfillment.

(3) The likelihood of a third-party seller winning the Buy Box competition against the marketplace operator increases: (i) with the number of sellers uses operator-managed fulfillment services, and (ii) when third-party sellers offer lower prices than the marketplace operator.

(4) The likelihood of a third-party seller that uses direct fulfillment winning the Buy Box competition against a seller uses operator-managed fulfillment services increases: (i) when the FBM seller offers a lower price than the FBA seller, and (ii) the product’s price is lower.

Conclusions

In online marketplaces, there is direct competition between third-party sellers and the marketplace operator if they sell the same product. Moreover, there is also

competition between types of third-party sellers, as they compete for sales of products on online marketplaces.

This study investigates the competitive results between the marketplace operator and third-party sellers and between third-party sellers with different methods of fulfilling orders. It is clear that the marketplace operator is more likely to win the competition against third-party sellers. It generally has lower prices than third-party retailers. Moreover, the marketplace operator controls the determinants of the Buy Box.

In competition between FBA and FBM retailers, FBA retailers have a competitive edge. They generally have lower prices than FBM sellers, and the marketplace operator may favor them in sales competition due to added fee revenues and more assurance over fulfillment quality.

Based on the competitive results, I examine the factors that may increase the likelihood of a third-party seller winning the competition against the marketplace operator, and the likelihood of a third-party seller that uses direct fulfillment winning the competition against a seller using operator-managed fulfillment services. My empirical analysis suggests the following results: The likelihood of a third-party seller winning the competition against the marketplace operator increases: (1) where there is a higher number of FBA sellers (holding total third-party sellers constant), and (2) when the lowest price from a third-party seller is lower than the marketplace operator's price. FBM sellers are more likely to win the Buy Box competition against FBA sellers: (1) when the FBM price is lower, and (2) when the product's price is low.

This study contributes to literature on competition on online marketplaces. First, this study reveals the competitive results between the marketplace operator and

third-party sellers and those between third-party sellers that do or do not use operator-managed fulfillment services. Second, the study highlights the inherent advantages of the marketplace operator and those of sellers using operator-managed fulfillment services vs. sellers that manage their own fulfillment. Third, the study shows that consumers are more likely to choose FBM sellers for low-risk products; that is when the product prices are low.

The findings provide practical implications for third-party sellers on online marketplaces.

My results suggest that third-party sellers may want to try to avoid direct competition with the marketplace operator. Moreover, they should consider using the marketplace operator's fulfillment services to increase their chances of making sales on the marketplace.

My findings also contribute to important antitrust considerations. Online marketplaces may create unfair competition between the marketplace operator and third-party sellers when the marketplace operator also offers direct sales. Marketplace operators appear to have inherent advantages when competing against third-party sellers. Moreover, the marketplace operators may favor sellers that increase their fee revenues. Both these issues raise potential antitrust concerns.

This study has several limitations. First, the study investigates competition between Amazon and the lowest-priced FBA and FBM sellers. Future research may use a more comprehensive data source with additional sellers and additional online marketplaces. Second, the study does not include seller characteristics, due to data limitations. It may be that FBA sellers and FBM sellers are inherently different, such

as in size and physical location. Third, the study analyzes only one category of products, restricting its generalizability to other categories of interest. Further research can employ a cross-category study to increase generalizability. Finally, the study uses Amazon Marketplaces as a case study. The findings of this study may only be generalized to the other marketplaces with similar governance structure. Future research may investigate competition in other online marketplaces and compare the differences.

Chapter 4: Using Marketplace Store Banners

Introduction

Introducing private labels[16] (a.k.a. store brands) has been considered as one of the most important strategies by retailers to improve their performance. According to the Private Label Manufacturers Association (PLMA) (2022), private labels sales grew by 1.9 billion from 2020 to 2021, and private label's market penetration was 17.7 % measured by dollar share and 19.6% measured by share of unit sales.

Both retailers and customers may benefit from private labels. Retailers can achieve greater profit margins on private labels, stronger negotiation power with manufacturers, and higher store loyalty from customers (Ailawadi et al., 2008; Ailawadi & Harlam, 2004; Chintagunta et al., 2002; Corstjens & Lal, 2000; González-Benito & Martos-Partal, 2012; Martos-Partal & González-Benito, 2011; Meza & Sudhir, 2010; Pauwels & Srinivasan, 2004). Private labels offer customers products of similar quality to those of non-private labels at lower prices (Pauwels & Srinivasan, 2004).

Once retailers decide to introduce private labels to a market, they can choose whether to use store-banner branding for their private labels. When a retailer uses store-banner branding, it attaches its name to the private label, clearly revealing the ownership link to the retailer (Keller et al., 2016, 2022).

[16] Private labels are sometimes called store brands. For online sales, private labels may be introduced by retailers or by marketplace operators. This study focuses on the private labels introduced by marketplace operators. Non-private labels in this study include the sales of all other (non-private label) products, including, national brands.

The impact of store-banner branding may depend on whether brand image spillover from the retailer to its private label is positive or negative (Keller et al., 2016). Positive spillovers may help to reduce customer uncertainty about the private label. However, if a retailer does not have a positive image, its name on a private label may create negative spillovers, reducing the appeal of the private label (Ailawadi & Keller, 2004).[17]

Extant literature on private labels has looked at the impact of store-banner branding for traditional brick-and-mortar retailers (for a review, see Sethuraman, 2009; Wu et al., 2021), however, there is little research that investigates this strategy in an online setting (Dawes & Nenycz-Thiel, 2014; González-Benito et al., 2015). E-tailers, especially online marketplaces that both offer direct sales for some products and allow third-party retailers to sell products via marketplaces, may be interesting to research for the following three reasons. First, e-commerce is a fast-growing consumer sales and distribution channel (M. Evans, 2021). Second, customers may have difficulty assessing quality on online marketplaces, thus the brand equity of the marketplace operator may be important to signal reliable product quality. Third, private label products on marketplaces may not have exclusive use of store banners. Marketplace operators may also use their marketplace banners (i.e., store banner) to other products sold on their marketplace. For example, Amazon attaches "Amazon Exclusives" or "Exclusive on Amazon" to non-private-label products it sells or are sold by third-party retailers on Amazon Marketplace. In this case, the marketplace operator uses store

[17] Some retailers use store banners for some products, but not for others. For example, the US based retailer Meijer brands some of its private labels with store banners (e.g., "Meijer" and "True Goodness by Meijer") and some without store banners (e.g., "Purple Cow" and "Falls Creek").

banner as an advertisement of the product rather than directly branding the product. Therefore, this study examines how the impact of store banners that are used directly in private label products' names (i.e., directly branding) may differ from the impact of using store banners on other (non-private-label) products sold on the marketplace as an advertisement.

Previous studies have examined the impact of store-banner branding on performance at the retailer level (e.g., Dhar & Hoch, 1997) and at the brand level (e.g., brand equity) (e.g., Keller et al., 2016; Rubio et al., 2020; Schnittka et al., 2015). In this study, I investigate how store-banner impacts sales at the product-level providing a finer-grained analysis of the impact. Therefore, the first objective of this study is to investigate whether both using store banner benefits the sales performance at the product level on online marketplaces.

Moreover, the impact of store-banner may vary across products at different price levels. There are a limited number of studies testing the moderating effect of product price on the impact of using store banner. For example, it was found that using store banner improves customer attitudes for mid-priced private labels, but not for low-priced private labels (Schnittka et al., 2015); and mid-price and high-price private labels contribute to a higher store loyalty than do low-price private labels when using store-banner branding (Rubio et al., 2020). The second objective of this study builds on this literature to test the moderating effect of product price on the impact of using store banner on product sales performance on online marketplaces.

Finally, I examine whether the impact of directly using store banner to brand private label products offered by the marketplace operator (i.e., the "store") and that of

including store banner outside the names of non-private-label products sold on the marketplace as an advertisement of the products differ.

Specifically, I address the following three research questions: (1) Is using store banner associated with better sales performance for a product on an online marketplace? (2) How does this performance vary between directly branding private-label products using store banner and adding store banner to non-private-label products as an advertisement? (3) How does the impact of using store banner vary for products at different price levels? The goal of this research is to provide relevant information to manufacturers or brand owners as they make decisions on whether to use the store banners for their products.

This study draws on the literature from store banner branding (e.g., Dhar & Hoch, 1997; Geyskens et al., 2018; Keller et al., 2016, 2022; Rubio et al., 2020) to analyze product-level data from the largest online marketplace in the U.S., Amazon.com. The study takes advantage of Amazon's sales of private labels that contain the Amazon name (i.e., are store banner branded) and other Amazon private label products that are not store banner branded, as well as the sales of (non-private-label) products with the Amazon store banner (i.e., "Amazon Exclusive") offered by Amazon and third-party sellers.

My results show that the sales performance for products is positively associated with using store banner for private label products introduced by the marketplace operator and for other non-private-label products mainly offered by Amazon and third-party retailers. However, for the non-private-label products (i.e., the Amazon

Exclusives), this positive association between using store banner as an advertisement and sales performances diminishes as the product price increases.

The rest of the study proceeds as follows. The next section reviews related literature and develops the hypotheses. I then describe the data. Thereafter, the analyses and estimation results are discussed. A final section presents a summary, theoretical contributions, practical implications, and limitations to this study.

Literature Review and Hypothesis Development

Retailers may choose to use store-banner branding and clearly reveal ownership of the private labels (Keller et al., 2016). Brand image spillovers from retailers to their private labels could be positive or negative (Keller et al., 2016). Positive spillovers may help to reduce customer uncertainty about the private labels. For example, customers may believe the private labels with a store-banner name are of good quality if they are familiar with the store-banner name or have a good impression of the store (Sethuraman & Gielens, 2014). However, when retailers fail to please customers with their private labels, a retailers' brand image may be damaged when using the store-banner name on private labels (Ailawadi & Keller, 2004).

Studies have examined the impact of store-banner branding on the performance private labels at the retailer level and at the brand level. For example, it has been found that attaching a store banner to a private labels increases the market share for a retailer (Dhar & Hoch, 1997), and has a positive impact on brand equity (Keller et al., 2016; Rubio et al., 2020; Schnittka et al., 2015). In this study, I investigate how branding private label products using store banner impacts their product-level sales performance,

and how using store banner on non-private-label products as an advertisement impacts their sales performance.

Previous studies use online grocery data to examine the impact of brand names on customer purchasing behavior. Degeratu, Rangaswamy, and Wu (2000) suggest that brands are more important for products with little information available online. Andrews and Currim (2004) find that customers often screen on the basis of brands. Pozzi (2012) reveals that customers are less willing to try new and/or small brands because it is difficult to verify product quality online. Moreover, customers use brand name as a signal of reliability for service quality (Brynjolfsson & Smith, 2001). As such, on online marketplaces, customers may be more willing to purchase products that attach the store banner to their product offerings.

Based on above discussion, I purpose the first two hypotheses as follows:

H1. Directly branding a private label product using store banner is positively associated with the product's sales performance.

H2. Using store banner on a non-private label product as an advertisement is positively associated with the product's sales performance.

Moreover, the impact of using store banner may vary across products depending on sales prices. Findings from a limited number of studies are inconsistent. Schnittka et al. (2015) found a positive association between store-banner branding and customer attitudes to private labels exists only for mid-priced (i.e., standard-tier) private labels, but not for low-priced (i.e., economy-tier or budget-tier) private labels. Rubio et al. (2020) found that mid-priced and high-priced private labels contribute to a higher store loyalty when store-banner branding is used. However, Schnittka et al. (2015) suggested

that the brand extension literature (e.g., John et al., 1998) may provide theoretical support for lower-priced products benefitting more from store banners than higher-priced products. The reasoning is that higher-priced products already have positive brand equity. Keller et al. (2016) suggests that the impact of store-banner branding on different-tiers of private labels depends on the retail and institutional environments.

Given the inconsistency across literature, competing hypotheses are presented on the moderating effect of product price. The competing hypotheses are summarized as follows:

H3. The positive relationship between using store banner and product sales performance strengthens as product price increases.

H4. The positive relationship between using store banner and product sales performance diminishes as product price increases.

Data

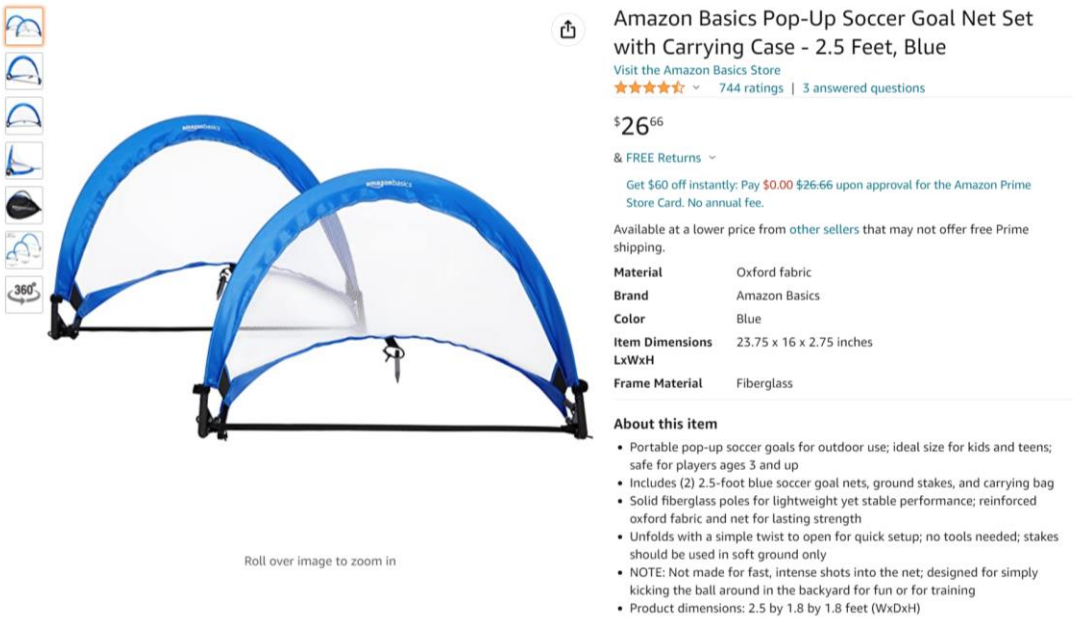
My data are generated from all bottom-level categories (i.e., the most specific categories) under the category of "Toys & Games" on Amazon.com. For example, the most specific category for a Jellycat bunny stuffed animal is "Toys & Games › Stuffed Animals & Plush Toys › Stuffed Animals & Teddy Bears". According to the sales rankings released by Amazon, the 100 best-selling products from each of these subcategories is used in the analysis.[18] Although best-selling products may not present a complete picture of the subcategory, they may account for a large percentage of subcategory sales. Similar to traditional retailers, Amazon introduced its private labels

[18] Note that some subcategories have fewer than 100 products in total. For those smaller subcategories, I used all of the products.

onto its marketplace. All the private-labeled products belong to Amazon's "Our Brands" collection. Amazon may directly brand its private labels using store banner, e.g., Amazon Basics and Amazon Essentials.[19] Figure 5 demonstrates an example of an Amazon private label product using direct store banner branding.

Figure 5: Example of Private Labels

(Direct Branding)



Source: https://www.amazon.com/dp/B0758BKVL5/

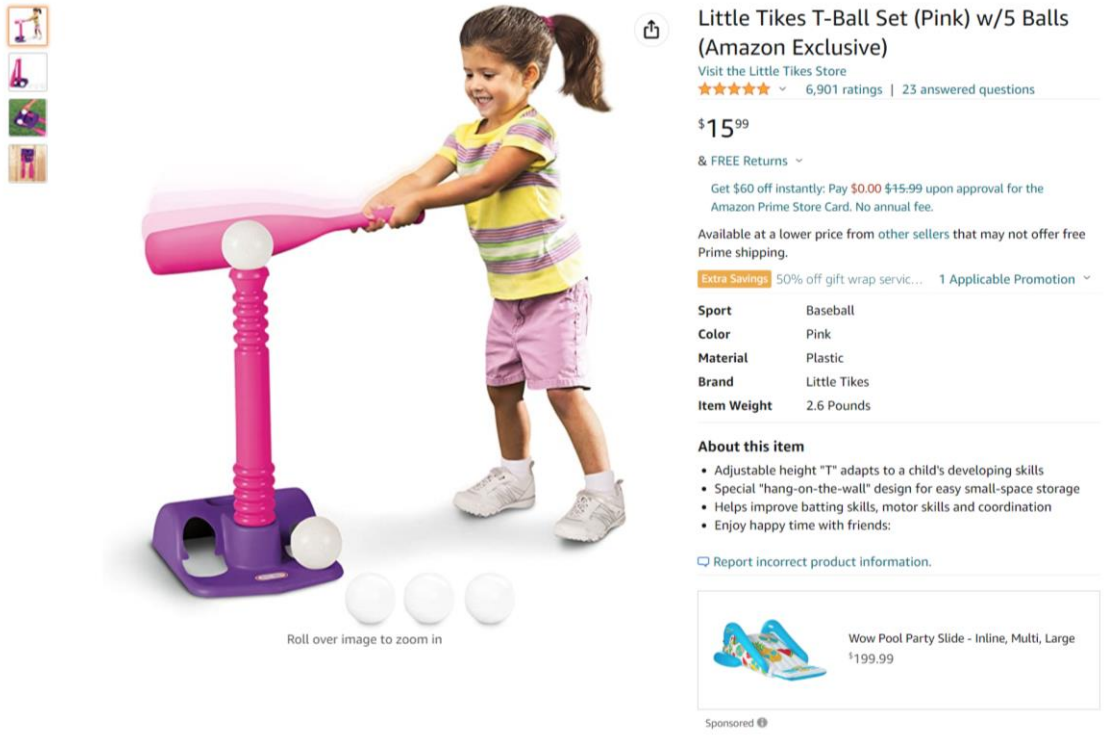
Accessed June 8, 2022.

[19] In the category of "Toys & Games", there is only one private label using store-banner branding, "Amazon Basics".

Amazon may also attach its store banner name to non-private label products on the Amazon Marketplace as an advertisement. These products are generally labeled as "Amazon Exclusive" or Exclusive on Amazon" (Amazon, 2022a). Figure 6 demonstrates an example of a non-private label product sold on Amazon Marketplace using Amazon banner branding.

Figure 6: Example of Non-Private Labels

(Using Store Banner as an Advertisement)



Source: https://www.amazon.com/dp/B01FVVKXEA

Accessed June 8, 2022.

Product-level data from the 100 best-selling products from all subcategories under the category of "Toys & Games" were collected from a third-party firm that monitors product information on Amazon.com. According to the sales rankings released by Amazon at the time, data for these products were collected between 6:00 p.m. and 12:00 a.m. Eastern Time (US) daily for 78 days (from July 1, 2021 to September 16, 2021).

The unit of analysis in this study is product-subcategory-date and refers to the situation for a given product in a given subcategory on a given date within the timeframe of my study. After removing observations with missing values, the sample includes a dataset of 2,171,463 observations for 117,431 products from 439 subcategories over 78 days.

Empirical Analysis

Econometric Model

To test my hypotheses, I model sales performance at the product-date level. The sales performance of a product can change over time, thus investigating a product over a period of time (daily for 78 days) adds variance to my dataset.

I use the sales ranks at the top-level category (i.e., "Toys & Games"), namely "Sales Rank", as the dependent variable. Amazon ranks products based on their sales at different category levels. Previous studies (e.g., Chevalier & Goolsbee, 2003; Sun, 2011) have found a log-linear relationship between sales rank and actual sales, thus sales rank may be used as a proxy for sales performance. The logged value of sales rank is used in the analysis.

To test H1 and H2 – a positive link between using store banner and the product's sales performance, I include a binary variable to measure whether store banner is used on a product namely "Store Banner". For private labels, the value, 1, indicates that the Amazon banner is directly included in the brand name; the value, 0, indicates that the product is not Amazon branded. For non-private labels, the value, 1, indicates that the Amazon banner is used on the product as an advertisement; the value, 0, indicates the cases when the Amazon banner is not used.

To test the moderating effect of product price on the relationship between using Amazon store banner and product sales performance (i.e., H3 and H4), I use a product's Buy Box winning price as a proxy for product price, namely "Price". An offer featured by the Buy Box indicates that the marketplace operator recommends this offer as the best offer, and that customers need not search for a better offer. As such, the price offered by the seller winning placement in the Buy Box becomes the most likely sales price for an order.

As the products used in this study may be sold by different types of sellers and from different subcategories, I control for both product and subcategory characteristics in my analysis.

First, I include two variables to control for product characteristics. I include the overall (star) rating of a product (namely "Product Rating"), ranging from 1 to 5, to measure perceived quality of the product. The higher the rating of a product, the more satisfied consumers are with the product, *ceteris paribus*. Product rating is independent of a seller's rating. I also use the total number of product reviews for a brand (namely

"Brand Strength") to assess the strength of a brand. The total number of reviews is used as a proxy to measure brand visibility and familiarity.

Second, I include three variables to control for the seller of a non-private label product:[20] "Amazon Sell" — a binary variable is included when Amazon offers direct sales of the product. The value, 1, indicates that Amazon directly sells the product. In this scenario, a consumer can find Amazon on the list of sellers for the product. The value, 0, indicates that Amazon does not directly sell the product but leaves sales to third-party sellers. Consumers will not find Amazon on the list of sellers for these products, so all the sellers will be third-party sellers. "FBA Offers" and "FBM Offers" — are two variables used to measure the number of offers that use fulfillment services provided by the marketplace operator (FBA) or direct fulfillment by third party retailers (FBM). "FBA Offers" measures the number of offers that use FBA services for a product, and "FBM Offers" measures the number of offers where third-party retailers directly fulfill orders.

Lastly, I include two subcategory characteristic variables that may impact a product's sales rank. First, I include a variable, "Category Concentration", to control for the subcategory-specific market concentration level. Second, I include total number of products for a subcategory in my sample (namely "Category Size").

Descriptive Statistics

Tables 17 and 19 provide descriptive statistics (e.g., means, standard deviations, minimums, and maximums) and a correlation matrix for the variables for Amazon

[20] All of Amazon private label products are sold by Amazon only in this study.

private labels sold by Amazon only. Tables 18 and 20 provide descriptive statistics (e.g., means, standard deviations, minimums, and maximums) and a correlation matrix for the variables for non-private labels. Among the 2,171,463 observations, 770 observations are for private labels, and 2,170,693 observations are for non-private labels.

Table 17: Descriptive Statistics (Amazon Private Labels)

(N = 770)

Variable	Mean	Std. Dev.	Min.	Max.
Sales Rank	52,080.07	93,871.71	1,259.00	637,313.00
Store Banner	0.76	0.43	0.00	1.00
Price	65.22	54.10	7.44	240.99
Product Rating	4.49	0.50	2.00	4.90
Brand Strength	4,989.02	2,282.72	2.00	11,401.00
Category Concentration	58.73	11.27	1.00	79.00
Category Size	98.55	7.92	51.00	100.00

Table 18: Descriptive Statistics (Non-Private Labels)

(N = 2,170,693)

Variable	Mean	Std. Dev.	Min.	Max.
Sales Rank	114,355.31	203,493.21	1.00	4,744,422.00
Store Banner	0.01	0.09	0.00	1.00
Price	31.40	58.32	0.11	3,699.89
Product Rating	4.46	0.43	1.00	5.00
Brand Strength	58,654.19	195,608.69	0.00	1,309,054.00
Amazon Sell	0.20	0.40	0.00	1.00
FBA Offers	1.66	3.37	0.00	94.00
FBM Offers	1.87	3.69	0.00	71.00
Category Concentration	55.55	17.42	1.00	95.00
Category Size	97.92	10.67	1.00	100.00

Table 19: Correlations Matrix of Variables (Amazon Private Labels)

(N = 770)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Sales Rank	1.00						
(2) Store Banner	-0.20***	1.00					
(3) Price	-0.01	-0.00	1.00				
(4) Product Rating	-0.72***	0.37***	0.29***	1.00			
(5) Brand Strength	-0.28***	0.54***	0.23***	0.44***	1.00		
(6) Category Concentration	-0.19***	0.03	0.42***	0.34***	0.36***	1.00	
(7) Category Size	-0.83***	0.32***	0.19***	0.91***	0.40***	0.33***	1.00

*** p<0.01, ** p<0.05, * p<0.1

Table 20: Correlations Matrix of Variables (Non-Private Labels)

(N = 2,170,693)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Sales Rank	1.00									
(2) Store Banner	-0.04***	1.00								
(3) Price	0.07***	0.01***	1.00							
(4) Product Rating	-0.14***	0.05***	-0.02***	1.00						
(5) Brand Strength	-0.10***	0.06***	-0.03***	0.14***	1.00					
(6) Amazon Sell	-0.12***	0.17***	0.03***	0.15***	0.38***	1.00				
(7) FBA Offers	-0.15***	0.05***	-0.07***	0.08***	0.13***	0.14***	1.00			
(8) FBM Offers	0.05***	0.00**	0.00*	0.14***	0.29***	0.36***	0.32***	1.00		
(9) Category Concentration	-0.32***	-0.02***	-0.07***	-0.08***	-0.08***	-0.08***	-0.04***	-0.26***	1.00	
(10) Category Size	-0.39***	0.01***	-0.06***	0.05***	0.03***	0.01***	0.06***	-0.04***	0.36***	1.00

*** p<0.01, ** p<0.05, * p<0.1

As reported in Tables 17 and 18, the sales rank for Amazon private label products in the category of “Toys & Games” ranges from 1,259 to 637,313, while the sales rank for a non-Amazon-private label products ranges from 1 to 4,744,422, suggesting that non-Amazon brands have a wider range of product sales levels. Among the 770 Amazon-private-label observations, 583 observations (75.71%) are Amazon banner branded and the rest 187 observations (24.29%) are not. Among the 2,170,693 non-private-label observations, 18,462 observations (0.85%) use store-banner as an advertisement and the remaining 2,152,231 observations (99.15%) do not.

The average Buy Box winning price for Amazon-private labels is $65.22 while the average price for non-private labels is lower at $31.40. The average product rating for private labels (non-private labels) is 4.49 (4.46) out of 5. This rating may indicate that customers are generally satisfied with the best-selling products for the category of “Toys & Games”. On average, private-label products are from brands with 4,989 reviews, while brands for non-private-label products have 58,654 reviews, suggesting that non-private labels may be better-known brands.

All the Amazon-private labeled products are sold exclusively by Amazon. Amazon directly sells non-private-label products 20.37% of the time (442,183 out of 1,728,510 observations). On average, a non-Amazon-private-labeled product has about 2 FBA offers and 2 FBM offers.

On average, there are about 59 brands in a subcategory that include private labels and 56 brands in a subcategory that includes non-private label products. About 97% of the observations for private labels (745 out of 770) and 95% of the observations for non-private labels (2,062,245 out of 2,170,693) are from subcategories with at least

100 products. The remaining products are from subcategories with fewer than 100 products.

Estimation Strategy

To test the impacts of using store banner to directly brand private labels on product sales and the impact of using store banner on non-private labels as an advertisement (i.e., H1 and H2), I estimate an ordinary least squares (OLS) regression model for the subsamples of private labels and non-private labels respectively using Equation (1):

$$\begin{aligned} ln(Sales\ Rank)_{ict} = {} & \beta_0 + \beta_1\,(Store\ Banner)_i + \beta_2\,ln(Price)_{ict} \\ & + \beta_3\,(Amazon\ Sell)_{ict} + \beta_4\,ln(FBA\ Offers)_{ict} \\ & + \beta_5\,ln(FBM\ Offers)_{ict} + \beta_6\,(Product\ Rating)_{ict} \\ & + \beta_7\,ln(Brand\ Strength)_{ict} + \beta_8\,(Category\ Concentration)_{ct} \\ & + \beta_9\,(Category\ Size)_{ct} + u_c + v_t + \varepsilon_{ict} \end{aligned} \quad (1)$$

To test the potential moderating effect of product price on the relationship between using store banner and product sales performance (i.e., H3), I add the interaction term between "Price" and "Store Banner" into Equation (1) as shown in Equation (2):

$$\begin{aligned} ln(Sales\ Rank)_{ict} = {} & \beta_0 + \beta_1\,(Store\ Banner)_i + \beta_2\,ln(Price)_{ict} \\ & + \beta_3\,(Store\ Banner)_i \times ln(Price)_{ict} \\ & + \beta_4(Amazon\ Sell)_{ict} + \beta_5\,ln(FBA\ Offers)_{ict} \\ & + \beta_6\,ln(FBM\ Offers)_{ict} + \beta_7\,(Product\ Rating)_{ict} \\ & + \beta_8\,ln(Brand\ Strength)_{ict} + \beta_9\,(Category\ Concentration)_{ct} \\ & + \beta_{10}\,(Category\ Size)_{ct} + u_c + v_t + \varepsilon_{ict} \end{aligned} \quad (2)$$

In Equations (1) and (2), *i* denotes product, *c* denotes subcategory, and *t* denotes time (date). I include subcategory fixed effects to control for unobserved differences among subcategories, and date fixed effects to control for potential changes in sales rank over time. I log "Sales Rank" "Price" "FBA Offers" "FBM Offers" and "Brand Strength" to reduce the potential impact from outlying observations. Dummies for subcategories and dates are included in all models to control for fixed effects. Cluster robust standard errors are calculated as they allow observations for the same product to potentially correlate.

Estimation Results

The estimation results for H1 and H2 are reported in Table 21. The results for the OLS model using the subsample of Amazon private labels are in Model (1), and the results for the model using the subsample of non-private labels are shown in Model (2).

The coefficients for "Store Banner" are positive and significant at the 0.01 level in both Models (1) ($\gamma = 0.9374$; $p < 0.01$) and (2) ($\gamma = 0.3083$; $p < 0.01$). These results suggest that directly branding a private label using store banner is positively associated with the product's sales ranking supporting H1; and that using store brand on a non-private label as an advertisement is also positively associated with the product's sales ranking, supporting H2.

Table 21: Estimation Results

	(1)	(2)	(3)
	Private Labels	Non-Private Labels	Non-Private Labels
Store Banner	0.9374***	0.3083***	0.9918**
	(0.2073)	(0.0808)	(0.4246)
ln(Price)	-0.0208	-0.0527***	-0.0513***
	(0.1123)	(0.0067)	(0.0066)
Store Banner * ln(Price)	-	-	-0.2093*
			(0.1240)
Product Rating	0.1107	0.2415***	0.2416***
	(0.4524)	(0.0081)	(0.0081)
ln(Brand Strength)	0.1607*	0.1067***	0.1067***
	(0.0804)	(0.0018)	(0.0018)
Amazon Sell	-	0.3222***	0.3220***
		(0.0149)	(0.0149)
ln(FBA Offers)	-	0.1675***	0.1677***
		(0.0065)	(0.0065)
ln(FBM Offers)	-	-0.1275***	-0.1275***
		(0.0048)	(0.0048)
Category Concentration	-0.0102	-0.0021***	-0.0021***
	(0.0115)	(0.0005)	(0.0005)
Category Size	0.0501	0.0054***	0.0054***
	(0.0500)	(0.0005)	(0.0005)
Constant	-13.6194***	-14.1294***	-14.1340***
	(4.9766)	(0.1953)	(0.1953)
Observations	770	2,170,693	2,170,693
R-squared	0.8051	0.6812	0.6813

*** p<0.01, ** p<0.05, * p<0.1

Cluster-Robust Standard Errors in Parentheses

The values of *ln(Sales Rank)* are reversed.

The logged value of *FBA offers* is set to -1 when the original value is 0.

The logged value of *FBM offers* is set to -1 when the original value is 0.

The logged value of *Brand Strength* is set to -1 when the original value is 0.

To test the potential moderating effect of product price on the relationship between using store banner and product sales, I add an interaction term between "Price" and "Store Banner" into the models when the main effect for "Price" is significant. In Model (2), the coefficient for "Price" is negative and significant at the 0.01 level ($\gamma = -0.0527$; $p < 0.01$), while the coefficient for "Price" is insignificant in Model (1) suggesting that a product's price is negatively associated with sales for non-private-label products but has no significant impact on sales rank for Amazon-private-label products. As a result, I add an interaction term between "Price and "Store Banner" into Model (2) to test the potential moderating effect of product price on the relationship between using an Amazon-store-banner and product sales for non-private labels.

The results of the OLS model with the interaction term for the subsample of non-private label products are shown in Model (3). The coefficient for "Store Banner" remains positive and significant at the 0.05 level ($\gamma = 0.9918$; $p < 0.05$), while the coefficient for the interaction term between "Price and "Store Banner" is negative and significant at the 0.1 level ($\gamma = -0.2093$; $p < 0.1$).

To further determine how using store banner impacts product sales according to product price, I sort the observations by price, divide the sample of non-private label products into four subsamples with the similar number of observations, and re-estimate Equation (1) over each of the four subsamples. The results for the models are reported in Table 22. Subsample results for products with prices less than $12 are reported in Model (4), results for products with prices between $12 and $17.99 are reported in Model (5), results for products with prices between $18 and $29.99 miles are reported

in Model (6), and results for products with prices greater than $29.99 miles are reported in Model (7).

As shown in Table 22, the coefficients for "Store Banner" are positive and significant for all the four subsamples, although at different confidence levels. The coefficient for "Store Banner" is significant at the 0.01 level in Subsample 1 (γ = 1.3510; $p < 0.01$), at the 0.1 level for Subsample 2 (γ = 0.2297; $p < 0.1$) and for Subsample 3 (γ = 0.2051; $p < 0.1$), and at the 0.05 level for Subsample 4 (γ = 0.3217; $p < 0.05$).

To test whether the coefficients are significantly different, I compare the 95% confidence intervals of the coefficients. As shown in Table 23, the 95% confidence intervals for the coefficients for Subsamples 2 through 4 (price between $12 and $17.99, between $18 and $29.99, and greater than $29.99) have a partial range in common but do not overlap with the confidence interval for Subsample 1 (price less than $12). These results suggest that the coefficients for the three higher-priced subsamples may not significantly vary, while that for the lower-priced subsample is significantly greater than for the three higher-price subsamples; indicating that the positive impact of using store banner on sales is significantly weakened for higher-priced non-Amazon-private-labeled products (equal to or greater than $12) compared to lower-priced non-Amazon-private-labeled products. Based on these results, H4 is supported suggesting that the positive relationship between using store banner branding and product sales diminishes as product price increases for non-private labels.

Table 22: Estimation Results ("Price" Subsamples)

(Non-Private Labels)

	(4) Subsample 1	(5) Subsample 2	(6) Subsample 3	(7) Subsample 4
Store Banner	1.3510***	0.2297*	0.2051*	0.3217**
	(0.3704)	(0.1387)	(0.1185)	(0.1289)
ln(Price)	0.0912***	0.0802	0.1050*	-0.1961***
	(0.0285)	(0.0745)	(0.0538)	(0.0143)
Product Rating	0.2523***	0.2672***	0.2387***	0.2106***
	(0.0153)	(0.0174)	(0.0167)	(0.0152)
ln(Brand Strength)	0.1035***	0.0957***	0.1185***	0.1018***
	(0.0032)	(0.0034)	(0.0035)	(0.0033)
Amazon Sell	0.4203***	0.3256***	0.2286***	0.3183***
	(0.0295)	(0.0328)	(0.0301)	(0.0243)
ln(FBA Offers)	0.1539***	0.1454***	0.1590***	0.1819***
	(0.0132)	(0.0129)	(0.0116)	(0.0110)
ln(FBM Offers)	-0.1010***	-0.1185***	-0.1418***	-0.0877***
	(0.0095)	(0.0101)	(0.0098)	(0.0088)
Category Concentration	-0.0005	-0.0025**	-0.0031***	-0.0050***
	(0.0009)	(0.0010)	(0.0008)	(0.0009)
Category Size	0.0059***	0.0059***	0.0049***	0.0045***
	(0.0008)	(0.0011)	(0.0009)	(0.0009)
Constant	-13.9486***	-14.2622***	-15.0610***	-13.6643***
	(0.4689)	(0.3411)	(0.2282)	(0.3250)
Observations	578,719	481,966	542,932	492,140
R-squared	0.7143	0.6812	0.6700	0.6970

*** p<0.01, ** p<0.05, * p<0.1

Cluster-Robust Standard Errors in Parentheses

The values of *ln(Sales Rank)* are reversed.

The logged value of *FBA offers* is set to -1 when the original value is 0.

The logged value of *FBM offers* is set to -1 when the original value is 0.

The logged value of *Brand Strength* is set to -1 when the original value is 0.

Table 23: Coefficient Estimates of “Store Branner” (“Price” Subsamples)

(Non-Private Labels)

	Subsample 1	Subsample 2	Subsample 3	Subsample 4
Coefficient	1.3510	0.2297	0.2051	0.3217
Standard Error	0.3704	0.1387	0.1185	0.1289
t	3.6500	1.6600	1.7300	2.5000
P > t	0.0000	0.0980	0.0830	0.0130
95% Confidence Interval	[0.6251, 2.0770]	[-0.0422, 0.5016]	[-0.0271, 0.4374]	[0.0691, 0.5744]

Now, I focus on the control variables in Models (1) through (3) in Table 21.

Product price may be considered as a control variable in Models (1) and (2). The coefficient for "Price" is negative and significant in Model (2) but is insignificant in Model (1) suggesting that product price is negatively associated with sales rank for non-private-label products but has no significant impact on sales ranks for Amazon-private labels. The coefficients for "Product Rating" are positively significant in Models (2) and (3) but is insignificant in Model (1). These results suggest that non-private-label products with better product ratings have higher sales rankings, while product rating has no significant impact on sales ranks for Amazon-private labels. The coefficients for "Brand Strength" are positive and significant in Models (1) through (3). These results suggest that a product from a brand with more reviews on Amazon has a better sales ranking.

Regarding the sellers for a non-private-label products, the coefficients for "Amazon Sell" are positive and significant in Models (2) and (3) suggesting that a non-private-label product directly sold by Amazon has a better sales rank than non-private-label products sold only by third-party retailers. The coefficients for "FBA Offers" are positive and significant while the coefficients for "FBM Offers" are negative and significant in Models (2) and (3). These results suggest that better sales rank for a non-private-label product is significantly related to a higher (lower) number of FBA (FBM) offers holding the number of FBM (FBA) offers constant.

Regarding the subcategory variables, none of the coefficients for "Category Concentration" and "Category Size" are significant in Model (1), suggesting that the sales ranks of Amazon private labels may not vary significantly across subcategories

by subcategory size and concentration. The coefficients for "Category Concentration" are negatively significant in Models (2) and (3), suggesting that non-private labels have better sales rankings in subcategories with lower concentration. The coefficients for "Category Size" are positively significant in Models (2) and (3) suggesting that non-private labels from the small subcategories (with fewer than 100 products) have lower sales rankings.

Overall, I generally provide support for my hypotheses. The results suggest the following findings:

(1) Sales performances for products are positively associated with directly branding private labels using store banner.

(2) Sales performances for products are positively associated with using store banner on non-private labels as an advertisement.

(3) For non-private labels, the positive relationship between using store banner and product sales performance diminishes as product price increases.

Conclusions

Marketplace operators may use store banner on both private labels to reveal ownership of a product and on non-private labels as an advertisement. This study examines how using store banner impacts product sales performance for products sold on an online marketplace. My empirical analysis suggests the following results. (1) Directly branding private labels is positively associated with their sales performances. (2) Using store banner on non-private labels as an advertisement is positively associated with their sales performances. (3) The positive relationship between using store banner as an advertisement and product sales performance diminishes as product

price increases, suggesting that lower-price (less than $12) non-private labels may benefit more from the additional connection with the marketplace store brand.

This study contributes to the store-banner branding strategy and online marketplaces literatures. First, the study provides the store-banner strategy literature with evidence supporting the positive impact of using store banner on product-level sales performance. Second, this study suggests the positive relationship between using store banner and product sales performance is significant for both private (directly branding) and non-private (using as an advertisement) labels on online marketplaces. Third, this study recognizes that the positive relationship between using store banner and product sales performance may vary by product price, and finds that for low-price non-private labels, the positive relationship between using store banner and product sales performance diminishes as product price increases.

The findings provide practical implications for marketplace operators and product manufacturers (or brand owners). Marketplace operators may consider directly branding their private labels using store banners. This study provides relevant information to manufacturers or brand owners as they make decisions on whether they should contract with the marketplace operator for permission to use the store banner on their products as an advertisement. I find that this is most important for low-priced products that can benefit most from association with the marketplace store brand.

This study has several limitations. First, there are only 770 observations for Amazon private labels in the data of this study. It may suggest that Amazon has limited inherent advantage or less willingness to develop its own private labels in the category of toys and games. Future research can investigate other categories in which private

labels are better developed and examine the differences from the findings of this study. Second, this study focuses on the category of toys and games, restricting its generalizability to other categories of interest. Further research can use a cross-category study. Third, the study uses sales ranks (a proxy for actual sales) as dependent variable. Future research can examine the impact of using store banners on profits if data are available. Finally, this study focuses on Amazon Marketplaces, restricting its generalizability to other online marketplaces with different brand images. Future research can investigate the employments of store banners in other online marketplaces and examine how brand images of marketplace operators impact the relationship between using marketplace store banners and product performances.

Chapter 5: Conclusions and Future Extensions

This dissertation examines competition on the largest online marketplace in the U.S., Amazon.com, and suggests the following findings:

First, when a marketplace operator and third-party sellers sell the same products on the marketplace, the third-party sellers are likely to lose the competition against the marketplace operator. Third party retailers may increase their chances of avoiding direct competition with the marketplace operator by selling unbranded products and marketing products that tend to be fulfilled by the marketplace operator.

Second, when third-party sellers use operator-managed fulfillment services, they tend to increase their chance of winning sales competitions against third-party retailers that fulfill their own orders. However, sellers using direct fulfillment may have a better chance to win this competition for low-priced products or if they can offer lower prices than their competitors.

Finally, using the marketplace store banner improves sales performance of both private label products and non-private label products sold on a marketplace. Lower-price, non-private label products may especially benefit from the connection with the marketplace operator's store brand. These manufacturers or brand owners may contract with the marketplace operator for permission to use the store banner on their products as an advertisement to improve sales performance.

Status of Research:

The first essay of this dissertation is being revised for resubmission at the *Journal of Business Logistics*. The second essay is targeted at *Management Science*. The third essay is targeted at *Production and Operations Management*.

This dissertation may highlight several opportunities for future extensions.

The first line of work can examine how characteristics of third-party sellers impact their competitiveness on online marketplaces. Third-party sellers may vary in customer rating, delivery speed, and return policy. A future study could include data on seller characteristics and examine their impact on seller performance. The findings would provide third-party sellers with factors that may improve their competitiveness on the marketplaces.

A second line of work would test whether tax collection policies impact the competitiveness of third-party sellers. Tax collection policies vary across states. Third-party sellers may be more competitive than the marketplace operator if customers consider sales tax as a component of the price. A future study could include data on seller location and tax collection policy and compare prices, including taxes for different states. The findings would provide third-party sellers with geographic preferences for better sales performance.

A third line of work would explore how the findings of my dissertation vary across different product categories. The marketplace operator's knowledge of product features and the best way to market the products may vary across different product categories. A cross-category study would examine the impact of the marketplace operator's knowledge/experience about a product on its decision to compete with third-party sellers, thus generalizing the findings to other categories of interest.

A fourth line of work could explore competition across online marketplaces. The strategies of direct sales, order fulfillment services, and private labels may vary across marketplaces. A future study could compare different strategies used by

marketplace operators and examine competition between third-party sellers and marketplace operators. The findings could provide implications for third-party sellers suggesting which type of marketplaces facilitate the success of the third-party sellers.

Bibliography

Ailawadi, K. L., & Harlam, B. (2004). An Empirical Analysis of the Determinants of Retail Margins: The Role of Store-Brand Share. *Journal of Marketing*, *68*(1), 147–165. https://doi.org/10.1509/jmkg.68.1.147.24027

Ailawadi, K. L., & Keller, K. L. (2004). Understanding retail branding: conceptual insights and research priorities. *Journal of Retailing*, *80*(4), 331–342. https://doi.org/https://doi.org/10.1016/j.jretai.2004.10.008

Ailawadi, K. L., Pauwels, K., & Steenkamp, J.-B. E. M. (2008). Private-Label Use and Store Loyalty. *Journal of Marketing*, *72*(6), 19–30. https://doi.org/10.1509/jmkg.72.6.019

Akerlof, G. A. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500. https://doi.org/10.2307/1879431

Amazon. (2021). Brand and Manufacturer in Consumer Electronics - Amazon Seller Central. *Amazon*. https://sellercentral.amazon.com/gp/help/external/help.html?itemID=G201226630

Amazon. (2022a). Amazon Accelerator. *Amazon*. https://sellercentral.amazon.com/gp/help/external/G52NQJE353XZGWN7

Amazon. (2022b). *Get started with Fulfillment by Amazon (FBA)*. https://sellercentral.amazon.com/help/hub/reference/G69031

Amazon. (2022c). *How the Featured Offer works*. https://sellercentral.amazon.com/help/hub/reference/G37911

Anderson, C. (2008). *The Long Tail: Why the Future of Business Is Selling Less of More*. Hyperion.

Andrews, R. L., & Currim, I. S. (2004). Behavioural differences between consumers attracted to shopping online versus traditional supermarkets: implications for enterprise design and marketing strategy. *International Journal of Internet Marketing and Advertising*, *1*(1), 38–61.

Arrow, K. J. (1963). Uncertainty and the Welfare Economics of Medical Care. *The American Economic Review*, *53*(5), 941–973. http://www.jstor.org/stable/1812044

Bakos, Y. (1998). The Emerging Role of Electronic Marketplaces on the Internet. *Communications of the ACM*, *41*(8), 35–42. https://doi.org/10.1145/280324.280330

Boyer, K. K., & Hult, G. T. M. (2005). Extending the supply chain: Integrating operations and marketing in the online grocery industry. *Journal of Operations Management*, *23*(6), 642–661. https://doi.org/https://doi.org/10.1016/j.jom.2005.01.003

Bresnahan, T., & Levin, J. (2013). *21. Vertical Integration and Market Structure* (pp. 853–890). Princeton University Press. https://doi.org/https://doi.org/10.1515/9781400845354-023

Brynjolfsson, E., Hu, Y. J. (Jeffrey), & Simester, D. (2011). Goodbye Pareto principle, hello long tail: The effect of search costs on the concentration of product sales. *Management Science*, *57*(8), 1373–1386. https://doi.org/10.1287/mnsc.1110.1371

Brynjolfsson, E., Hu, Y. J. (Jeffrey), & Smith, M. D. (2003). Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers. *Management Science*, *49*(11), 1580–1596. https://doi.org/10.1287/mnsc.49.11.1580.20580

Brynjolfsson, E., & Smith, M. D. (2001). *The Great Equalizer? Consumer Choice Behavior at Internet Shopbots* (No. 4208–01). https://doi.org/10.2139/ssrn.290323

Caves, R. E., & Bradburd, R. M. (1988). The empirical determinants of vertical integration. *Journal of Economic Behavior & Organization*, *9*(3), 265–279. https://doi.org/https://doi.org/10.1016/0167-2681(88)90037-6

Chevalier, J., & Goolsbee, A. (2003). Measuring Prices and Price Competition Online: Amazon.com and BarnesandNoble.com. *Quantitative Marketing and Economics*, *1*(2), 203–222. https://doi.org/10.1023/A:1024634613982

Chintagunta, P. K., Bonfrer, A., & Song, I. (2002). Investigating the Effects of Store-Brand Introduction on Retailer Demand and Pricing Behavior. *Management Science*, *48*(10), 1242–1267. https://doi.org/10.1287/mnsc.48.10.1242.274

Chiu, Y.-L., Hsu, Y.-T., Mao, X., & Wang, J.-N. (2021). An Empirical Study of Holiday Season Discounts: A Comparison Between Third-Party Marketplace Sellers and Fulfilled by Walmart Sellers. *SAGE Open*, *11*(2), 21582440211024180. https://doi.org/10.1177/21582440211024179

Cho, S.-H., Fang, X., & Tayur, S. (2015). Combating Strategic Counterfeiters in Licit and Illicit Supply Chains. *Manufacturing & Service Operations Management*, *17*(3), 273–289. https://doi.org/10.1287/msom.2015.0524

Choi, T.-M. (2019). Blockchain-technology-supported platforms for diamond authentication and certification in luxury supply chains. *Transportation Research Part E: Logistics and Transportation Review, 128*, 17–29. https://doi.org/https://doi.org/10.1016/j.tre.2019.05.011

Corstjens, M., & Lal, R. (2000). Building Store Loyalty through Store Brands. *Journal of Marketing Research*, *37*(3), 281–291. https://doi.org/10.1509/jmkr.37.3.281.18781

Dawes, J., & Nenycz-Thiel, M. (2014). Comparing retailer purchase patterns and brand metrics for in-store and online grocery purchasing. *Journal of Marketing Management*, *30*(3–4), 364–382. https://doi.org/10.1080/0267257X.2013.813576

Degeratu, A. M., Rangaswamy, A., & Wu, J. (2000). Consumer choice behavior in online and traditional supermarkets: The effects of brand name, price, and other search attributes. *International Journal of Research in Marketing*, *17*(1), 55–78. https://doi.org/https://doi.org/10.1016/S0167-8116(00)00005-7

Dellarocas, C. (2012). Double Marginalization in Performance-Based Advertising: Implications and Solutions. *Management Science*, *58*(6), 1178–1195. http://www.jstor.org/stable/41499548

Dhar, S. K., & Hoch, S. J. (1997). Why Store Brand Penetration Varies by Retailer. *Marketing Science*, *16*(3), 208–227. https://doi.org/10.1287/mksc.16.3.208

Eadicicco, L. (2019, April 11). Jeff Bezos says independent sellers on Amazon are "kicking" the online retail giant's "butt" in sales. *Business Insider*. https://www.businessinsider.com/jeff-bezos-shareholders-letter-third-party-

sellers-are-kicking-amazons-butt-2019-4

Etumnu, C. E. (2022). A competitive marketplace or an unfair competitor? An analysis of Amazon and its best sellers ranks. *Journal of Agricultural Economics*, *n/a*(n/a). https://doi.org/https://doi.org/10.1111/1477-9552.12495

Evans, D. S., Hagiu, A., & Schmalensee, R. (2008). *Invisible engines: how software platforms drive innovation and transform industries*. MIT press.

Evans, M. (2021). Global E-Commerce Market To Expand By $1 Trillion By 2025. *Forbes*. https://www.forbes.com/sites/michelleevans1/2021/03/25/global-e-commerce-market-to-expand-by-us1-trillion-by-2025/?sh=104e548d6cc0

Frazier, G. L., & Lassar, W. M. (1996). Determinants of Distribution Intensity. *Journal of Marketing*, *60*(4), 39–51. https://doi.org/10.1177/002224299606000405

Gawer, A., & Cusumano, M. A. (2002). *Platform Leadership: How Intel, Microsoft, and Cisco Drive Industry Innovation*. Harvard Business School Press.

Geyskens, I., Keller, K. O., Dekimpe, M. G., & de Jong, K. (2018). How to brand your private labels. *Business Horizons*, *61*(3), 487–496. https://doi.org/https://doi.org/10.1016/j.bushor.2018.01.015

González-Benito, Ó., & Martos-Partal, M. (2012). Role of Retailer Positioning and Product Category on the Relationship Between Store Brand Consumption and Store Loyalty. *Journal of Retailing*, *88*(2), 236–249. https://doi.org/https://doi.org/10.1016/j.jretai.2011.05.003

González-Benito, Ó., Martos-Partal, M., & San Martín, S. (2015). Brands as substitutes for the need for touch in online shopping. *Journal of Retailing and*

Consumer Services, *27*, 121–125. https://doi.org/https://doi.org/10.1016/j.jretconser.2015.07.015

Hagiu, A., & Spulber, D. (2012). First-Party Content and Coordination in Two-Sided Markets. *Management Science*, *59*(4), 933–949. https://doi.org/10.1287/mnsc.1120.1577

Hagiu, A., & Wright, J. (2015). Marketplace or reseller? *Management Science*, *61*(1), 184–203. https://doi.org/10.1287/mnsc.2014.2042

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/https://doi.org/10.1016/0304-405X(76)90026-X

Jiang, B., Jerath, K., & Srinivasan, K. (2011). Firm Strategies in the "Mid Tail" of Platform-Based Retailing. *Marketing Science*, *30*(5), 757–775. https://doi.org/10.1287/mksc.1110.0656

John, D. R., Loken, B., & Joiner, C. (1998). The Negative Impact of Extensions: Can Flagship Products Be Diluted? *Journal of Marketing*, *62*(1), 19–32. https://doi.org/10.2307/1251800

Keller, K. O., Dekimpe, M. G., & Geyskens, I. (2016). Let Your Banner Wave? Antecedents and Performance Implications of Retailers' Private-Label Branding Strategies. *Journal of Marketing*, *80*(4), 1–19. https://doi.org/10.1509/jm.15.0154

Keller, K. O., Dekimpe, M. G., & Geyskens, I. (2022). Adding budget and premium private labels to standard private labels: Established empirical generalizations, emerging empirical insights, and future research. *Journal of Retailing*, *98*(1), 5–

23. https://doi.org/https://doi.org/10.1016/j.jretai.2022.02.004

Khan, R. (2019, May 10). Counterfeits - Amazon, Etsy, eBay, Instagram, And Others Duping Consumers And Damaging Innovation. *Forbes*. https://www.forbes.com/sites/roomykhan/2019/05/10/counterfeits-amazon-etsy-ebay-instagram-and-others-duping-consumers-and-damaging-innovation/?sh=379f26616002

Kim, M., Kim, S., & Lee, Y. (2010). The effect of distribution channel diversification of foreign luxury fashion brands on consumers' brand value and loyalty in the Korean market. *Journal of Retailing and Consumer Services*, *17*(4), 286–293. https://doi.org/https://doi.org/10.1016/j.jretconser.2010.02.006

Knee, J. A. (2018). Why Some Platforms Are Better Than Others. *MIT Sloan Management Review*, *59*(2), 18–20.

Lai, G., Liu, H., Xiao, W., & Zhao, X. (2022). "Fulfilled by Amazon": A Strategic Perspective of Competition at the e-Commerce Platform. *Manufacturing & Service Operations Management*, *24*(3), 1406–1420. https://doi.org/10.1287/msom.2022.1078

Leiblein, M. J., & Miller, D. J. (2003). An empirical examination of transaction- and firm-level influences on the vertical boundaries of the firm. *Strategic Management Journal*, *24*(9), 839–859. https://doi.org/10.1002/smj.340

Lusch, R. F., Dunne, P. M., & Gable, M. (1990). *Retail management*. Thomson South-Western.

Marketplace Pulse. (2018, December 3). Amazon Marketplace Is the Largest Online Retailer. *Marketplace Pulse*.

https://www.marketplacepulse.com/articles/amazon-marketplace-is-the-largest-online-retailer

Martos-Partal, M., & González-Benito, Ó. (2011). Store brand and store loyalty: The moderating role of store brand positioning. *Marketing Letters*, *22*(3), 297–313. https://doi.org/10.1007/s11002-010-9126-x

Meza, S., & Sudhir, K. (2010). Do private labels increase retailer bargaining power? *Quantitative Marketing and Economics*, *8*(3), 333–363. https://doi.org/10.1007/s11129-010-9085-9

Nguyen, D. H., de Leeuw, S., Dullaert, W., & Foubert, B. P. J. (2019). What Is the Right Delivery Option for You? Consumer Preferences for Delivery Attributes in Online Retailing. *Journal of Business Logistics*, *40*(4), 299–321. https://doi.org/https://doi.org/10.1111/jbl.12210

Oxley, J. E. (1997). Appropriability Hazards and Governance in Strategic Alliances: A Transaction Cost Approach. *The Journal of Law, Economics, and Organization*, *13*(2), 387–409. https://doi.org/10.1093/oxfordjournals.jleo.a023389

Parker, G., Van Alstyne, M., & Jiang, X. (2017). Platform Ecosystems: How Developers Invert the Firm. *MIS Quarterly*, *41*(1), 255–266. https://doi.org/10.25300/misq/2017/41.1.13

Pauwels, K., & Srinivasan, S. (2004). Who Benefits from Store Brand Entry? *Marketing Science*, *23*(3), 364–390. http://www.jstor.org/stable/30036704

Pegram, R. M. (1965). Selecting and evaluating distributors. *National Industrial Conference*.

Pop, V., & Schechner, S. (2020, June 11). Amazon to Face Antitrust Charges From EU Over Treatment of Third-Party Sellers - WSJ. *The Wall Street Journal*. https://www.wsj.com/articles/amazon-to-face-antitrust-charges-from-eu-over-treatment-of-third-party-sellers-11591871818

Pozzi, A. (2012). Shopping Cost and Brand Exploration in Online Grocery. *American Economic Journal: Microeconomics*, *4*(3), 96–120. https://doi.org/10.2307/23249912

Private Label Manufacturers Association. (2022). Store Brand Facts. *Private Label Manufacturers Association*. https://www.plma.com/about_industry/store_brand_facts

Qin, X., Liu, Z., & Tian, L. (2020). The strategic analysis of logistics service sharing in an e-commerce platform. *Omega*, *92*, 102153. https://doi.org/https://doi.org/10.1016/j.omega.2019.102153

Rabinovich, E., & Bailey, J. P. (2004). Physical distribution service quality in Internet retailing: service pricing, transaction attributes, and firm attributes. *Journal of Operations Management*, *21*(6), 651–672. https://doi.org/https://doi.org/10.1016/j.jom.2003.11.004

Rabinovich, E., & Evers, P. T. (2003). Product Fulfillment in Supply Chains Supporting Internet-Retailing Operations. *Journal of Business Logistics*, *24*(2), 205–236. https://doi.org/https://doi.org/10.1002/j.2158-1592.2003.tb00052.x

Rao, S., Goldsby, T. J., Griffis, S. E., & Iyengar, D. (2011). Electronic Logistics Service Quality (e-LSQ): Its Impact on the Customer's Purchase Satisfaction and Retention. *Journal of Business Logistics*, *32*(2), 167–179.

https://doi.org/10.1111/j.2158-1592.2011.01014.x

Rao, S., Griffis, S. E., & Goldsby, T. J. (2011). Failure to deliver? Linking online order fulfillment glitches with future purchase behavior. *Journal of Operations Management*, *29*(7–8), 692–703. https://doi.org/10.1016/j.jom.2011.04.001

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with cmp. *Stata Journal*, *11*(2), 159–206. http://www.stata-journal.com/article.html?article=st0224

Rubio, N., Villaseñor, N., & Yagüe, M. (2020). The role of private label tiers and private label naming strategies in the relationship between private label brand equity and store loyalty. *Journal of Product & Brand Management*, *29*(1), 124–138. https://doi.org/10.1108/JPBM-09-2018-2017

Scheer, L. K., Kumar, N., & Steenkamp, J.-B. E. M. (2003). Reactions to Perceived Inequity in U.S. and Dutch Interorganizational Relationships. *Academy of Management Journal*, *46*(3), 303–316. https://doi.org/10.5465/30040624

Schnittka, O., Becker, J.-M., Gedenk, K., Sattler, H., Villeda, I. V., & Völckner, F. (2015). Does Chain Labeling Make Private Labels More Successful? *Schmalenbach Business Review*, *67*(1), 92–113. https://doi.org/10.1007/BF03396925

Schoenherr, T., Bendoly, E., Bachrach, D. G., & Hood, A. C. (2017). Task Interdependence Impacts on Reciprocity in IT Implementation Teams: Bringing Out the Worst in Us, or Driving Responsibility? *Production and Operations Management*, *26*(4), 667–685. https://doi.org/10.1111/poms.12671

Sethuraman, R. (2009). Assessing the External Validity of Analytical Results from

National Brand and Store Brand Competition Models. *Marketing Science*, *28*(4), 759–781. https://doi.org/10.1287/mksc.1080.0455

Sethuraman, R., & Gielens, K. (2014). Determinants of Store Brand Share. *Journal of Retailing*, *90*(2), 141–153. https://doi.org/https://doi.org/10.1016/j.jretai.2014.04.002

Sun, L., Lyu, G., Yu, Y., & Teo, C.-P. (2020a). Fulfillment by Amazon versus fulfillment by seller: An interpretable risk-adjusted fulfillment model. *Naval Research Logistics (NRL)*, *n/a*(n/a). https://doi.org/10.1002/nav.21897

Sun, L., Lyu, G., Yu, Y., & Teo, C. P. (2020b). Cross-Border E-Commerce Data Set: Choosing the Right Fulfillment Option. *Manufacturing & Service Operations Management*, *23*(5), 1297–1313. https://doi.org/10.1287/msom.2020.0887

Sun, M. (2011). How Does the Variance of Product Ratings Matter? *Management Science*, *58*(4), 696–707. https://doi.org/10.1287/mnsc.1110.1458

Tadrzak, A. (2022). *How to Win the Amazon Buy Box and Make More Sales*. DataFeedWatch. https://www.datafeedwatch.com/blog/amazon-buy-box

Tian, L., Vakharia, A. J., Tan, Y. (Ricky), & Xu, Y. (2018). Marketplace, Reseller, or Hybrid: Strategic Analysis of an Emerging E-Commerce Model. *Production and Operations Management*, *27*(8), 1595–1610. https://doi.org/10.1111/poms.12885

Tracy, R., Mattioli, D., & McKinnon, J. D. (2020, June 12). California Is Examining Amazon's Business Practices - WSJ. *The Wall Street Journal*. https://www.wsj.com/articles/california-is-examining-amazons-business-practices-11591987233

Vieira, P. (2020, August 14). Amazon Faces Antitrust Probe in Canada - WSJ. *The*

Wall Street Journal. https://www.wsj.com/articles/amazon-faces-antitrust-probe-in-canada-11597414448?mod=searchresults&page=1&pos=3

Wang, Q., Li, B., & Singh, P. V. (2018). Copycats vs. Original Mobile Apps: A Machine Learning Copycat-Detection Method and Empirical Analysis. *Information Systems Research*, *29*(2), 273–291. https://doi.org/10.1287/isre.2017.0735

Wu, L., Yang, W., & Wu, J. (2021). Private label management: A literature review. *Journal of Business Research*, *125*, 368–384. https://doi.org/https://doi.org/10.1016/j.jbusres.2020.12.032

Zellner, A., & Theil, H. (1962). Three-Stage Least Squares: Simultaneous Estimation of Simultaneous Equations. *Econometrica*, *30*(1), 54–78. https://doi.org/10.2307/1911287

Zhu, F., & Liu, Q. (2018). Competing with complementors: An empirical look at Amazon.com. *Strategic Management Journal*, *39*(10), 2618–2642. https://doi.org/10.1002/smj.2932

Zhu, F., & Sun, S. (2019). JD: Envisioning the Future of Retail. *Harvard Business School Case*, *618–051*.