Effect of Image Quality on Facebook Marketplace Bidding

Summer 2021 - W241 Final Report

Jaclyn Andrews Alyssa Augsburger John Lee Sanjay Saravanan

Abstract

Does increasing photo quality cause the perceived value of a good to increase?
As the world continues to go through a digital revolution, online selling of used goods has increased with the rise of platforms like Facebook Marketplace and PoshMark. Just like how in person retailers want to know how to best display their merchandise, individual online sellers also want an edge. If photo quality has a significant impact on perceived value, then online sellers will benefit from putting in the time to take quality photos. We design an experiment with four sellers who post 90 items for sale on Facebook Marketplace in four different cities. Each seller is randomly assigned to post each item with a control or treatment photo. A control photo is a low quality image of the item and a treatment photo is a high quality image of the item. Each posting features identical product descriptions. The maximum bid that each item receives in control and treatment is compared. This comparison and regression models show that an item in treatment receives a 50% higher bid on average than an item in control. With these findings, we recommend that sellers take the time to take high quality photos in order to elevate potential buyers' perceptions of their goods.

Background

There are two specific experiments (of many) that show that a buyer's willingness to pay increases due to an intervention on the product. The *Significant Objects Project*[1] finds that by adding a story along with each of their 100 items being sold, buyers are willing to pay more for the item. They measure, on average, that their items are sold at 2800% of the purchase price due to this intervention. *Resnick et al*[2] find that selling items on eBay from an established identity, as opposed to selling the same item with a new seller, increases the selling price of an item by 8.1%. Both experiments measure the price of sales as an outcome variable.

Additionally, several other studies look into the effect of photos on experiment participants' feelings toward items. *Hou et al*[3] concludes that adding pictures to food menu items has a positive effect on attitudes, willingness to pay, and purchase intention. They gather data from a 7-point Likert-scale questionnaire to draw these conclusions. Their research summarizes many more similar studies. One study of interest by Edell and Staelin[4] shows that unframed pictures (where verbal information and pictures of the brand are not related) have a negative picture effect that leads to a poorer product recall. These studies appear to utilize a survey approach to measure the concept that photos affect human perception of products. From these previous studies, we see that how an item is presented can impact a person's perceptions and actions, and want to explore this further.

Research Question

As the world continues to go through a digital revolution, online selling of used goods has increased with the rise of platforms like Facebook Marketplace and PoshMark. Just like how in person retailers want to know how to best display their merchandise, individual online sellers also want an edge. The scope of our experiment is to determine if increasing photo quality of products on Facebook Marketplace causes an increase in the amount online buyers are willing to offer for a good.

Hypothesis

Our hypothesis is that a centered, brighter image of a product leads to a higher quality photo, which will cause buyers to be willing to pay more for a product. We reach this hypothesis based on our own experiences using online marketplaces, discussions with friends and family on their experiences with online marketplaces, and specifically Edell and Staelin's experimental results.

Experiment Design

Pre-Experimental Survey

Survey Design

Prior to conducting our experiment, we first conduct a survey in order to obtain a treatment effect estimate that will be used in a power analysis to determine the number of items we need to post on Facebook Marketplace. Our pre-experimental survey is created and conducted through Qualtrics and consists of a few demographic questions and then ten questions with a photo of an item asking the participant to assume they are interested in purchasing the item as they enter the amount they are willing to pay for it.

The items shown are common household items ranging in price from $14 to $115. Each item is displayed in a randomized order and is randomly assigned to either control or treatment. Control and treatment consists of the exact same photo with the item centered, but edited in different ways. The control photo is edited to be low quality by decreasing the image's exposure and brilliance levels and increasing the noise reduction. The treatment photo is edited to be higher quality by increasing the image's exposure, brilliance, highlights, shadows, contrast, brightness, and saturation levels.

In addition to the ten item photos, every survey includes two items that have the same quality photo across all survey takers to help control for individual differences in overall value perception. In total, each survey contains the same twelve unique items. We choose to use friends and family as our survey audience to maximize the chances of the participants being engaged throughout the entirety of the survey and providing honest answers. We provide an incentive to take the survey and enter all participants who provide their email address into a raffle for four $50 Amazon gift cards. Additionally, we create referral links so that anyone who refers someone to take our survey gains an additional raffle entry for every person they refer.

Survey Results

We received 272 responses and after filtering by predetermined conditions to exclude noisy and duplicate data, there are 247 responses remaining. These predetermined conditions are outlined in Appendix B.

Figure 1 shows the number of responses per item (0 is control, 1 is treatment) to illustrate that this pre-experimental survey has an approximately balanced dataset.

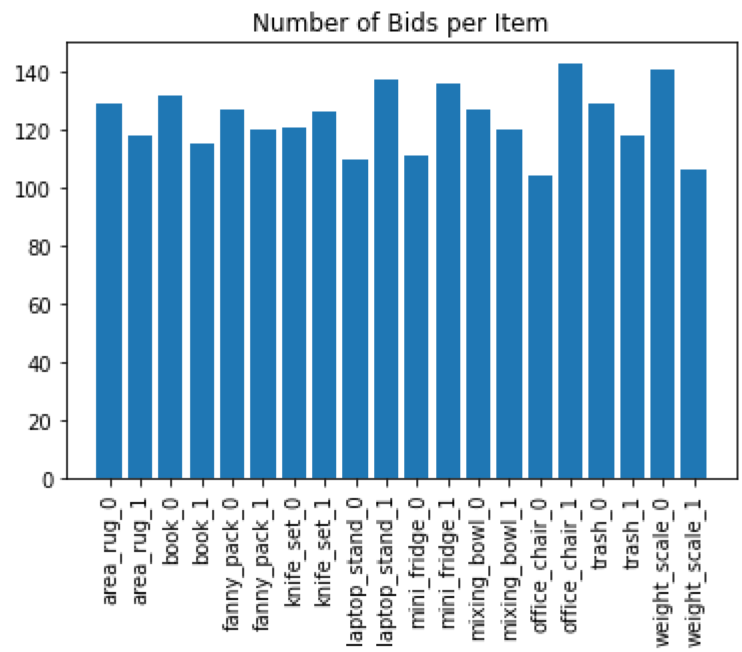


Figure 1. Number of bid responses per item. Items appended with “_0” are the control photo and items appended with “_1” are the treatment photo.

Table 1 shows the average offer price per item. There appears to be a positive average treatment effect across a majority of the items.

Item	Control Mean Offer	Treatment Mean Offer	Difference
area_rug	$31.27	$32.34	$1.07
book	$5.08	$5.91	$0.84
fanny_pack	$11.84	$11.57	-$0.28
knife_set	$14.29	$14.56	$0.27
laptop_stand	$12.89	$14.16	$1.27
mini_fridge	$64.42	$60.85	-$3.58
mixing_bowl	$13.98	$14.02	$0.03
office_chair	$39.66	$41.48	$1.82
trash	$29.34	$29.43	$0.09
weight_scale	$12.14	$13.19	$1.05

Table 1. Control and treatment mean offers and differences in dollars.

Survey Models

We create three different models using the data we collect from our survey. Our simple model regresses offer price on photo quality. Our second model adds in the retail price of the item and several covariates for the participant: offer they provided on an anchor item, age, gender, marital status, and employment status. It also includes interaction terms for photo quality paired with gender and marital status. The third model does not use the same interaction terms as the first model and instead interacts photo quality with retail price.

Each of the three models shown in Figure 2 has a significant treatment effect and honing in on the 10% effects, we note that based on the standard errors, the effect is likely between ~7% and ~13%. When comparing the three models, we notice that the addition of covariates does not help in reducing the treatment standard errors which is an unexpected result. Additionally, the retail price covariate appears to have a statistically significant effect which supports the statement that higher-priced items would tend to garner higher bid amounts.

	Dependent variable:		
	log(max bid + 1)		
	[simple]	[demographic HTEs]	[price HTE]
	(1)	(2)	(3)
photo_quality	0.105***	0.065*	0.109***
	(0.034)	(0.036)	(0.038)
factor(gender)6_female		0.083***	0.056**
		(0.031)	(0.022)
factor(gender)9_declined		-0.059	-0.047
		(0.382)	(0.126)
factor(marital)2_married		-0.062	-0.045*
		(0.040)	(0.026)
factor(marital)3_declined		0.440**	0.056
		(0.178)	(0.127)
retail_price		0.020***	0.021***
		(0.0003)	(0.0004)
vacuum		0.008***	0.008***
		(0.0003)	(0.0003)
Constant	2.823***	0.953***	0.935***
	(0.025)	(0.204)	(0.205)
Age	No	Yes	Yes
Employment	No	Yes	Yes
Gender Interaction	No	Yes	No
Marital Interaction	No	Yes	No
Retail Price Interaction	No	No	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 2. Log-Linear models of maximum bid for pre-experimental survey. All interaction terms included are interacted with the photo quality treatment effect.

Although our survey does produce a significant treatment effect, the effect is fairly small. One common feedback by our survey participants post-survey is that there is no noticeable difference between photos of items. In other words, the feedback describes that the differences between the lower quality photos compared to that of higher quality is not obvious. Based on this feedback, we therefore increase the difference in control and treatment photo quality when conducting our experiment on Facebook Marketplace, aiming for a larger treatment effect. Examples of both treatment and control photos for survey and experiment can be found in Appendix E.

Experiment Overview

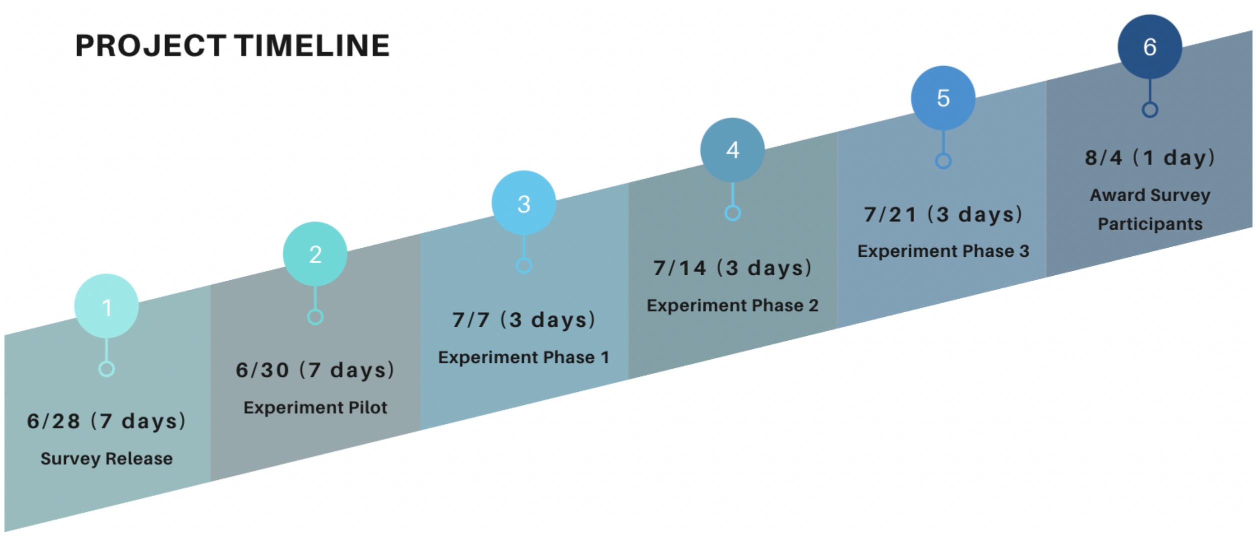
Our experiment is a between-subjects design, illustrated in Figure 3, that is conducted on the Facebook Marketplace platform, posting items locally and removing visibility from friends to avoid skewed offers from peers. Ninety items are posted four times with identical descriptions, a link to the original retail item, and a request to message an offer. The randomized design is blocked on the item level, ensuring that each item gets posted twice with a low quality photo (control) and twice with a high quality photo (treatment). With posts restricted to local markets, each Facebook user will only ever see one version of the posting. Each post is marked as “available” for three days and then marked as “sold” on the marketplace. The highest offer is recorded as the primary outcome variable, with secondary outcomes including number of views, messages and bids. Seller (or location) and item type will be used as covariates in regression to explain some variance in the final offers. The participants of our field experiment will be browsers of Facebook Marketplace and potential buyers in the Denver, Washington D.C., San Jose and Austin areas. See Appendix C, D, E and F for more details on experiment design.

	N_A	R	X	$Y_{1,2,3,4}$
N_1	N_B	R	X	$Y_{1,2,3,4}$
	N_C	R	O	$Y_{1,2,3,4}$
	N_D	R	O	$Y_{1,2,3,4}$
	N_A	R	X	$Y_{1,2,3,4}$
N_2	N_B	R	O	$Y_{1,2,3,4}$
	N_C	R	X	$Y_{1,2,3,4}$
.	N_D	R	O	$Y_{1,2,3,4}$
.				
.	N_A	R	X	$Y_{1,2,3,4}$
N_{90}	N_B	R	O	$Y_{1,2,3,4}$
	N_C	R	O	$Y_{1,2,3,4}$
	N_D	R	X	$Y_{1,2,3,4}$

Key:

N_1, N_2, ... N_{90} = Items
N_A, N_B, N_C, N_D = Sellers
R = Randomized
X = Treatment
O = Control
$Y_{1,2,3,4}$ = Outcomes measured

Figure 3. ROXO diagram illustrating experimental design. The subscript "1, 2, 3, 4" indicates the four outcome variables measured - views, messages, offers and maximum bid.



Comparison of Potential Outcomes

Our experiment aims to measure the potential outcome of the maximum bid an item will receive on Facebook Marketplace given it is either posted with a high or low quality photo. We also use our secondary outcomes (number of views, messages, and offers received) as other potential outcomes to measure the treatment effect. When a potential buyer views Facebook Marketplace in search of an item, they are presented with an assortment of items. A view for an item gets recorded only when a potential buyer clicks on the item to view more details about that item. A message gets recorded only when a potential buyer sends a message to the seller about the item. Finally, a bid amount gets recorded only if a potential buyer wants to purchase the item and sends the seller a message indicating how much they will pay for it.

Randomization

We use a blocked randomization design, blocking by item. Each item we post is one block, with two of those blocks illustrated in Figure 4. For example, one item that is posted is an area rug. This item is randomly assigned to have the treatment photo posted by two sellers and the control photo posted by two sellers. Each seller posts 30 items per week for three weeks at the same local time, and the weekly items are chosen randomly. Items remain "available" for three days each and then are marked as sold. Each seller posts the items in a different city, eliminating any concerns of spillover, or the same potential buyers receiving both treatment and control for a single item.

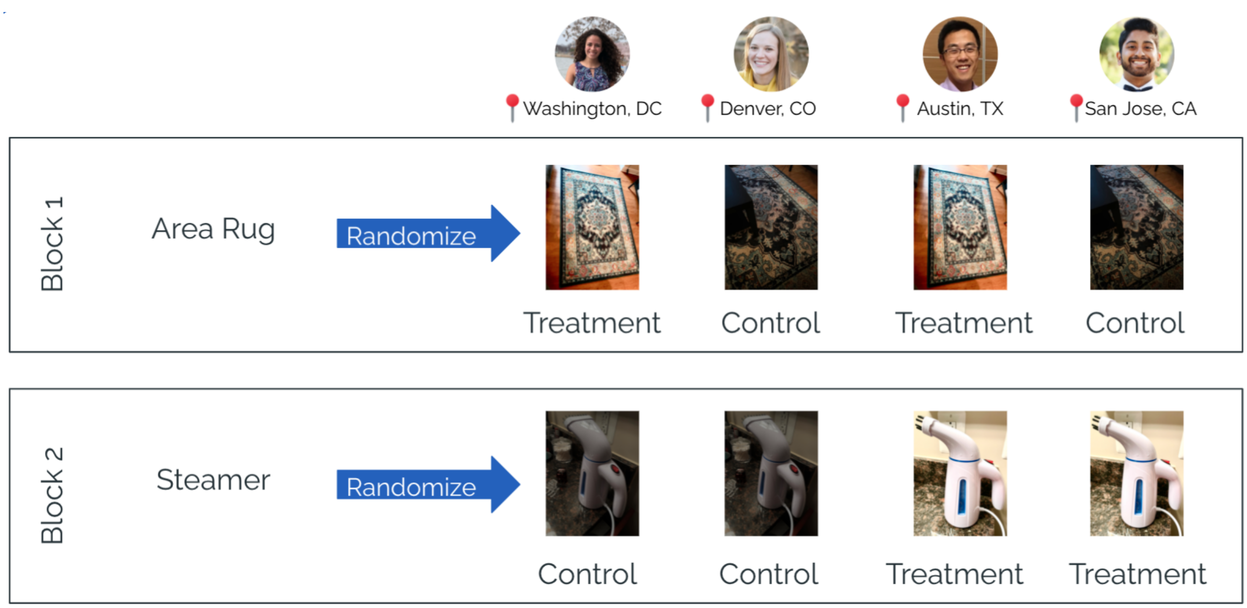


Figure 4. Illustration of experiment block randomization on item. Two out of 90 total experiment blocks are shown.

Treatment

Each item is posted on Facebook Marketplace with treatment and control. The treatment is a photo of the item with the item centered in the photo. Additionally, the image's exposure, brilliance, highlights, shadows, contrast, brightness, and saturation levels are increased. The control photo quality is based on what we determine to be low quality photos that we find on the Facebook Marketplace platform. The control is a photo of the item that is not centered in the photo and includes more background noise. Additionally, the image is edited by decreasing the exposure and brilliance levels, while increasing the noise reduction. See Appendix E for examples of treatment and control photos.

CONSORT

The subjects of our experiment are considered to be the items themselves and not humans browsing Facebook Marketplace. We only consider items that we physically have access to so that we could customize the photography, have an original retail price of no more than $300, and an obtainable link to the item posted for sale on the original retailer's website. Each item is posted by each of four sellers and is randomly assigned to be posted with a treatment or control photo. As shown in Figure 5, this results in 180 treatment posts and 180 control posts, or a total of 360 posts. For each post, we collect data for number of views, numbers of messages, number of bids, and maximum bid.

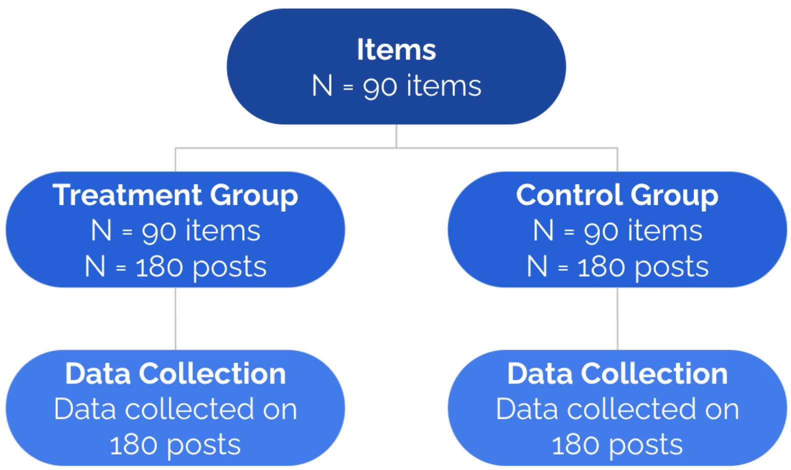


Figure 5. Flow diagram illustrating number of experimental subjects.

Power Calculation

We conduct a power analysis to determine the number of items to include in our experiment. The three factors affecting power that we vary in our analysis are the magnitude of the treatment effect, the variance in outcomes, and number of items.

Our analysis consists of a series of simulations in which we first take a large bank of 1,000 theoretical items and randomly assign each item a retail price within the range of $10 - $200, mimicking our experiment design. Anchoring the maximum bid for control image quality at half the retail price, we then add noise to every item and for each seller based on average income in their city. We then calculate potential outcomes to treatment by adding in the treatment effect with additional noise to the potential outcomes to control. Then, for each combination of noise and treatment effect, we loop through 1-200 items, run 500 simulations for each item count, and record the percentage of those simulations resulting in a statistically significant treatment effect as a proxy for power.

The power analysis results in six simulations with a low (5%) and high (10%) treatment effect and three levels of noise shown in Figure 6. Two of the simulations show that over 170 items would be required to reach 80% power which is unfeasible with limitations in time and resources, but 90 items would be enough for the other four simulations. We land on using 90 items for our experiment which will require us to either have a high treatment effect or minimal noise. To try and ensure our treatment effect is high enough, we adjust the photo quality in our control photos to be even further from our treatment photos.

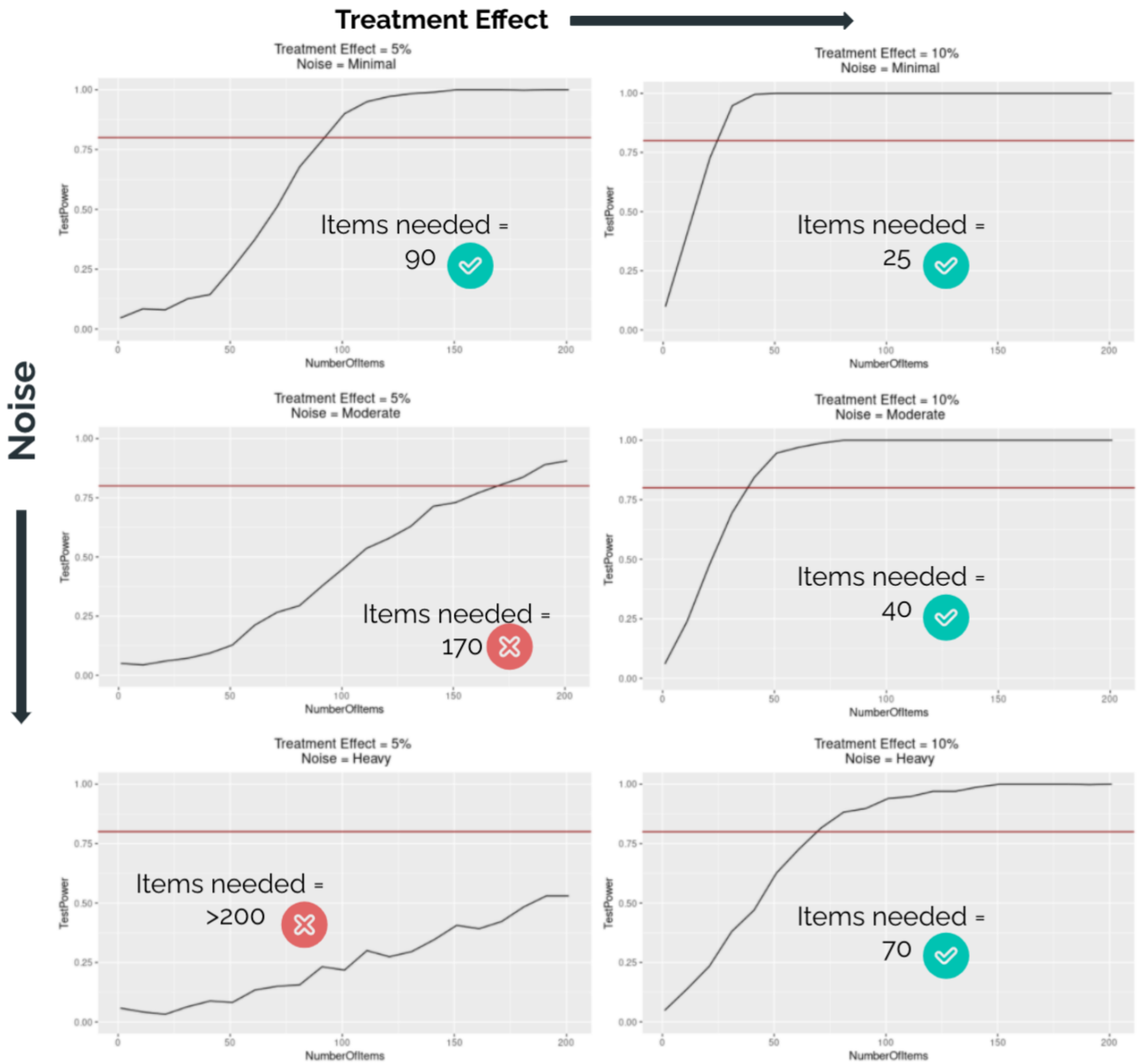


Figure 6. Power calculations plot with 6 variations. A low (5%) and a high (10%) treatment effect are shown on the left and right columns, respectively. Three levels of noise are displayed from top to bottom. Noise was added from a random distribution by seller, item and overall. The x-axis displays the number of items used and the y-axis represents the simulated power.

Results & Analysis

Data & Outcomes

Our main outcome variable is the maximum bid that an item receives. For any item that does not receive a single bid, we treat this as a maximum bid of $0 since an individual seller with no bids would make $0 off that item in reality. Data for our secondary outcome variables is shown in Figure 7. We discover that most postings receive at least 1 view, about half of the postings receive at least 1 message, and about one-third of the postings receive at least 1 bid.

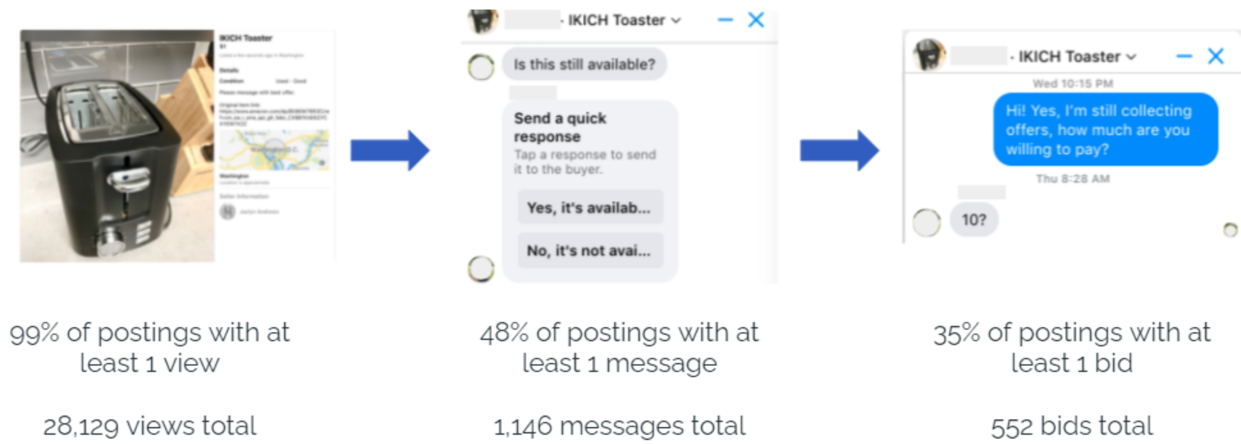


Figure 7. Posting coverage and total counts of secondary outcome variables.

Several covariates of interest are seller, item, phase, and high/low retail price. The seller and item variables are necessary for the blocked random design where we block by item and randomize by seller. These are essential because each seller sells in different cities (with varying average income-earners), responds to potential buyers at different speeds, and has different Facebook Marketplace accounts including different names and profile pictures. Additionally, these are necessary because of the varying retail price and popularity among buyers (ie. an office chair may garner more bids than a baby bassinet). The differences in average outcome variables by each seller is shown in Figure 8. Blocking reduces the noise or variance in the data. Although the phase variable is initially considered as a covariate, we notice that the variable's variance is ultimately absorbed by blocking on item. Because each item is only assigned to one phase, the phase and item variables have perfect multicollinearity. Finally, the high/low retail price variable is helpful in separating the variance of the high retail price items (greater than $50) and low retail price items (less than $50).

seller	mean_views	mean_messages	mean_number_of_bids	mean_max_bid
<chr>	<dbl>	<dbl>	<dbl>	<dbl>
Alyssa	68.6	3.54	1.91	9.26
Jaclyn	84.1	3.11	1.47	11.12
John	67.7	2.66	1.40	11.10
Sanjay	92.0	3.42	1.36	12.36

Figure 8. Mean values of outcome variables grouped by each seller.

Note that covariate imbalance is not present in our regression. By our experiment design, each item is listed twice in control and twice in treatment, with a total of 45 items listed in control and treatment by each seller. As such, our control and treatment samples have perfect covariate balance. See distribution of treatment to control per seller in Appendix E.

Regression Models

We create several regression models with robust standard errors (RSE) that regress the four outcome variables on the treatment variable and covariates. Our linear and log-linear regression models of the "Max bid" outcome variable are displayed in Figures 10 and 11, respectively. To clarify, these are the formulas of the specific models:

Linear:

1) **Simple:**
   Max Bid ~ Treatment
2) **Seller & Item:**
   Max Bid ~ Treatment + Seller + Item
3) **Seller & Item & High/Low Retail:**
   Max Bid ~ Treatment + Seller + Item + High/Low Retail + High/Low*Treatment

Log-Linear:

4) **Simple:**
   Log(Max Bid+1) ~ Treatment
5) **Seller & Item:**
   Log(Max Bid+1) ~ Treatment + Seller + Item
6) **Seller & Item & High/Low Retail:**
   Log(Max Bid+1) ~ Treatment + Seller + Item + High/Low Retail + High/Low*Treatment

The linear models show the dollar amount difference between control and treatment, but may not be generalizable. Specifically, the range of our items' retail prices varies from $8 to $300, so a $1 increase may not mean as much for the $300 product as it could for the $8 product. The log-linear model shows the percent difference between control and treatment, but may not be generalizable because every maximum bid needs to be increased by $1 to avoid a log(0) error that would be caused by items that do not receive any bid. The $1 increment is arbitrary but within the range of the retail prices of the items. We show different models that add $0.001 or $100 in Appendix H. The combination of the linear and log-linear models, each shown in the *Tables & Figures* section, supports the conclusion that there indeed exists a treatment effect.

Our linear regression models of the secondary outcome variables are displayed in Figure 12 and summarized in Table 2. All of these outcome variables are regressed in a similar fashion:

7) **# of Views/Messages/Offers:**
   Views/Messages/Offers ~ Treatment + Seller + Item + High/Low Retail + High/Low*Treatment

The outcomes of these models are assumed to be proxies for maximum bid. That is, if the number of views, messages, and offers increase, the maximum bid may increase as well, resulting in a mediation effect. Therefore, we would expect these additional linear regression models to also have a positive treatment effect.

Tables & Figures

We show the simple average treatment effect with no covariates of each outcome variable in Figure 9 below. The treatment photos produce more views, more messages, more offers, and a higher maximum bid on average, as expected. Without looking at any covariate effects, we see a 45% higher bid on average when the photo was treated to a higher quality.

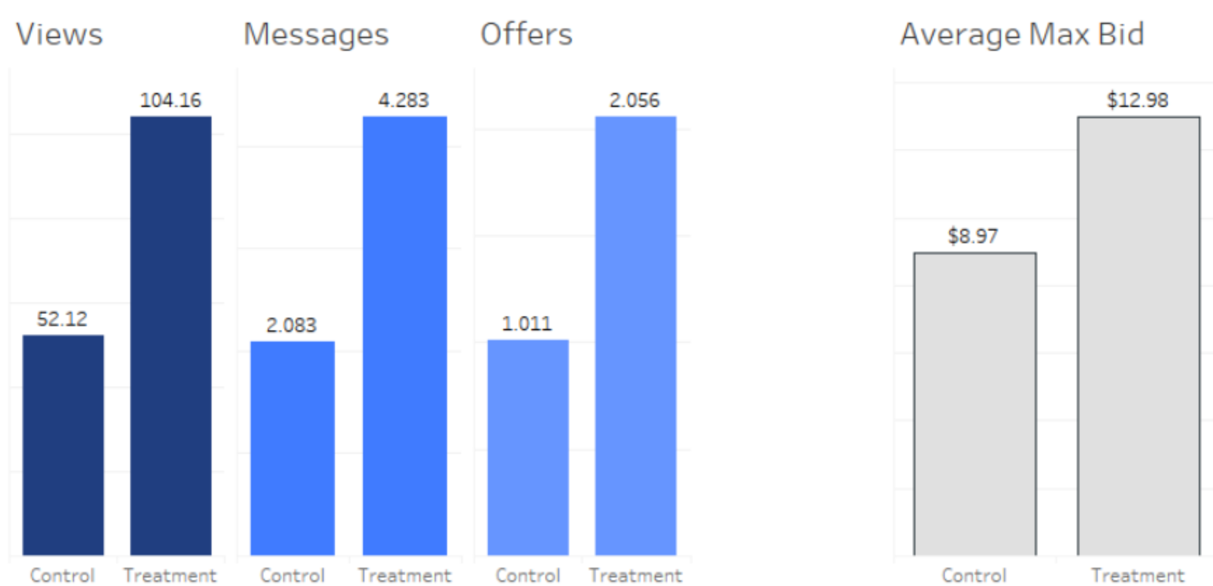


Figure 9. Average treatment effect of outcome variables. Each bar is labeled with the average value of the outcome per item and each y-axis represents the outcome variable.

In the linear maximum bid models shown in Figure 10, we see a significant treatment effect in the Simple and Seller & Item models, but not in the third model. The robust standard error decreases as more covariates are introduced. The results of the third model suggest that on average, a seller will receive a bid $1 higher for low-priced items and $7 higher for high-priced items. While these results may be statistically significant, the wide range of item prices and types lead us to find that the result is not particularly useful. Therefore, we instead decide to take the log of maximum bids to get a percent difference interpretation. Note that the high/low retail covariate is not shown in the figure because it has perfect multicollinearity with the item covariate. This occurs in models shown afterwards as well.

	Dependent variable:		
	max bid		
	[Simple]	[Seller&Item]	[Seller&Item&High/LowRetail]
	(1)	(2)	(3)
treatment	4.040*	3.890**	1.200
	(2.180)	(1.870)	(0.799)
factor(seller)Jaclyn		1.480	1.750
		(2.750)	(2.730)
factor(seller)John		1.630	1.650
		(2.430)	(2.420)
factor(seller)Sanjay		2.670	2.710
		(2.450)	(2.440)
treatment:high_retail			5.890
			(3.960)
Constant	8.940***	-0.888	-2.570
	(1.450)	(4.120)	(5.160)
Item	No	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 10. Linear regression models of maximum bid. High retail in a binary variable referring to items with an original retail price of over $50.

In the log-linear models shown in Figure 11, we see that there is a significant treatment effect across all three models. The robust standard error also continues to decrease as more covariates are added. Our third model with the additional interaction term shows that high priced items have a higher treatment effect as compared to low priced items, as expected.

	Dependent variable:		
	log(max bid + 1)		
	[Simple]	[Seller&Item]	[Seller&Item&High/LowRetail]
	(1)	(2)	(3)
treatment	0.434***	0.416***	0.298**
	(0.167)	(0.143)	(0.132)
factor(seller)Jaclyn		0.186	0.197
		(0.215)	(0.216)
factor(seller)John		0.223	0.224
		(0.203)	(0.204)
factor(seller)Sanjay		0.324	0.325
		(0.201)	(0.202)
treatment:high_retail			0.258
			(0.303)
Constant	0.887***	0.209	0.135
	(0.112)	(0.800)	(0.845)
Item	No	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 11. Log-linear regression models of maximum bid. High retail in a binary variable referring to items with an original retail price of over $50.

For the secondary outcome linear models shown in Figure 12, we apply the same covariates as seen in our model for the maximum bid that has the lowest standard error. We note that the treatment also has a significant effect on each of these three outcomes. The treatment effect for the number of views is the highest. On average, low retail price items receive an additional 21 views in treatment, while more expensive items receive an additional 86 views in treatment. See Table 2 for a summary. Based on all of our models, we conclude that increasing photo quality not only increases the price that buyers on Facebook marketplace are willing to pay, but also increases the number of offers, views and messages that an item receives.

	Dependent variable:		
	[# of Views]	[# of Messages]	[# of Offers]
	(1)	(2)	(3)
treatment	20.900***	1.020***	0.436***
	(6.250)	(0.326)	(0.161)
treatment:high_retail	65.400**	2.640*	1.420
	(26.900)	(1.550)	(0.914)
Constant	-11.500	-0.857	-0.249
	(30.700)	(1.690)	(1.060)
Item	Yes	Yes	Yes
Seller	Yes	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 12. Linear regression models of secondary outcomes. High retail in a binary variable referring to items with an original retail price of over $50.

	Low Retail Price	High Retail Price
# of Views	+21	+86
# of Messages	+1	+3.6
# of Offers	+0.4	+1.9

Table 2. Summary of linear regression models of secondary outcomes. The values represent the change in secondary outcomes that the model predicts would occur based on if the item has a low or high original retail price.

Conclusion

Our motivation for conducting a Facebook Marketplace experiment is to determine if photo quality has an effect on offer prices. The answer to this question can provide actionable insights for sellers to make more money from selling their used goods. Our pre-experimental Qualtrics survey taken by friends and family shows that value perception is dependent on photo quality, with approximately 10% higher offers on high quality photos compared to low quality photos. The concept is then further explored through an experiment collecting true offers from individual interested buyers, where results are even more extreme, showing a nearly 50% increase in bid with higher quality photos, accounting for both variance in items and across sellers.

Limitations & Future Enhancements

There are several limitations to this experiment that may introduce bias and limit its generalizability. We are aware of the fact that Facebook Marketplace has different algorithms that are applied to various postings that simply cannot be accounted for. It is possible that Facebook chooses to boost and promote certain items that are listed for sale. This could cause the treatment effect to be misstated as it is possible that Facebook's promotion causes an increase in maximum bid offered, views, messages, and offers. Additionally, it is possible for potential buyers in a local market to view all of the items that a seller posts for sale. This could therefore bias someone to be more interested in an item, causing our treatment effect to again be misstated. Many potential buyers send the seller a message before eventually making an offer. The rate at which the seller responds could have an impact on whether or not the buyer makes an offer and how much they actually choose to offer. As a result, this could possibly lead to another misstatement of our treatment effect. Furthermore, each of the items is posted for sale for three days. It is possible that we may see different results if the items are posted for a longer duration, which would be an interesting test for a future experiment.

Our results show that there is a statistically significant difference between the maximum bid that sellers receive for an item with a high quality photo versus a low quality photo, but there are potential limitations to the scope under which our experimental conclusion holds. Our experiment is conducted in four distinct cities across the U.S., so we don't have evidence about a treatment effect in suburban locations, other cities, or even other countries. Other specific parameters in our experiment that may confine the scope of our results include the fact that we only use Facebook Marketplace and not other selling platforms, our products do not exceed more than a couple hundred dollars in retail price, a "best" offer system is used instead of asking for a certain price, only one photo is associated to each posting, and a longer description of each product is not included beyond the original retail link. Under different conditions, the resulting treatment effect could have been different.

References

1. Browning, Keith. “The Experiment That Proves the Value of Stories.” Business Solutions on LinkedIn, 10 Dec. 2019, business.linkedin.com/en-uk/marketing-solutions/blog/posts/live-with-marketers/2019/The-experiment-that-proves-the-value-of-stories.

2. Resnick, Paul, et al. “The Value Of Reputation On EBAY: A Controlled Experiment.” Http://Www.si.umich.edu/~Presnick/Papers/Postcards/, 3 Jan. 2006.

3. Yuansi Hou, Wan Yang, Yixia Sun, Do pictures help? The effects of pictures and food names on menu evaluations, International Journal of Hospitality Management, Volume 60, 2017, Pages 94-103, ISSN 0278-4319, https://doi.org/10.1016/j.ijhm.2016.10.008. (https://www.sciencedirect.com/science/article/pii/S0278431916303188)

4. Edell, Julie & Staelin, Richard. (1983). The Information Processing of Pictures in Print Advertisements. Journal of Consumer Research. 10. 45-61. 10.1086/208944.

Appendix

Appendix A - Timeline and Phases

We choose to post the 90 items in three different phases, posting 30 items in each phase, as we are not aware of Facebook's limits on the number of items that are allowed to be posted in a day. In addition, we do not have the resources to respond to messages for 90 items all at one time. Our original plan was to keep each item posted online for seven days, yet Facebook unfortunately blocked one seller from its marketplace for two hours. Our postings also raised suspicions and at times, we received annoyed retorts about the fact that items were still listed for sale but did not seem like any sale was truly being made. As a result of our fear of being blocked on Facebook Marketplace (possibly for even longer periods of time), we decided to shut down the postings after three days.

Appendix B - Pre-Experimental Survey

Following is a list of predetermined conditions to remove noisy survey responses in our data:

1) **Duplicated Email:** We only include each user's first response. Multiple responses may indicate violation of the excludability assumption due to respondents who may have been exposed to both control and treatment for the same item.
2) **Survey Duration:** We only include responses that took longer than 60 seconds to complete the full survey. Short responses may indicate violation of the excludability assumption because respondents may not have actually bid based on the photos but rather, to just finish the survey and potentially win a prize.
3) **Consistent Offers:** We only include responses that did not bid the same price for <u>all</u> items. Consistent offers for all items may indicate violation of excludability assumption with similar reasoning as mentioned previously.
4) **Finished:** We only include responses which are complete. Incomplete responses indicate attrition which biases our results.

Appendix C - Facebook Marketplace

Figure A1 below displays the Facebook Marketplace website. Users are shown various items for sale. A user can filter the items by location, category, price, delivery method, and item condition. Additionally, a user can use the search feature to search for a specific item.

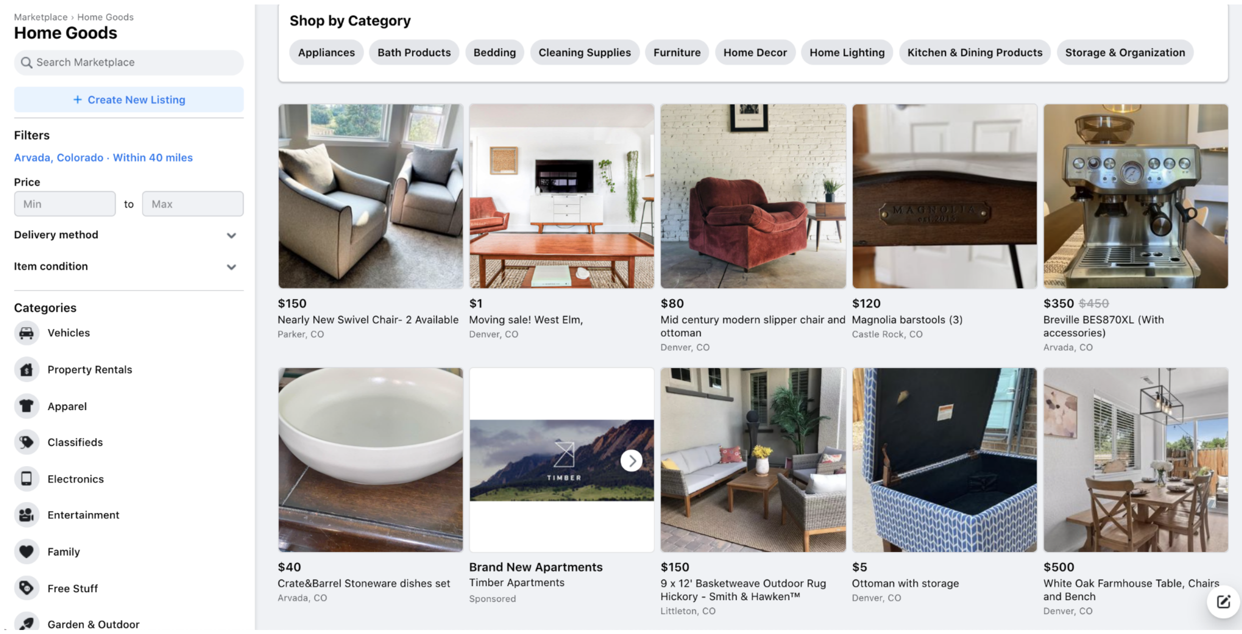


Figure A1. Facebook Marketplace website.

Appendix D - Item Selection

The items we select to post on Facebook Marketplace range in value from $8 to $300 as depicted in Figure A2 histogram shown below.

Figure A2. Histogram of the retail price of items in the experiment.

For items we wish to post on Facebook Marketplace, we require that we are able to obtain a link to a website with the original item. The items consist of various household items ranging from kitchen items to baby items to outdoor furniture. The complete list of items, from which we randomly select the final set of 90 to post, are listed in Table A1 shown below.

Items to Post			
2 outdoor throw pillows	Desk chair	Knife set	Sand free mat
Adirondack chair	Desk lamp	Lamp	Shop vacuum
Air fryer	Diaper caddy	Laptop stand	Silver towel hook
Airpods	Dinnerware set	Magazine stand	Smart plug
Alarm clock	Dishwasher basket	Magic keyboard	Spyder Victor Paintball Gun
Area rug	Dog bed	Magic mouse	Steamer
Baby bath tub	Dog life jacket	Mixing bowls	Stethoscope
Baby gate	Door handle	Nest cam	Stroller bassinet
Baby lounger	Doormat	Nest thermostat	Table lamp
Baby swing and bouncer	Dresser	Nursing pillow	Tabletop clock
Bath toy	Drying rack	Office chair	Thermoflask
Battery hand warmer	Dumbbells, 25 lbs	Outdoor kickback rocker chair	Tire traction chains
Best trash can ever	Echo dot	Outdoor lumbar pillow	Toaster
Bike tire pump	Fanny Pack	Paper shredder	Towel warmer
Bike trainer	Forehead thermometer	Patio set	Tower fan
Black towel hook	Fox high pressure shock pump	PC US5 Paintball Gun	Trash can
Bontrager shock pump	Google chromecast	Pet gate	Travel clock
Book	Haircut scissors	Picture frame	Utensil Crock
Bookshelf	Hamper	Popcorn maker	Vacuum
Cheese board	Hand vacuum	Printer	Weight Scale
Coasters	Hanging shelves	Pull up bar	Wire basket
Coat rack shelf	Hisense mini fridge	Roku streaming stick	Xbox controller
Console table	Humidifier	Rug	Yakima ski rack
Cookbook	Instant pot	Runner rug	Yoga blocks
Cuisinart griddler	Keurig	Ryobi drill and saw	Zero gravity chairs

Table A1. List of all items considered for posting for sale in the experiment.

Out of the items listed, we randomly select 30 items to post during each of the three phases of the experiment, summing up to a total of 90 items. However, issues arose due to Facebook's Marketplace policy. Specifically, we were flagged and restricted by Facebook from posting the Stethoscope in Phase 2. As a result, each seller removed the Stethoscope from the experiment leaving only 29 items remaining for this phase. In Phase 3, we decided to post 31 items to account for the missing item in Phase 2 and also decided *not* to post the paintball guns since these may also be flagged.

Appendix E - Examples of Treatment and Control Photos

The photos that we use for the experiment are designed to create a treatment effect as measured by our pre-experimental survey results. Specifically, we follow the image filtering strategies for high quality (treatment) and low quality (control) photos listed in Table A2 shown below.

High Quality Photo Filters	**Low Quality Photo Filters**
Increase exposure	Decrease exposure
Increase brilliance	Decrease brilliance
Increase highlights	Increase noise reduction
Increase shadows	Change angles
Increase contrast	Off Center
Increase brightness	Including other objects in the photo
Increase saturation (a little)	

Table A2. Adjustment categories for high quality and low quality photos.

While "increase" or "decrease" is a relative scale, the photo filtering strategy truly creates a treatment effect as measured in both the survey and the actual experiment. Our survey indicated a mild treatment effect with our initial amount of filtering and therefore, we increased the difference in photo quality for our experiment. The following Table A3 are examples of survey control, experiment control and treatment photos for each item. We note that the experiment control photos utilize more "bad picture filters" than the survey control photos.

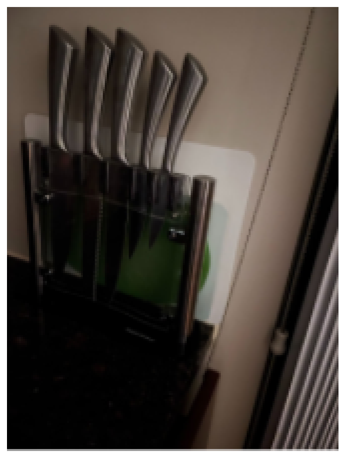
Survey Control	Experiment Control	Treatment
		
		
		

Table A3. Examples of survey-control, experiment-control, and treatment photos used in the pre-experimental survey and the experiment.

Figure A3 shows the number of control and treatment photos listed grouped by seller. The distribution of each seller's control and treatment items listed is fairly close. Each seller lists 90 photos in total and there are a total of 180 control and 180 treatment photos posted.

seller <chr>	treatment <int>	items listed <int>
Alyssa	0	51
Alyssa	1	39
Jaclyn	0	42
Jaclyn	1	48
John	0	46
John	1	44
Sanjay	0	41
Sanjay	1	49

Figure A3. Number of control and treatment photos listed per user in the Facebook Marketplace experiment.

Appendix F - Examples of Facebook Posts and Responses

Each item is posted with the same format. We standardize all required and optional fields provided in Facebook Marketplace such as the title, price of item, category of item, condition of item, description about the product, location, and functionality to block friends from viewing the post.

The *titles* are created to provide a sufficient amount of detail that summarizes the product. Our goal is to minimize the number of questions that potential buyers may ask as we believe that the more questions they have, the less likely they are willing to place a bid on the product if we ignore their questions. Answering questions would deviate from the apples-to-apples approach and introduce more variance into the experiment.

The item is posted for sale with a *price* of $1. Facebook Marketplace does not allow for $0 and we want to select a number that grabs potential buyers' attention and bid on the product while not anchoring their bid at a higher price.

The *category* of item is selected to best match the actual product, hence, targeting audiences who are already searching for this type of product. We believe that actual sellers of the product would approach this method similarly.

The *condition* of the item is marked "Used - Good" as this is a common scenario when selling used products.

The item's *description* instructs potential buyers to message the seller with their best offer. The description also included a link to the website with the original item. Providing the link to the original item also helps reduce the number of questions we would receive as discussed above.

The item's *location* is selected to be either Denver, Washington D.C., San Jose or Austin based on the randomization that occurs pre-experiment.

The option of *blocking* Facebook friends from viewing these posts is selected to avoid bidding without intent to purchase by friends or family, which could lead to bias.

Figure A4 shows a screenshot of a Facebook Marketplace post as seen by potential buyers.

Figure A4. A sample post on Facebook Marketplace.

During the span of time when each item is “active” on Facebook Marketplace, potential buyers could message us to place a bid or ask questions. We received many messages asking if the item is still available. Each seller provided the same response to this question and responded stating that the item is still available and asked the potential buyer how much they were willing to pay. We did not answer any specific questions about the product such as those regarding condition, age, or specific model. An example is shown in Figure A5.

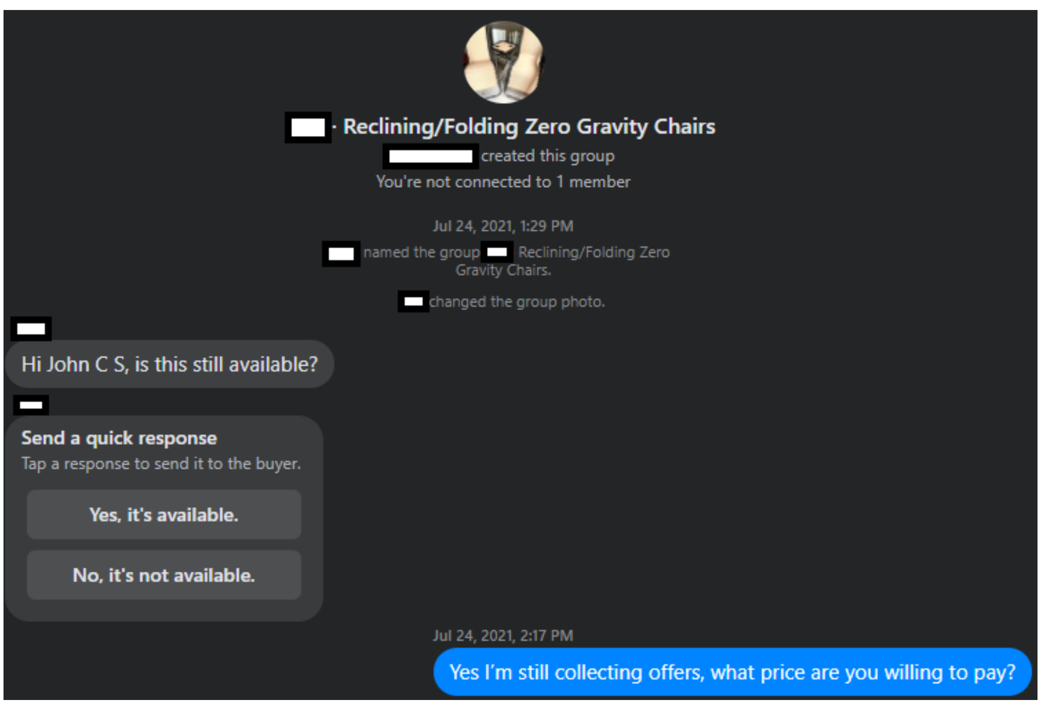


Figure A5. A sample response (blue) to a Facebook Marketplace message (not blue).

Appendix G - Pilot

To test out our experiment workflow, we conduct a pilot with two items. Each item is posted for a total of seven days and we collect data on the maximum bid, number of views, messages, and offers that they each receive. We did not have any issues with our pilot and proceeded with the same methods for conducting our final experiment.

Appendix H - Experiment Log-Linear Regression Model

Here, we display two sets of models that vary the value added to the maximum bid of $0. To reiterate, these log-linear models are affected by the log(0) error, which occurs when we have items with bids of $0. The log-linear models that we show in the report add $1 to each item to correct this issue, but $1 is rather arbitrary. We investigate with other values to add, $0.001 and $100, which are in range of the retail prices of the items.

We see in Figure A6, with adding $0.001, that the treatment effect is higher for all three models while in Figure A7, with adding $100, the treatment effect is lower for all three models. The reason is that by adding $0.001, a percentage difference of a $5 treatment effect is quite large compared to adding $100, where the same $5 treatment effect is not as large of a percentage difference.

Most of these models show statistical significance for the treatment variable except for the third model when adding $100. We see that our upper bound of adding $100 starts to show statistical insignificance, failing to reject the hypothesis that there is no treatment effect of high quality images. $100 becomes an unreasonable value as it approaches the maximum retail priced item of $300. It is not expected that a *used* item in our item list would sell for $100 more, especially if most of the retail prices are under $300. Therefore, we believe that adding $1 in our actual model, as reported in the results section, is reasonable.

	Dependent variable: log(max bid + 0.001)		
	[Simple]	[Seller&Item]	[Seller&Item&High/LowRetail]
	(1)	(2)	(3)
treatment	1.390***	1.330***	1.230**
	(0.503)	(0.448)	(0.489)
factor(seller)Jaclyn		0.562	0.572
		(0.666)	(0.671)
factor(seller)John		0.713	0.714
		(0.641)	(0.644)
factor(seller)Sanjay		0.995	0.996
		(0.649)	(0.652)
treatment:high_retail			0.232
			(0.940)
Constant	-4.090***	-5.840*	-5.900*
	(0.339)	(3.010)	(3.080)
Item	No	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure A6. Log-Linear models of maximum bid + $0.001. High retail in a binary variable referring to items with an original retail price of over $50.

	Dependent variable: log(max bid + 100)		
	[Simple]	[Seller&Item]	[Seller&Item&High/LowRetail]
	(1)	(2)	(3)
treatment	0.033**	0.032**	0.011
	(0.017)	(0.014)	(0.007)
factor(seller)Jaclyn		0.013	0.015
		(0.021)	(0.021)
factor(seller)John		0.014	0.014
		(0.019)	(0.019)
factor(seller)Sanjay		0.023	0.023
		(0.019)	(0.018)
treatment:high_retail			0.045
			(0.030)
Constant	4.680***	4.600***	4.590***
	(0.011)	(0.037)	(0.045)
Item	No	Yes	Yes
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure A7. Log-Linear models of maximum bid + $100. High retail in a binary variable referring to items with an original retail price of over $50.