W241 Final Project: Does Price Signaling on Craigslist Affect Ad Responses?

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Abstract

We investigate whether the commonplace practice of including a price reference in one's advertisement on Craigslist, the United States' largest secondhand marketplace, meaningfully influences the number of prospective buyers that respond to an ad, which may help increase the likelihood of a successful sale. We administered a field experiment that utilizes a clustered randomization design at the city level, in which we posted nearly identical Craigslist ads for four common household items with varying price references across 12 major U.S. cities and found that ads with higher price references tended to elicit more responses than the same ads with lower price references and those with no price references. Our findings were robust after controlling for city-specific features including population, per capita income, and poverty rate. We also present qualitative information about how prospective buyers responded to our ads, including the offer amounts provided, which may help us anecdotally understand how prospective buyers respond to ads that include prices versus those that do not. We stop short of drawing any causal claims between our treatments and response characteristics such as offer amounts, as such outcomes are naturally susceptible to post-treatment bias.

Background

The emergence of online advertising and internet commerce has revolutionized consumer behavior, and changed the ways that willing sellers and buyers interact with each other. In a competitive market environment, price is perhaps the most important factor impacting a consumer's decision to purchase a desired item, whether online or in a store. Since the perceived value of an item can vary widely by consumer, buyers often rely heavily on perceptual heuristics to make purchasing decisions on products. To this end, we consider how the presence of different price points, including the absence of a price, impacts prospective buyers' decisions to bid on an item.

Few studies have explicitly examined whether a price reference ("anchor") impacts the willingness of prospective buyers to bid on an item. A much richer literature exists that addresses how consumers assess prices when deciding whether to make a purchase, and specifically the importance of price anchors in influencing an individual's willingness to pay (Drolet [2004]).

Research on consumers' perception of price, and how consumers construct their preferences, suggest that individuals often do not hold well-defined notions of value, and may therefore be susceptible to potentially irrelevant signals or influences when judging value (J. Bettman [1998]). In this vein, the impact of a price anchor on an individuals' willingness to pay is often viewed as being dependent upon the factors that consumers consider when making purchasing decisions, which may be divorced from the fundamental value of the good itself (D. Ariely [2003], (et al. [1998])).

Although some may consider the inclusion of a reference price to be a natural element of advertisements for used goods, there is nothing to necessitate that this be the case. We seek to examine whether the existence of a price point and whether differences between price points impact the willingness of prospective buyers to respond to product advertisements in the online secondary market.

1 Research Questions and Hypotheses

We pose two explicit but related research questions and corresponding hypotheses:

1. **Does the inclusion of a price reference increase the number of offers relative to the exact same ad without a price "treatment"?**

   We anticipate that advertisements with no price reference (such as an explicit asking price or reference to how much the product is worth from a retailer) will elicit more offers than advertisements with a price reference, as buyers will be more willing to offer the intrinsic value they assign to an item if they are not deterred by a reference point that may be farther from this value.

2. **Does an ad with a higher price elicit more or less responses than the same ad with a lower price?**

   When comparing advertisements with different price points, we posit that those with a lower price are likely to elicit more offers than those referencing a higher price, because - absent any incremental differences between products and prospective buyers - the lower-priced item should compare favorably to a greater number of bidders' intrinsic value of the item.

2 Experimental Design

This experiment seeks to determine whether including a price reference in advertisements on Craigslist results in a meaningful change in the number of prospective buyers that respond to an advertisement.

A cluster randomization design was selected for practicality, with the city level as the intervention unit. We randomly assigned treatments (ad types) to 12 different major U.S. cities, which were themselves selected at random from a list of 23 of the largest major metropolitan areas with Craigslist markets. We randomly assign treatments to ensure that assignment to the treatment group is statistically independent of all observed or unobserved variables.

2.1 The Craigslist Platform

We chose Craigslist.org as our platform for carrying out the field experiment instead of a number of other popular online second hand marketplaces such as OfferUp.com and Facebook Marketplace. The Craigslist platform is ideal in that it has highly active local markets across the U.S. and allows for an unlimited number of anonymous and fee-free ad listings. Other platforms generally require the creation of a personal profile which is linked to the ads. It would be difficult to disentangle identifiable characteristics of the seller with our price treatment which would violate our price treatment's exclusion restriction (e.g. the perceived gender of the profile might somehow affect the number of responses to an ad rather than the varying price treatments which we seek to test).

Craigslist also allows for postings to be confined to local markets, which helps preserve non-interference of the treatments. To avoid the possibility that subjects are not exposed to multiple treatment ads, we ensure that each product is listed only once in any geographic market and check to ensure the markets are sufficiently distanced from each other following our randomization procedure. Because the platform is anonymous, buyers are unable to coordinate their offers with each other which rules out spillover from undermining treatment excludability.

2.2 Treatments and Randomization Protocol

For our treatment, we utilize three advertisement types, which are identical in all respects except for price point. The first ad type - administered to the control group - shows no price, but instead only solicits the prospective buyer's best offer. The second ad type - administered to the first treatment group - shows the full Manufacturer's Suggested Retail Price (MSRP) for the product in question, and also asks for the prospective buyer's best offer. We refer to these advertisements as the "high price" advertisements throughout the paper. The third and final ad type - administered to the second treatment group - shows a 25 percent discount to the full MSRP for the product in question, and asks for the prospective buyer's best offer. We refer to these advertisements as the "low price" advertisements throughout the paper.

Outside of their differential approach to including a price point, the ads are identical within each product category. Moreover, near-identical language[1] is used for advertisements across products (see Appendix A for more information).

We select four different product types to post, which we believe represent a broad assortment of commonplace consumer goods. These include a computer, a blender, a couch, and a bicycle. In addition to appealing to different markets of individuals, a cursory examination of the relevant Craigslist sites revealed that each is actively exchanged on the platform, and the goods are therefore appropriate candidates to generate variance in response frequency.

In selecting 12 cities to serve as intervention units, we opted for larger markets to be able to generate a sufficient sample size within our two-week time constraint. The trade-off with our city selection process is that our findings may only generalize to larger U.S. urban markets rather than to smaller markets as well. Among our 12 major U.S. markets, we performed simple random assignment of our three ad types to four distinct cities each (see Table 1).

[1]Several studies like J. Bettman [1977] have demonstrated that product description affects the price that consumers are willing to pay for the item.

Table 1: Group Assignments

	City	Ad Group
1	Atlanta	No price
2	Austin	Full MSRP
3	Boston	25% discount
4	Chicago	25% discount
5	Dallas	No price
6	Denver	No price
7	Detroit	Full MSRP
8	Houston	Full MSRP
9	Los Angeles	25% discount
10	Miami	No price
11	Minneapolis	25% discount
12	New York	Full MSRP

In each of the above cities, all four products were posted with the assigned ad type. In other words, Atlanta was assigned to the "no price" ad category. As a result, the bike, computer, blender, and couch were all posted onto the relevant Atlanta Craigslist sites without any price points, soliciting only the prospective buyer's best offer.

For the purposes of analysis, we grouped the observations into 3 groups based on ad type (no price, low price, and high price), with each group containing 16 observations (4 products posted 4 times each).

Justification for Treatment Levels

We assessed the full MSRP and 25 percent discount to MSRP price treatment levels as the most credible price points at which to elicit responses. We assumed that buyers were reasonably well-informed of the existing MSRP of the products. As a result, any attempt to set a higher price point than the MSRP would be likely to elicit very few responses since buyers could simply buy from the manufacturer and avoid any risk associated with buying from the Craigslist counterparty.

We also felt that a price point that was too low would be interpreted as a signal that the product's quality was somehow compromised, and would dissuade prospective buyers from responding to the ad (though we do not believe the same interpretation applies to the absence of a price point entirely). For these reasons, we thought the full MSRP and a 25 percent discount to MSRP were sufficiently different to meaningfully impact how prospective buyers would respond to each, while not seeming unreasonable.

We intentionally left out a firm asking price to avoid the perception that we would be obliged to follow through with the sale if a respondent actually accepted our sale price. This design choice was intended to increase the variance of offers over more common ads designed to actually achieve a sale. We did not respond to - or follow up on - any messages from prospective buyers, as this would represent a second stage of the experiment that falls outside the scope of our current study.

2.3 Excludability and Non-interference Assumptions

To assess whether our estimators are unbiased, we examine whether the core assumptions of excludability and non-interference are met.

Excludability: By randomizing based on major urban areas across the United States, we attempt to ensure that our schedule of potential outcomes excludes from consideration factors other than the treatment. The randomization process should ensure that there are no systematic differences between the control and treatment groups. We believe this is the case since any differences among the cities in our sample should not have an impact on the outcome of interest, the number of responses that each ad type elicits.

Non-interference: We administer only one ad type (treatment) per city (across all products), thereby removing the possibility that multiple ads for the same product could influence bidders' willingness to respond to any particular ad. We also ensure that - aside form the treatment - all other details of the advertisements are equivalent for the same product across cities. Additionally, we post all ads across a uniform two-week period. For these reasons, we can reasonably expect that the potential outcomes for each city are stable irrespective of the treatment assigned to other cities.

2.4 Randomization Diagnostic: Covariate Balance Check

In Table 2, we examine whether our three ad groups (no price, low price, and high price) are balanced on three local market characteristics of interest: population, per capita income, and poverty rate. These three covariates are chosen because we believe they could affect the ad responses and were used in similar studies (Doleac and Stein [2013]). In Table 3, we calculate the covariates' means for the three groups and test whether the covariates' means are different among the three groups. In particular, we conduct t-tests for three possible advertisement pairings: no price versus high price, no price versus low price, and low price versus high price.

Table 2: Average Market Characteristics

	Low Price	High Price	No Price
Population (In Million)	1.72	3.76	0.78
Per Capita Income (log)	10.53	10.30	10.49
Poverty Rate (%)	18.66	19.61	18.71

Table 3: T-test Results (p-values)

	Low Price vs No Price	High Price vs No Price	High Price vs Low Price
Population	0.0001474	1.60E-10	1.67E-05
Per Capita Income	0.1409	5.26E-06	4.20E-10
Poverty Rate	0.9211	0.3568	0.2431

Despite randomizing on city assignment, our markets turn out to be imbalanced on per capita income and population among the three groups because of a relatively small number of city samples (n=12). We expect the imbalance would be mitigated if we expanded our sample to more cities in a future expanded experiment. We control for these market demographic variables in regression analysis to more precisely estimate between-group differences.

2.5 Outcome Variables

Our key outcome measure is a count of responses to our various ad types among prospective buyers. We reason that a higher number of responses is an optimal outcome as it plausibly helps the seller increase the likelihood of a successful sale. This of course falls short of telling us anything about the quality of responses (serious versus non-serious offers, higher versus lower offer amounts, offers versus questions about the product, etc.).

We present ad response characteristics in the following section but avoid drawing causal inferences between our treatment ads and the contents of the messages (i.e. prospective buyers' offer prices), because such outcomes are conditional on subjects having responded, which does not necessarily result in a randomly drawn subset from the population of prospective buyers. In other words, any information from the messages themselves would be conditioned on a certain type of subject having responded to a particular ad, thereby potentially biasing the outcomes (J. Montgomery [2018]).

2.6 Campaign Timeline and Implementation Details

We listed the ads over a two-week period between October 27, 2020 and November 10, 2020. All products were posted nearly simultaneously at 9 PM EST from three different Google email accounts (used to clearly separate and manage the response data) and taken down at around the same time on the final day of the experiment. Ads were posted to the "bikes", "appliances", "furniture", and "computers" sub-categories in the "For Sale" section of the website.

We refreshed the ads every 48 hours (the earliest time frame possible) so that they would appear at the top of each product category on the platform to keep the postings consistently visible. Although this external intervention very likely generated an increase in the number of responses to a given ad, refreshing the ads should have affected the visibility of all ads equally, preserving the ability to detect differences between our ad groups. If we had not refreshed the ads, it is possible that certain types of products would have become less visible to buyers depending on how active each product category was on Craigslist. For example, in markets where there were much more used couch ads than used bike ads, our couch ads would have fallen further down the listings pages and become less visible than the bike ads, influencing ad response counts.

On the second day of the campaign, a handful of the computer ads were removed, likely as a result of the platform's algorithm catching postings that characterized these ads as duplicate listings because of their highly specific product description. We slightly adjusted the posting language by removing some unnecessary technical information about the computer across listings in all markets and promptly reposted the computer ads within the hour after they were removed.

We assess that this had minimal effect on reducing response counts as the downtime was fairly short relative to our two-week window and removals occurred nearly equally across all ad-types, thus preserving our ability to detect between-group differences. We did not encounter any additional auto-removal of postings for the remainder of the experiment.

3 Results

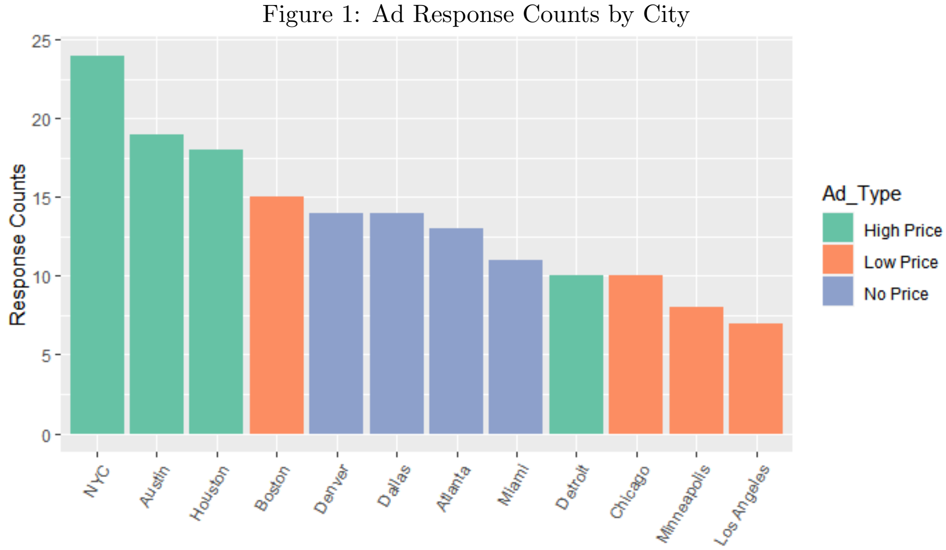
We first discuss results related to our key outcome variable: ad response counts. We then provide qualitative information about ad responses that supplements our analysis.

3.1 Ad Response Counts

Exploratory Data Analysis

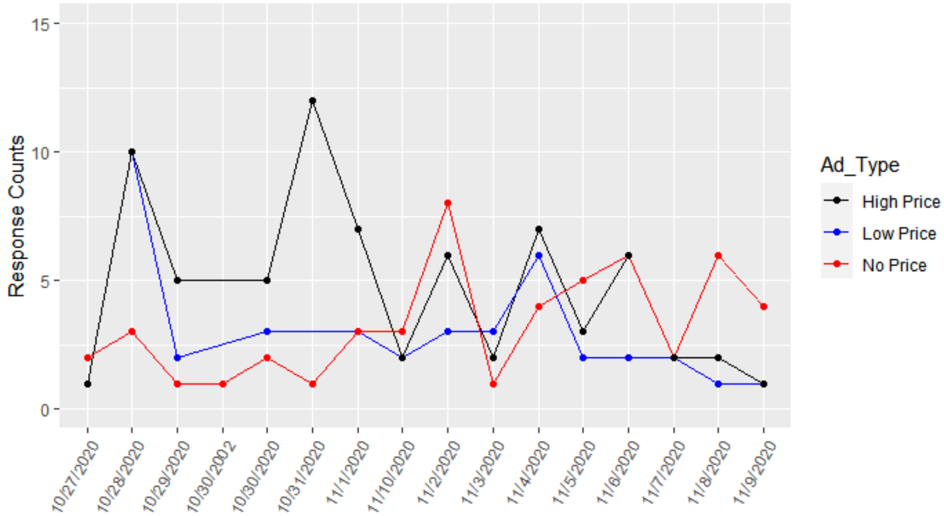
Across product types, we received 52 responses to our no price ads, 40 responses to our low price ads, and 71 responses to our high price ads.

Figure 1: Ad Response Counts by City



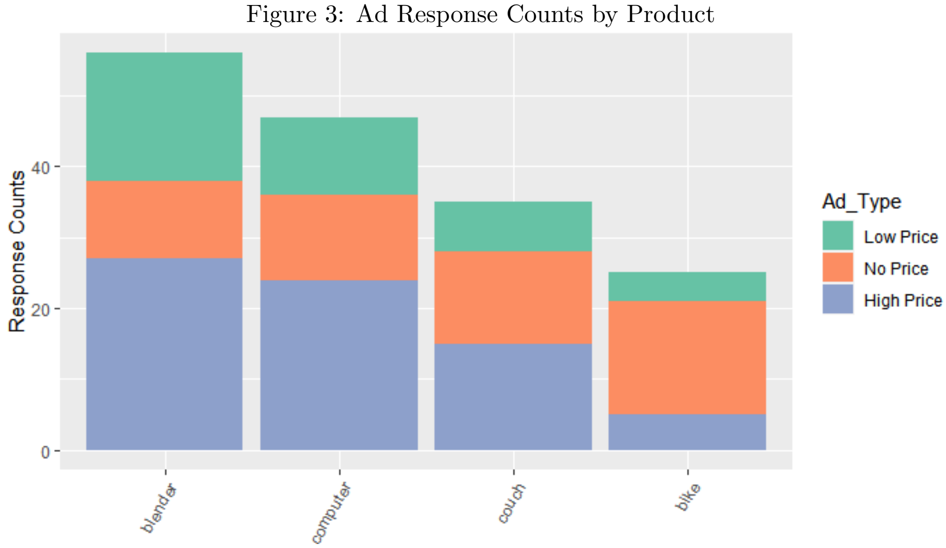
With respect to the timing when responses were received, a time series of the ad responses by treatment group assignment suggests that the high and low priced ads received responses from prospective buyers far more rapidly than those ads in the control group (i.e. those not providing a price). The no price category appears more variable with respect to the timing of when responses were received, whereas the high and low priced ads tended to exhibit more responses at the beginning of the experiment period, and declined as the period progressed.

Figure 2: Ad Response Counts by Date



The number of responses varied widely by product, with over 50 responses received for the blender and slightly over 20 for the bike.

Figure 3: Ad Response Counts by Product



The number of responses appears to follow a fairly clean division in which high priced ads received the largest count of responses, while the ad type with the lowest number of responses varied by product type.

Statistical Analysis of Response Counts

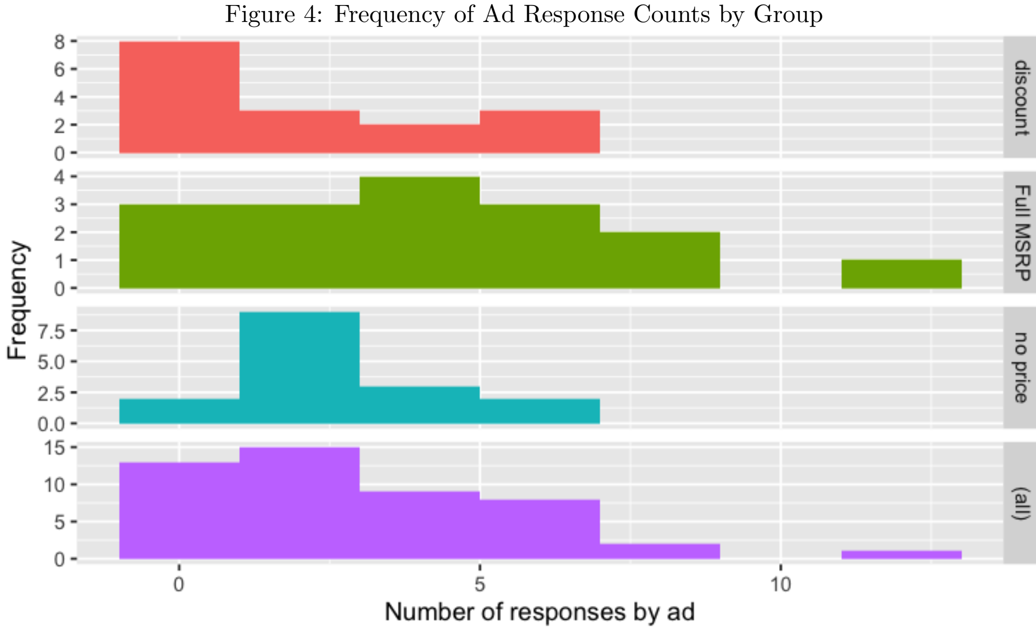
Response counts between low price to no price and high price to no price ad groups were not statistically significantly different, thereby partially refuting our first hypothesis. Response counts among high price ads were statistically significantly greater than response counts among low price ads at the 1 percent confidence level using a chi-square test for homogeneity, thereby refuting both our first and second hypotheses. Results are reported in Table 4 below.

Table 4: Count Comparisons

Group Comparison	Response count ratio	P-value
Low Price to No price	40:52	0.211
High Price to No price	71:52	0.087
High Price to Low Price	**71:40**	**0.003**

We next applied a poisson regression to measure ad response effects, an ideal form to model response counts.[2] Our sampling distribution in Figure 4, shown by ad type and across all ads, conforms nicely to such a distribution.

Figure 4: Frequency of Ad Response Counts by Group



We present the differences in expected log ad response counts generated by a standard poisson regression among all ad group pairings in columns (1)-(3) of Table 5. Columns (4)-(6) detail the same group pairings as in (1)-(3) but with the addition of covariates, which help us control for market features that could meaningfully affect response counts. We report clustered standard errors to account for assignment having been randomly assigned at the city level (Cameron and Trivedi [2009]).

[2]We avoided fitting a negative binomial regression because we did not observe overdispersion within our sample (the standard deviation of our response counts did not exceed the mean response counts and both parameters were close to each other). In an expanded version of our study in which we dramatically increase the number of ads posted, we might expect to see many zero response ads, in which case we could have applied a zero-inflated poisson regression.

Table 5: Poission Regression Models

	Dependent variable:					
	Differences in Log Response Count					
	(1)	(2)	(3)	(4)	(5)	(6)
Low price vs No price	−0.262			−0.203		
	(0.172)			(0.204)		
High price vs No price		0.311*			0.292***	
		(0.159)			(0.053)	
High price vs Low price			0.574**			0.952***
			(0.224)			(0.159)
Population (millions)				−0.068	0.040***	−0.021
				(0.081)	(0.005)	(0.026)
Per capita income (log)				0.525	0.206**	1.398***
				(0.398)	(0.086)	(0.491)
Poverty Rate (percent * 100)				−0.006	−0.022***	0.001
				(0.015)	(0.003)	(0.012)
Constant	1.179***	1.179***	0.916***	−4.162	−0.603	−13.754***
	(0.050)	(0.050)	(0.165)	(4.437)	(0.944)	(5.281)
Observations	32	32	32	32	32	32
Log Likelihood	−68.161	−75.623	−82.010	−67.440	−72.442	−78.151
Akaike Inf. Crit.	140.322	155.245	168.021	144.879	154.884	166.301

City-clustered SEs in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Consistent with our response counts in Table 4, ads with a higher price reference tended to generate more responses than ads with a lower price across all products (column 3 row 3), even after controlling for city population, per capita income, and percent of people living in poverty (column 6 row 3).

Ads with a higher price reference induce an increase in the expected log response count by 0.95 (alternatively, a 1.6 times greater increase in response counts)[3] over identical product listings with a lower price. The difference is highly statistically significant at the 0.01 level.

Interestingly, while there was no statistically significant log difference between the high price and no price ad responses at the 0.05 level (column 2 row 2), once we added market controls, the difference became statistically significant, showing a small increase in the log response count by 0.29 (or about 0.34 times increase of the high price over the no price ads) (column 5 row 2).

Heterogeneous Treatment Effects

We lacked the statistical power to detect whether or not response count differences between ad groups varied by product type. With a larger sample size, we could have tested whether or not ad type and product interaction terms generated statistically significantly different outcomes. For example, for a product like a rare antique, an ad without a price may have generated less responses than an ad with a price point compared to differences between a more commonplace item, because a majority of buyers might have had no way to value the item and would thus be deterred from responding.

[3]The effect size in percent change terms for our point estimate is given by $\exp(0.952) - 1 = \mathbf{1.59 \mathit{or} 159\%}$

3.2 Ad Response Qualities

We supplement our main response count findings with some ancillary qualitative ad response data to more thoroughly observe if there are any particular types of patterns that stem from our different ad types. We summarize some potentially interesting ad response features in Table 6 below.

Table 6: Ad Response Characteristics

Response Features	High price ad	Low price ad	No price ad
Response including offer	63.4%	75.0%	69.2%
Average offer (Percent of MSRP price)	37.8%	35.8%	34.5%
Maximum offer (Percent of MSRP price)	70.4%	70.4%	96.0%
Had a product question	19.7%	15.0%	11.5%
Asked for seller's best price	8.5%	17.5%	21.2%
Used polite language	31.0%	40.0%	36.5%

Of the 165 responses received, just over two-thirds provided an offer price as requested in the ad description. This ranged from 63 percent of responses containing an offer for high price ads, to 75 percent of responses containing an offer for low price ads.

On average, those providing offers across all ad types generally offered slightly over one-third of the MSRP value, irrespective of ad type. The maximum offer provided was similar for the low and high price groups (around 70 percent of the total MSRP), but the no price group contained an outlier offer of nearly the entirety of the actual MSRP.

Around one-fifth of responses to the high priced ad contained questions regarding the product, about five percentage points higher than the low priced ad and 10 percentage points higher than the no price ad. This may be intuitive, as a higher asking price may elicit more discernment on the part of prospective buyers.

About one-fifth of respondents to the no price ad solicited a price from the seller, even though our instructions were for them to provide their best offer. This may be viewed as a separate bargaining tactic through which buyers may not want to reveal their presumption of a fair price out of fear that they may be unaware that the price is in fact much lower.

Interestingly, respondents to high price ads were less polite in that they often provided only an offer or a question without any salutation, and this was outsized when compared to the other ad types.

Finally, from the perspective of a seller, what typically matters is not the number of responses one received, but instead, how one obtains the maximum possible offer for a given product. We summarize the ad types that generated the maximum offer for each product in the Table 7.

Table 7: Max Offers by Ad Type

Product	Max offer (% of MSRP)	Ad Type with Highest Offer
Bike	70.42	High Price
Blender	68.30	High Price & Low Price (Tied)
Computer	96.03	No Price
Couch	68.92	High Price

Anecdotally, the maximum offers for the bike, blender, and couch were all near 70 percent of the items' respective MSRP values, and were made in response to the high price ads. Interestingly, the computer, when advertised without a price, solicited an outlier offer of 96 percent of MSRP (a $1,200 offer for our Macbook from a prospective buyer in Dallas, TX).

4 Conclusion

Our field experiment found that ads listed with a higher price (at full MSRP) received meaningfully more responses than nearly identical ads listed at a 25 percent discount and those listed without prices, even after controlling for characteristics of local markets that might influence the number of responses. This conclusion refutes our hypothesis in which we expected lower price or no price ads to give buyers more flexibility to bid on items than high priced ads, but we propose several possible explanations for why this latter finding may have occurred.

First, we do not formally statistically evaluate responses by those that ask questions versus those that provide offers (or those that do both). It may very well be that high price ads solicit a higher volume of responses because many prospective buyers are inquiring into specifics of the product before making a purchase at such a high price. Therefore, it may be that individuals are more vociferous into inquiring about high priced items without necessarily submitting an offer.

Secondly, it is possible that those individuals browsing Craigslist are looking to buy goods at a steep discount to resell for a profit. They may be naturally more inclined to bid on relatively higher-priced items because they might believe they have more room to capture greater resale profits. Anecdotally, a significant subset of our offers for high priced ads appear to be for lower value offers (roughly less than one-third of the item's MSRP value), suggesting that this might be a possible buyer motivation.

Thirdly, because of the very open nature of communication between buyers and sellers on the Craigslist platform, prospective buyers could be responding to sellers as a means of obtaining additional information about a given product to inform their judgment of its value, rather than necessarily seeking to lock-in a purchase. This may manifest itself most prominently for higher-priced items because presumably those seeking to sell items for a higher price could have a greater burden to vouch for the quality of the product, and can therefore be best placed to respond to questions.

Lastly, we can not exclude the possibility that the conclusions we draw are only applicable to the products and price points that we selected. While we attempted to select a diverse array of products in the hopes that pooling them would capture how responses may vary in a representative manner across products, it was outside the scope of our study to sample an even greater number of products (and different models/versions of such products) to ascertain whether our findings will be repeated when considering a different, expanded sample. The same is true with the price points - It was outside the scope of this document to apply many more price points which may reflect different response characteristics for different ad treatments than those which we observed in the present study. For those reasons, we refrain from extrapolating our findings to a broader set of products or price points than we are able to corroborate.

Recommendations for Future Studies

Follow-on experiments should establish a significantly larger pool of advertisements beyond our 48-ad sample, randomize to a much larger pool of local Craigslist markets, and potentially extend to other secondhand marketplaces to see if price inclusion effects generalize beyond large urban U.S. Craigslist markets. To more robustly re-test our hypothesis, we also recommend increasing the visibility of the price reference (mentioning it with higher frequency or making the price much larger in the image), increasing the number of different price points, and testing other products outside of our four items.

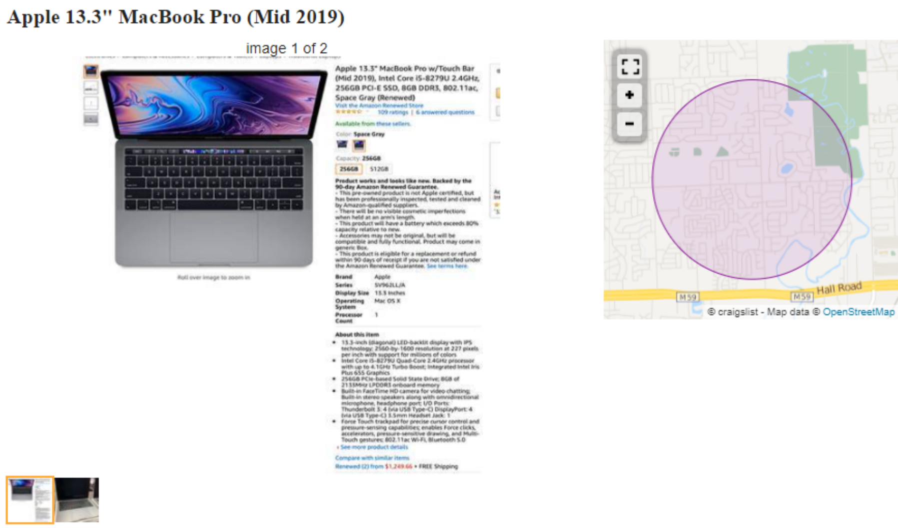
Additionally, while we only tested the inclusion of a single price reference in each advertisement, it would also be interesting to test the inclusion of a price reference and an explicit asking price that is at varying percentages lower than the price reference, to see if communicating the discount influences number of responses (e.g. "this iPhone retails for $999 but I'm willing to let it go for $500"). We also recommend testing the influence of other ad features such as the quality and number of images included, language about willingness to deliver the item within a certain distance, listing the recency of the item's original purchase, and testing the use of specific keywords or phrases (e.g. item is "hardly used", "comes from a smoke and pet-free home", etc.).

Appendix A Product Ad Samples

Of the 48 ads posted, we provide screenshots showing the High Price ads (full MSRP) for each product for reference. The low price ad variants included the exact same language but with the lower (25% off MSRP price), and the no price ad variants did not include any pricing language. The first image of each ad included a second reference to the price point, and the second image showed a used version of the product to boost the legitimacy of the ads.

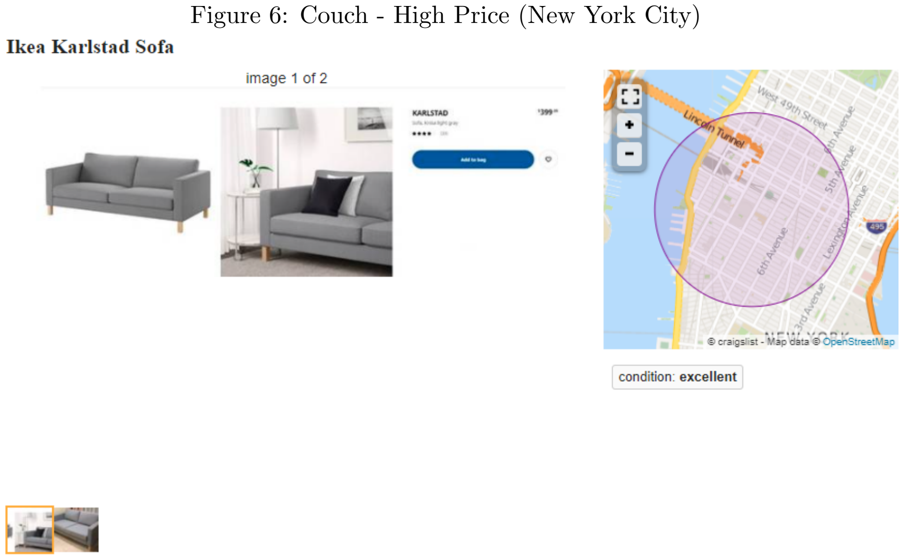
1. **Computer - High Price (Detroit)** Great condition 13.3-inch i5 MacBook Pro with Touch Bar and Touch ID. Retails for $1,249. If this ad is still up, it means the product is still available. Please include your best offer in your response. Thank you!

Figure 5: Computer - High Price (Detroit)



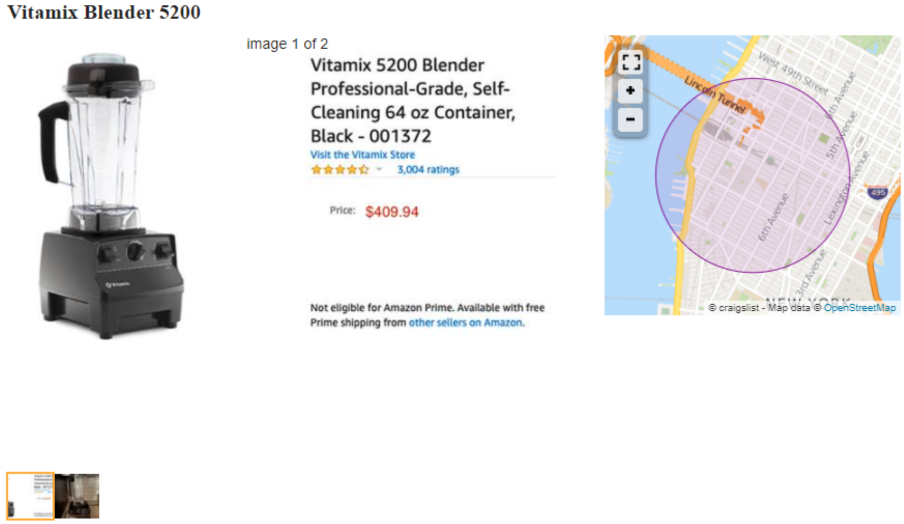
2. **Couch - High Price (NYC)** Great condition Ikea Karlstad Sofa. Retails for $399. If this ad is still up, it means the product is still available. Please include your best offer in your response. Thank you!

Figure 6: Couch - High Price (New York City)



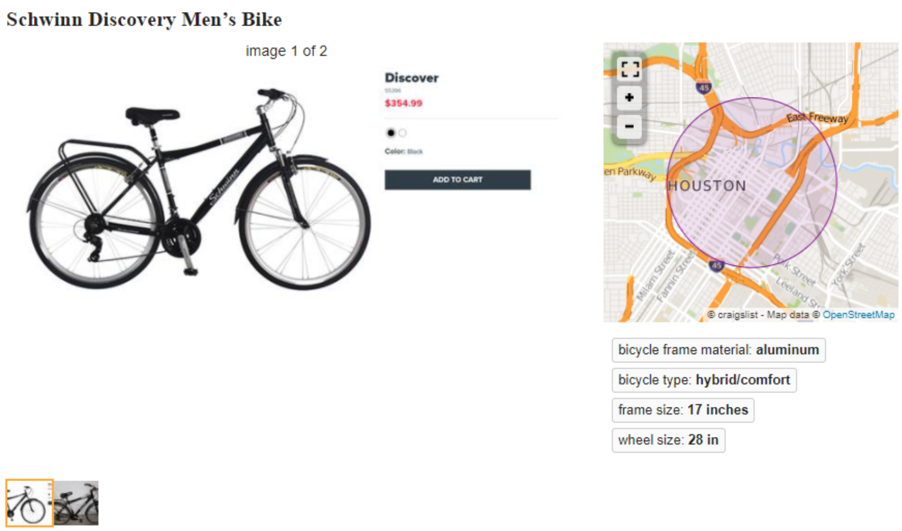
3. **Blender - High Price (NYC)** Great condition Vitamix 5200 Blender. Retails for $410. If this ad is still up, it means the product is still available. Please include your best offer in your response. Thank you!

Figure 7: Blender - High Price (New York City)



4. **Bicycle - Full MSRP (Houston)** Great condition Schwinn Men's Bike. Hardly ever used. Local pickup, cash offers only. This retails for $355. If this ad is still up, it means the product is still available. Please include your best offer in your response. Thank you!

Figure 8: Bicycle - Full MSRP (Houston)



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