– UC Berkeley Economics Honors Thesis –

Effect of Value-Added-Services on Customer Reviews in a Platform Marketplace

Evidence from "Fulfilled by Amazon" on Amazon.com

Author:

Shankar Krishnan †

Advisor:

Dr. Steven Tadelis

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Abstract

Value-added services in a platform marketplace economy are considered a key mechanism by which platform intermediaries can attract sellers and consumers and incentivize them to stay on the platform. These value-added services are considered a competitive advantage for the platform intermediary and have varied effects on both sellers and consumers. This paper explores these assumptions by using product, seller, and customer-review data from Amazon. Amazon introduced one of their main services, "Fulfilled By Amazon," on September 19, 2006. We seek to determine the effect of the "Fulfilled by Amazon" service on customer reviews to draw a conclusion on the effect of value-added services on customer reviews in an e-commerce platform economy.

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1 Introduction

Ecommerce has changed the way consumers engage with sellers. Rather than directly buying from sellers, consumers engage with a platform marketplace that connects sellers and consumers. Prominent examples of tenured incumbents in this space are Amazon.com and Ebay.com, with players such as Uber, DoorDash and TaskRabbit gaining prominence in recent years.

In order to remain competitive and keep both sellers and consumers on the platform, often called being 'sticky', platform marketplaces often provide additional value to both sellers and consumers rather than merely connecting them. These additional 'value-added services' ensure that the platform can stay sticky while also bringing new sellers and consumers onto the platform. Amazon.com, as the largest player in this space, has experimented with many of these value-added services, such as the well-known Prime 2-day shipping service.

This paper analyzes the other major shipping service Amazon.com offers: Fulfilled by Amazon. Fulfilled by Amazon is a shipping service Amazon.com offers to sellers to ease their burden of shipping. According to Amazon.com:

> "With Fulfillment by Amazon (FBA), you store your products in Amazon's fulfillment centers, and we pick, pack, ship, and provide customer service for these products. FBA can help you scale your business and reach more customers." [1]

"Fulfilled by Amazon" has been perceived as a major value-add for sellers on Amazon's platform. Introduced back in 2006, the service allows sellers who struggle with scale and shipping costs to take advantage of Amazon's wider reach. This in turn means that sellers can focus on better value adds, whether it is re-investing in their product or their customer service or otherwise. Additionally, the "Fulfilled by Amazon" brand might inspire confidence in consumers who are basically purchasing something which has a "badge of approval". As such, it might also have an adverse effect on sellers who do not opt-in to the "Fulfilled by

[1] "Fulfillment by Amazon (FBA)", Amazon, Amazon.com, https://sell.amazon.com/fulfillment-by-amazon

Amazon" service, as they may be perceived as less reliable. "Fulfilled by Amazon" is an especially important value add in the context of Amazon as one of Amazon's main value propositions is delivery-related aspects; as such, understanding the impact of this service on customers reviews will be a directional indicator of whether the value of joining the platform (Amazon.com) justifies the costs. Hereafter I will refer to "Fulfilled by Amazon" through the acronym FBA as per convention and the official acronym used by Amazon.com.

This paper argues that FBA usage, at the seller level, has a statistically positive effect on seller reviews. FBA usage occurs at the product level – sellers can choose, for each product, whether to sell it through FBA. As such, any seller is a 'seller that uses FBA' if they sell one or more product(s) through FBA. However, we also analyze the incremental effect of the number of products that a seller sells through FBA. We find that the percentage of products a seller sells using FBA has a statistically significant positive impact on seller reviews.

The intuition behind this goes back to the base reasons why we believe Amazon.com introduced FBA: the value add of managed shipping as-a-service. In any Amazon.com marketplace, we can classify sellers into two categories: those that sell 'hard to ship' products, and those that sell 'easy to ship' products. Of course, there exists selection bias at this level. The sellers that sell 'hard to ship' products are more likely to opt into FBA, and those that sell 'easy to ship' products are less likely to opt into FBA. As such, we would assume that within these categories, those that sell "hard to ship" would have lower reviews which would increase due to FBA. For "easy to ship" products, it is easier to procure a higher rating, so FBA would not increase these as much. However, most people in this category would not have FBA anyway, so any existing overall effect of FBA in the 'easy to ship' category would be dampened regardless.

As such, this selection bias should not have a significant impact on our overall effect, and can be accounted for by controlling for the 'easy to ship' and 'hard to ship' categories. I discuss this further and how exactly I control for this directionally in the empirical analysis. Indirectly, we are also testing the importance of shipping on reviews. Our assumption is that the difficulty of shipping products would, in one way or another, have an effect on the end-consumer experience.

2 Literature Review

Much work has been done on customer reviews in a platform, and some work has also been conducted on "Fulfilled by Amazon" specifically. This study would contribute to that literature by relating the two, as there is sparse literature on the empirical impact of "Fulfilled by Amazon" on customer reviews specifically.

On the context of the 'value-added services' addressed frequently in this prospectus, the foundational piece by Geoffrey Parker and Marshall Van Allstyne (2014) provides excellent context and defines the field. It discusses the definition of platforms as a two-sided intermediary that brings together producers, sellers in this case, and consumers. Importantly, the part that is most relevant to this paper is when they discuss 'launch strategies' – how to bring sellers and consumers onto the platform. Here, they discuss subsidies, 'seed' users, micro-launches, and piggybacking off of other networks. I would like to explore whether a platform value-add could be modeled as a 'subsidy'; usually subsidies are just paying consumers to join the platform, or reducing the application fee, but I am trying to determine how non-monetary subsidies affect user growth and attrition. Other facets discussed are governance models such as open platforms or extremely regulated ones (which is expanded upon in Tadelis (2016)), and competition between platforms.

The literature also discusses "Fulfilled by Amazon" specifically, which validates that it is an interesting enough policy-change by Amazon to look into. First is a theoretical paper by Lai, Liu, and Xiao (2018) which delves into the impact of FBA on profit, but from a theoretical perspective, describing how the price sensitivity and profit of Third party sellers and Amazon would change based on the FBA policy. It also explores other options such as Original Equipment Manufacturer sales, where Amazon can act as a re-seller for parts sold by equipment manufacturers. Second is an empirical paper "Competing with complementors: An empirical look at Amazon. com." by Feng Zhu and Qihong Liu that looks at this policy from the other angle; it looks at the effect of FBA on third party sellers as well as consumer demand. By analyzing products on a time interval, it determines what happens when Amazon enters the delivery market through various mechanisms, one of them being FBA. It treats FBA as an outcome, analyzing how many sellers choose to switch to "Fulfilled by Amazon" during the treatment period, rather than explicitly determining the relationship between "Fulfilled by Amazon" and customer reviews. However, it provides important context as it includes and analyzes many of the variables of interest for this paper.

Finally, given that our outcome variable is customer reviews, we must account for customer reviews, and how they can be used as an indicator of customer perceptions listed in section 1. Tadelis (2016) takes a game theory and literature review approach to analyzing organized feedback (reviews, etc.) and the effect on platform systems. What it shows is that, in general, these sort of feedback mechanisms are an effective mechanism for assessing the 'edge' of products/sellers/customers. In other words, these are great at assessing 'extremely bad' or 'extremely good' products/sellers/consumers, and as such they technically fulfill their function by helping individuals filter out the most harmful actors on the platform and aim towards the most beneficial. However, there are a lot of biases in the middle, and this is the area where future research must delve into in order to truly determine whether platforms can self-regulate through reviews as a feedback mechanism, or if there are some external or non-review related checks needed.

As such, the literature addresses the three pieces of the puzzle this paper addresses: Value-Added Services, FBA, and Customer Reviews. At the same time, there is a sufficient gap in the literature such that a discussion of the quantitative impact of FBA, analyzed as a value-added service, on customer reviews, would significantly add to the literature in this field.

3 Data

I used the Keepa Dataset (keepa.com) that is already cleaned, which lists information in two forms, producing 98 files which were ultimateily aggregated into one data set (Table 1).

Table 1 was directly downloaded from Keepa, and contains information on the 'top' 100 sellers on Amazon.com in terms of their sales rank. However, it initially did not have the field *Percent_FBA*. This category is an aggregation of information in Tables 2 through 96.

Before delving into Tables 2 through 96, we must understand the concept of the 'buy box'. For consumers visiting Amazon.com, they are given an option to "Add to Cart"; the seller whose product is added to the customer's cart for that product "owns" the buy box. Customers have the option to purchase through alternate sellers, but a seller who owns the buy box empirically captures a disproportionate majority of product sales.

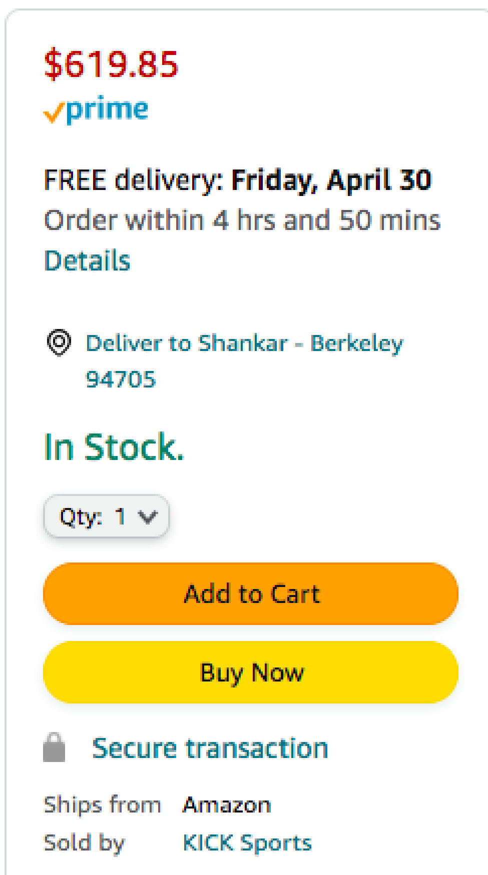

Figure 1: Example Buy Box from Amazon.com

Tables 2 through 96 contain data at the seller level. For each Seller in our dataset, I randomly selected 500 of the products (or all of their products if they were selling less than 500) they were selling as of January 26th, 2021, where they owned the buy box. For each of these sellers, I calculated what percentage of those products they were selling through FBA. This percentage was inputted for each seller in Table 1 as *Percent_FBA*. Given the variation in the dataset, this percentage is a good directional indicator of what percentage of their total products they sell through FBA.

I chose to look only at products where sellers owned the buy box, as these are the products most likely to generate reviews, which is our ultimate outcome variable. If a seller sells a product but does not own the buy box, they will not get reviews for that product (as it will not sell), and the FBA status of that product is meaningless to our data-set, as that FBA status has a 0% chance of being reviewed. As such, even if the buy box is correlated with sales, sales are correlated with reviews which is our outcome variable of interest.

Table 1: Seller Data Fields

COLUMN	*Definition*
SALES RANK	Rank of Seller (Amazon Sales Rank)
SELLER NAME	Listed name of Seller
SELLER ID	Unique ID of Seller
REVIEW	Reviews for Seller
REVIEW COUNT	Number of reviews for Seller
USES FBA	Binary; whether Seller uses FBA
VERIFIED LISTINGS	Number of verified listings
SELLING PRIMARILY	Primary category seller sells in
SELLING PRIMARILY (PERCENT)	Percent of products in primarily-sold category
PERCENT FBA	Percent of products sold through FBA

Note: Percent FBA not in original table, as noted above

Table 2: Products sold by Sellers (Data Fields)

COLUMN	*Definition*
PRODUCT TITLE	Listed Title of Product on Amazon.com
REVIEWS	Review for the Product
REVIEW COUNT	Number of reviews for Product
BUY BOX SELLER	Seller name who owns Buy Box for Product
BUY BOX SELLER ID	Unique ID of Seller who owns Buy Box
BUY BOX FBA	Binary; whether buy box is FBA
URL	URL of listing
ASIN	Unique identifier of Product

Note: Each of tables 2 through 96 have the same columns and respective meanings

Information in tables 2 through 97 was grouped by Buy Box Seller ID aggregating based on the percentage of products which had Buy Box FBA = True. Then, this was joined with Table 1 on Seller ID (by matching Buy Box Seller ID to Seller ID). The code used to accomplish this task is included in the appendix.

It is important to note here that there are two types of reviews: Seller Reviews and Product Reviews. When a consumer reviews a product, they have a choice of reviewing either the seller or the product. The review for the seller is indexed to the Unique Seller ID, but the review for the product is indexed to the ASIN (Product ID) of the Product. However, it is impossible to parse from the product review which seller owned the buy box at the time of a consumer's purchase, and as such which seller sold the product that the consumer is reviewing. In other words, Product Reviews are not linked to Seller IDs. As such, we discounted all product reviews as our outcome of interest is seller reviews, and how consumers are reviewing and therefore perceiving sellers. I assume that buyers are cognizant enough to the fact that they are choosing to review a seller and not reviewing a product by accident. This is a fair assumption given that there is no default, and a consumer has to actively make a choice whether they "review the seller" or "review the product." Indeed, there may be some biases based on which button is listed first on the consumer's screen, but given that there are only two options the chance of confusion due to cognitive overload is highly unlikely; as such, it is a reasonable assumption that the order does not matter in this particular case. Therefore, we assume that Seller Reviews are an accurate indicator of how the consumer feels about the Seller.

4 Results

4.1 Study Design

Our study design was a simple linear regression, which exploited variation as follows:

1) Consider the top sellers overall on the platform by sales rank. I found that sales rank, which is an Amazon-proprietary ranking of "sales performance", is correlated with a larger amount of information overall. In other words, I am controlling first for the volume of information and having sufficient variation at the seller and FBA level. This holds up with intuition, as we would assume that the best performing sellers would also have a higher volume of sales and associated information about reviews associated with those sales. Second, I am controlling for sellers who are similar across unidentifiable characteristics; we can assume that "top sellers" would tend to make 'good' decisions and generally have good relationships with their customers all else equal (i.e. they don't have terrible customer service, terrible products, or anything else that would bias their ratings).

2) Given information about whether each seller uses FBA and the associated seller rating for each of these seller, determine the empirical relationship between FBA and seller ratings.

3) Given information about what percentage of products each seller sells using FBA, determine the empirical relationship between the percentage of products sold by FBA and seller ratings. This gives a more accurate indicator of the relationship between FBA and seller ratings, as it approximates the incremental effect of a seller making more products FBA, all else equal.

We introduced the following controls to account for variation that arose from various sources of bias, including the selection bias discussed in section 1:

1) Primary Product Category: We originally hypothesized that selection bias into FBA would be based on the difficulty of shipping each product. However, there is variation here at the seller and product level, as each seller might have a different definition of "difficult-to-ship" or different products might be more difficult to ship based on their makeup. However, we can reasonably assume that similar products have a similar "difficulty to ship," and that products within the same category are quite similar. As such, by controlling for the primary product category, we control for the "difficulty to ship" of products.

2) Number of Reviews: Bias may be introduced based on the number of reviews that a seller has, as a product with a high rating but a low frequency of reviews may be arbitrarily inflated by bias in either direction. As such, by controlling for the number of reviews, we control for variance arising from this fact.

4.2 Regressions

I ran three regressions, testing our relationships described in 4.1. The first regression tested the existence of the relationship as defined under our hypothesis and initial conditions, and created the foundations for our analysis. The second regression tested the effect of FBA on Seller Reviews, while the third regression dived deeper into this relationship by conditioning on a subgroup of sellers.

4.2.1 Regression 1: Basic Regression comparing Existence of FBA and Ratings

The first regression I tested was the relationship between FBA (whether the seller sold any products using FBA) and Seller Ratings. Below is the regression equation with controls:

$$SellerRating = \beta_0 + \beta_1 FBA + \beta_2 ReviewCount + \sum_{c=1}^{20} \beta_{c+2} TopCategory_c + \epsilon_i \qquad (1)$$

There are 21 product categories total, and as such 1 is omitted. Below is a summary table which only includes β_0 and β_1.

Table 3: Effect of FBA on Seller Ratings

	Dependent variable: Rating	
	FBA	FBA with Controls
	(1)	(2)
FBA	3.497^{***}	3.488^{***}
	(0.753)	(1.076)
Constant	91.388^{***}	92.792^{***}
	(0.549)	(2.407)
Observations	181	181
R^2	0.107	0.298
Adjusted R^2	0.103	0.200
Residual Std. Error	5.057 (df = 179)	4.774 (df = 158)
F Statistic	21.559^{***} (df = 1; 179)	3.049^{***} (df = 22; 158)
Note:		*p<0.1; **p<0.05; ***p<0.01

As we can see from regression (2), sellers with at least one FBA product have ratings on average that are 3.488 percentage points higher than those that have zero FBA products. This effect is statistically significant at the 1% level.

This relationship is quite strong, especially as we are considering top sellers. Given that we know that seller ratings matter for sellers at the high end of these ratings (as discussed in section 2), every percentage point matters for these sellers. As such, if the introduction of one or more FBA product could raise ratings on average by over 3 percent, we see that FBA has a significant positive impact on how consumers perceive sellers, and that this value-add indeed adds value for sellers and consumers alike. We assume that the majority of this effect comes from sellers who sell a majority of their products (rather just one) through FBA, but will test that in the next regression.

4.2.2 Regression 2: Relationship between percent of products sold through FBA and corresponding seller ratings

This regression tested whether a seller increasing the percentage of products that they sell through FBA would increase their seller ratings. This more directly tests the relationship between how much a seller uses FBA and their corresponding rating. As such, it more directly tests how important FBA is to seller ratings, as compared to the first regression. This is the regression equation with controls:

$$SellerRating = \beta_0 + \beta_1 PercentFBA + \beta_2 ReviewCount + \sum_{c=1}^{20} \beta_{c+2} TopCategory_c + \epsilon_i \quad (2)$$

Table 4: Effect of FBA Percentage on Seller Ratings

	Dependent variable: Rating	
	FBA	FBA with Controls
	(1)	(2)
PercentFBA	0.053^{***}	0.051^{***}
	(0.008)	(0.011)
Constant	91.090^{***}	92.816^{***}
	(0.477)	(2.320)
Observations	181	181
R^2	0.203	0.348
Adjusted R^2	0.199	0.257
Residual Std. Error	4.778 (df = 179)	4.602 (df = 158)
F Statistic	45.685^{***} (df = 1; 179)	3.828^{***} (df = 22; 158)
Note:		*p<0.1; **p<0.05; ***p<0.01

As we can see from B_1 here, a 1 Percentage Point increase in the percent of products a seller sells with FBA increases their rating by 0.051 Percentage Points on average. This effect is statistically significant at the 1% level. In context, moving from 0% to 100% of FBA products would increase the average rating by 5.1%.

What is fascinating here is that we can isolate an effect between FBA-enablement and Seller Ratings. By choosing to sell a product through FBA, a Seller increases their likelihood of a positive rating, and the more products a Seller sells through FBA the higher rating they will have. This indicates that FBA is instrumental to the consumer experience, and validates our intuition that delivery is an integral part of the customer experience on Amazon.

4.2.3 Regression 3: Relationship between percent of products sold through FBA and corresponding seller ratings conditional on Seller selling at least one product through FBA

This regression deep dived into the FBA sub-category in our data set. Given the subset of sellers who are selling at least one product through FBA, I tested whether a seller increasing the percentage of products that they sell through FBA would increase their seller ratings. The regression equation was the same as in Equation 2, but only had 96 observations as there were 96 sellers who sold through FBA (FBA=TRUE). The regression equation is reproduced below for ease of access:

$$SellerRating = \beta_0 + \beta_1 PercentFBA + \beta_2 ReviewCount + \sum_{c=1}^{20} \beta_{c+2} TopCategory_c + \epsilon_i \quad (3)$$

Table 5: Effect of FBA Percentage on Seller Ratings for FBA Sellers

	Dependent variable: Rating	
	FBA	FBA with Controls
	(1)	(2)
PercentFBA	0.071***	0.049***
	(0.014)	(0.015)
Constant	89.431***	92.310***
	(1.132)	(2.729)
Observations	96	96
R^2	0.227	0.449
Adjusted R^2	0.219	0.293
Residual Std. Error	4.427 (df = 94)	4.213 (df = 74)
F Statistic	27.611*** (df = 1; 94)	2.871*** (df = 21; 74)
Note:		*p<0.1; **p<0.05; ***p<0.01

As we can see from B_1 here, a 1 Percentage Point increase in the percent of products a seller sells with FBA increases their rating by 0.049 Percentage Points on average. This effect is statistically significant at the 1% level. In context, moving from 0% to 100% of FBA products would increase the average rating by 4.9%.

This effect is quite similar to Regression 2, which is quite promising. However, it is a little damper than the effect in Regression 2 (0.051). This makes sense intuitively, and also justifies that this is a stronger regression for two key reasons.

First, this indicates a stronger effect directly between FBA and ratings, as we remove the effect of 'bad sellers.' Let us recall that our previous definition of those who would opt-out of FBA were those who sold items that were 'easy to ship'. But what if these sellers were not perfectly rational, and instead acted against their own self interest? In this context, then, we can define 'bad sellers' as sellers who choose not to opt into FBA but still are terrible at shipping. As such, they would have worse ratings. But we cannot adequately determine whether they have worse ratings because they are terrible at shipping, or because they are just 'bad sellers' across multiple dimensions. As such, by focusing in on those sellers who opted-in to FBA, whether they needed it or not, we can remove the effect of 'bad sellers' that would have likely received poor ratings even without FBA. These 'bad sellers', if they truly exist, would bias our effect in Regression 2 upwards, as they make us believe that it is FBA that is causing the higher ratings, on average, rather than just the fact that sellers that are worse across other dimensions tend to opt-out of FBA as well.

However, the fact that our results are quite similar is very promising, as it indicates that there are very few of these 'bad sellers' in our original data set. This is also by design, as indicated earlier in section 4, as we only took top sellers by the aforementioned 'sales-rank.'

Second, we remove the effect of '0% FBA sellers'. Given our percentage based model, we are comparing two groups. One group is 96 sellers who have high non-zero ratings and have high percentages of FBA products. The second group is 85 sellers who have high non-zero ratings and have 0% of FBA products. As such, any incremental difference between these two groups is amplified by the fact that the latter group has 0% FBA, and all of the effect is attributed to the difference in FBA percentages between the two groups. As such, we remove this upward-bias and more accurately temper our results in this regression.

4.2.4 Extension: Hard vs. Easy to Ship

Our main extension is to test our belief of what "hard to ship" necessarily means, rather than controlling for categories. We classified the following categories as hardtoship: "Automotive", "Electronics", "Industrial & Scientific", "Patio, Lawn & Garden", and "Home & Kitchen." As such, we ran the following regression for both (1) all 181 sellers and (2) the 96 sellers who use FBA:

$$SellerRating = \beta_0 + \beta_1 PercentFBA + \beta_2 ReviewCount + \beta_3 hardtoship \tag{4}$$

$$+\beta_4 PercentFBA * hardtoship + \epsilon_i \tag{5}$$

Table 6

	Dependent variable: Rating	
	All 181 Sellers	96 FBA Sellers
	(1)	(2)
PercentFBA	0.047***	0.065***
	(0.009)	(0.018)
hardtoship	−3.177**	−0.719
	(1.413)	(2.344)
PercentFBA x hardtoship	0.040**	0.013
	(0.019)	(0.028)
Constant	91.394***	89.219***
	(0.697)	(1.681)
Observations	181	96
R^2	0.228	0.234
Adjusted R^2	0.210	0.200
Residual Std. Error	4.744 (df = 176)	4.480 (df = 91)
F Statistic	12.967*** (df = 4; 176)	6.948*** (df = 4; 91)
Note:		*p<0.1; **p<0.05; ***p<0.01

The effect of PercentFBA is still statistically significant and positive at the 1% level. The interaction effect (PercentFBA x hardtoship) is statistically significant at the 5% level for all 181 sellers. This demonstrates the incremental effect of PercentFBA on hardtoship products specifically, and follows our intuition that a 1 Percentage Point increase in the percent of products a seller selling hardtoship products sells with FBA increases their rating by 0.040

Percentage Points on average.

In context, this is fascinating. For easy-to-ship products, for every 1 percentage point increase in the percentage of products sold through FBA, a seller sees an increase in ratings by 0.047 on average. This effect practically doubles for hard-to-ship products, as the incremental additional effect for hard-to-ship products described before (0.040) is very close to 0.047. This confirms our intuition that FBA, being a primarily shipping-based service, benefits sellers selling hard-to-ship products more than those that do not, and also confirms the importance of shipping to customer ratings.

The coefficient on hardtoship is also statistically significant and a large (in terms of magnitude) negative. This also confirms our intuition, as it proves that for hard-to-ship products ratings are on average significantly lower than for those that are not hard-to-ship. This could be due to various factors, but the easiest explanation is that for hard-to-ship products there is greater difficulty, variability, and as such a greater chance of negative customer experience. The incremental effect that FBA has on hard-to-ship products as described above is 0.040, which also means that a seller going from selling 0% of products through FBA to 100% would be expected to increase average ratings by 4%. This is more than enough to overcome the -3.117% lower ratings for hard-to-ship products, and proves that FBA improves ratings for hard-to-ship products beyond even the average rating for those that are not hard-to-ship. In other words, FBA does not only 'equalize the playing field' and make average ratings for hard-to-ship products equivalent to those for easy-to-ship products; it in fact makes hard-to-ship products have better ratings on average than those that are easy-to-ship.

Within sellers selling FBA, the effect is not statistically significant. This could be for many reasons. First, this regression ignores all of the sellers that have 0% FBA ratings; given that a lot of our variation and a lot of the effect is contained within this extensive margin of going from 'no FBA' to 'FBA,' by removing this data we lose a lot of significance. Further, the amount of data points are halved, so the standard errors would be expected to double, which we see is the case. Improving the sample size and variability of the data would help us avoid these pitfalls and is a good avenue for further analyses.

5 Discussions

These results are quite promising both for the literature discussed earlier and in the context of our central question: Do self-purported value-added services actually add value, or do they only add the perception of value?

As we can clearly see, FBA has a significant positive implication on customer reviews. Given that customer reviews are a good indicator of customer perceptions of a seller, this indicates that FBA is valuable to consumers on the platform, as it improves their experiences.

However, we also have discussed how customer reviews are important to sellers, as for sellers in the top rung every percentage point matters; consumers and the platform alike take these ratings into account when evaluating them. As such, FBA is valuable to sellers on the platform as well.

This discussion is also important in larger contexts when discussing customer perception. Reviews are important as they are a collective proxy for many indicators of customer perception, which is a subjective metric that is difficult to capture. This includes customer confidence in the product, customer perception of the product, and end-to-end customer experience with the entire process (order to delivery to product experience). Combining the two, then, seeing the effect of "Fulfilled by Amazon" on customer reviews help us understand those intangibles and how "Fulfilled by Amazon" affects customer perception and experience.

Additionally, "Fulfilled by Amazon" is an especially important value add in the context of Amazon as one of Amazon's main value propositions is delivery-related aspects; as such, understanding the impact of this service on customers reviews will be a directional indicator of whether the value of joining the platform (Amazon.com) justifies the costs.

We have also proven, to an extent, that delivery is an integral part of the customer experience on Amazon.com. FBA is a primarily delivery-related service, and given that a delivery-related service has a substantial impact on customer experience, we can reasonably conclude that customers consider delivery seriously when evaluating sellers.

This also is important when concerning ourselves with platform regulation. For example, is Amazon justified in prioritizing sellers who use FBA, or is that anti-competition given that this could be seen as bias? The evidence in this paper points to the fact that Amazon has an empirical reason for prioritizing sellers who use FBA: they are better sellers who provide a better user experience for the end-customer.

The argument would go as follows. Amazon, as an intermediary between sellers and consumers, should prioritize sellers and consumers that are beneficial to the platform. Sellers that are beneficial to the platform would be ones that are beneficial to consumers, and vice versa. There is no incentive for either Amazon or the consumer to engage with a seller that does not provide value for either of them. As Amazon should be responsible to the every day customer, they have platform curation responsibilities. The evidence from this paper proves that sellers that do not use FBA are bad for the platform, as they have lower customer ratings. Because FBA improves ratings, it helps the end customer and helps Amazon as well. As such, Amazon is justified prioritizing sellers who use FBA.

6 Conclusion

As such, this paper dives deep into the "Fulfilled By Amazon" policy of Amazon.com in order to test the impact on customer reviews. This paper finds a statistically significant and strong relationship between FBA and Seller Ratings, indicating both that delivery is an integral part of the customer experience and that FBA improves customer perceptions of sellers.

Further analysis might need to be done to determine the delivery-related aspects of this.

Analyses that take into account fragility or a more quantitative approach to classify "difficult to ship" products would enhance the literature and further the analyses done in this paper.

This paper can be used as a part of a larger piece to justify platform curation and the responsibilities of platforms like Amazon.com to leverage the value-added services they use to add further value to consumers and sellers alike.

By doing so, Amazon actually promotes a "Free Market" rather than a "Free for all Market" which ignores the platform regulations required to ensure value for both sellers and consumers.

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Appendix: Data Transformation and Cleaning

[ ]:
```
#Imports
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from scipy.stats import norm
import itertools
from ipywidgets import interact, interactive

import hashlib
%matplotlib inline

sns.set(style="dark")
plt.style.use("ggplot")

def get_hash(num):
    """Helper function for assessing correctness"""
    return hashlib.md5(str(num).encode()).hexdigest()
```

[ ]:
```
#Import Base Product Data
prod117 = pd.read_csv("Product_Finder.2021_01_17.products.csv")
prod121 = pd.read_csv("Product_Finder.2021_01_26.products.csv")
```

[ ]:

[ ]:

[ ]:
```
#Concatenate Product Data
concat = pd.concat([prod117, prod121])
```

[ ]:
```
#Loop through rest of Product Data and append to current data
for i in range(1, 78):
  temp_tbl = pd.read_csv("Product_Finder.2021_01_26.products" + " (" + str(i) +␣
 ↪")" + ".csv")
  concat = pd.concat([concat, temp_tbl])
```

```
[ ]: #concatenate additional Product Data
     csv1 = pd.read_csv("Product_Finder.2021_01_12.products.csv")
     concat = pd.concat([concat, csv1])
```

```
[ ]: #Loop through rest of additional Product Data and append to current data
     for i in range(1, 10):
       temp_csv = pd.read_csv("Product_Finder.2021_01_12.products" + " (" + str(i) +␣
      ↪")" + ".csv")
       concat = pd.concat([concat, temp_csv])
```

```
[ ]:
```

```
[ ]: import re
```

```
[ ]: re.search('\(([0-9]+%\s)?(.*)\)', "3rd Party (A1DCPNQKKEISZB)").group(2)
```

```
[ ]: 'A1DCPNQKKEISZB'
```

```
[ ]: #function to parse Seller ID from Raw Data
     def parseSellerID(x):
       try:
         return re.search('\(([0-9]+%\s)?(.*)\)', x).group(2)
       except:
         return x
```

```
[ ]: #Apply parseSellerID to data and place output in SellerID column
     concat["SellerID"] = concat["Buy Box Seller"].apply(lambda x: parseSellerID(x))
```

```
[ ]: #Clean FBA data and place output in FBA column
     concat["FBA"] = concat["Buy Box: Is FBA"].apply(lambda x: 1 if x == "yes" else␣
      ↪0)
```

```
[ ]: #Group to create cleaned output
     concat.groupby(["SellerID"]).mean().to_excel("cleaned_concat_seller_2.xlsx")
```