Gender discrimination in online marketplaces: Evidence from the Facebook marketplace in Pakistan

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Abstract

We audit the Facebook marketplace in the patriarchal context of Pakistan and conduct an experimental evaluation to measure gender bias. We contact sellers who regularly sell on the platform using a weekly census of marketplace listings. We reach out to them twice, once as each gender, using carefully crafted bargaining scripts. Our findings show no evidence of gender discrimination in prices or other buying aspects such as bargaining time, order completion probability, delivery time, and product quality. However, we find significant discrimination against females in the form of unsolicited communication attempts, indicating potential harassment of female buyers. The linguistic analysis shows that sellers are significantly more verbose with females and use honorifics less often than males when addressing females. Our results shed light on novel barriers that may hinder women's participation in online marketplaces, particularly in patriarchal contexts like Pakistan.

Keywords: discrimination, online-marketplaces, taste-based discrimination, statistical-discrimination, harassment, language-processing.

JEL Codes: J71, D91, C93

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1 Introduction

Gender discrimination in low-income countries is an enduring and pressing issue that significantly impedes individual advancement and overall socioeconomic development (Duflo, 2012). In recent times, online marketplaces have emerged as potential catalysts for change in this context. They possess the unique capacity to break free from conventional constraints and offer women a platform for active participation in commerce. Through their digital infrastructure, these platforms hold the potential to grant women in marginalized communities access to a broader market, effectively circumventing many of the offline gender-based limitations they routinely encounter. Despite their transformative potential, there is limited empirical evidence concerning online marketplaces' role in ameliorating gender discrimination. Addressing this knowledge gap, this study seeks to document and analyze instances of gender-based discrimination, specifically on Facebook Marketplace in Pakistan.

To investigate gender discrimination, we designed a well-powered experiment to audit the Facebook marketplace in Pakistan. Based on a repeated weekly census of listings on the marketplace, we contact sellers who regularly sell on the marketplace through buyer profiles that unambiguously signal gender without revealing caste, ethnicity, or other economic markers. Each seller is contacted twice, once by each gender, following carefully crafted and pre-determined bargaining scripts. We record and analyze economic variables such as offered prices, delivery discounts, and product characteristics for each gender. In addition, we record any unsolicited attempts from sellers at communicating with each gender, such as messages, phone calls, friend requests, etc. We also perform linguistic analysis to document differences in the tone and feel of the sellers' language. This paper presents unique evidence on not just gender discrimination in prices and product characteristics but also on other facets of online interactions that may be a hurdle in the inclusion of women in the online marketplaces of patriarchal societies such as Pakistan.

We find no systematic difference in prices by the gender of the buyer. This effect is precisely estimated for most stages of bargaining. On non-price outcomes, we find that the sellers are likelier to complete the order for female buyers than male buyers. However, we find no significant evidence of discrimination against any gender in outcomes such as whether the order is delivered conditional on the placement of the order, the time it took to deliver the order from the day of order, whether the product was of higher quality than the other gender, and finally, whether the delivered product is same as ordered by the buyer.

Regarding unsolicited communication attempts (our measure of harassment), we document significantly higher advances toward female buyers than males. In particular, we document a significantly higher incidence of post-transaction messages from sellers to females. In addition, female buyers received 1.5 phone calls and 1.5 messages for every call or message received by the male buyer. Similarly, the incidence ratio of receiving unsolicited messages on Facebook and WhatsApp is about nine times more than male buyers. Female buyers also receive a disproportionately large number of friend requests on Facebook compared to their male counterparts. These results show substantial discrimination in how female buyers are approached or harassed after participation in the marketplace.

Online markets provide not just lower costs of transactions, but in the local context of Pakistan, they also allow women to more fully participate in markets that may traditionally be thought of as being socially segregated (anecdotally, Hafeez Centre, one of the biggest markets of computers, laptops, and mobile phones in Lahore, is unwelcoming for women). Our research implies that although online marketplaces lower the cost of accessing these previously hard-to-access markets for women, they come at the cost of the same old threat of sexual harassment and unwelcome advances. Our results are similar in spirit to Cook et al. (2019), where the authors find that in the context of the United States, the gender pay gap continues to hold in the online rideshare market, Uber, and like them, we find that biases carry over to online markets more generally.

The paper makes several contributions to the rich literature on gender discrimination. It contributes most directly to the large experimental literature on gender discrimination (see Croson and Gneezy (2009) and Neumark (2018) for an excellent survey of this literature). While there is abundant evidence of discrimination against women, there is an active debate on the nature and mechanism of the observed discrimination. Specifically, there is expanding experimental literature disaggregating the presence of taste-based from statistical discrimination in all manner of markets (Bohren et al., 2019), with the most extensive perhaps being the growing stream using correspondence studies (see, for example, Guryan and Charles (2013)). Our proposed research contributes to this literature by highlighting the nature of discrimination in an online marketplace setting of a developing country where sexual harassment is widespread (Duflo, 2012). To our knowledge, this is the first study that systematically investigates sexual harassment against women in a product market setting.

This paper contributes most directly to an emerging literature on discrimination on online platforms. Ayres et al. (2015) documents discrimination against blacks in auction prices on eBay. Hannák et al. (2017) documents discrimination by race and gender on online freelancing platforms, TaskRabbit and Fiverr. Asad et al. (2020) studies discrimination against black managers on Amazon's online platform Mechanical Turk. Similarly, Edelman et al. (2017) finds discrimination against blacks on Airbnb. To the best of our knowledge, there is no study on gender discrimination in an online product marketplace. Our study is the first to systematically document gender discrimination in such a setting.

This paper is more narrowly related to field studies on discrimination in bargaining. Examples include sex and race differences in bargaining over car prices (Ayres and Siegelman, 1995), race, age, and sex differences in bargaining over sports cards (List, 2004), sex differences in bargaining over taxi fares in Peru (Castillo et al., 2013), partisan differences in taxi fares in Ghana (Michelitch, 2015), and sex differences in prices of antimalarial drugs in Uganda (Fitzpatrick, 2017). These studies mostly point to statistical discrimination as the source of outcome differences (e.g., assumptions about the valuation of a taxi ride in the Castillo et al. (2013) or about the valuation of antimalarial drugs in Fitzpatrick (2017)). However, in our setting, we explore a unique channel of taste-based discrimination, which is not explored in any of the earlier studies. This channel stems from the prevalence of sexual harassment in our setting. We conjecture that sellers in our setting may prefer to deal with women because they derive positive utility from interacting with the opposite sex and are willing to offer them better prices. This particular explanation leads to women being harassed by the same sellers. This is a novel mechanism via which, while prices may seem to favor women, they come at the cost of significantly high non-market factors that may discourage female participation in markets.

Another contribution of this project lies in the experimental control of the bargaining process. A large literature in economics documents women's inability to negotiate better deals (see Exley et al. (2020) for discussion of related issues) as the reason for poorer outcomes for women. In our research, we control the bargaining strategy, allowing us to eliminate such concerns and explain any bias observed as being solely driven by the seller.

Our methodological contribution stems from the unique bargaining design in which we send repeated signals of buyers' valuation to the sellers, and that helps us determine whether the outcome differences are driven by differences in seller perceptions of buyer values or due to consistent gendered taste biases that stay stable across these signals. We can disentangle belief-based discrimination (Phelps, 1972) from taste-based discrimination (Becker, 1957). Note that taste-based discrimination in our setting can go in either direction. For example, consider taste-based discrimination due to in-group bias (see, for example, Chen and Li (2009)); in this case, we expect male sellers to consistently charge higher prices to women buyers, regardless of the product type. On the other hand, taste-based bias may also induce a preference for negotiating with female buyers, leading to lower prices.[1]. Our design allows us to disentangle belief-based discrimination from aggregate taste-based discrimination. The sign of aggregate taste-based discrimination against women will indicate in-group favoritism (positive) or a preference for women (negative).

The rest of the paper proceeds as follows. In Section 2, we present the conceptual framework underlying the price-setting behavior of the seller. Section 3 presents the experiment design. Section 5 presents the results, followed by concluding remarks in Section 6.

2 Conceptual Framework

This section presents a conceptual framework highlighting the behavioral forces involved in price-setting behavior. Our setup is inspired by Bohren et al. (2019). The framework presented here is closely tied to our experiment design and helps inform the treatments.[2]

[1] This is similar to what is documented in (Castillo et al., 2013) where tax drivers exhibit a preference for women riders and quote lower fares to them in exchange for the company of women riders.

[2] See DellaVigna (2018) for motivation on designing experiments using a model of behavior.

Consider a buyer who has observable group identity $g \in \{F, M\}$ and unobservable valuation for a good $v \sim N(\mu_g, 1/\tau_v)$ with mean $\mu_g \in \mathbb{R}$ and precision $\tau_v > 0$. The buyer makes a sequence of offers at times $t = 1, 2, ...$ to the seller. Each offer reveals a signal, $s_t = v + \eta_t$, of the true valuation of the buyer, where $\eta_t \sim N(0, 1/\tau_{\eta t})$ is an independent random shock with precision $\tau_{\eta t} > 0$. Lower signal precision at time t reflects greater uncertainty in valuation. This precision can be interpreted as the amount of subjectivity in judgment involved in evaluating valuation, with lower precision implying greater subjectivity. We assume that the valuation for good is fixed across time,[3] and higher valuation generates the higher expected signal.

A seller quotes a price to the buyer, $p_t \in \mathbb{R}$. Before quoting the price at time t, the seller observes the buyer's gender g, history of the past signals by the buyer $h_t = (s_1, ..., s_{t-1})$, where $h_1 = \emptyset$, and signal s_t. A seller's type θ_i determines her preferences and inference model, including her subjective belief about the relationship between gender and valuation. We assume that the seller's cost of production of the good is zero, and the seller's payoff from quoting a price p to a buyer of gender g is given as

$$\pi_{ig} = -\left(p - (v + c_g^i - \delta_g^i)\right)^2 \tag{1}$$

where c_g^i is a type-specific taste parameter à la Becker (1957). Normalize $c_M^i = 0$. $c_F^i > 0$ corresponds to distaste from transacting with female buyers. δ_g^i captures the type-specific benefit or perverse gratification from harassing the buyer of gender g à la Basu (2003). Normalize $\delta_M^i = 0$. $\delta_F^i > 0$ corresponds to positive utility from harassing a female buyer. The seller has subjective prior beliefs $\hat{\mu}_g$ about the average valuation of a buyer of gender g.[4]

A seller of type θ_i has a preference for transacting with male buyers if $c_F^i > 0$. A seller of type θ_i has a preference for harassing female buyers if $\delta_F^i > 0$. A seller of type θ_i has a belief favoring male buyers if $\hat{\mu}_M^i < \hat{\mu}_F^i$.

[3] This is equivalent to assuming that the discount factor in the bargaining model is equal to unity, i.e., the buyer is patient and values the same price trade equally at different time periods.

[4] A seller can have a misspecified model of the relationship between gender and valuation, in that case, the seller's subjective belief may differ from the true population average valuation, $\hat{\mu}_g^i \neq \mu_g$.

The seller learns about the buyer's valuation from the history of counter offers. Her posterior belief about valuation is derived using the Bayes rule, given her model of inference. Each seller chooses the price that maximizes her expected payoff with respect to her posterior belief about valuation. Suppose a seller has type θ_i and let

$$p_i(h,s,g) \equiv arg \ \underset{p\in\mathbb{R}}{max} \hat{E}_i \left[-\left(p-(v+c_g^i-\delta_g^i)\right)^2 |h,s,g\right] \tag{2}$$

denote the optimal price conditional on observing history h and signal s from a buyer of gender g, where $\hat{E}_i$ denotes the expectation with respect to her model of inference. Then, the optimal price in period t is

$$p_i(h_t,s_t,g) = \hat{E}_i[v|h_t,s_t,g] + c_g^i - \delta_g^i \tag{3}$$

Discrimination is the disparate quoting of prices based on the group to which the buyer belongs, i.e., gender, rather than on individual attributes, i.e., signal and history. Gender discrimination occurs when a male and female buyer with the same history and signal receives different prices. Let

$$D_i(h,s) \equiv p_i(h_t,s,F) - p_i(h_t,s,M) \tag{4}$$

denote the difference between type θ_i's quoting of prices to a male and female buyer conditional on observing history h and signal s.

2.1 Discrimination in First Price

We first examine how the preferences and beliefs impact the first quoted prices by the seller. Consider the quoting of a price to a buyer of gender g by a seller who has subjective prior beliefs $(\hat{\mu}_F, \hat{\mu}_M)$ about average valuation, taste parameter c_F, harassment parameter δ_F, and observes signal s_1. The initial signal has conditional distribution $s_1|v \sim N(v, 1/\tau_{\eta_1})$. Given the prior beliefs and signal distribution, the seller's posterior belief about valuation conditional on observing s_1 is normally distributed, $v|s_1 \sim N\left(\frac{\tau_v\hat{\mu}_g+\tau_{\eta_1}s_1}{\tau_v+\tau_{\eta_1}}, \frac{1}{\tau_v+\tau_{\eta_1}}\right)$. From 3, the optimal price is equal to

$$p_1(h_1,s_1,g) = \frac{\tau_v\hat{\mu}_g + \tau_{\eta_1}s_1}{\tau_v+\tau_{\eta_1}} + c_g^i - \delta_g^i \tag{5}$$

Higher signals and higher expected valuation result in higher first prices - the optimal first price is strictly increasing in s_1 and $\hat{\mu}_g$.

Discrimination in the first price depends on the seller's preferences and prior beliefs about valuation. From 5, first price discrimination is independent of the signal and equal to

$$D(h_1, s_1) = \frac{\tau_v}{\tau_v + \tau_{\eta_1}}(\hat{\mu}_F - \hat{\mu}_M) + c_F^i - \delta_g^i \tag{6}$$

There is discrimination against females in the first price, i.e., $D(h_1, s_1) > 0$, if the seller has unfavorable beliefs about valuation ($\hat{\mu}_F > \hat{\mu}_M$) and/or if the distaste towards women is greater than the utility from harassment ($c_F > \delta_F$). On the other hand, the discrimination in the first price could be in favor of women, i.e., $D(h_1, s_1) < 0$, if the sellers benefit from harassing females ($\delta_F > 0$) more than the distaste from interacting with them ($c_F < \delta_F$). The intuition is that the seller benefits from harassing the female buyer and is willing to accept a lower price for the perverse gratification of harassment. Of course, the effect of distaste and harassment may cancel out each other, in which case, the discrimination in the first price arises solely due to differences in beliefs about valuations.

Equation 6 shows that varying the level of subjectivity in judgment differentially impacts initial discrimination depending on whether it is due to preferences (distaste or harassment) or beliefs. This comparative static can be used to identify the source of discrimination.

2.2 Discrimination in Sequential Prices

We now study how discrimination evolves across a sequence of offers from the buyer. Beginning in the second period, signals from the buyer provide information about the buyer's valuation. In our experimental setting, the buyer is always requesting a discount, which, in the terminology of this model, is equivalent to sending signals such that $s_1 > s_2 > s_3 > ... > s_n$, and since such signals are expected to reveal the buyer's low valuation, it can reasonably be assumed that the precision of the signal is increasing which each request for a discount i.e., $\tau_{\eta_1} < \tau_{\eta_2} < ... < \tau_{\eta_n}$. In the second period, the seller observes the signal s_2 and once again uses the Bayes rule to form a posterior about the buyer's valuation, i.e., the seller posterior belief on observing s_2 is normally distributed, $v|s_1, s_2 \sim N\left(\frac{\tau_v \hat{\mu}_g + \tau_{\eta_1} s_1 + \tau_{\eta_2} s_2}{\tau_v + \tau_{\eta_1} + \tau_{\eta_2}}, \frac{1}{\tau_v + \tau_{\eta_1} + \tau_{\eta_2}}\right)$. From 3, the optimal price is now equal to

$$p_2(h_2, s_2, g) = \frac{\tau_v \hat{\mu}_g + \tau_{\eta_1} s_1 + \tau_{\eta_2} s_2}{\tau_v + \tau_{\eta_1} + \tau_{\eta_2}} + c_g^i - \delta_g^i \tag{7}$$

Comparing quoted prices to gender g in time period 1 (equation 5) and time period 2 (equation 7) reveals that any difference in prices between the two periods is driven by the seller's beliefs about the buyer's valuation since the preference parameters are assumed to be fixed over time.[5]

The price discrimination in period 2 is analogous to discrimination in period 1, indicating that the price discrimination against females is driven positively by beliefs and distaste against female buyers and negatively by perverse gratification from harassment.

$$D(h_2, s_2) = \frac{\tau_v}{\tau_v + \tau_{\eta_1} + \tau_{\eta_2}} (\hat{\mu}_F - \hat{\mu}_M) + c_F^i - \delta_g^i \tag{8}$$

Comparing discrimination across time periods helps us identify the source of the discrimination, i.e.,

$$D(h_1, s_1) - D(h_2, s_2) = \frac{\tau_v \tau_{\eta_2}}{(\tau_v + \tau_{\eta_1} + \tau_{\eta_2})(\tau_v + \tau_{\eta_1})} (\hat{\mu}_F - \hat{\mu}_M)$$

indicating that the difference in discrimination between the two periods is purely driven by differences in the beliefs about the valuations of each gender.

As buyers send more signals (request discounts), the n-period discrimination is given by:

$$D(h_n, s_n) = \frac{\tau_v}{\tau_v + \tau_{\eta_1} + \tau_{\eta_2} + ... + \tau_{\eta_n}} (\hat{\mu}_F - \hat{\mu}_M) + c_F^i - \delta_g^i \tag{9}$$

Equation 9 reveals that discrimination due to differences in beliefs (first term) decreases with an increase in the precision of the signals (τ_{η_i} for $i = 1, 2, ...$). This implies that as $\tau_{\eta_i} \to \infty$,

[5] However, it is possible that the taste parameters (δ_g^i and c_g^i) get activated only after some communication has taken place between the buyer and the seller. So, the initial offer may not include the effect of distaste or harassment, and only when the buyer starts negotiating does the seller feel the urge to harass the buyer or get disutility from the interaction. Our model does not allow for this dynamic endogeneity of preferences.

the discrimination against female buyers arises only due to the preference of sellers, i.e.;

$$D(h_n, s_n) \quad \rightarrow \quad c_F^i - \delta_F^i \quad \text{as} \quad n \rightarrow \infty \tag{10}$$

Consistent with Fitzpatrick (2017), we are postulating that discrimination in the first price can arise due to the beliefs or preferences of the sellers; however, any discrimination in the final prices must only be due to differences in preferences towards a gender. However, we can only identify the net effect of distaste and perverse gratification in our experiment and cannot isolate the discrimination from each preference source. This implies that any discrimination in final prices could be against females if the distaste outweighs the perverse gratification. Conversely, discrimination favoring females would imply that perverse gratification is the dominant driving force of favorable discrimination in final prices. Of course, the two forces may cancel each other out, and we may not observe discrimination in any direction.

3 Experiment Design

In this section, we outline our experiment design.

3.1 Sellers

We select sellers who regularly post on the Facebook marketplace as these are likely using the marketplace as a business. Specifically, we restrict to sellers who have posted at least 50 posts on Marketplace using their profile and are selling unused products. The reason to restrict to these sellers, in contrast to households selling an item or two, is twofold; 1) it allows us to contact a seller multiple times and order the same item from both male and female buyers; 2) it is more representative of the sellers that primarily exist on Facebook marketplace in Pakistan.

3.2 Buyers

We create buyer profiles such that the profile name is an unambiguous signal of gender and does not reveal other ethnic, caste, or economic markers. To arrive at the representative list of names, we rely on 2018 tax directory data published by the central tax authority, the Federal Board of Revenue (FBR), of Pakistan. FBR publishes a list of names and the amount of tax paid by each individual in the country annually. The latest published directory of 2018 has information on more than 2.7 million taxpayers. We tabulate the most frequent first names by gender and last names for both genders combined and then randomly assign first names to last names.[6] We exclude caste, sect, or ethnic indicators (such as Khan, Chaudhry, Sheikh, Rao, etc.) from names to disallow potential contamination with ethnic or caste effects. The list of selected names is given in Table A3. To avoid suspicion, we do not approach the same seller with profiles that share the last name or first name; instead, each seller is contacted using two entirely different names.

3.3 Products

The Facebook marketplace has a variety of products under various categories. To get a sense of products listed on the marketplace, we conducted a census around Lahore, Pakistan, on January 05th, 2022. The summary of posts in various categories is presented in Table A1. There are a total of 31,120 posts on the marketplace as of the date of the census, which are categorized by Facebook into 177 generic categories using an algorithm. There is a large variation in the kind and price of products within and across categories. Due to budgetary constraints and to allow for a wide range of products, we restrict to the top ten most frequently listed categories for which the 75th percentile of posted price is less than PKR 3,500 ($\approx$20 USD). This gives us categories of arts, health, home-decor, bags, shoes, mens, womens, kids-clothing, bedding, and portable-audio-video. Table A2 provides a brief description of each of these categories.[7] Some categories (such as clothing and shoes) have products that come in various sizes, designs, or colors; for these products, we negotiate for

[6] In Pakistan, men's first names are pre-dominantly assigned as last names for children and wives.

[7] There is obvious overlap between some categories, for example, women's shoes are likely to be categorized under both the categories of shoes and women.

the product that is listed first.[8] We exclude products that require customization, such as engraving a name, etc. A wide range of categories allows us to examine discrimination across a broader spectrum and is more representative of overall discrimination on the platform. After restricting to these categories, we further invoke a rule of contacting a seller if the posted price of a post is below PKR 2,000. Some posts in the selected categories are listed without any information on price; in such cases, we contact the respective seller and stop the bargaining process if the first quoted price is above PKR 2,000.[9]

3.4 Bargaining script

Once a product and a seller are selected, bargaining starts with a first message by a randomly selected gendered profile that asks for the price of the posted item (irrespective of the existence of the poster price). Once an offer is quoted by the seller, the buyer responds by asking for a discount without giving any counteroffer.[10] There are three possible reactions to this; first, the seller asks the buyer to quote a price (path A); second, the seller quotes a discounted price (path B); third, the seller refuses to give any discount. In all three cases, we exhaust the bargaining process and nudge the seller into giving discounts as much as possible. Broadly speaking, either the seller will concede to giving a discount or refuse. Upon agreement of the final price, which may be the discounted or the original stated price, the negotiation ends, and the buyer moves the discussion toward order. As shown in the model, the difference in the first quoted price in this setup reflects preference and belief-based discrimination; however, the difference in the final price is only driven by the preferences. So if there are any differences in the final price for male and female buyers, we interpret that as driven by the seller's preferences. The exact flow chart of the negotiation process is presented in Figure XX. We also outline two bargaining transcripts of chats in Table XX that are assigned to each seller randomly; for example, transcript-1 may get randomly assigned to the female buyer, followed by the deterministic assignment of transcript-2 to the male

[8] On some occasions, the designs/options are shared by a seller over messages; in these cases, we stick with the rule of selecting the first presented option.

[9] We expect that the sellers might have more room to price discriminate for products listed without posted prices.

[10] As mentioned earlier, the negotiation stops if the quoted price is above PKR 2,000.

buyer.

3.5 Ordering

The ordering process starts after the buyer and seller have agreed on the price. Each buyer for a seller is randomly assigned to one of the two ordering scripts as given in Figure B3 and Figure B4. For example, script-1 may get randomly assigned to the female buyer, followed by the deterministic assignment of script-2 to the male buyer. The ordering scripts begin by confirming the mode of payment. We only proceed with the order if cash on delivery is acceptable.[11] It is during the ordering stage that the buyer shares their contact details, including the address for delivery. Each seller is assigned to two different addresses, one for each buyer, in a random order, i.e., each seller mails products to two different addresses (once for male buyers and once for female buyers).

3.6 Post-Delivery

After an order has been delivered, we download all conversations with the seller on Facebook, Whatsapp, and text. We also record the entire call log history with each seller. Upon delivery, we inspect the item thoroughly to see any differences in quality between the two genders. We take photos of items delivered for both genders to note such changes. This also helps us identify if the product delivered is the same as the product shown in the post.

3.7 Harassment and Tone of Language

We analyze the conversations between the buyers and sellers to detect any non-economic margins of discrimination. For this purpose, each conversation was evaluated by at least three annotators following carefully drafted guidelines. The annotators labeled the seller's responses on professionalism, politeness, courteousness, flirtatiousness, informality, rudeness, and offensiveness. These guidelines were developed after a thorough review of the literature on language processing. Our conversation involved a mixture of Roman Urdu, English,

[11] Given the low penetration of financial products in Pakistan, cash on delivery is the most common payment method for online shopping.

and scripted Urdu, which makes it difficult to predict feelings and tone using off-the-shelf machine-learning algorithms such as Ranganath et al. (2013).[12]

In addition, to capture the long-term cost of engaging in online markets, we track the unsolicited attempts of communication (messages, calls, friend requests, etc.) for each buyer account and phone number for three months. These measures provide us with an understanding of the non-pecuniary aspect of engaging in online markets for each gender.

3.8 Sample Size

Our choice to use within-subject design is motivated by concerns to maximize power. Bellemare et al. (2014) show that a between-subject design requires between 4 to 8 times more subjects than a within-subject design to reach an acceptable 80 percent level of statistical power. Similarly, List et al. (2011) shows that within-subject design dramatically reduces the variance of the unobserved component, increasing the precision of the estimated average treatment effects. Therefore, in the presence of considerable variation in subjects' behavior towards gender, the benefits of within-subject design are significant. However, a disadvantage of within-subjects design is the possibility of order effects, i.e., subjects' behavior may depend on the order of the treatment. We address the latter concern by randomizing the order in which each gender contacts the seller. In addition, to ensure such effects are minimal, we contact a seller only twice, once with a male and once with a female account.

We conducted a brief pilot of the design before the experiment's launch to determine the required sample size and get a sense of the minimum detectable effect. Based on the pilot results, we designed our experiment to detect a difference in prices between males and females of 0.25 standard deviations.[13] Given our within-subject design, we can detect this effect by contacting 128 sellers twice (256 contacts).[14] We also anticipated conducting multiple hypothesis testing; therefore, our sample size should be adjusted (List et al., 2019).

[12] There is though a burgeoning literature on text analysis of roman urdu using language processing programs, see, for example, Mehmood et al. (2019); Ghulam et al. (2019); Chandio et al. (2022); Mehmood et al. (2020) among other studies.

[13] Our pilot had average difference in prices of ≈20 PKR with standard deviation of the difference at ≈85. This is admittedly based on very few observations and is only suggestive of any effect size.

[14] We use Stata's *power pairedmeans* command to calculate the sample size.

We arbitrarily change the probability of type-I error from the conventional 0.05 to the more conservative value of 0.01. This increases the required number of sellers to 191. We rounded that up and aimed to negotiate prices with 200 randomly selected sellers twice (400 purchases). As explained in Section 4, we, in fact, were able to negotiate and agree on prices with 224 sellers each, which required contacting 619 sellers, further increasing the power.

3.9 Experiment Flow

The experiment flows as follows;

1. At the beginning of each week, we census posts that meet the criteria specified in sub-section 3.3. This census records the basic information of each post, such as product name, category, and posted price.

2. From the census in step 1, we randomly select one of the ten selected categories.

3. From the selected category, we randomly draw a post and check if the selected post is posted by a seller that meets the criteria specified in sub-section 3.1. If the post is already drawn before or the seller is previously selected for another post, we redraw a post.

4. Once a post is selected, we randomly select a gender with which to contact the seller and then select a random profile from the list of four profiles of the selected gender.

5. Once the profile is selected, we negotiate with the seller as explained above in sub-section 3.4.

6. After the conclusion of negotiation, we order the item as explained in sub-section 3.5.

7. After the order is placed, we track the delivery and any attempted communication by the seller as outlined in sub-section 3.7.

8. To contact the seller for the selected post the second time, we re-randomize without replacement from steps 4 to 7. To avoid suspicion, we ensure that the second contact is made after at least 24 hours of the first contact with the seller.

9. We repeat steps 2 to 8 to get more observations.

10. We repeat steps 1 to 9 every week until the target number of purchases is reached.

3.10 Data Collection Protocol

In this subsection, we outline the data collection protocol that we follow during the experiment stage. These protocols are administered by two research assistants (RAs), which we label as RA1 and RA2.

1. At the beginning of each week, RA1 runs a script that completes a census of posts on the Facebook marketplace from the previous week.

2. This is followed by RA1 running another script called "Selecting a seller for first round". This script selects a post and a seller that can be contacted in light of the experimental protocol outlined above. The script randomly assigns gender, buyer profile, bargaining script, and ordering script. On each day, RA1 runs this script 6 times to bargain with 6 different sellers.

3. Each time a post is selected, RA1 assigns a unique identifier to the selected post (with suffix "M" (for male) or "F" (for female) depending on the assigned gender) and downloads all the pictures of the product and save the contents of the post as a pdf document.

4. RA1 then start the bargaining process by closely following the assigned script, potentially leading to the ordering process that is followed using the assigned script.

5. On each day, RA2 runs a script called "Selecting a seller for second round". This script assigns, without replacement, the gender, buyer profile, bargaining script, and ordering script to the post selected in step 2 above.

6. RA2 then start the bargaining process by closely following the assigned script, potentially leading to the ordering process that is followed using the assigned script.

7. At the end of each day, RA1 and RA2 record all bargaining and ordering proceedings in a Google Doc. This sheet records the entire bargaining process, including the evolution of prices, basic information about the seller, product, and order details.

8. Upon receipt of delivery, RA1 and RA2 record information such as delivery charge, delivery time, packaging, product characteristics, and product quality. At this stage, the RAs also record pictures of the packaging and receipt.

9. At the end of each week, the RAs gather all products received and inspect each one carefully to see if there are any differences in quality between the two genders. The RAs also take and save pictures of each product.

10. On the products, RAs label a tag with an identifier (from step 3 above).

11. At the end of each week, the RAs create a backup record of all the communications with the sellers. This includes backup of Facebook, WhatsApp, SMS, and call logs.

4 Data

This section describes the data collected as part of this experiment.

We ran the experiment for about seven and a half months, from March 25th, 2022, to November 8th, 2022. We initiated bargaining with 670 sellers for 1,236 bargaining attempts during this period. A total of 142 instances were identified in which bargaining was initiated from one gender but not the other. These discrepancies primarily stemmed from a coding error responsible for assigning sellers to buyers, the post removed after one contact, or instances where one of the research assistants failed to initiate/continue the conversation with the corresponding seller. As these observations violate the experimental protocol, lack data on both genders, and impede the feasibility of within-subject comparisons, we have excluded them from the analysis. This leaves us with 1,094 bargaining attempts with 547 sellers.[15]

[15] As per the pre-registration, our target was to collect data on 400 transactions from 200 sellers. Since every contact with a seller did not lead to the transaction's completion (defined as an agreement on the final price or delivery of the item), we continued contacting the sellers until we reached the target number of transactions. Our final sample has a slightly higher number of contacts where the bargaining could lead to agreement on the final price for both genders (444) and a much lower number of attempts where bargaining could lead to the item's delivery (325).

Table 1: Summary of Bargaining Data

	Buyer Gender		
	Female 532 (50%)	Male 532 (50%)	Total 1064 (100%)
Bargaining outcome			
Order completed	223 (42%)	194 (36%)	417 (39%)
Seller stopped responding	120 (23%)	139 (26%)	259 (24%)
Item unavailable	66 (12%)	71 (13%)	137 (13%)
Quoted price > threshold price	67 (13%)	73 (14%)	140 (13%)
Seller required advance payment	56 (11%)	55 (10%)	111 (10%)
Delivery after order completion			
Received	167 (75%)	154 (79%)	321 (77%)
Not Received	55 (25%)	40 (21%)	95 (23%)
Price bargaining completed			
No	231 (43%)	253 (48%)	484 (45%)
Yes	301 (57%)	279 (52%)	580 (55%)
Price bargaining completed for both genders			
No	309 (58%)	309 (58%)	618 (58%)
Yes	223 (42%)	223 (42%)	446 (42%)
Product Category			
arts	45 (8%)	45 (8%)	90 (8%)
bags	66 (12%)	66 (12%)	132 (12%)
bedding	50 (9%)	50 (9%)	100 (9%)
health	56 (11%)	56 (11%)	112 (11%)
home-decor	37 (7%)	37 (7%)	74 (7%)
kids-clothing	57 (11%)	57 (11%)	114 (11%)
mens	53 (10%)	53 (10%)	106 (10%)
portable-audio-video	47 (9%)	47 (9%)	94 (9%)
shoes	62 (12%)	62 (12%)	124 (12%)
womens	59 (11%)	59 (11%)	118 (11%)
Product Orientation			
Female Oriented	263 (49%)	263 (49%)	526 (49%)
Neutral but Female	122 (23%)	122 (23%)	244 (23%)
Male Oriented	93 (17%)	93 (17%)	186 (17%)
Neutral but Male	54 (10%)	54 (10%)	108 (10%)

Table 1 provides an overview of the collected data categorized by the gender of buyers. Out of the 1,094 attempted negotiations, approximately 38 percent culminated in successful order completions, with a notably higher success rate observed among female buyers. The remaining instances where orders could not be finalized were attributed to various factors, including seller unresponsiveness (26 percent), product unavailability (12 percent), quoted prices exceeding the established threshold of PKR 2,000 (13 percent), and sellers requiring advance payments (10 percent). Furthermore, not all orders placed resulted in successful deliveries, with only 77 percent of orders ultimately being fulfilled, with a higher proportion among male buyers. Regarding price data, approximately 53 percent of negotiations resulted in an agreement on the final price. However, for within-subject comparisons, we would need prices for both genders per seller; this was reached for only 41 percent of sellers. The products are almost equally represented across the ten categories; however, there is a disproportionate number of female-oriented products (48 + 24 72 percent).

We present information on sellers by seller's gender in Table 2. Overall, 63 percent of our sellers are male. On average, male sellers have more friends and followers than female sellers. Most sellers (61 percent) use their personal Facebook accounts to sell items on the marketplace, while others have dedicated accounts for selling items. Female sellers are relatively less likely to use their personal accounts for marketplace activities. Most seller profiles are public (more so for male sellers than females). For public profiles, we can observe the activity on profiles, and we observe that more than one-third of our sellers tend to post religious content on their Facebook timelines. Most of our sellers are single or do not publicly display their marital status, with females being more likely to reveal their married status (possibly to avoid potential suitors). Finally, we can observe that male sellers post personal photos more frequently on their public profiles.

Table 2: Summary of Sellers Data

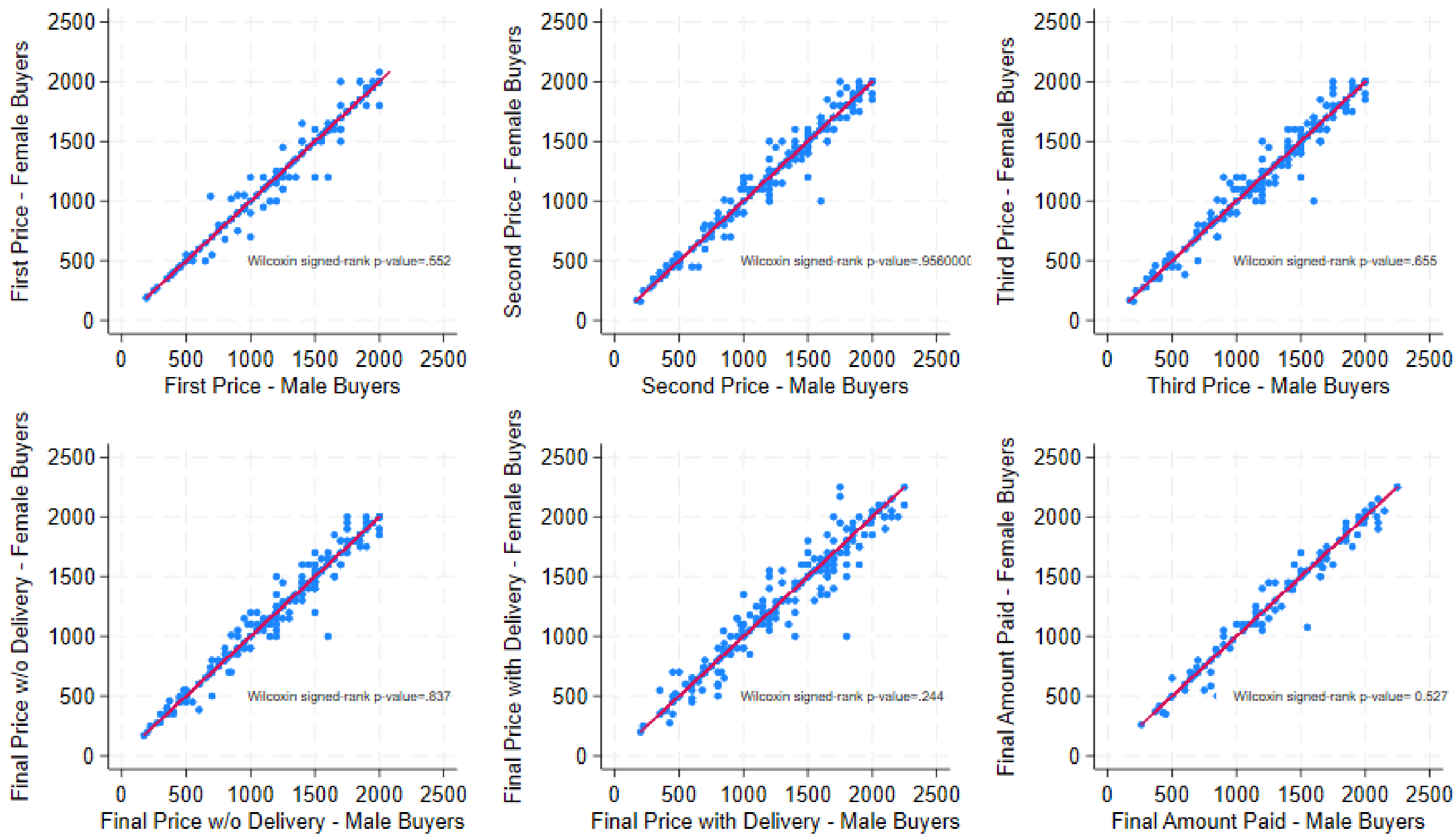
	Seller Gender		
	Female	Male	Total
	202 (37%)	340 (63%)	542 (100%)
Number of Friends (mean)	260	465	389
Number of Followers (mean)	503	5270	3608
Business/Personal Account			
Personal	110 (54%)	219 (64%)	329 (61%)
Business	52 (26%)	77 (23%)	129 (24%)
Not Known	40 (20%)	44 (13%)	84 (15%)
Public/Private Profile			
Public	125 (62%)	242 (71%)	367 (68%)
Private	50 (25%)	63 (19%)	113 (21%)
Not Known	27 (13%)	35 (10%)	62 (11%)
Religious reference on profile			
No	111 (55%)	206 (61%)	317 (58%)
Yes	21 (10%)	47 (14%)	68 (13%)
Not Known	70 (35%)	87 (26%)	157 (29%)
Marital Status			
Not Known	164 (81%)	248 (73%)	412 (76%)
Single	13 (6%)	66 (19%)	79 (15%)
Married	25 (12%)	25 (7%)	50 (9%)
Divorced	0 (0%)	1 (0%)	1 (0%)
Selfies/Personal photos on Profile			
Yes	36 (18%)	152 (45%)	188 (35%)
No	120 (59%)	127 (37%)	247 (46%)
Not Known	46 (23%)	61 (18%)	107 (20%)

5 Results

5.1 Bargaining in Prices

In this subsection, we investigate potential gender-based differences in prices. For this analysis, we restrict it to observations from sellers where bargaining could lead to an agreement on a final price by both genders, thereby allowing within-subject comparisons. Figure 1 presents the raw quoted prices from sellers at various stages of negotiation. While some minor fluctuation around the 45-degree line indicates some variability, overall, we do not see a significant price differential in one direction at any bargaining stage. To test this, we employed the Wilcoxon signed-rank test (Wilcoxon, 1945) to evaluate the equality of price distributions for each matched pair. These results consistently indicate no overall statistically significant difference in prices.

Figure 1: Comparison of Prices to Males and Females Buyers



Furthermore, we utilized a linear mixed-effects model with clustered standard errors at the seller level (following de Chaisemartin and Ramirez-Cuellar (2024)) to estimate the price differences at each negotiation stage, as summarized in the Panel A of Table 3. Initially, female buyers receive slightly more favorable first-price offers, though this difference is statistically indistinguishable from zero. However, as the bargaining process unfolds, this distinction diminishes and eventually becomes negligible for the final agreed-upon prices. It is worth noting that sellers treat female buyers favorably regarding delivery charges, sometimes waiving or handling deliveries themselves. This practice appears to tip the scale slightly in favor of female buyers. Nevertheless, these price variations also fail to reach statistical significance. In light of these results, we conclude that, on average, there are no systematic price differences between male and female buyers at any stage of the bargaining process.

We also present the results by the seller's gender in Panels B and C of Table 3. Once again, we confirm that there is no significant difference in prices for male and female buyers by the seller's gender. While male sellers start bargaining by offering slightly lower prices (though insignificantly different from zero) to female buyers, these differences are further lowered as bargaining evolves.

5.2 non-Price Bargaining Outcomes

We present evidence of discrimination in non-price outcomes in Table 4 and Table 5. Panel A of Table 4 shows no statistical difference in outcomes such as the probability of withdrawing from bargaining (column 1), the number of stages it takes to agree on a price (column 2), and the probability of requiring advance payment before the delivery of order (column 3). However, interestingly, we find that the sellers are significantly more likely to complete the order for female buyers than male buyers (column 3), which is primarily driven by female sellers as shown in column 4 of Panel C.[16]

Table 5 presents results for relevant outcomes after the order placement. We do not observe any statistically significant differences in the probability of the order being delivered

[16] An order is labeled "incomplete" if a seller becomes non-responsive, does not accept cash on delivery, or reports the item as out of stock.

Table 3: Effect of Buyer's Gender on Prices

Panel A: All Sellers

	(1) First Price	(2) Second Price	(3) Third Price	(4) Final Price	(5) Final Price w/ Delivery	(6) Amount Paid
Female	-3.36	-0.77	-1.37	-1.13	-8.61	-12.47
	(5.03)	(5.87)	(6.01)	(5.98)	(9.02)	(9.38)
Constant	1300.96***	1246.18***	1236.85***	1234.79***	1320.68***	1365.69***
	(32.48)	(31.78)	(31.70)	(31.70)	(32.91)	(37.28)
Observations	446	446	446	446	446	276
Clusters/Sellers	223	223	223	223	223	169

Panel B: Male Sellers

	First Price	Second Price	Third Price	Final Price	Final Price w/ Delivery	Amount Paid
Female	-5.62	-0.60	-0.17	-0.13	-4.30	-14.99
	(6.14)	(7.60)	(7.78)	(7.75)	(11.99)	(10.11)
Constant	1270.75***	1215.99***	1205.33***	1202.28***	1277.31***	1340.43***
	(40.39)	(39.48)	(39.37)	(39.36)	(40.08)	(44.97)
Observations	302	302	302	302	302	191
Clusters/Sellers	151	151	151	151	151	117

Panel C: Female Sellers

	First Price	Second Price	Third Price	Final Price	Final Price w/ Delivery	Amount Paid
Female	1.37	-1.13	-3.90	-3.21	-17.65	-6.81
	(8.79)	(8.85)	(9.00)	(8.98)	(12.20)	(20.43)
Constant	1364.32***	1309.49***	1302.96***	1302.96***	1411.64***	1422.32***
	(53.90)	(52.85)	(52.66)	(52.66)	(56.59)	(66.87)
Observations	144	144	144	144	144	85
Clusters/Sellers	72	72	72	72	72	52

Note: The table presents the results of a linear mixed-effects model with clustered standard errors at the seller level. 'Female' is the binary variable taking value one if the buyer's gender was assigned as female, zero otherwise. The 'First Price' corresponds to the first privately quoted price by the seller to a buyer at the start of the bargaining process. Similarly, the 'Second Price' and 'Third Price' reflect the prices quoted during the second and third stages of bargaining, while the 'Final Price' is the finally agreed price between the buyer and seller in response to the outlined bargaining process. 'Final Price w/ Delivery' add delivery charges, if any, to the 'Final Price.' 'Amount Paid' is the amount paid by the buyer at the time of the product's delivery. All prices are in PKR. Data in all panels is restricted to observations where the buyers and sellers could agree on a final price. Panel A includes all the sellers, while Panels B and C restrict data to male and female sellers. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

conditional on order placement (column 1), the time it takes, in days, to deliver the product conditional on the delivery of the order (column 2), the probability that a delivered product is of higher quality than opposite gender (column 3), and the probability the order is same as ordered by the buyer (column 4). Panels B and C confirm no differences in these outcomes by the seller's gender.

5.3 Sentiment and Language Analysis

We perform a linguistic analysis of sellers' responses to examine if they treat either gender differently. We employ OpenAI's GPT-4 (OpenAI et al., 2023) for a nuanced sentiment and language analysis of conversations between buyers and sellers, where communication often blends Urdu (in Roman or traditional script) and English. GPT-4, the latest iteration of the Generative Pre-trained Transformer models, stands out for its exceptional language understanding and generation capabilities. Its architecture is designed to handle diverse datasets, making it uniquely suited for analyzing the intricacies of mixed-language conversations in the local context (Baktash and Dawodi, 2023). We leveraged GPT-4 to assess various aspects of seller communication, including clarity, politeness, formality, enthusiasm, courtesy, friendliness, assertiveness, calmness, cultural appropriateness, and flirtatiousness.

GPT-4 uses its extensive training data and advanced natural language understanding capabilities to analyze text. It assesses linguistic features such as word choice, sentence structure, and context to classify the tone and style of communication. For instance, politeness can be inferred from courteous phrases, formal language from the absence of colloquialisms, and calmness from measured non-confrontational expressions. This process involves GPT-4's ability to contextualize conversations, recognizing subtle cues that align with the characteristics of each category. For each trait, it assigns values between 0 and 1, where closer to 1 indicates a stronger presence of the trait.

Table 6 presents the results from a linear mixed-effects model with clustered standard errors at the seller level for various traits. We find that sellers, on average, are significantly more verbose when bargaining with female buyers, driven primarily by male sellers. We also find that sellers are relatively informal and more enthusiastic with female buyers. On other

Table 4: Effect of Buyer's Gender on non-Price Outcomes - Pre Delivery Outcomes

Panel A: All Sellers

	(1) (2) Response Bargaining Time Withdrawal	(3) Bargaining Stages	(4) Required Advance	(5) Order Completed	
Female	-4.08	-0.04	0.03	0.00	0.05**
	(3.17)	(0.02)	(0.03)	(0.01)	(0.02)
Constant	25.24***	0.26***	1.42***	0.10***	0.36***
	(5.25)	(0.02)	(0.03)	(0.01)	(0.02)
Observations	982	1064	1064	1064	1064
Clusters/Sellers	517	532	532	532	532

Panel B: Male Sellers

	Response Bargaining Time Withdrawal	Bargaining Stages	Required Advance	Order Completed	
Female	-4.85	-0.04	0.03	0.01	0.04
	(3.99)	(0.03)	(0.04)	(0.02)	(0.03)
Constant	26.02***	0.27***	1.47***	0.10***	0.41***
	(6.81)	(0.02)	(0.04)	(0.02)	(0.03)
Observations	619	667	667	667	667
Clusters/Sellers	327	335	335	335	335

Panel C: Female Sellers

	Response Bargaining Time Withdrawal	Bargaining Stages	Required Advance	Order Completed	
Female	-2.70	-0.03	0.03	-0.01	0.07*
	(5.34)	(0.03)	(0.05)	(0.02)	(0.03)
Constant	23.79**	0.24***	1.35***	0.12***	0.29***
	(8.13)	(0.03)	(0.04)	(0.02)	(0.03)
Observations	363	397	397	397	397
Clusters/Sellers	193	200	200	200	200

Note: The table presents the results of a linear mixed-effects model with clustered standard errors at the seller level on various outcomes before the delivery of the product. 'Female' is the binary variable taking value one if the buyer's gender was assigned as female, zero otherwise. The 'Bargaining Withdrawal' is a binary variable that takes a value one if a seller withdraws from the bargaining by not responding to the buyer. 'Bargaining Stages' refers to the number of stages before the price is finalized. 'Require Advance' takes a value of one when a seller requires advance payment before the item's delivery and a value of zero otherwise. 'Order Completed" is a binary variable that takes value one if the bargaining led to the successful placement of the order for the item. Panel A includes all the sellers, while Panels B and C restrict data to male and female sellers. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Effect of Buyer's Gender on non-Price Outcomes - Post Delivery Outcomes

Panel A: All Sellers

	(1) Order Delivered	(2) Delivery Time	(3) High Quality	(4) Same as Ordered
Female	-0.04	4.06	0.00	0.02
	(0.04)	(3.93)	(0.02)	(0.04)
Constant	0.78***	45.76***	0.03*	0.82***
	(0.03)	(4.13)	(0.01)	(0.03)
Observations	417	321	321	321
Clusters/Sellers	265	214	214	214

Panel B: Male Sellers

	Order Delivered	Delivery Time	High Quality	Same as Ordered
Female	-0.08	2.62	0.01	0.02
	(0.04)	(4.00)	(0.02)	(0.04)
Constant	0.81***	49.20***	0.02	0.82***
	(0.03)	(4.88)	(0.01)	(0.04)
Observations	287	223	223	223
Clusters/Sellers	184	149	149	149

Panel C: Female Sellers

	Order Delivered	Delivery Time	High Quality	Same as Ordered
Female	0.06	7.62	-0.02	0.03
	(0.06)	(8.74)	(0.05)	(0.07)
Constant	0.71***	37.67***	0.07	0.82***
	(0.06)	(7.68)	(0.04)	(0.06)
Observations	130	98	98	98
Clusters/Sellers	81	65	65	65

Note: The table presents the results of a linear mixed-effects model with clustered standard errors at the seller level on various outcomes after the delivery of the product. 'Female' is the binary variable taking value one if the buyer's gender was assigned as female, zero otherwise. The 'Order Delivered' is a binary variable that takes a value of one if the order was delivered conditionally on order placement; otherwise, it is zero. 'Delivery Time' corresponds to the number of days it takes for the order to be delivered, conditional on order placement. 'High Quality' is a binary variable that takes a value of one when the delivered produce is of higher quality than the opposing gender and zero otherwise. "Same as Ordered' is a binary variable that takes a value of one if the delivered produce was the same as ordered, zero otherwise. Panel A includes all the sellers, while Panels B and C restrict data to male and female sellers. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

traits, such as politeness, clarity, friendliness, and assertiveness, we do not find differential treatment for any gender. Except female sellers exhibit slight friendliness towards the in-group. Notably, the baseline levels of politeness, clarity, friendliness, and assertiveness are already high at 82, 77, 75, and 72 percent, respectively. In contrast, most conversations are relatively less formal (66 percent) and even less enthusiastic (51 percent).

5.4 Unsolicited communication attempts

We present evidence of discrimination in unsolicited communication attempts in Table 7. The table presents exponentiated coefficients from Poisson regressions of count variables (such as the number of calls or messages received per day) on gender (Cameron and Trivedi, 2022). We document a significantly higher incidence of post-transaction messages from sellers to females than male buyers. Specifically, on average, sellers send about 1.5 messages to a female buyer for one message to a male buyer. These messages are typically marketing messages, confirming order delivery, requesting to review the order, etc. In addition, female buyers received 1.5 phone calls and 1.5 messages for every call or message received by the male buyer. Similarly, the incidence ratio of receiving unsolicited messages on Facebook and WhatsApp is about nine times more than that of male buyers. Females also receive a disproportionately higher share of friend requests on Facebook than their male counterparts. These results show substantial discrimination in how female buyers are approached or harassed after participation in the marketplace.

5.5 Heterogeneity

The average treatment effect can vary with the observable characteristics of sellers and products. Here, we examine how average treatment effects vary by the seller characteristics, such as the seller's gender, and product characteristics, such as the gender orientation of the sold product. These tests allow us to examine the characteristics likely driving the average treatment effects and provide a deeper understanding of how the treatment effects vary by these factors.

Table 6: Linguistic Analysis of Seller's Responses

Panel A: All Sellers

	(1) Verbose	(2) Polite	(3) Clear	(4) Formal	(5) Enthusiastic	(6) Friendly	(7) Assertive
Female	44.08***	0.01	0.02	-0.02**	0.02*	0.01	0.01
	(13.24)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	303.80***	0.82***	0.77***	0.66***	0.51***	0.75***	0.72***
	(12.56)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	982	963	963	963	963	963	963
Clusters/Sellers	517	516	516	516	516	516	516

Panel B: Male Sellers

	(1) Verbose	(2) Polite	(3) Clear	(4) Formal	(5) Enthusiastic	(6) Friendly	(7) Assertive
Female	57.16**	-0.00	0.01	-0.02*	0.02	0.00	0.02
	(17.58)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	317.19***	0.83***	0.76***	0.66***	0.52***	0.76***	0.71***
	(15.53)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	619	608	608	608	608	608	608
Clusters/Sellers	327	326	326	326	326	326	326

Panel C: Female Sellers

	(1) Verbose	(2) Polite	(3) Clear	(4) Formal	(5) Enthusiastic	(6) Friendly	(7) Assertive
Female	24.33	0.02	0.02	-0.03	0.03	0.03*	-0.00
	(19.31)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Constant	279.45***	0.80***	0.78***	0.67***	0.50***	0.72***	0.73***
	(21.14)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	363	355	355	355	355	355	355
Clusters/Sellers	193	193	193	193	193	193	193

Note: The table presents the results of a linear mixed-effects model with clustered standard errors at the seller level for various traits from sellers' language analysis. 'Female' is the binary variable taking value one if the buyer's gender was assigned as female, zero otherwise. 'Verbose' captures the verbosity of the seller (in words per message) when interacting with a particular gender, 'Polite', 'Clear', 'Formal', 'Enthusiastic', 'Friendly', and 'Assertive' assume values between 0 and 1, where closer to 1 indicates a stronger presence of the trait. Panel A includes all the sellers, while Panels B and C restrict data to male and female sellers. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Incidence of Unsolicited Communication Attempts

	(1) Post-Transaction Message	(2) Phone Call	(3) Phone Message	(4) Facebook Message	(5) Whatsapp Message	(6) Friend Requests
Female	1.04	1.38***	1.58***	9.50**	9.50***	1.9e+07
	(0.04)	(0.10)	(0.07)	(7.06)	(0.82)	(2.9e+10)
Constant	5.97***	0.24***	0.63***	0.00***	0.12***	0.00
	(0.18)	(0.01)	(0.02)	(0.00)	(0.01)	(0.00)
Observations	417	2504	2504	2504	2504	2504

Exponentiated coefficients; Standard errors in parentheses

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

Note: The figure presents results from Poisson regression of count variables on gender. Post-Transaction Message (column 1) captures the number of times a seller message the buyer after the completion of the transaction. Phone Calls (column 2) and Phone Messages (column 3) measure the number of calls and messages received per day per buyer during the experiment. Similarly, Facebook Message (column 4) and Whatsapp Message (column 5) measure the number of messages received on Facebook and Whatsapp per day for each buyer during the duration of the study.

	All Sellers		Male Sellers		Female Sellers	
	(1)	(2)	(3)	(4)	(5)	(6)
	First Price	Final Price	First Price	Final Price	First Price	Final Price
Buyer Gender						
Female	-18.95*	-21.70	-15.69	-17.31	-39.28	-35.87
	(10.41)	(17.98)	(10.68)	(21.45)	(27.59)	(28.36)
Product Orientation						
Female Oriented	-38.02	-24.79	-30.70	-28.44	-151.99	-116.32
	(75.00)	(77.35)	(86.95)	(87.68)	(151.92)	(171.00
Female × Female Oriented	14.92	11.78	4.23	11.26	48.70*	19.50
	(11.65)	(20.47)	(12.90)	(25.16)	(28.31)	(30.29)
Marital Status of Seller						
Single	-91.29	-85.97	-72.38	-75.67	-96.32	-49.63
	(98.62)	(99.00)	(117.35)	(114.63)	(166.16)	(186.10
Female × Single	8.83	72.48***	16.52	78.83**	-10.30	46.94
	(12.18)	(25.81)	(11.71)	(31.80)	(36.41)	(34.42)
Religious Content on Seller Profile						
Yes	52.22	-3.32	1.45	-12.53	106.81***	15.97
	(43.30)	(56.04)	(87.63)	(87.37)	(37.06)	(51.15)
Female × Yes	7.43	-24.07	7.89	-30.60	1.48	-11.49
	(11.41)	(21.42)	(14.86)	(28.28)	(14.03)	(26.62)
Constant	1329.21***	1353.60***	1306.75***	1314.72***	1471.39***	1508.26*
	(66.70)	(71.03)	(78.43)	(80.39)	(145.47)	(164.08
Observations	448	448	304	304	144	144
Clusters/Sellers	224	224	152	152	72	72

Cluster/Seller robust standard errors in parenthesis

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

6 Conclusion

At the heart of addressing gender discrimination lies the stark reality that individuals in low-income countries face. Here, the struggle for equal rights and opportunities often takes on a more profound significance. In this context, the emergence of online marketplaces presents a glimmer of hope. These digital platforms not only offer a space for economic empowerment but also have the potential to dismantle traditional gender roles and biases that perpetuate inequality. Online marketplaces can help challenge societal norms, expand educational and vocational horizons, and foster financial independence by allowing women in low-income countries to participate in commerce.

This paper investigated gender discrimination on the demand side of the Facebook online marketplace in Pakistan and documented various interesting results. On the one hand, male and female buyers face no differential treatment on economic variables such as prices and product quality, but on the other, female buyers disproportionately encounter higher advances towards them through messages, calls, and friend requests. In patriarchal contexts like Pakistan, these advances can hinder women's full participation in economic transactions because they may face heightened pressure from their male family members to shield themselves from advances made by other men.

The paper has several limitations which may be explored further in future research. For example, this paper has focused on product prices at the bottom of the price distribution; it is likely that discrimination plays out differently in high-ticket items such as cars, properties, etc. Additionally, our only signal of gender is name, and we avoid using photographs or other information in profiles to provoke sellers. Sellers likely respond differently if profiles have pictures or other sensitive information. For example, seeing how sellers respond to profiles with seemingly attractive pictures might reveal interesting insights. In that aspect, our results should be considered the lower bound of discrimination.

This paper has focused on the demand side of the market. To properly realize the potential of the online marketplace in addressing gender discrimination, there needs to be an investigation into the supply side and the experiences women face when participating in these marketplaces as entrepreneurs. This is an important margin to explore and may have far-reaching implications for women's inclusion and empowerment in marketplaces.

References

Asad, S. A., Banerjee, R., and Bhattacharya, J. (2020). Do workers discriminate against their out-group employers? Evidence from an online platform economy.

Ayres, I., Banaji, M., and Jolls, C. (2015). Race effects on eBay. *The RAND Journal of Economics*, 46(4):891–917.

Ayres, I. and Siegelman, P. (1995). Race and gender discrimination in bargaining for a new car. *American Economic Review*, pages 304–321.

Baktash, J. A. and Dawodi, M. (2023). Gpt-4: A Review on Advancements and Opportunities in Natural Language Processing.

Basu, K. (2003). The economics and law of sexual harassment in the workplace. *Journal of Economic Perspectives*, 17(3):141–157.

Becker, G. S. (1957). *The economics of discrimination.* University of Chicago Press.

Bellemare, C., Bissonnette, L., and Kröger, S. (2014). Statistical power of within and between-subjects designs in economic experiments.

Bohren, J. A., Imas, A., and Rosenberg, M. (2019). The Dynamics of Discrimination: Theory and Evidence. *American Economic Review*, 109(10):3395–3436.

Cameron, A. C. and Trivedi, P. K. (2022). Count-data models. In *Microeconometrics Using Stata*, volume II, chapter 20, pages 1021–1032. Stata Press, second edition.

Castillo, M., Petrie, R., Torero, M., and Vesterlund, L. (2013). Gender differences in bargaining outcomes: A field experiment on discrimination. *Journal of Public Economics*, 99:35–48.

Chandio, B. A., Imran, A. S., Bakhtyar, M., Daudpota, S. M., and Baber, J. (2022). Attention-Based RU-BiLSTM Sentiment Analysis Model for Roman Urdu. *Applied Sciences*, 12(7):3641.

Chen, Y. and Li, S. X. (2009). Group Identity and Social Preferences. *The American Economic Review*, 99(1):431–457.

Cook, C., Diamond, R., Hall, J., List, J. A., and Oyer, P. (2019). The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers.

Croson, R. and Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature*, 47(2):448–74.

de Chaisemartin, C. and Ramirez-Cuellar, J. (2024). At What Level Should One Cluster Standard Errors in Paired and Small-Strata Experiments? *American Economic Journal: Applied Economics*, 16(1):193–212.

DellaVigna, S. (2018). Structural Behavioral Economics. In *Handbook of Behavioral Economics: Applications and Foundations*, volume 1, pages 613–723. North-Holland.

Duflo, E. (2012). Women empowerment and economic development. *Journal of Economic Literature*, 50(4):1051–79.

Edelman, B., Luca, M., and Svirsky, D. (2017). Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment. *American Economic Journal: Applied Economics*, 9(2):1–22.

Exley, C. L., Niederle, M., and Vesterlund, L. (2020). Knowing when to ask: The cost of leaning in. *Journal of Political Economy*, 128(3):816–854.

Fitzpatrick, A. (2017). Shopping While Female: Who Pays Higher Prices and Why? *American Economic Review*, 107(5):146–149.

Ghulam, H., Zeng, F., Li, W., and Xiao, Y. (2019). Deep Learning-Based Sentiment Analysis for Roman Urdu Text. *Procedia Computer Science*, 147:131–135.

Guryan, J. and Charles, K. K. (2013). Taste-based or statistical discrimination: The economics of discrimination returns to its roots. *Economic Journal*, 123(572):417–432.

Hannák, A., Wagner, C., Garcia, D., Mislove, A., Strohmaier, M., and Wilson, C. (2017). Bias in online freelance marketplaces: Evidence from taskrabbit and fiverr. In *Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing*, pages 1914–1933.

List, J. a. (2004). The Nature and Extent of Discrimination in the Marketplace: Evidence From the Field. *Quarterly Journal of Economics*, 119(1):49–89.

List, J. A., Sadoff, S., and Wagner, M. (2011). So you want to run an experiment, now what? Some simple rules of thumb for optimal experimental design. *Experimental Economics*, 14:439–457.

List, J. A., Shaikh, A. M., and Xu, Y. (2019). Multiple hypothesis testing in experimental economics. *Experimental Economics*, 22:773–793.

Mehmood, F., Ghani, M. U., Ibrahim, M. A., Shahzadi, R., Mahmood, W., and Asim, M. N. (2020). A Precisely Xtreme-Multi Channel Hybrid Approach for Roman Urdu Sentiment Analysis. *IEEE Access*, 8:192740–192759.

Mehmood, K., Essam, D., and Shafi, K. (2019). Sentiment Analysis System for Roman Urdu. pages 29–42.

Michelitch, K. (2015). Does Electoral Competition Exacerbate Interethnic or Interpartisan Economic Discrimination? Evidence from a Field Experiment in Market Price Bargaining. *American Political Science Review*, 109(1):43–61.

Neumark, D. (2018). Experimental Research on Labor. *Journal of Economic Literature*, 56(3):799–866.

OpenAI, :, Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., Avila, R., Babuschkin, I., Balaji, S., Balcom, V., Baltescu, P., Bao, H., Bavarian, M., Belgum, J., Bello, I., Berdine, J., Bernadett-Shapiro, G., Berner, C., Bogdonoff, L., Boiko, O., Boyd, M., Brakman, A.-L., Brockman, G., Brooks, T., Brundage, M., Button, K., Cai, T., Campbell, R., Cann, A., Carey, B., Carlson, C., Carmichael, R., Chan, B., Chang, C., Chantzis, F., Chen, D., Chen, S., Chen, R., Chen, J., Chen, M., Chess, B., Cho, C., Chu, C., Chung, H. W., Cummings, D., Currier, J., Dai, Y., Decareaux, C., Degry, T., Deutsch, N., Deville, D., Dhar, A., Dohan, D., Dowling, S., Dunning, S., Ecoffet, A., Eleti, A., Eloundou, T., Farhi, D., Fedus, L., Felix, N., Fishman, S. P., Forte, J., Fulford, I., Gao, L., Georges, E., Gibson, C., Goel, V., Gogineni, T., Goh, G., Gontijo-Lopes, R., Gordon, J., Grafstein, M., Gray, S., Greene, R., Gross, J., Gu, S. S., Guo, Y., Hallacy, C., Han, J., Harris, J., He, Y., Heaton, M., Heidecke, J., Hesse, C., Hickey, A., Hickey, W., Hoeschele, P., Houghton, B., Hsu, K., Hu, S., Hu, X., Huizinga, J., Jain, S., Jain, S., Jang, J., Jiang, A., Jiang, R., Jin, H., Jin, D., Jomoto, S., Jonn, B., Jun, H., Kaftan, T., Kaiser, , Kamali, A., Kanitscheider, I., Keskar, N. S., Khan, T., Kilpatrick, L., Kim, J. W., Kim, C., Kim, Y., Kirchner, H., Kiros, J., Knight, M., Kokotajlo, D., Kondraciuk, , Kondrich, A., Konstantinidis, A., Kosic, K., Krueger, G., Kuo, V., Lampe, M., Lan, I., Lee, T., Leike, J., Leung, J., Levy, D., Li, C. M., Lim, R., Lin, M., Lin, S., Litwin, M., Lopez, T., Lowe, R., Lue, P., Makanju, A., Malfacini, K., Manning, S., Markov, T., Markovski, Y., Martin, B., Mayer, K., Mayne, A., McGrew, B., McKinney, S. M., McLeavey, C., McMillan, P., McNeil, J., Medina, D., Mehta, A., Menick, J., Metz, L., Mishchenko, A., Mishkin, P., Monaco, V., Morikawa, E., Mossing, D., Mu, T., Murati, M., Murk, O., Mély, D., Nair, A., Nakano, R., Nayak, R., Neelakantan, A., Ngo, R., Noh, H., Ouyang, L., O'Keefe, C., Pachocki, J., Paino, A., Palermo, J., Pantuliano, A., Parascandolo, G., Parish, J., Parparita, E., Passos, A., Pavlov, M., Peng, A., Perelman, A., Peres, F. d. A. B., Petrov, M., Pinto, H. P. d. O., Michael, Pokorny, Pokrass, M., Pong, V., Powell, T., Power, A., Power, B., Proehl, E., Puri, R., Radford, A., Rae, J., Ramesh, A., Raymond, C., Real, F., Rimbach, K., Ross, C., Rotsted, B., Roussez, H., Ryder, N., Saltarelli, M., Sanders, T., Santurkar, S., Sastry, G., Schmidt, H., Schnurr, D., Schulman, J., Selsam, D., Sheppard, K., Sherbakov, T., Shieh, J., Shoker, S., Shyam, P., Sidor, S., Sigler, E., Simens, M., Sitkin, J., Slama, K., Sohl, I., Sokolowsky, B., Song, Y., Staudacher, N., Such, F. P., Summers, N., Sutskever, I., Tang, J., Tezak, N., Thompson, M., Tillet, P., Tootoonchian, A., Tseng, E., Tuggle, P., Turley, N., Tworek, J., Uribe, J. F. C., Vallone, A., Vijayvergiya, A., Voss, C., Wainwright, C., Wang, J. J., Wang, A., Wang, B., Ward, J., Wei, J., Weinmann, C., Welihinda, A., Welinder, P., Weng, J., Weng, L., Wiethoff, M., Willner, D., Winter, C., Wolrich, S., Wong, H., Workman, L., Wu, S., Wu, J., Wu, M., Xiao, K., Xu, T., Yoo, S., Yu, K., Yuan, Q., Zaremba, W., Zellers, R., Zhang, C., Zhang, M., Zhao, S., Zheng, T., Zhuang, J., Zhuk, W., and Zoph, B. (2023). GPT-4 Technical Report.

Phelps, E. S. (1972). The Statistical theory of Racism and Sexism. *American Economic Review*, 62(4):659–661.

Ranganath, R., Jurafsky, D., and McFarland, D. A. (2013). Detecting friendly, flirtatious, awkward, and assertive speech in speed-dates. *Computer Speech & Language*, 27(1):89–115.

Wilcoxon, F. (1945). Individual comparisons by ranking methods. *Biometrics*, 1:80–83.

A Tables

Table A1: Summary of Posts on Facebook Marketplace

	N	Non-Missing	Min	Max	Mean	SD	P25	P50	P75
Category									
arts	1,870	1,309	12	650,000	3,447	18,516	1650	2200	2900
health	1,859	1,284	11	123,466	1,594	4,842	500	1000	1600
furniture	1,810	1,513	11	3,150,000	27,861	91,422	1500	11500	30000
misc	1,784	1,344	11	9,000,000	287,721	1,046,039	600	1999	15000
cell-phones	1,708	1,672	11	1,111,111	29,653	42,051	14000	22500	32000
home-decor	1,562	1,110	11	150,000	3,261	9,659	500	1150	2500
kitchen-products	1,394	1,098	11	999,999	7,065	38,067	650	1699	5000
bags	1,373	1,004	11	35,000	2,172	1,654	1499	2000	2700
shoes	1,224	977	14	40,000	2,367	1,979	1350	1950	3000
mens	1,176	1,002	13	60,000	2,004	2,396	1000	1610	2400
womens	1,151	846	12	100,000	3,250	6,521	1699	2450	3200
kids-clothing	1,068	811	11	40,000	2,031	3,334	800	1499	2250
bedding	1,061	844	12	40,000	2,353	2,484	1150	1550	3000
computers	945	867	12	299,000	31,552	38,854	4000	19500	45000
appliances	840	709	12	999,999	18,146	59,726	1500	5000	16000
portable-audio-video	658	612	15	35,000	1,952	2,762	615	1400	2300
kids	619	555	12	160,000	4,883	9,657	750	2500	5500
home-lighting	614	439	11	125,000	3,263	8,586	649	1600	3200
autoparts	485	430	11	8,100,000	218,213	657,383	1200	7000	44000
home-audio-video	416	386	50	499,999	19,516	49,836	1295	3374.5	16000
media	414	344	30	1,234,567	8,608	67,990	400	1149.5	2200
cables-adaptors	359	333	40	123,456	1,415	7,093	220	350	850
security-cameras	339	306	25	65,000	9,082	9,576	3499	5000	15000
tools	336	302	11	1,350,000	39,645	141,324	1234	4200	16500
bath-products	335	289	14	40,000	3,151	4,313	600	2200	4200
cell-phone-accessories	335	321	16	240,000	8,740	22,281	400	800	5800
home-heating-cooling	334	288	11	3,024,884	23,808	180,980	1449.5	2350	7500
scrap-metal	247	176	11	9,000,000	476,584	1,413,558	287.5	4350	111728
powersports	215	184	14	7,000,000	567,503	1,006,186	45000	122500	700000

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Table A1: Summary of Posts on Facebook Marketplace

	N	Non-Missing	Min	Max	Mean	SD	P25	P50	P75
guitars-basses	210	197	111	600,000	19,059	49,309	7000	10000	17500
video-games-consoles	210	200	50	240,000	13,733	26,036	1075	4050	15000
printers-scanners-fax	207	178	31	1,300,000	44,753	149,826	3500	14000	27999
sports-gear	205	163	18	69,999	4,826	9,011	700	2000	5000
costumes	200	139	13	25,000	1,743	2,600	400	1150	2200
power-adapters-chargers	189	178	15	111,111	2,940	10,265	400	778	1560
outdoor-recreation-gear	188	172	14	365,000	21,984	44,676	2700	8750	21000
cleaning-supplies	181	174	11	80,000	4,328	6,787	2000	3200	4000
baby-clothing	178	128	12	3,899	1,234	761	500	1242	1625
motorcycles	158	141	70	850,000	78,734	86,762	35000	68000	95000
antiques	128	89	14	3,645,000	51,545	385,830	950	1700	11500
exercise-fitness	125	105	15	176,699	24,520	38,072	975	6999	27000
planners	103	79	20	2,375,000	79,691	290,007	850	1600	8500
outdoor-cooking-equipments	102	88	99	1,000,000	51,029	133,602	3500	14500	35000
chalkboards	100	74	25	8,100,000	126,176	942,710	965	2000	12500
shipping-containers	73	55	45	7,070,000	354,560	1,286,983	550	1650	5300
adidas-hoodies	65	53	150	5,500	1,609	721	1300	1550	1800
bathroom-faucets	65	56	12	19,500	4,460	4,015	692.5	5000	6650
dolls	61	45	100	12,345	1,809	2,047	750	1200	2000
flash-drives	60	56	42	23,500	3,793	4,907	925	1775	4500
audio-equipment	55	41	123	250,000	31,396	42,559	6500	17000	45000
label-makers	53	38	45	7,100,000	350,369	1,486,417	720	2649.5	7500
toy-vehicles	53	51	75	975,000	34,879	158,960	550	1000	2500
car-electronics	51	48	35	350,000	16,468	51,054	2800	4750	11000
stuffed-animals	51	40	100	16,500	2,904	4,200	350	1025	2650
walnut-lumber	50	44	16	88,000	5,045	18,006	500	1000	2050
cash-registers	49	38	85	1,700,000	170,627	407,561	1200	8500	35000
asphalt-paving	47	38	15	4,700,000	725,165	1,120,706	10000	216000	1600000
heated-blankets	45	33	150	123,456	11,007	29,165	1500	3150	6500
shoe-shine-kits	43	27	17	20,000	2,628	3,949	350	1799	3100

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Table A1: Summary of Posts on Facebook Marketplace

	N	Non-Missing	Min	Max	Mean	SD	P25	P50	P75
tire-machines	41	33	12	1,325,000	417,831	491,094	5000	120000	800000
apple-pencils	40	36	123	515,000	71,480	95,116	14999.5	57500	83999.5
tongue-and-groove-planks	40	34	65	1,234,645	82,356	269,014	350	1349.5	4500
electric-blankets	38	26	186	123,456	8,782	23,606	1900	3325	7500
caps	36	27	22	15,000	2,505	2,706	1199	2000	2800
cat-supplies	36	29	50	11,935	2,490	3,401	465	1050	2500
pretend-play-toys	36	30	480	20,000	2,853	4,349	950	1470	2150
microscopes	34	25	35	2,495,000	186,803	631,048	350	3000	7500
square-steel-tubes	34	27	20	123,456	16,275	33,713	220	1690	18000
fill-dirt	33	31	123	8,100,000	1,806,247	2,159,147	13000	1600000	2550000
pedestal-sinks	33	25	123	6,900,000	282,012	1,378,761	2000	4500	8500
stainless-steel-sinks	32	23	149	250,000	29,237	54,918	6000	11800	27000
lockers	31	23	365	10,000	3,105	2,449	1700	2500	3500
tailored-clothing	29	23	149	30,000	3,832	6,757	800	1450	4000
educational-toys	26	24	280	3,500	1,315	972	599.5	959.5	1899
action-figures	25	20	300	5,400	2,113	1,554	1020	1750	2787.5
bird-supplies	24	19	1,100	17,000	7,592	4,634	3500	7500	11500
cork-boards	23	16	25	5,850	1,641	1,381	675	1575	2150
dollhouses	23	19	15	45,000	6,248	11,230	1000	1600	4950
melodica-instruments	23	22	800	200,000	23,227	42,670	1950	13999.5	18000
pianos-keyboards	23	20	12	46,000	12,316	13,681	1675	4150	19500
fathers-day-gifts	19	16	150	3,850	1,259	1,156	335	1087.5	1775
nebulizers	19	11	123	21,500	6,066	6,945	2000	3500	5000
pallet-jacks	19	17	122	2,200,000	249,076	550,057	11700	42500	125000
quartz-counter-tops	19	15	123	1,234,567	87,699	317,370	470	3000	18000
wooden-toys	19	15	15	16,000	2,365	4,044	290	1450	2000
corrugated-sheets	17	12	95	850,000	75,342	244,063	124	2240	11500
bird-wildlife-accessories	16	13	80	1,799	891	687	300	500	1650
birthday-decorations	16	7	220	2,200	1,041	937	220	500	2000
laser-pointers	15	12	350	1,600	1,056	489	535	1075	1525

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Table A1: Summary of Posts on Facebook Marketplace

	N	Non-Missing	Min	Max	Mean	SD	P25	P50	P75
safety-jackets	14	8	450	5,500	2,955	1,822	1545	2800	4500
white-noise-machines	14	13	380	43,000	10,923	13,584	1499	2000	20000
corded-phones	13	11	45	4,000	1,004	1,156	200	585	1500
desk-organizers	13	12	110	7,200	1,481	1,996	300	750	1825
accordions	12	10	800	200,000	31,730	59,714	6000	16500	22000
cameras	12	9	1,000	138,000	53,556	41,368	23000	52000	65000
magnifying-glasses	12	9	399	2,955	1,389	801	799	1600	1700
round-pens	12	9	123	21,500	6,736	7,654	1500	4500	5000
landline-phones	11	10	1,150	26,500	5,480	7,846	2000	2450	3000
alpinestars-motorcycle-riding-gear	10	8	300	16,000	5,831	5,551	1175	4500	9500
pet-collars-leashes	10	8	123	4,000	1,321	1,377	375	922.5	1924.5
teacher-supplies	10	9	248	9,500	2,866	2,927	600	2450	3500
centrifuges	9	4	135	40,000	14,034	17,779	3067.5	8000	25000
ice-melt	9	6	123	21,500	8,887	8,663	4200	4750	18000
nike-windbreaker-jackets	9	6	1,000	7,000	2,431	2,269	1234	1675	2000
pet-feeding-supplies	9	8	300	14,999	3,162	4,892	600	1600	2799.5
puzzles	9	7	170	780	370	196	250	350	400
roof-trusses	9	6	123	21,500	8,887	8,663	4200	4750	18000
walkie-talkies	9	9	150	240,000	38,850	77,588	3500	9500	15000
bicycles	8	8	3,500	245,000	81,500	99,335	10000	24250	167500
microphones	8	8	370	15,999	6,406	5,862	1190	4749	11500
paper-cutters	8	5	50	12,500	3,034	5,313	399	970	1250
toilets	8	6	450	1,100,000	184,583	448,462	600	1924.5	2599
cars	7	4	999	1,320,000	404,000	622,003	15499.5	147500	792500
laminators	7	6	140	1,250	412	424	150	267.5	399
the-grinch-shirts	7	7	170	1,250	527	404	170	300	750
couples-shirts	6	4	18	1,500	1,067	704	659	1375	1475
fog-machines	6	5	3,500	25,000	12,900	8,532	6000	15000	15000
packers-nfl-apparel	6	4	240	15,500	4,835	7,150	920	1800	8750
readymade-clothing	6	3	12	2,700	1,304	1,347	12	1200	2700

Continued on the next page

Table A1: Summary of Posts on Facebook Marketplace

	N	Non-Missing	Min	Max	Mean	SD	P25	P50	P75
school-supplies	6	4	123	1,800	626	792	151.5	289.5	1099.5
studio-monitors	6	2	32,000	75,500	53,750	30,759	32000	53750	75500
credit-card-readers	5	4	35	67,000	18,046	32,718	92.5	2575	36000
envelopes	5	4	399	2,000	1,400	750	824.5	1600	1975
floor-tiles	5	4	138	2,200	662	1,025	144	155	1180
journal-notebooks	5	5	499	1,800	850	535	650	650	650
mail-organizers	5	5	250	1,080	566	378	250	400	850
mont-blanc-pens	5	5	399	4,500	1,650	1,656	600	1250	1500
mothers-day-gifts	5	5	350	2,700	950	984	499	599	600
paper-shredders	5	5	395	650,000	132,309	289,424	399	1250	9500
rf-modulators	5	4	1,490	70,000	18,618	34,255	1490	1490	35745
rolling-storage-carts	5	5	395	650,000	131,309	289,962	399	1250	4500
safes	5	5	18,000	3,900,000	1,084,876	1,670,697	30000	126378	1350000
whiteboards	5	3	799	2,000	1,266	643	799	1000	2000
a4-paper	4	4	50	20,000	6,375	9,357	250	2724.5	12499.5
award-ribbons	4	4	395	650,000	163,011	324,660	397	824.5	325625
drums	4	2	7,499	9,500	8,500	1,415	7499	8499.5	9500
gift-cards	4	3	550	9,000	3,400	4,850	550	650	9000
iphone-xr-black	4	3	33,000	75,000	52,667	21,127	33000	50000	75000
packing-moving-boxes	4	4	1,600	239,000	61,650	118,236	2050	3000	121250
place-card-holders	4	4	395	650,000	163,011	324,660	397	824.5	325625
plexiglass-shields	4	4	395	650,000	163,011	324,660	397	824.5	325625
poly-mailer-bundles	4	4	395	650,000	163,011	324,660	397	824.5	325625
stationery-sets	4	4	99	1,350	537	556	199	349	874.5
usb-adapters	4	4	700	1,799	1,275	451	975	1300	1574.5
wedding-decorations	4	3	2,700	24,950	10,517	12,514	2700	3900	24950
apple-iphone-xr-unlocked	3	3	33,000	49,500	40,833	8,282	33000	40000	49500
bubble-wrap	3	3	65	700	421	325	65	499	700
electric-scooters	3	3	8,000	60,000	30,000	26,907	8000	22000	60000
guitar-pedals	3	2	400	70,000	35,200	49,215	400	35200	70000

Continued on the next page

Table A1: Summary of Posts on Facebook Marketplace

	N	Non-Missing	Min	Max	Mean	SD	P25	P50	P75
insulation-boards	3	2	550	750	650	141	550	650	750
pendleton-apparel	3	2	500	1,900	1,200	990	500	1200	1900
software	3	3	500	13,500	5,167	7,234	500	1500	13500
string-instruments	3	3	4,000	13,500	10,167	5,346	4000	13000	13500
apartments-for-rent	2	2	25,000	38,000	31,500	9,192	25000	31500	38000
boats	2	2	50,000	94,000	72,000	31,113	50000	72000	94000
fire-extinguishers	2	2	500	15,000	7,750	10,253	500	7750	15000
houses-for-rent	2	1	2,200,000	2,200,000	2,200,000	.	2200000	2200000	2200000
jewelry	2	1	250	250	250	.	250	250	250
juneteenth	2	1	1,200	1,200	1,200	.	1200	1200	1200
micro-sd-cards	2	2	2,675	3,600	3,138	654	2675	3137.5	3600
peg-boards	2	2	291	399	345	76	291	345	399
pvc-pipes	2	2	6,999	6,999	6,999	0	6999	6999	6999
remote-car-starters	2	2	8,000	12,500	10,250	3,182	8000	10250	12500
ti-84-calculators	2	1	2,000	2,000	2,000	.	2000	2000	2000
trucks	2	2	1,290,000	2,558,500	1,924,250	896,965	1290000	1924250	2558500
vending-machines	2	1	7,800	7,800	7,800	.	7800	7800	7800
wind-instruments	2	2	123	45,000	22,562	31,733	123	22561.5	45000
batteries	1	1	1,234	1,234	1,234	.	1234	1234	1234
clipboards	1	1	500	500	500	.	500	500	500
garagesale	1	1	250,000	250,000	250,000	.	250000	250000	250000
playstation-5-controllers	1	1	16,000	16,000	16,000	.	16000	16000	16000
scissors	1	1	399	399	399	.	399	399	399
townhouses-for-rent	1	0	.	.	.	.			
trophies	1	1	399	399	399	.	399	399	399
vintage-school-desks	1	1	399	399	399	.	399	399	399
water-features	1	1	450	450	450	.	450	450	450
water-softeners	1	1	600	600	600	.	600	600	600
Total	31,120	25,151	11	9,000,000	44,657	352,746	1000	2200	8000

Note: This table summarizes the census of posts from Facebook Marketplace as of January 05th, 2022. Column N indicates the number of posts against a category, and Non-Missing indicates the number of posts with a positive posted price. Min, Max, Mean, and SD indicate the price's minimum, maximum, mean, and standard deviation by each category, respectively. P25, P50, and P75 are the 25th, 50th, and 75th percentiles of the posted price.

Table A2: Description of Selected Categories

Category	Description
arts	This mainly includes clothing articles for men and women with calligraphy, embroidery, and artwork.
health	This includes a variety of products ranging from skincare, hair care, beauty products, etc.
home-decor	This includes home decoration products such as frames, vases, clocks, lamps, etc.
bags	This includes bags such as handbags, wallets, clutches, pouches, etc. for men and women.
shoes	This includes shoes such as sandals, sneakers, boots, etc. for men and women.
mens	This includes products such as clothes, shoes, wallets, caps, etc. for men.
womens	This includes products such as clothes, shoes, wallets, caps, etc. for women.
kids-clothing	This includes clothing articles for kids.
bedding	This includes bed-sheets, comforter sets, pillows, blankets, etc.
portable-audio-video	This mainly includes earphones, headphones, portable speakers, etc.

Note: This table presents the description of categories that are selected for the study.

Table A3: Names of Buyers

First Name	Last Name	Gender
Shazia	Ali	Female
Samina	Rehman	Female
Saima	Iqbal	Female
Ayesha	Ahmed	Female
Muhammad	Iqbal	Male
Ahmed	Ali	Male
Abdul	Rehman	Male
Ali	Ahmed	Male

Notes: The table presents the selected names of buyers used for the experiment.

B Figures

Figure B1: Bargaining Script 1

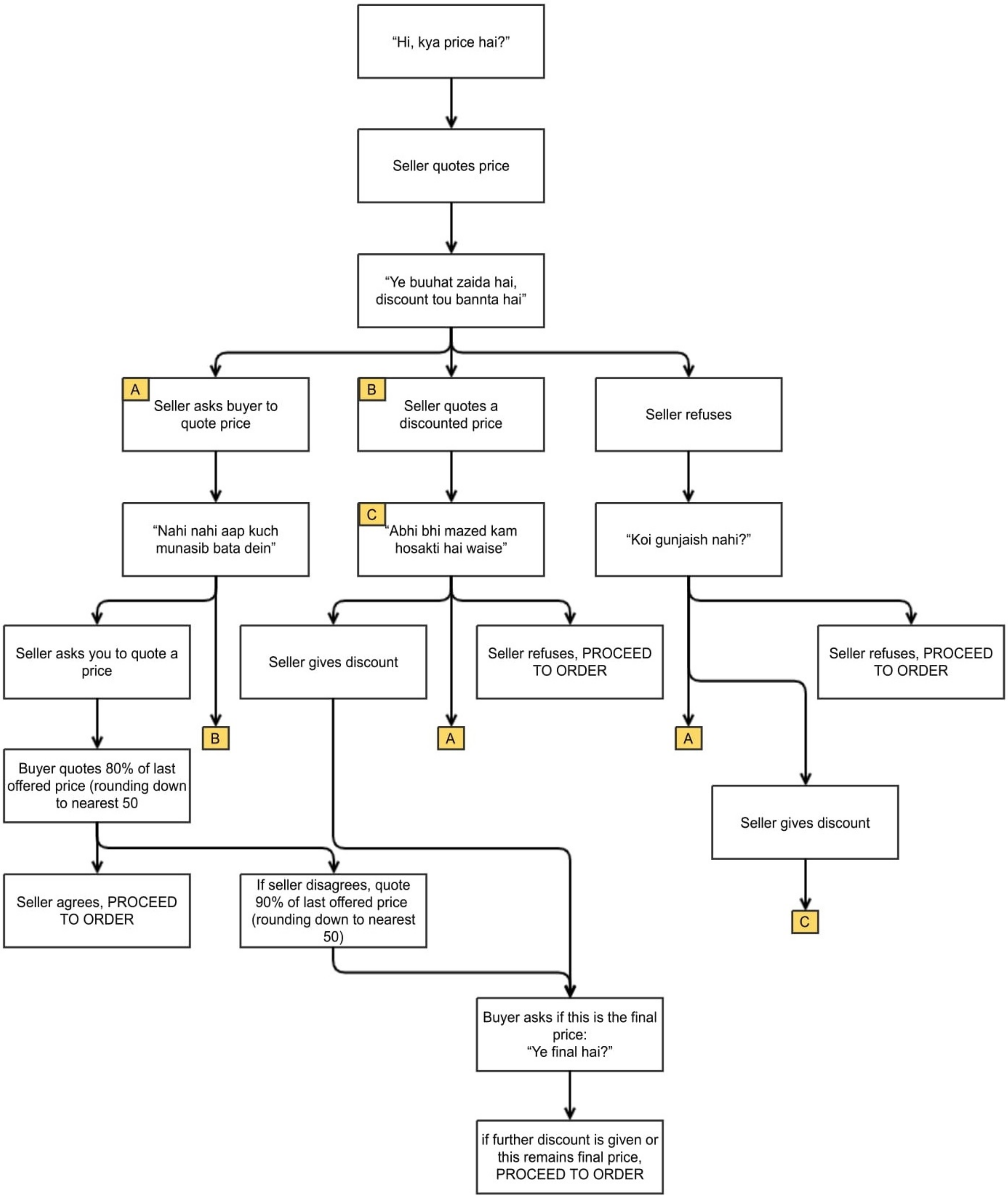

Figure B2: Bargaining Script 2

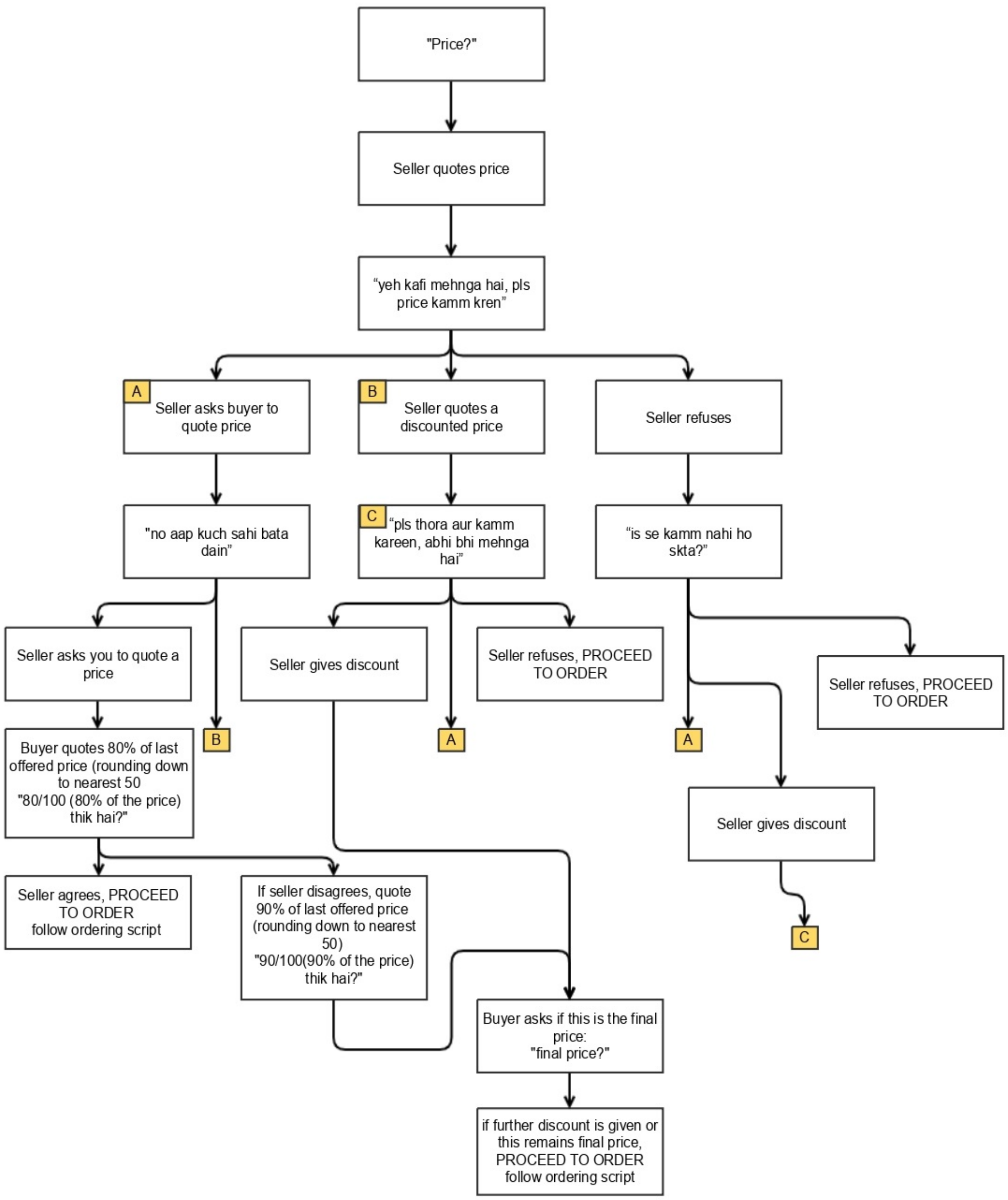

Figure B3: Ordering Script 1

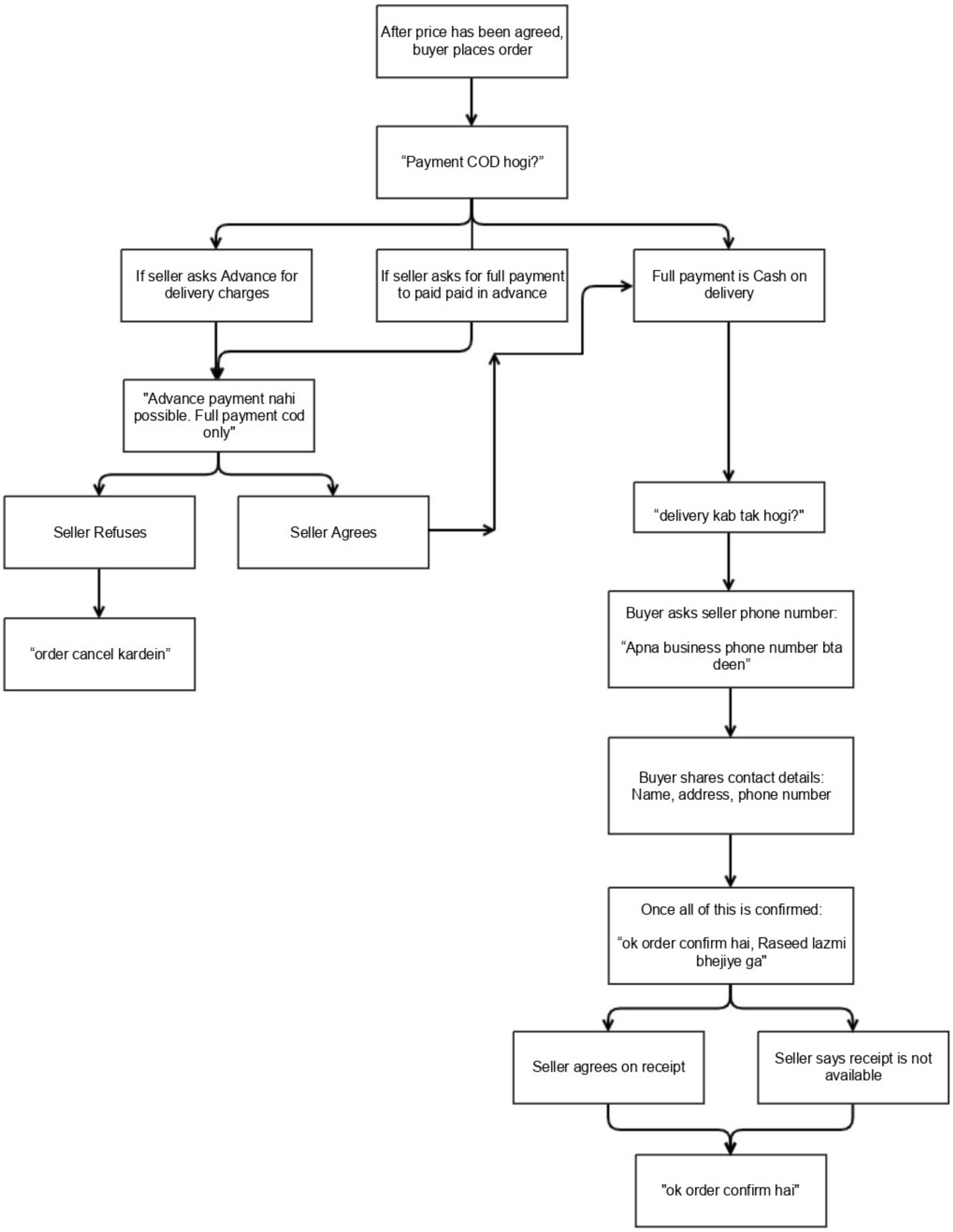

Figure B4: Ordering Script 2